Eye Tracking Social Preferences

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Acknowledgement: This paper was partly conceived when Funaki was visiting Tilburg University. We thank Cristina Bicchieri, Luc Bissonnette, Colin Camerer, David Cooper, Eric van Damme, Francesco Guala, Eline van der Heijden, Jan Willem Lindemans, Peter McNally, Wieland Mueller, Charles Noussair, Rik Pieters, Ernesto Reuben, Koji Shirai, Martin Strobel, Stefan Trautmann, Erik Trulin, David Vonka, Gari Walkowitz, Steve Ziliak and participants at the ESA meeting in Lyon, the IMEBE meeting in Granada, the M-BEES Symposium in Maastricht, and seminar participants in Innsbruck, Koblenz, Norwich, and Tilburg for helpful comments and discussions. Financial support from JSPS KAKENHI Grant (23530231) and the Mozaiek Grant by the Netherlands Organization Scientific Research (NWO) are gratefully acknowledged.

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Abstract

We hypothesize that if people are motivated by a particular social preference, then choosing in accordance with this preference will lead to an identifiable pattern of eye movements. We track eye movements while subjects make choices in simple three-person distribution experiments. We characterize each choice 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 movement data. The evidence indicates that distributional choices are broadly consistent with the choice rule implied by eye movements. In other words, 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 eye movements. This correspondence lends credibility to the behavioral relevance of social preferences models.

Keywords: social preferences, experiments, eye tracking, information processing

Eye Tracking Social Preferences

Over the last two decades, several models have been proposed to describe non-selfish behavior. One 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 & Miller, 2002; Bolton,1991; Bolton & Ockenfels, 2000; Charness & Rabin, 2002; Cox, Friedman, & Sadiraj, 2008; Fehr & Schmidt, 1999; Kirchsteiger, 1994; Levine, 1998). The standard empirical approach is to have subjects make choices that affect income distributions in order to make inferences about these social preferences. Such inferences may be plagued by identification problems though. The same set of choices may be consistent with various behavioral models. Clever designs and advanced statistical techniques have helped to assess the descriptive relevance of various models, but in the end inferences always rely on the assumption that the models are not mis-specified. As Glimcher, Camerer, Fehr, and Poldrack (2009) put it: "By definition, choices alone provide a limited way to distinguish theories in the face of rapid production of alternative theories" (p. 4). More refined designs can show that observed decisions are consistent with preference A and inconsistent with preference B. However, it is often hard to rule out that there is yet another preference (C), which one perhaps has not thought of, which is also consistent with the observed decisions. In this sense, it is reassuring if not only the choices are consistent with a theory, but also process data are.

In the current paper we propose to view social preferences, not only as models that predict choices, but also as algorithms that describe which information is acquired prior to these choices (Glimcher et al., 2009). If a social preference model is both predictive for a subject's choices and informative for the information acquisition process that lead to these choices, this should lend credibility to the behavioral relevance of that model. If, on the other hand, a preference model is consistent with a subject's choices but not with the information acquisition process, the posited preferences are probably not real drivers of the subject's choices. For example, suppose a subject's choices are consistent with the maximin preference but she does not process the payoff information necessary to maximize this preference, then there must be an alternative model that explain these choices.

In the present paper we use eye tracking methodology to examine whether social preference models are informative for the information acquisition processes that precede these choices. We hypothesize that if an individual is actually motivated by a particular social preference, then he or she will acquire information accordingly, which will be reflected by a distinct pattern of eye movements. The hypothesis is based on the supposition that different choice rules require different information to be acquired and processed, which will be reflected in different eye movements.

Motivated by this supposition, we performed the following analysis. We tracked subjects' eye movements while they made choices in a series of three person dictator games of the same type as in Engelmann and Strobel (2004). Subjects decide about the payoffs of two other subjects, while they cannot affect their own payoffs. We classified 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. Note that minimizing envy is a short-hand for an aversion to disadvantageous inequality as in Fehr and Schmidt (1999), which is different from the meaning of envy-freeness in more traditional resource allocation games. We also classified subjects according to how well their eye movements fit the same three choice rules. We recorded how long a subject looked at specific payoff information (gaze time), how often they looked at it (fixation count), and how often they moved between specific pieces of payoff information (saccades). We used these data to generate predictions about the choice rule that each subject seemed to be using. A key design feature that allowed us to do this was that, after the preference-based decisions, we also tracked subjects' eye movements while they were *instructed* (and incentivized) to choose in accordance with the three choice rules. Hence, we know what the eye movements look like when it is very likely that subjects actually implement these choice rules. For instance, we find that when subjects are instructed to minimize envy their eyes move relatively often between the highest payoffs and their own payoffs. We use this information about the eye movements to predict which choice rule a subject is implementing when making preference-based decisions.

The results suggest that there is a significant correspondence between social preferences models and eye movements. If a subject's choices are consistent with a particular type of social preference, this also tends to be reflected in the 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 eye movements. One could say that the revealed social preferences are not just 'as if', they are also descriptive of the information acquisition processes 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, different preferences are associated with distinct, identifiable and intuitive eye movement patterns. Moreover, subjects' eye movement data have significant predictive power for their choices.

There are several other methods that can be used to generate process data about the cognitive processes underlying 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, eye tracking data are comparatively easy to analyze and interpret. Eye tracking also has distinctive advantages relative to Mouselab data (Payne, Bettman, & Johnson, 1993) and think-aloud protocols (Russo, Johnson, & Stephens, 1989). Eye movements are automatic processes that can be recorded in a non-intrusive way, without inducing purposeful reasoning (Glöckner & Betsch, 2008; Lohse & Johnson, 1996).

Eye tracking methodology has been mainly used by psychologists and marketing researchers (see, e.g., Duchowksi, 2007). Recently, some studies in behavioral economics have used eye tracking, for example, to study acquisition of payoff information in games (Hristova & Grinberg, 2005), learning in games (Knoepfle, Wang, & Camerer, 2009), decision making under time pressure (Reutskaja, Nagel, Camerer, & Rangel, 2011) or the relationship between pupil dilation and deception (Wang, Spezio, & Camerer, 2010). A study closer in spirit to ours is Arieli, Ben-Ami, and Rubinstein (2011), which investigates eye movements while subjects play two-person distribution games. Their interest is mainly in investigating whether subjects pay attention to the payoffs of the other individual. The results indicate that most subjects process information about the payoff of the other individual even in case their choices suggest that they are not concerned about these payoffs. In our study self-interest is not at stake and we focus exclusively on the social component of preferences. Another related study is Fiedler, Glöckner, Nicklish, and Dickert (2013) which uses eye tracking to investigate whether subjects with different social value orientations exhibit different patterns of information search in social dilemmas. A very interesting finding is that a stronger deviation from pure self-interest, as measured by the Ring Measure of social values, is associated with a higher degree of attention towards others' payoffs, and more transitions from and towards others' payoffs in a (non-strategic) money allocation task as well as in a (strategic) public good dilemma. Social value orientations measure how someone trades off own money versus other's money which is different from the social preferences we consider which is more about how someone allocates money among different others. Another difference is that Fiedler et al. (2013) concentrate on between-measure predictions while we focus on within-measure relationships.

Our study also features a methodological contribution in the use and modeling of eye track data. 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, since the choices are incentivized, we can be as good as certain 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 objective, empirically guided modeling and interpretation of the eye track data. In principle, this procedure can also be applied to other areas of interest such as cognitive sophistication, learning or testing psychological models such as heuristics and biases.

Experimental Design and Procedure

Experimental Games

Our experiment employs simple three person distribution (dictator) games similar to those in Engelmann and Strobel (2004). The game is presented in the form of a 3 by 3 matrix in which the person number 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

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

We run 18 different games (payoff matrices). All games share the following properties: in each game, 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 medium payoff, and person 3 always has the lowest payoff. Appendix A 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 (in the spirit of Engelmann & Strobel, 2004) to focus on the social component of preferences. Thus, 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 medium income and does not have his or her own income at stake (just as in the corresponding games in Engelmann & 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 87% of the choices overall.

The 18 games are different in three ways. First, in 12 of the games the three different choice rules give conflicting predictions and in 6 games they give overlapping predictions. This allows for an assessment of the predictive power of both the individual choice rules and the three rules in combination. Second, there are two versions of each game, the only difference being that the allocations A and C are switched. This is to control for the potential gaze time bias toward the first column. Third, payoff differences were varied across games.

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 subjects are aware of the fact that their 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 a vendor-reported spatial accuracy of 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 see 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 defined a separate AOI for each cell of the matrices with the buffer zones of 30 pixels for 1024*768 screen resolution. Thus we recorded how often a subject looked into each cell (fixations frequency), how long he or she looked in the cell (gaze time), and the types of transitions from one cell to another (saccades).

Noise in the data can originate from different sources. One is that certain eye movements are not recorded, for example, because subjects moved their heads too much or because the eyes were outside the view of the camera. Another possibility is that eyes fixate just outside an area of interest while the information in that area is still processed. Also, it is possible that subjects scan certain information even if it does not guide their decisions, or that they look at information without processing it.

Experimental Procedure

The experiment was conducted in the CentERlab in Tilburg University, the Netherlands. In total, 51 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 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 (see Appendix B for the complete set of instructions). In Part 1 the subjects had to choose a preferred allocation as person 2 in each of the 18 games described above (see Appendix A). The order in which the subjects played the 18 games was determined randomly before the experiment, and was the same for all subjects. 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 because their decisions only mattered if they were selected as Person 2 and when they were selected as Person 2, their payoffs would always be 9.

In part 2, subjects were instructed to choose in line with three successive choice rules in 8 games per choice rule. The 24 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) for 8 games, then instructed to choose the allocation which gives highest minimum payoff (Maxi-min) for another 8 games, and, finally, instructed to choose the allocation that gives the lowest difference between the maximum payoff and person 2's payoff (Mini-envy) in 8 games. Subjects were informed that they would receive 0.20 Euro for each "correct" answer in each of the 24 games in Part 2. It was decided - before we did any data analysis - that subjects who made too many mistakes in Part 2 of the experiment would be excluded. The data of subjects who misunderstood the instructions of any of the three rules were considered to be uninformative. Therefore, subjects who answered half or more of the 8 questions of either of the 3 rules incorrectly were dropped from the data set. This affected 5 of the original 51 subjectss. The remaining 46 subjects in total made only 14 mistakes in the 1104 questions. Leaving these 14 observations out of the analysis hardly makes a difference.

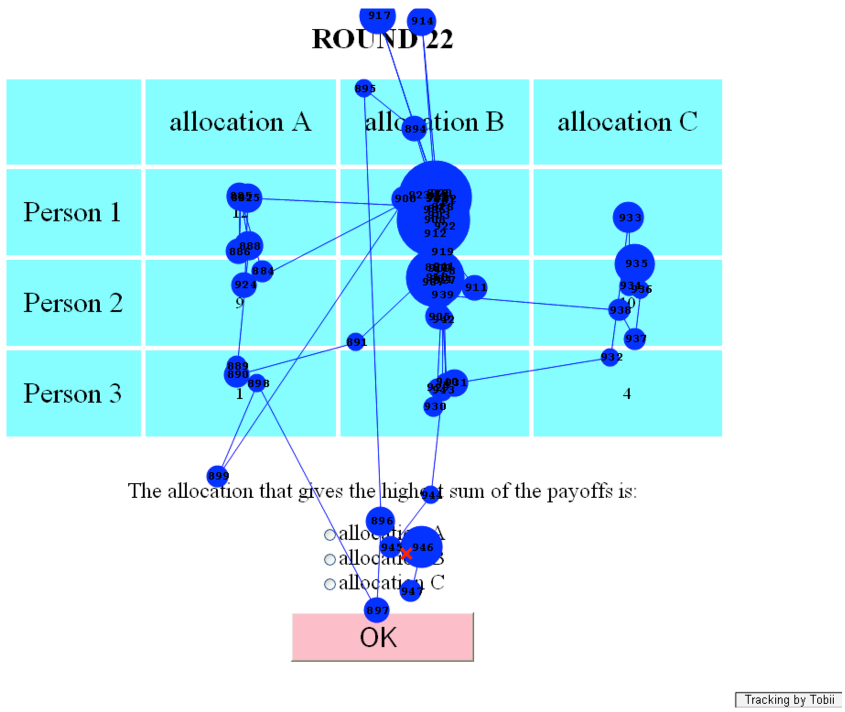
The instruction also included an understanding test to check if a subject understood the task. The instructions were provided to subjects on paper. The rest of the experiment was computerized (see Appendix C for a sample screen). In total each subject made 42 decisions; 18 of these were preference based and 24 were rule based. The experiment lasted about 30 minutes on average. Participants earned on average 15 Euro including 2 Euros participation fee.

Eye Tracking Data

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 on the gaze time data. We also counted the 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. Note 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 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 choose (Shimojo, Simion, Shimojo, & Scheier, 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. Adding information about the column gaze times would further increase the predictive power of the eye-movements data. But the improvement would be a mere result of the location of the choices. For example, the Maxi-min choice is more often located in the second column than in the first or third column. Using column gaze times can pick up information on the location of different choices but this location is to a large extent arbitrary. For the purpose of our paper, it should not be included to inflate the predictive power of the eye-movements data.

Second, we construct five 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. Then, 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. 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. Finally, SAC_ WITHIN_AOIS contains the saccades that remain within the same AOI. 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.

A notable feature of the data is that the averages of all variables are quite similar for Part 1 and Part 2. Moreover, the averages differ across the three different rules (see Figure D1 for more details on how the proportions of gaze time and saccades differ among the three rules). The differences tend to be intuitive. For example, when subjects are induced to choose in line with Maxi-min, their average gaze time is relatively longer in row 3 that is, the row containing the payoffs of person 3 who always has the lowest payoff, compared to when subjects are induced to choose in line with the other two rules. A more systematic analysis of the differences that identify the different choice rules is contained in the next subsection.

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 movement 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 movement variables, denoted by the vector E_{it}. So the following model is estimated:

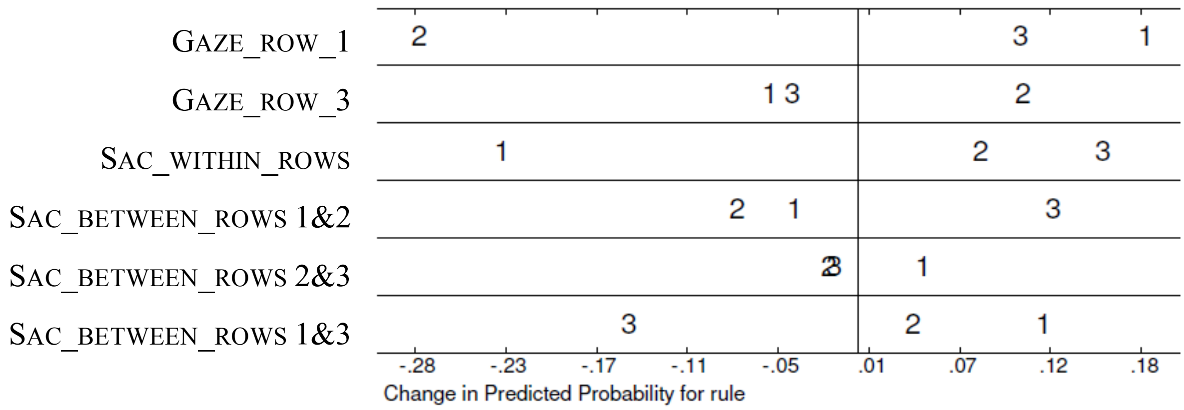
$$\Pr(C_{it} = k) = \frac{\exp(E'_{it}\beta_k)}{1 + \sum_{j=1}^{2}\exp(E'_{it}\beta_j)} \qquad for \quad k = 1,\ 2$$

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

Table D1 in Appendix D presents the details of the estimated model. For only 17 subjects' data we are able to estimate parameters for the multinomial logit model at the individual level. For the remaining subjects the model did not convergence, probably due to insufficient number of observations. That is why we base the analysis on one model fitted to all subjects. In 86% of the cases the model correctly predicts the choice rule that is being implemented. 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 of Figure 2 indicates that a one standard deviation increase in the proportion of gaze time in row 3 (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 the proportion of saccades between row 1 and 2 (SAC_BETWEEN_ROWS12) increases the predicted probability that rule 3 (Mini-envy) is used by about 12%. Again this makes sense as Mini-envy involves a comparison between the payoffs of Person 1 and Person 2. An increase in the proportion of saccades between row 1 and 3 (SAC_BETWEEN_ROWS13), on the other hand, is associated with an increase in the use of rule 1 (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. Overall there is a clear and intuitive structure in the eye movement data.

Figure 2. Change in predicted probabilities of the three choice rules



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.

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. Note that these fractions do not generally add up to one because in 6 of the 18 rounds the prescriptions of the three rules overlap. 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 2 shows the distribution of the dominant rule for the 45 subjects. For one subject there was a tie between two rules and we exclude this subject from the analysis. 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 2. Classification based on choices

Dominant rule (choice data)	# subjects	Consistent choices
Maxi-sum	10	164/180 91%
Maxi-min	26	422/468 90%
Mini-envy	9	122/162 75%
Total	45	708/810 87%

Note: to calculate the proportion of consistent choices for each rule, we divide the number of choices that are in line with the rule, made by the subjects who are classified by that rule, divided by the total number of choices made by the same subjects.

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% (5/18) of the choices being consistent with it.[1] 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 are in line with this rule. Overall, 87% of the choices are consistent with the dominant rule. This suggests that our focus on these three basic preferences rules is not very restrictive.

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 subject's 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).

[1] For 6 out 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. The data, however, show that for 36% of the subjects (16/45) all 18 choices are consistent with the dominant choice rule, for 42% (19/45) the dominant rule captures 14 to 17 of the choices, and for the remaining 22% of the subjects (10/45) between 11 and 13 of the choices are consistent with the dominant choice rule. Moreover, for 73% of the subjects (33/45) the dominant choice rule captures at least 8 choices more than the next best rule. Apart from the one subject with a tie, there are 5 subjects (11%) for whom the dominant rule captures only 2 choices more than the next best rule.

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 3. 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

Note: Kappa = 0.38, p < .001

The final step is to confront the classification based on choices with the classification based on eye movements. Table 3 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 correspondence is highly significant 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 preference, the information acquisition process revealed by the eye movements suggests the same. We also performed a "placebo test" using the second-most dominant rule based on the eye movements (rather than the dominant rule) and related that to the dominant rule using the choice data. Doing so we find only 7 out of 45 subjects for whom the two rules correspond (instead of 28 out of 45 when we relate the two dominant classifications).

As yet another alternative to the main analysis in Table 3, we also related the frequencies with which individual subjects chose in line with each of the three choice rules (f_i^k) to the predicted probabilities that they do so according to the multinomial logit model of the eye movements (p_i^k). Table E1 in Appendix E provides details. We find a significant positive correlation between f_i^k and $p_i^{k'}$ on the diagonal (i.e., if k = k') and negative correlations off-diagonal. This indicates that subjects who choose relatively often in line with a specific choice rule are also predicted to do so based on their eye movements.

To check for robustness, we also use 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) is essential. This turns out to be the case indeed. The correspondence between choice data and eye movement data is substantially stronger when both pieces of information are included in the logit model. The correspondence does not improve though if we focus on rounds 10 to 18 rather than on all rounds, as in the main analysis.

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 movement data identify the same dominant rule. The more experienced subjects are with a particular game, the better the fit between choice and process data.

We also examined whether the 'strength' of the eye movements information mattered. We analyzed whether the correspondence is better for subjects for whom the eye movement data provide stronger evidence on the choice rule they appear to be using. The classification over the columns of Table 3 is based on the prediction derived from the logit model. This prediction ($p_i^{max} \equiv \max_{k \in \{1,2,3\}} \{\frac{1}{18} \sum_t p_{it}^k\}$) varies substantially over the 45 subjects. We did a median split and divided the subjects into those with relatively strong evidence on the rule they implement (i.e., a high value of p_i^{max}) and those with relatively weak evidence. It turns out that the correspondence between choice data and eye movement 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 movement data, the closer the fit to the choice data.

Finally, we also explore whether the eye track data are predictive for the choice a subject makes on a round by round basis. For each subject and for each of the 18 rounds, we take the actual choice as the dependent variable and we take the choice predicted by the eye movements as the explanatory variable (using the M-logit model). The result shows that the eye movement predictors have significant power in predicting subjects' choices [chi2 (4) = 25.12, $p < 0.001$]. If we take the choice with the highest predicted probability as the predicted choice, then 67% of the choices are predicted correctly. Moreover, one may wonder whether the eye movement data have identification power in the rounds in which the choice data cannot distinguish between the different preferences. Recall that there were 6 rounds in which the three preferences rules overlap and all predict the same allocation. It turns out that for 56% (25 out of 45) of the subjects, the eye movement data correctly predict the dominant choice rules in those rounds (as inferred from the choices in the other 12 rounds). This correspondence is significant at $p = 0.049$ with Fisher's exact test. This suggests that in situations in which choice data cannot disentangle different choice rules, eye tracking data can help identify subjects' preferences.

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 movement data.

Exploring the misclassifications

What is the reason that for 17 subjects the two classifications do not match? In this section we explore some possible explanations.

One possibility is that some subjects make choices that are inconsistent or contain an element of randomness. Recall that subjects 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 prefers 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 show that the match between the two classifications (Table 3) is weaker for the inconsistent subjects than for consistent ones. There are 24 subjects who make an inconsistent choice at least once in the non-overlapping rounds, and for 13 of these (54%) the two classifications correspond. Of the 21 consistent subjects, there are 15 (71%) for whom the classifications correspond. The difference between the two groups, however, is not statistically significant (Chi-square test, p = .117). A somewhat related analysis uses response times. With a median split analysis we find that subjects who make decisions relatively quickly (below median response times) display a weaker correspondence between the two classifications (52%) than subjects who take relatively long to make a decision (73%). The difference is not significant (Chi-square test, p=.155).

Another possibility is that some subjects have other preferences than the three basic types we elicit. One indication for this is that subjects sometimes make choices that 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 that is in line with all of the three choice rules. Still, there are 15 subjects who make at least one choice that is not in line with this allocation. 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. Of these 15 subjects there are 8 (53%) with a mismatch (i.e., who are not on the diagonal of Table 3), whereas of the other 30 subjects, there are only 9 (30%) for whom the classifications do not match. The difference between the two groups of subjects marginally significant at the 10% level with one-sided chi-square test (Chi-square test, p = .128). This suggests that one potential reason for the misclassifications is that some subjects act in accordance with a preference that is not captured by the three rules we consider.

Finally, 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. One possibility is that some of these misclassified subjects are actually motivated by inequality aversion (a convex combination of Maxi-min and Mini-envy) or by quasi-maximin (a convex combination of Maxi-min and Maxi-sum). If the component of Maxi-min dominates, the choice data will classify these subjects as Maxi-min. At the same time, the eye track data may suggest otherwise as subjects are not merely acquiring information which allows them to maximize the minimum payoff, they are also acquiring information to evaluate the envy (Mini-envy) or the efficiency (Maxi-sum) associated with the different allocations. Thus, it cannot be ruled out that subjects who are classified as Maxi-min are in fact inequality averse or quasi-maximin. This exemplifies that inferences based on choices have their limits as there is always a possibility that there are other choice rules that one has not taken into consideration. This also provides an illustration of how eye tracking data can be used as a complimentary source of information. If a subject's information acquisition pattern does not correspond to the choice inferences, this may hint at the possibility of mis-specification, which could then lead to the investigation of alternative preference models.

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 simply act inconsistently, as well as for the possibility that some subjects act on preferences which are not modeled.

Conclusion

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 believe this lends credibility to the behavioral relevance of social preferences models, as well as the inferential methods used to identify them.

Our analysis indicates that there is structural information in the eye movement data. Even though less than perfect, the observed correspondence between choice and process data is significant and meaningful. 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 meaningful, especially in view of the noise that typically accompanies both choice and process data. Moreover, it is noteworthy that the eye tracking data have significant predictive power for the ensuing decisions that individuals make.

There are some obvious limitations to our study. First of all, our experiment employs a relatively small number of subjects, and also the sample size within each choice-rule is relatively small. Social preferences vary across individuals and this heterogeneity may not be accurately represented in a small sample. Other features of the design, such as the use of allocation games that are relatively simple and in which no self-interest is at stake, may also affect the results of our study. Moreover, the model we use to generate predictions is based on the pooled eye movements data. It might be preferable to estimate individual-specific models. This would allow for more flexibility in the design of the games (e.g., allowing for counterbalancing of player positions across subjects) and would also accommodate individual heterogeneity of preferences and information acquisition. So, as always, one should be careful not to generalize too casually. Still, we believe our study warrants a positive perspective on the correspondence between choice data and eye movements data in the domain of social preferences.

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Appendix A

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 B

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 C

Sample Screens

Figure C1: Sample screen for 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

Figure C2: Sample screen for 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

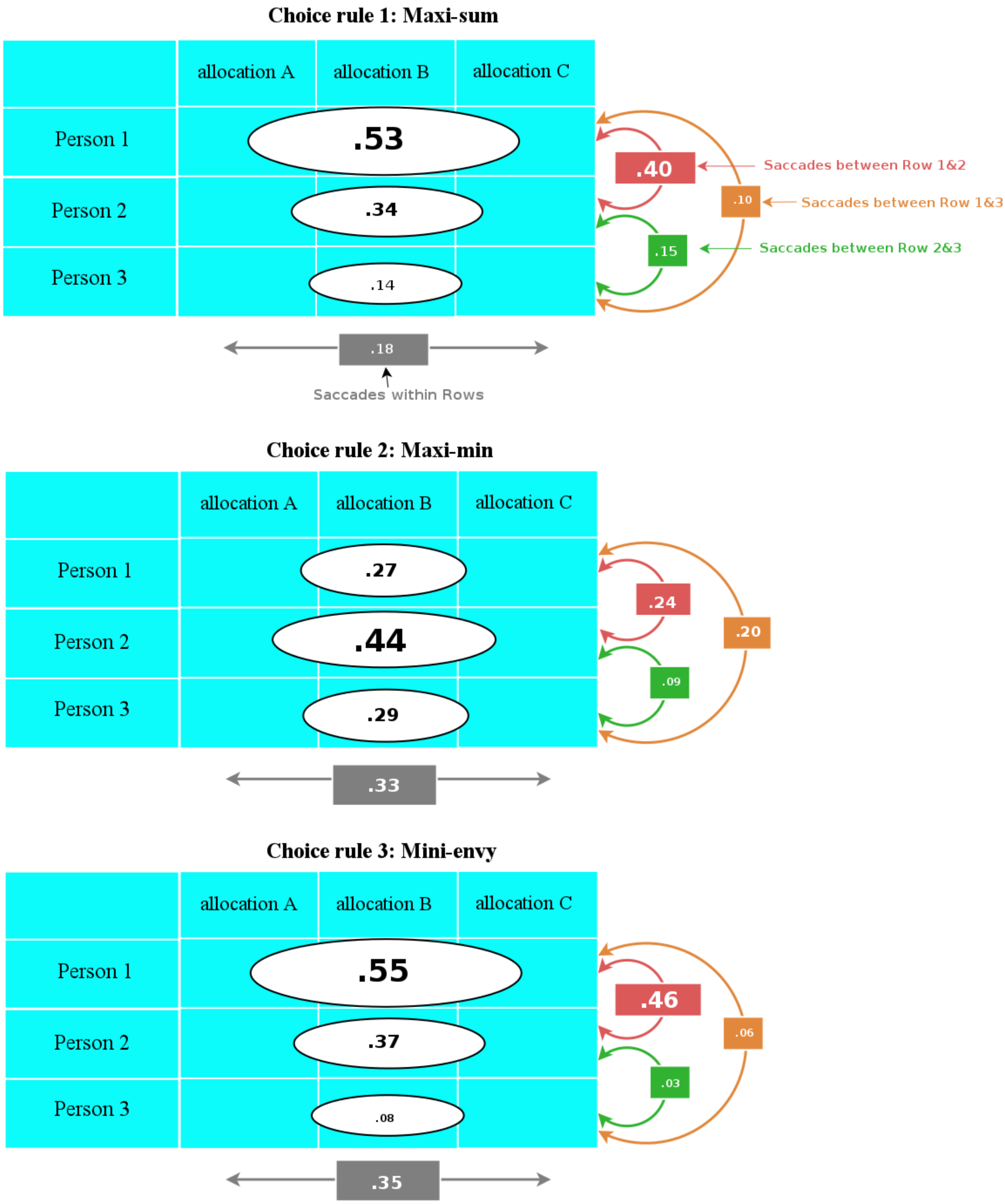
The allocation that gives the highest sum of the payoffs is:

- allocation A
- allocation B
- allocation C

ok

Appendix D

Figure D1: Different proportions of gaze time and saccades for the 3 rules in Part 2



Note: this figure depicts, for each choice rule, the proportion of average gaze time in each row (person), as well as the proportions of average saccades between rows.

Table D1

Multinomial logit model for the choice rule in Part 2

	Maxi-sum		Maxi-min	
	coeff.	(robust s.e.)	coeff.	(robust s.e.)
GAZE_ROW_1	0.659	(0.915)	-5.408***	(1.130)
GAZE_ROW_3	-0.051	(1.630)	2.713**	(1.337)
SAC_WITHIN_ROWS	-4.643***	(0.855)	-1.176	(0.968)
SAC_BETWEEN_ROWS12	-2.000**	(0.845)	-2.477**	(1.202)
SAC_BETWEEN_ROWS23	0.939	(1.156)	-0.023	(1.070)
SAC_BETWEEN_ROWS13	4.947**	(2.027)	3.641*	(1.926)
CONSTANT	1.403	(1.032)	2.988**	(1.288)
N = 993, loglikelihood = -792.6				
Wald Chi2 = 124.6 (p<.0001), Pseudo R2 = 0.273				

Notes: Model estimated with Mini-envy as the base category. Observations are clustered at the subject level. *, **, *** denotes significance at the 10%, 5%, and 1% level, respectively.

Appendix E

Correlation between choice frequencies and predictions

The classification in Table E1 is based on the dominant choice rules and the dominant predictions according to the eye movements. Here we present an alternative, but related, analysis that uses more detailed (continuous) information about the underlying choice frequencies and predictions. Specifically, we correlate the frequencies with which individuals choose in line with choice rule *k* (f_i^k) to the average probabilities they are predicted to use choice rule *k′* according to the multinomial logit model of the eye movements ($p_i^{k'} = \frac{1}{18}\sum_t p_{it}^{k'}$), where *k* and *k′* are taken from the set {Maxi-sum, Maxi-min, Mini-envy}. Table E1 presents the results. It can be seen that these correlations are significantly positive for *k* = *k′*, and that they are negative whenever *k*≠*k′*.

Table E1

Correlations between the fractions of choices in line with a rule and the predicted probabilities of choosing in line with a rule based on eye movements

		Predicted probabilities based on eye movements		
		Maxi-sum	Maxi-min	Mini-envy
Fractions of choices	Maxi-sum	**.231****	-.140	-.091
	Maxi-min	-.070	**.239****	-.168**
	Mini-envy	-.085	-.120	**.205*****

Note: Each cell gives a correlation coefficient based on paired observations of 45 subjects. *, **, *** denotes significance at the 10%, 5%, and 1% levels, respectively.