Social motives in a patient with bilateral selective amygdala lesions: Shift in prosocial motivation but not in social value orientation

Running title: Social motives & amygdala lesions

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Abstract

Humans hold social motives that are expressed in social preferences and influence how they evaluate and share payoffs. Established models in psychology and economics quantify social preferences such as general social value orientation, which captures people's tendency to be prosocial or individualistic. Prosocials further differ by how much they maximize joint gains or minimize inequality. Functional neuroimaging studies have linked increased amygdala activity in prosocials to payoff inequality between self and other. However, it is unclear whether amygdala lesions alter social motives. We used two tasks to test a patient with selective bilateral amygdala lesions and three healthy samples (a priori matched control sample $N = 20$, online sample $N = 603$, student sample $N = 40$), which allowed us to assess and model social motives across a relatively large number of participants. In a social value orientation task, the patient was categorized as prosocial and her social value orientation score did not differ from healthy participants. Importantly, the patient differed in prosocial motivation by maximizing joint gains rather than minimizing payoff inequality. In a joint payoff evaluation task, Bayesian model comparisons revealed that participants' evaluations were best described by models, which link participants' evaluations to the payoff magnitude and to inequality. Overall, amygdala lesions did not seem to alter general social value orientation but shifted prosocial motivation toward maximizing joint gains.

Keywords

Amygdala Lesion, Prosociality, Allocation Preferences, Social Cognition, Decision-Making

Highlights

- We tested social motives in an amygdala lesions patient and three healthy samples
- The amygdala lesion patient was prosocial as the majority of healthy participants
- The patient differed in underlying prosocial motivation by maximizing joint gains
- In contrast, most healthy prosocial participants minimized inequality
- Joint payoff evaluations were best described by models including inequality aversion

Introduction

The functioning of social groups builds upon individuals cooperating and sharing payoffs with each other. Humans hold social motives that are expressed in their social preferences and influence how they evaluate and share payoffs with each other (MacCrimmon & Messick, 1976). Psychological and economic models assume that individuals' preferences for payoff allocations depend—in addition to self-gains—on several social motives such as maximizing joint gains and minimizing inequality (Fehr & Schmidt, 1999; Murphy et al., 2011). Functional neuroimaging studies have linked individual differences in amygdala responses to social motives during the evaluation of allocations (Haruno & Frith, 2010; Liu et al., 2019). Here, we investigated whether amygdala lesions have an impact on social preferences and motives in the context of sharing monetary payoffs between oneself and an anonymous other by testing a patient with selective bilateral amygdala lesions and comparing her to an a priori matched control sample.

Social Value Orientation (SVO) refers to how individuals evaluate and allocate payoffs for themselves and others (Messick & McClintock, 1968). General SVO can be measured on a continuous scale that captures the amount of a common payoff a person is willing to sacrifice for another person's payoff (Murphy et al., 2011). To facilitate the interpretability of the continuous SVO scores, people can be classified into at least four different SVO categories that partition the possible range of SVO scores. Empirically, most people are prosocials (maximizing own and others' payoffs and minimizing inequality) and many are individualists (maximizing own payoffs). Fewer people are categorized as competitive (maximizing the difference between own and others' payoffs) or altruistic (maximizing others' payoffs) (Murphy et al., 2011). With additional SVO items, prosocials can be further positioned on two continua: One for joint gain maximization (maximizing the sum of one's own and another person's payoffs) and another for inequality aversion (minimizing the difference between one's own and another person's payoffs). These two continua are typically compiled into one so-called prosocial motivation score.

Distinct SVO categories have repeatedly been associated with differences in cooperative behavior. In laboratory experiments, prosocials contribute more to group interests than individualistic and competitive persons (e.g. De Cremer & Van Lange, 2001). In real life, prosocials engage more in behavior that facilitates long-term collective interests, such as pro-environmental actions (Joireman et al., 2001) or volunteering (Van Lange et al., 2011).

Several functional neuroimaging studies in humans suggest that individual differences in SVO relate to differences in amygdala activity when allocation options are presented (Haruno et al., 2014; Haruno & Frith, 2010; Liu et al., 2019; Tanaka et al., 2017). Specifically, prosocials and individualists differed in their dorsal amygdala activity related to the absolute difference between payoffs for the self and for another person—a measure of overall inequality (Haruno & Frith, 2010). That is, while amygdala activity was positively correlated with absolute payoff differences in prosocials during payoff presentation, it was slightly negatively correlated with absolute payoff differences in individualists (Haruno & Frith, 2010). A recent functional neuroimaging study refined this picture (Liu et al., 2019): Greater deviations of the currently presented allocation from the individually preferred allocation elicited greater amygdala activity on a trial-by-trial basis. In addition, amygdala activity related to deviations from the preferred allocation positively correlated with inequality aversion in prosocials but not individualists (Liu et al., 2019).

Animal studies provide further evidence for the importance of the amygdala for prosocial preferences. Electrophysiological measurements in rhesus macaques revealed enhanced synchronization between the basolateral amygdala and the rostral anterior cingulate gyrus for prosocial decisions in contrast to suppressed synchronizations in antisocial decisions (Dal Monte et al., 2020). Bilateral lesions in the basolateral amygdala in rats resulted in lower preferences for mutual rewards, indicating that the integrity of the basolateral amygdala facilitates prosocial preferences (Hernandez-Lallement et al., 2016).

Thus, human and animal studies point toward a role of the amygdala for social motives but it is unclear if amygdala lesions influence prosocial preferences in humans. Here, our primary aim was to investigate the impact of selective bilateral amygdala lesions on allocation decisions and preferences by comparing a patient with amygdala lesions to a group of a priori age- and gender-matched healthy individuals. In secondary, exploratory analyses, we compared the patient to a larger group of participants that was matched post hoc. Based on the neuroimaging findings that show relationships between amygdala activity and prosocial preferences (Haruno & Frith, 2010; Liu et al., 2019), we hypothesized a less prosocial SVO (i.e., less prosocial payoff allocations) in a patient with Urbach-Wiethe (UW) syndrome (a disease characterized by amygdala calcification) than in controls. In addition, we tested how well different social motives—such as inequality aversion—describe participants' evaluations of given payoff allocations, by comparing eight different economic models.

We adopted the same tasks as Haruno & Frith (2010) and used two complementary approaches to assess social motives. First, the SVO task provides an individual characterization of social preferences by having participants choose between different payoff options for the self and another person. The SVO task is similar to so-called "dictator games" (Engel, 2011) in the sense that one person single-handedly determines how allocations should be split between the self and another person. This other person has no say in the decision. Primary items (Figure 1a & 1d) in the SVO task assess general SVO and secondary items (Figure 1b & 1d-e) specify the type of prosocial motivation. Second, in the joint payoff evaluation (JPE) task, participants evaluate the desirability for a series of given joint payoff pairs. We extended the modeling approach of Haruno and Frith (2010) and compared how well eight different economic models describe participants' evaluations in the JPE task. We assessed three healthy samples to provide distributions of SVO and to identify the model that best describes participants' evaluations of monetary allocations. Specifically, we tested one control sample for the UW patient. We also tested two additional samples to characterize the behavior of a wider population. That is, our primary aim was to compare the UW patient with an a priori matched control group. Our secondary aims were to compare the patient to a larger post hoc matched sample and to provide data on social motives of a relatively large number of participants.

Methods

Participants

UW patient. One of two female monozygotic twins (age 43 years) with Urbach-Wiethe (UW) syndrome—a congenital disorder leading to amygdala calcification (Newton et al., 1971)—was tested at the University of Bonn. Both patients have been characterized neurologically and behaviorally in earlier studies (Hurlemann et al., 2007; Talmi, Hurlemann, Patin, & Dolan, 2010). In this study, the patient previously called BG or patient 2 was tested. Her twin sister was not tested because she suffered from a psychiatric condition (Scheele et al., 2019). Below, we list several earlier findings obtained from the same lesion patient. The patient has an average intelligence but exhibits impairments in phonemic fluency and short-term concentration (Talmi et al., 2010). She shows impairments in the recognition of fearful facial expressions (Becker et al., 2012; Hurlemann et al., 2007) and in the prioritization of threatening facial expressions (Bach et al., 2015). She has aberrations in startle responses during fear-eliciting scenes, in threat processing (Becker et al., 2012). In approach-avoidance conflict tasks, she shows reduced loss adaptation (Korn et al., 2017) and decreased vigor of escape from threat (Bach et al., 2019). Furthermore, she has a smaller and less complex social network (Becker, 2012).

Healthy samples. In total, we acquired three separate healthy samples (for which we specify details in the next sections): First, an age- and gender-matched control sample was tested in the laboratory. Second, we acquired an online sample that allowed us to compare the UW patient to a rather large subgroup of this online sample that was matched post hoc for secondary, exploratory analyses. Third, a student sample was tested in the laboratory. For interested readers, we report the behavioral results from the full online sample and the student sample, but we did not compare the UW patient to these two samples. Inclusion criteria for all healthy samples were age between 18 and 60 and German mother tongue. Additional exclusion criteria for the laboratory samples were self-reported psychiatric or neurological diagnoses or drug abuse. In all samples and for all analyses, we excluded participants with intransitive answers on the SVO measure (see the paragraph on SVO scores below). Following specific methodological conventions and considerations, further participants needed to be excluded for specific analyses (see below and Supplementary Table 1 for details).

(1) An age- and gender-matched control sample (original $N = 23$; after exclusion for intransitive answers $N = 20$, age: $M = 41.60$, $SD = 3.91$) was recruited from the general population and tested at the Psychiatric University Hospital Zurich.

(2) A more diverse online sample (original $N = 628$; after exclusion for intransitive answers $N = 603$, 377 female, 4 participants chose not to disclose their gender; age: $M = 37.70$, $SD = 11.64$) was recruited via SoSci Panel, which is associated to a German online survey system called SoSci Survey (Leiner, 2019). The administrators of the SoSci Panel offered the opportunity to invite participants who had signed up for the SoSci panel out of interest and receive no monetary reimbursement. Participants of the online sample were tested via SoSci Survey and completed a series of unrelated tasks (described in Korn et al., 2018). This allowed us to compare the UW patient to a rather large matched subgroup of this

online sample by choosing—post hoc—female participants within the age range of 36 - 49 years (to match the age range of the control sample) (N = 91, age: M = 41.99, SD = 3.60). We label this subsample "online subgroup."

(3) To provide more evidence that the general findings in the two tasks hold, we additionally tested a student sample (original N = 41; after exclusion for intransitive answers N = 40, 26 female; age: M = 24.35, SD = 3.81) at the University Medical Center Hamburg-Eppendorf.

Self-reported income range. The UW patient did not differ from the control sample and the matched subgroup of the online sample with respect to self-reported income ranges. Participants were asked to indicate their monthly income range on a scale with the lowest option (no personal income) and the highest option (above 6500 CHF or above 4000 €; in the online sample, participants also had the option to not indicate their income range). Income ranges for the two currencies were converted using current information about Swiss and German purchasing power parities acquired from the Federal Statistical Office of Switzerland (BFS, 2018). A Bayesian single-case analysis (for details see methods section) revealed that an estimated 88.77% (95% CI [74.28, 97.23], p = .225, two-tailed) of the control sample and 63.23% (95% CI [54.90, 71.14], p = .735, two-tailed) of the online subgroup would have a lower income than the UW patient, indicating no significant income differences between the UW patient and the healthy controls. An exploratory analysis revealed no association between income level and primary SVO scores (Spearman's r = -.05, p = .836, N = 20) in the control group. Furthermore, income level and prosocial motivation scores were not significantly correlated (Spearman's r = -.09, p = .758, N = 15) in the prosocial participants of the control group (secondary items are only interpretable in prosocial participants; see methods section below for details). We found no significant correlation between income level and primary SVO scores (Spearman's r = -.02, p = .857, N = 91) in prosocial participants of the matched subgroup of the online sample. Likewise, we found no association between income level and the prosocial motivation scores (Spearman's $r = .05$, $p = .699$, $N = 66$) in prosocial participants of the online subgroup.

Reimbursement and ethics. The laboratory samples (i.e., the UW patient, the control, and student samples) received a show-up fee plus a variable amount depending on their own and on another participants' decisions in the SVO task. Participants in the online sample participated out of interest and did not receive monetary reimbursement. Therefore, participants of the online sample made hypothetical choices. Participants in the laboratory gave written informed consent prior to data collection and the study (including the form of taking consent) was approved by the local ethics committees. As mentioned above, the online sample was recruited via the SoSci Panel. These participants had voluntarily signed up to receive invitations to online studies and chose freely to take part in our study. They were informed about the study similar to the participants in the laboratory and could freely stop taking part in the online study. Due to the online format, participants did not give explicit informed consent in written form. Before conducting the online experiment, we consulted the ethics committee in Zurich: At the time point of testing, online studies were deemed exempt if they used this type of questionnaire stimuli and if they only collected data from participants who remained anonymous (i.e., we collected no contact information at all and had never intended to do so). We only included participants who completed the relevant sections (i.e. demographic questions, SVO and JPE task) of the online study.

Tasks

All participants performed the SVO Slider Measurement (Murphy et al., 2011) and a joint payoff evaluation (JPE) task (Haruno & Frith, 2010). Moreover, the UW patient and the control and student samples completed a series of unrelated tasks (Bach et al., 2019; the remaining tasks will be reported elsewhere). Data of the laboratory samples were acquired using the MATLAB (Mathworks, Natick, MA) toolbox Cogent (http://www.vislab.ucl.ac.uk/cogent.php). Data of the online sample were acquired via SoSci Survey (Leiner, 2019).

In both tasks, participants were asked to respond to payoff combinations for themselves and another anonymous person. The anonymous other person was introduced as another participant in the same study. It was made clear that the other person would be reimbursed based on the participant's decisions in the SVO task, just as the participant was reimbursed based on another person's decisions in the SVO (except for the participants of the online sample who made hypothetical choices).

SVO Slider Measurement. We adopted a commonly used task (Murphy et al., 2011) to identify participants' SVO using the six primary items for the general SVO score and the nine secondary items for the prosocial motivation score. Figure 1 provides an outline and Supplementary Figure 1 visualizes a specific example item in detail. Participants were asked to indicate their preferred allocation of payoffs for themselves and another anonymous person sequentially for each item. Specifically, each SVO item consists of a continuum of 9 different options for joint payoffs for self and another person.

Primary items (used for calculating the SVO scores) are delimited by a circle (centered at 50 points with a diameter of 50 points; Figure 1c). Intermediate payoff options lie on a line between the endpoints on the circle. For example, item 6 ranges from the first option with 100 points for self and 50 points for other to the ninth option with 85 points for self and 85 points for other (Figure 1a & c). A more prosocial participant would choose one of the options close to 85 for self and 85 for other, while a more individualistic participant would choose one of the options close to 100 for self and 50 for other.

Secondary items (used for calculating the prosocial motivation scores) allow a differentiation between two different motivations for being prosocial: joint gain maximization and inequality aversion. For example, item 9 ranges from the first option with 100 points for self and 70 points for other to the ninth option with 50 points for self and 100 points for other (Figure 1b & d-e; Supplementary Figure 1). An inequality averse participant would choose one of the options close to the identity line, while a joint-gain-maximizing participant would choose one of the options closer to the upper right corner of the item space. Supplementary Figure 2 visualizes (absolute) inequality and join gain of all secondary items.

See the section on Data analysis below for details on the calculation of the SVO score from primary items and of the prosocial motivation score from secondary items. One decision was randomly chosen and participants were paid accordingly (they received the payoff for self from their choice and the payoff for other from another participant's choice).

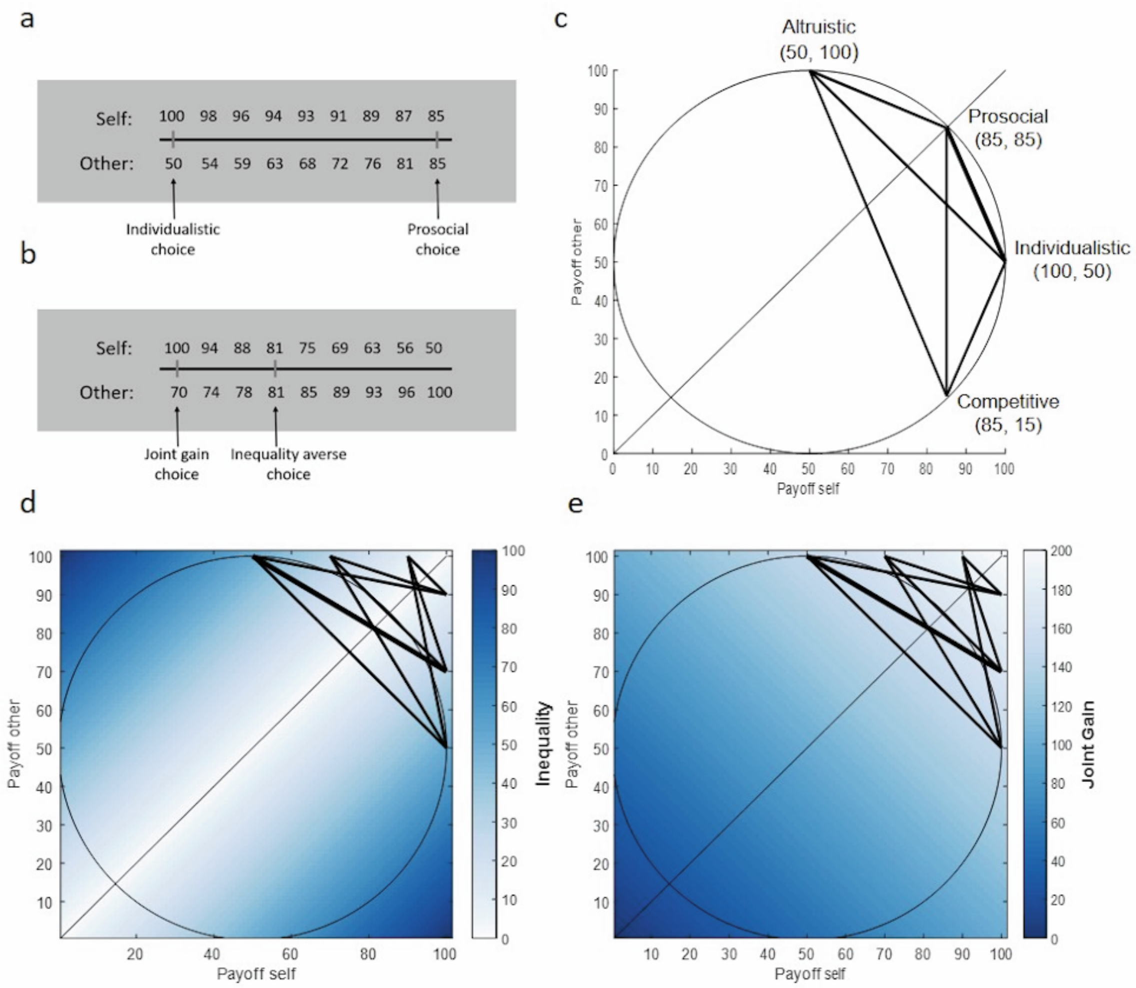

Figure 1: SVO task and allocation plane for primary and secondary items

a. Example of one of the six primary SVO slider items. **b.** Example of one of the nine secondary SVO slider items. **c.** Allocation plane for the six primary items with payoffs for the self on the x-axis and payoffs for the other on the y-axis. The circle delimits the endpoints of the primary items. Black lines indicate payoffs for the nine options of each primary item. The item depicted in (a) corresponds to the bold line ranging from (100, 50) to (85, 85). The locations of the four idealized SVO categories (altruistic, prosocial, individualistic, and competitive) are mapped. **d. & e.** Allocation plane for the nine secondary items with payoffs for the self on the x-axis and payoffs for the other on the y-axis. Black lines indicate payoffs for the nine options of each secondary item. The item depicted in (b) corresponds to the bold line ranging from (100, 70) to (50, 100). **d.** The color map illustrates the gradient of inequality between payoffs for self and other across the allocation plane. Absolute inequality is lowest on the identity line. **e.** The same nine secondary items as in (d) are depicted but here the color map illustrates the gradient of joint gain (joint payoffs) across the allocation plane. Joint gain is highest at the rightmost and uppermost point of the allocation plane. See Supplementary Figure 1 for numerical details on an exemplary item. See Supplementary Figure 2 for the depiction of the SVO and JPE items in terms of (absolute) inequality and joint gain. See Supplementary Figures 3 & 4 for choice distributions across the SVO items.

Joint Payoff Evaluation (JPE) Task. All participants subsequently performed a task established by Haruno and Frith (2010). Pairs of payoffs for the participant and an anonymous other were presented sequentially in a randomized order. For example, the payoff combination for item 1 is 23 points for self and 177 points for other (see Supplementary Figure 2 & Supplementary Table 2 for all 36 items). As in the SVO task, payoff combinations were defined by two orthogonal dimensions: outcomes for self and outcome for other. Payoffs were uniformly sampled from a circle (centered at 100 points with a diameter of 100 points). That is, all payoff options lie on the circle. In contrast to the SVO task, participants were not asked to choose among different options. Instead, in the JPE task participants were asked to rate each single pair of payoffs on a 4-point Likert scale (1 = least preferable, 4 = most preferable). The social context was controlled in both tasks since participants did not meet the other person and did not receive feedback about the other person's choices. Participants' evaluations were used as dependent variables in economic models (see below). The laboratory samples completed all 36 items of the task. The online sample only completed 12 of the 36 items (every third item) due to time constraints in the online assessment, which also included unrelated tasks (described in Korn et al., 2018).

Data Analysis

All statistical analyses were done using MATLAB (Mathworks, Natick, MA) and all statistical tests are two-tailed. Bar charts were produced in R (R Core Team, 2019) using the package "ggplot2" (Wickham, 2016) and the raincloud plots of Figure 2 were produced in R using the packages "ggplot2" and "RainCloudPlots" (Allen et al., 2018; Allen et al., 2019).

Use of samples. Our primary results were derived from data acquired in the laboratory from a matched control sample: We compared the results of the UW patient to the control sample in the SVO task and the JPE task. In addition, as secondary, exploratory analyses, we provide a comparison with the age- and gender-matched subgroup of the online sample, which allowed us to compare the UW patient to a larger sample that was tested in a similar but less comparable design (i.e., tasks were done online and participants answered only one-third of the items in the JPE task). For interested readers, we also provide the behavioral results of the full online sample and the student sample.

SVO scores. The SVO score was computed from the six primary items. The SVO score is the polar angle in a Cartesian coordinate system with payoffs to self on the x-axis and payoffs to the other person on the y-axis. This angle captures how much a participants were willing to sacrifice their own payoff for the other person's payoff. The smaller the angle, the more a participant cares for self and the closer the angle to 90°, the more a participant cares for the other person (Figure 1c). Continuous SVO scores were used for analyses and are depicted in Figure 2a. Based on these continuous SVO scores and on the bins established by

Murphy et al. (2011), participants were assigned to one of the four categories (altruistic, prosocial, individualistic, and competitive). For example, per definition, an ideal individualist would choose the option that maximizes the payoff for self on each of the items. This principle leads to specific idealized boundaries between the four SVO types. Category boundaries were set symmetrically between the idealized SVO type scores (for details see Murphy et al., 2011).

Prosocial motivation scores. To identify the underlying motivation of prosocial preferences, we followed the procedure described in Murphy et al. (2011) for analyzing the nine secondary items of the SVO task. (The code provided by Murphy and colleagues and our publicly available code provide details).

First, an "inequality distance score" quantifies how distant the chosen payoff options are from the options that ideally minimize absolute inequality for the secondary items of the SVO task. Essentially, the payoff ranges of the nine secondary items intersect the diagonal identity line (Figure 1d & e). The closer a chosen payoff option is to the identity line, the more equal are the payoffs for self and other (Figure 1d; Supplementary Figures 1 & 2).

Second, a "joint-gain distance score" quantifies how distant the chosen payoff options are from the options that ideally maximize joint gain for the secondary items of the SVO task. The more to the upper right corner of the coordinate system a chosen option is the higher is the joint gain (Figure 1e; Supplementary Figures 1 & 2).

These two scores are combined into participants' "prosocial motivation score," which is a single index ranging from 0 (perfect inequality aversion) to 1 (perfect joint gain maximization). That is, this prosocial motivation score is calculated as the inequality distance score divided by the sum of the inequality distance score and the joint-gain distance score. Based on this prosocial motivation score, each participant with consistent prosocial choices in primary and secondary items can be categorized as inequality averse (prosocial motivation score ≤ 0.5) or joint gain maximizing (> 0.5). In addition to participants' SVO scores and categories, the rank order of participants' social preferences can be assessed to check if participants make prosocial choices on the secondary items. We followed the recommendations by Murphy et al. (2011) and only analyzed prosocial motivation scores from participants who were categorized as prosocials on both primary and secondary items (see Supplementary Table 1).

Comparison of SVO and prosocial motivation scores. To investigate whether the UW patient differs in her social preferences from the healthy population, we compared her SVO score—and because she was prosocial also her prosocial motivation scores (see results)—to the control sample and a matched subgroup of the online sample.

We conducted a Bayesian single-case analysis using the SingleBayes software (Crawford & Garthwaite, 2007), which applies Bayesian Monte Carlo methods to test the null hypothesis that a patient's score is an observation from the control population. Bayesian single-case analyses are considered robust against deviations from normal distribution (Crawford & Garthwaite, 2006), and provide Bayesian *p* values, and point (percentile) and interval estimates (Bayesian credibility intervals [CI]) for the percentages of the control groups that would obtain a lower score than the UW patient.

Model-based analyses of the JPE task. We compared eight different economic models that tested for different social motives. These economic models took the form of linear regressions on each individual participant's evaluations of the desirability of a joint payoff (on a scale from 1 to 4) in the JPE task. In line with Haruno and Frith (2010) and Liu et al. (2019), the models assume participants' utility of the given payoff pairs to be linear functions of different predictors (plus an intercept term).

Results

SVO task: Comparison of SVO scores between the UW patient and controls

The UW patient was categorized as prosocial, as was the majority of the control sample (80%) and the other healthy samples (79-81%; see Table 1 for distributions of SVO categories across all samples). Testing for our primary hypothesis, we found no evidence for a difference in SVO scores between the UW patient (*SVO score* = 33.43) and the healthy control sample (M = 32.78, SD = 15.02) (see Figure 2a for overall SVO scores and Supplementary Figure 3 for choice distributions across all primary items). That is, using a Bayesian single-case method, we found that an estimated 51.64% of the control sample (95% CI [34.57, 68.58], p = .967) would have a lower SVO score than the UW patient, indicating no difference between the patient and the healthy population. Additionally, in exploratory analyses, the UW patient did not differ from the matched subgroup of the online sample (online subgroup: M = 31.24, SD = 12.4; percentile estimated = 56.95, 95% CI [48.76, 64.9], p = .861). In other words, the UW patient was quite close to the mean of the tested healthy samples in terms of her general SVO score.

Table 1. Distribution of SVO categories across all samples.

	UW patient	Control sample	Online subgroup	Online sample	Student sample
Altruistic	0	0	0	1 (<1)	0
Prosocial	1	16 (80)	74 (81)	474 (79)	32 (80)
Individualistic	0	3 (15)	16 (18)	120 (20)	8 (20)
Competitive	0	1 (5)	1 (1)	8 (1)	0

Total N	1	20	91	603	40

Participants in the categories according to SVO are given as N (%). This table lists all participants who are categorized as prosocial according to the primary items. See Supplementary Table 1 for exclusion criteria.

SVO task: Comparison of prosocial motivation scores between the UW patient and controls

Since the UW patient was categorized as prosocial, we could look into the secondary items to identify her underlying prosocial motivation (as the secondary items are only applicable if a participant made prosocial choices in the primary items). The UW patient differed from the majority of prosocials in her prosocial motivation score. While 100% of the prosocials in our control sample (and 88-94% of the participants in the other healthy samples) were motivated to minimize inequality, the UW patient was motivated to maximize joint gains (see Figure 2b, Table 2, and Supplementary Figure 4 for distributions of prosocial motivation scores, categories, and choice patterns, respectively). The Bayesian single-case analysis showed that an estimated 99.5% of the healthy population would have a lower prosocial motivation score, i.e., would be more inequality averse, than the UW patient (UW patient: *score* = 0.651; control sample: *M* = 0.207, *SD* = 0.142, percentile estimate = 99.54, 95% CI [96.87, 99.99], *p* = .009). The UW patient did also differ from the matched subgroup of the online sample (online subgroup: *M* = 0.193, *SD* = 0.171, percentile estimate = 99.5, 95% CI [98.43, 99.93], *p* = .009). Thus, even at the Bonferroni corrected alpha level of $p < .025$ the difference in prosocial motivation scores of the UW patient and the control group was robust.

The proscocial motivation score combines inequality aversion and joint gain maximization. Therefore, we analyzed the respective scores separately. The UW patient did not differ from controls in her inequality distance score (UW patient: *score* = 0.16; control sample: *M* = 0.08, *SD* = 0.07, percentile estimate = 85.62, 95% CI [68.06, 96.3], *p* = .288; online subgroup: *M* = 0.06, *SD* = 0.05, percentile estimate = 97.43, 95% CI [94.26, 99.21], *p* = .051; Figure 2c). But she differed in her joint-gain distance score (UW patient: *score* = 0.09; control sample: *M* = 0.27, *SD* = 0.05, percentile estimate = 0.18, 95% CI [0.00, 1.46], *p* = .004; online subgroup *M* = 0.25, *SD* = 0.06, percentile estimate = 0.51, 95% CI [0.07, 1.6], *p* = .01; Figure 2d).

Table 2. Distribution of prosocial motivation across all samples.

	UW patient	Control sample	Online subgroup	Online sample	Student sample
Prosocial – IA	0	15 (100)	62 (94)	382 (88)	23 (88)
Prosocial – JG	1	0	4 (6)	50 (12)	3 (12)
Total N	1	15	66	432	26

Participants are given as N (%). Prosocial motivation scores are given for all participants who are prosocial according to primary and secondary items (which is why the total numbers can be lower than the number of prosocials listed in Table 1). IA = Inequality aversion, JG = Joint gain maximization. See Supplementary Table 1 for exclusion criteria.

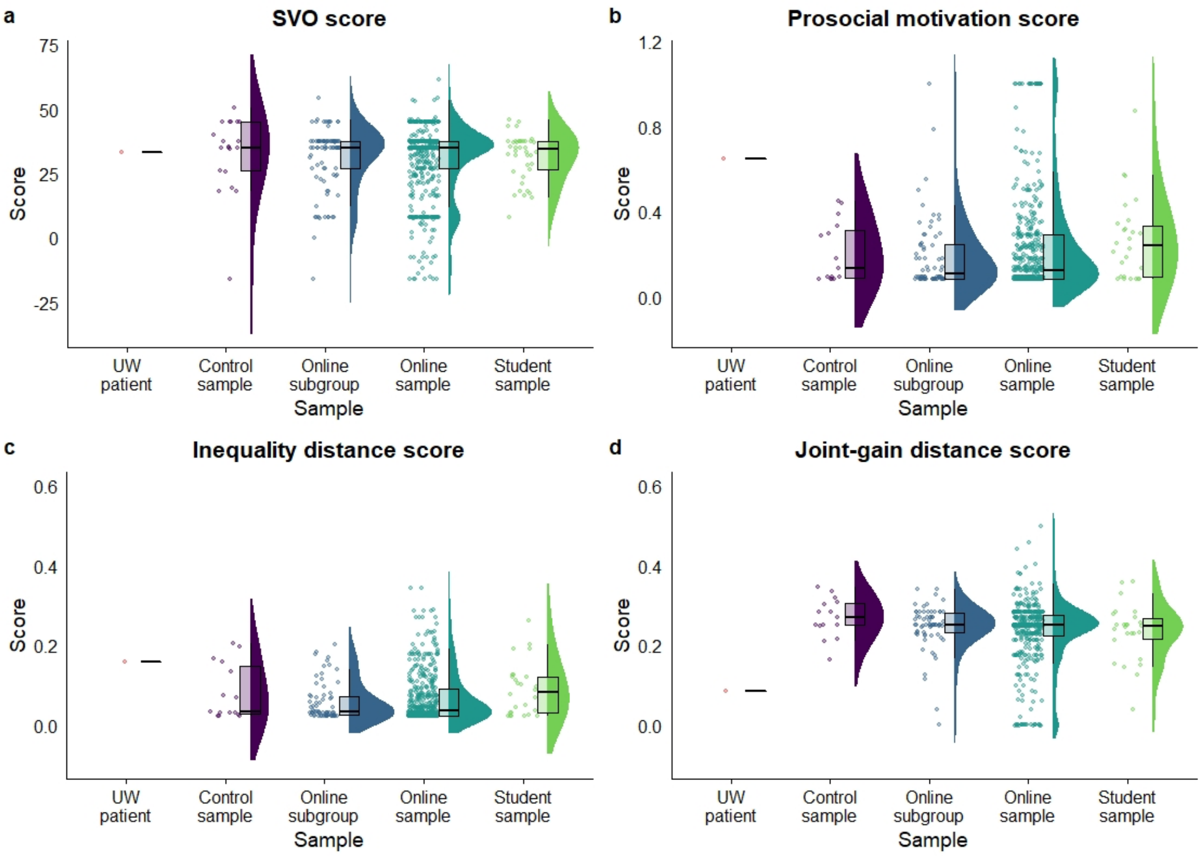

Figure 2. SVO scores and prosocial motivation scores

Raincloud plots showing the distribution of (**a**) SVO scores, (**b**) prosocial motivation scores, (**c**) inequality distance scores, and (**d**) joint-gain distance scores. We compared the UW patient to the age- and gender-matched control sample and the online subgroup. The UW patient did not differ from these healthy individuals with respect to SVO but showed a higher prosocial motivation score—and specifically a lower joint-gain distance score—which indicates relatively higher joint gain maximization. Data from the online sample and the student sample are depicted for interested readers but were not directly compared to the UW patient.

Prosocial motivation scores, inequality distance scores, and joint-gain distance scores are depicted for participants categorized as prosocial according to their SVO scores (i.e., for participants with SVO scores between 22.45 and 57.15). The prosocial motivation score is calculated as the inequality distance score divided by the sum of the inequality distance score and the joint gain distance score. Therefore, the prosocial motivation scores range from 0 (perfect inequality aversion) to 1 (perfect joint gain maximization).

The central mark indicates the median, boxes depict 25- and 75-percentiles. The upper (and lower) whiskers extend from the upper (and lower) edges of the box to the largest (and smallest) value within a range of maximal 1.5 times the interquartile range. All data points including extreme data points are shown. For visualization, we also plot estimated distributions. Note that the kernel density estimation for the density plot generates data that fall outside the bounds of the original data. Therefore, the values on the y-axis in (b) extend to 1.2 although the maximum score is bounded to 1. See Supplementary Figures 3 & 4 for choice distributions on all SVO items.

The prosocial motivation score of the UW patient is very unlikely to have arisen by chance, i.e., by the patient making random choices. We simulated 10,000 random answers for the nine secondary items according to a uniform distribution (i.e., equal probabilities for choosing each of the nine options for each item). As expected due to random answers, only a subset of 6.2 % (i.e., 620) of these 10,000 simulated "participants" were prosocial on both primary and secondary items. The score of the UW patient (or score at least as extreme in the joint gain direction) was only obtained in 0.005 % of these 620 simulated participants. Taken together, this speaks for a difference in the underlying motivation for prosocial preferences in the UW patient compared to the healthy population.

JPE task: Comparison of economic models for allocation evaluations

For allocation evaluations in the JPE task, the Inequality & Joint-gain model performed best in the UW patient (i.e., had the lowest Bayes factor; Figure 3). The Fehr-Schmidt model was a close runner-up and performed second best. The Fehr-Schmidt model considers the payoff for self, disadvantageous inequality (self gets less than other), and advantageous inequality (other gets less than self). Mathematically, the Fehr-Schmidt model for the JPE task is equivalent to the model formulation used by Haruno and Frith (2010) and to a formulation that replaces payoffs for self by joint gains (see Appendix in the Supplementary Material).

In all healthy samples, the Inequality & Joint-gain model fitted second best and the Fehr-Schmidt model fitted best (using Bayesian model comparisons according to fixed-effects analyses based on log-group Bayes factors; Figure 3). These fixed-effects analyses neglect variability between participants. We therefore, performed random-effects analyses by calculating protected exceedance probabilities. We found that the Inequality & Joint-gain model had higher protected exceedance probabilities than the Fehr-Schmidt model in all healthy samples (Supplementary Table 4). This implies that the Inequality & Joint-gain model performed better (i.e. had a lower BIC) in more participants than the Fehr-Schmidt model (Supplementary Table 5)—but for those participants, for whom the Fehr-Schmidt model was better, it tended to be better by a larger margin.

Taken together, two related models performed well in the JPE task across samples. Both models consider inequality and gain magnitudes. However, the employed version of the JPE task did not allow a good distinction between the fit of the Inequality & Joint-gain model and the Fehr-Schmidt model. We therefore cannot conclude that a different economic model better explained the evaluations of the UW patient.

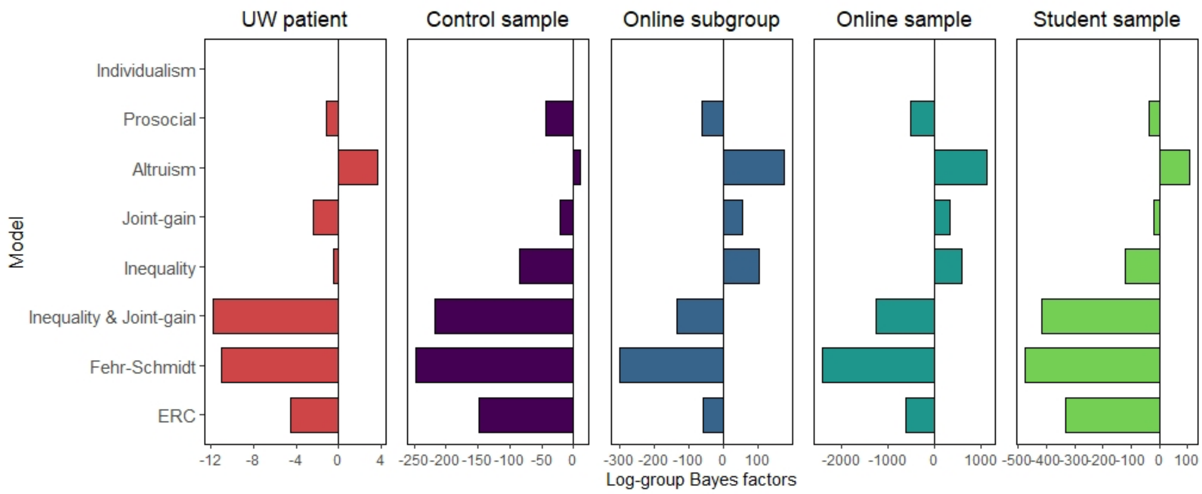

Figure 3. Model comparisons in the JPE task according to fixed-effects analyses

Log-group Bayes factors relative to the first model (Individualism). The presented fixed-analyses according to log-group Bayes factors assume that every participant uses the same model. The Inequality & Joint-gain model performed best in the UW patient. The Fehr-Schmidt model performed best in all healthy samples. Lower numbers indicate better model fit. See Supplementary Tables 4 & 5 for random-effects analyses, which assume that different participants may use different models. ERC, Equity, Reciprocity, Competition model.

JPE task: Comparison of parameter estimates from the inequality & join-gain model between the UW patient and controls

We tested whether parameter estimates from the Inequality & Joint-gain model differed between the UW patient and healthy participants (both in the control sample and in the online subgroup). Using Bayesian single-case analysis, we found no evidence for differences in the two parameter estimates of interest: 1) inequality (patient: *estimate* = -.011; control sample: M = -0.011, SD = 0.004, percentile estimate = 50.01%, 95% CI [32.66, 67.37], p = .999; online subgroup: M = -0.007, SD = 0.005, percentile estimate = 19.48%, 95% CI [13.23, 26.8], p = .39) and (2) joint-gain (patient: *estimate* = 0.005; control sample: M = 0.0036, SD = 0.002, percentile estimate = 71.2%, 95% CI [53.63, 85.59], p = .576; online subgroup: M = 0.004, SD = 0.002, percentile estimate = 73.02%, 95% CI [65.05, 80.18], p = .54). Parameter estimates are numerically small because the predictors are in a range from 0 to 200 and the dependent variables are ratings in a range from 1 to 4.

In sum, we found no evidence for differences between the UW patient and controls in their evaluations of the payoff allocations included in the used JPE task.

Discussion

This case study investigated the impact of amygdala lesions on allocation decisions and preferences. In addition, we provide rather large datasets of healthy participants to characterize various social motives in a wider population. Based on previous neuroimaging findings and evidence in nonhuman primates and rodents, we hypothesized that the UW patient would have less prosocial preferences due to the amygdala lesions and that this would be reflected in her SVO score and possibly the parameters of the economic model describing allocation preferences. We did not find evidence for a less prosocial SVO in the UW patient compared to the healthy population. Since the UW patient was categorized as prosocial, we looked into the prosocial motivation score, which describes the underlying motivations for prosocial SVO. We found that the UW patient's motivation was to maximize joint gains rather than to minimize inequality. All three of our healthy samples showed similar distributions for prosocial motivation scores. Strikingly, a Bayesian single-case analysis revealed that an estimated 99.5% of the healthy control sample would have a lower prosocial motivation score than the UW patient. The distinctiveness of the UW patient's prosocial motivation score was driven by higher joint gain maximization rather than lower inequality aversion. The prosocial motivation score of the UW patient is unlikely to have arisen by chance (as determined by simulations).

In addition, we compared several economic models on participants' evaluations of joint payoffs in the JPE task and found that the Inequality & Joint-gain model and the Fehr-Schmidt model were the two best performing models—both of which include metrics for inequality and joint- or self-gain. We found no differences in parameter estimates of the UW patient and control groups. Apart from questions of power and specificity with regard to the used version of the JPE task, it could be that a choice context is needed to detect an effect that would correspond to the difference between the UW patient and controls in prosocial motivation as revealed by the SVO task: In the JPE task, participants make judgments indicating their evaluation of joint gain and inequality. In contrast, the secondary items of the SVO task force participants to make a decision between these competing motives.

This study was motivated by a neuroimaging finding that the amygdala was the only brain region in which prosocials and individualists differed with respect to tracking the absolute inequality between payoffs for self and other (Haruno & Frith, 2010). A recent neuroimaging study suggested that the amygdala encodes a social-value-distance signal in prosocials (Liu, 2019). Our results speak against a generally less prosocial SVO in a patient with amygdala lesions but are complementary to the neuroimaging findings that showed intra- and inter-individual relationships of the amygdala with metrics of inequality (Haruno & Frith, 2010; Liu et al., 2019). Thus, the amygdala might be functionally and causally involved in setting the specific motivation for prosocial allocations. To determine whether this specific motivation is encoded in the amygdala further studies combining a computational approach with neuroimaging will be needed (Charpentier & O'Doherty, 2018). Mathematically speaking, the UW patient maximized the sum of the payoffs to self and other rather than minimized the differences between the two payoffs. This makes specific predictions for future neuroimaging studies that could pit these (and potentially other) prosocial motivations against each other. Neuroimaging studies could also elucidate the interplay of the amygdala with other brain regions such as the (dorso-)medial prefrontal cortex (Banks et al., 2007) or the insula (Bebko et al., 2015).

Our findings suggest the intriguing possibility that the amygdala might have a rather specific role in the processing of social motives with respect to trading off the maximization of joint gains versus the minimization of inequality. Finer-grained underlying prosocial motivations could also be captured in mathematically defined economic models specified for tasks that separate these prosocial motivations (e.g., by generating allocation tasks that sample the whole allocation plane for self and other). In this sense, our findings could help inform novel modeling and theorizing in psychology and behavioral economics.

We note the general limitation of case studies in terms of sample size. Furthermore, UW syndrome leads to amygdala calcification early in life, hence compensatory mechanisms might have promoted the development of a prosocial preference. A conceptual replication in patients who acquired amygdala lesions later in life would be desirable (Bach et al., 2019). Our findings cannot disentangle the role of different subregions of the amygdala (such as the basolateral amygdala or the central-medial amygdala) since the UW patient tested here shows calcifications in the entire bilateral amygdala (Hurlemann et al., 2007). Human lesion studies commonly consider the amygdala as a unified structure; with the exception of studies on lesions patients with selective basolateral amygdala damage (de Gelder et al., 2014; Klumpers et al., 2015; Koen et al., 2016; Rosenberger et al., 2019; van Honk et al., 2013). The available neuroimaging studies on social motives did not try to separate amygdala nuclei which would require high resolution and possibly an independent method to identify them on an individual basis (e.g. Abivardi & Bach, 2017; Bach, Behrens, Garrido, Weiskopf, & Dolan, 2011). Thus, testing prosocial preferences in patients with more specific lesions would be interesting.

We deem it generally interesting to extend our approach to more vivid tasks with live social interactions and non-monetary incentives because the amygdala has been related to multiple social learning processes (Hurlemann et al., 2010; Olsson & Phelps, 2007). Specifically, an intriguing recent study showed that participants with selective basolateral amygdala damage did not learn to adjust their behavior to the trustworthiness of their interaction partners in a repeated trust game (Rosenberger et al., 2019). It would be worthwhile to see whether the prosocial motivation to maximize joint gain, which might be linked to the amygdala, leads to impaired adaptation during repeated interactive decisions (such as in dictator games, which correspond to the SVO task, trust games, or prisoners' dilemma). Relatedly, live social interactions often entail emotional facial expressions. Since UW patients show aberrations in processing fearful or threatening facial expressions (Bach et al., 2015; de Gelder et al., 2014), it would be interesting to test if social motives would change if the interaction partners enact emotional facial expressions.

To summarize, while our results do not support a generally less prosocial SVO in the UW patient, they indicate a shift toward the motivation for maximizing joint gain in the UW patient with respect to healthy controls.

Author Contributions

CWK, DRB, and RH planned the experiments. CWK, DRB and, RH collected the data. LMD and, CWK analyzed the data. LMD, RH, DRB, and, CWK wrote the manuscript.

Data availability

The behavioral data that support the findings of this study are available on GitHub (https://github.com/LisaDoppelhofer/SocialMotives_2021).

Code availability

The MATLAB code for this study is available on GitHub (https://github.com/LisaDoppelhofer/SocialMotives_2021).

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplementary Material

Supplementary Methods

Economic models for the JPE task.

(1) Individualism model: $U = \alpha * \$Self$

In the individualism model, utility (U) depends linearly on the payoff for self ($Self).

(2) Prosocial model: $U = \alpha * \$Self + \beta * \$Other$

In the prosocial model (McClintock, 1972), utility (U) is a weighted sum of the linear payoffs for self ($Self) and other ($Other).

(3) Altruism model: $U = \beta * \$Other$

In the altruism model, utility (U) solely depends on the payoff for other ($Other).

(4) Joint-gain model: $U = \alpha * (\$Self + \$Other)$

The joint gain-model considers the total welfare of self and other but does not distinguish between payoffs for self and other.

(5) Inequality model: $U = \alpha * abs(\$Self - \$Other)$

The inequality model considers the absolute difference between the payoffs for self and other.

(6) Inequality & Joint-gain model:

$$U = \alpha * abs(\$Self - \$Other) + \beta * (\$Self + \$Other)$$

The Inequality & Joint-gain model is a linear combination of the inequality model and the joint-gain model.

(7) Fehr-Schmidt model:

$$U = \alpha * \$Self + \beta * \max(\$Other - \$Self, 0) + \gamma * \max(\$Self - \$Other, 0)$$

The Fehr-Schmidt (Fehr & Schmidt, 1999) model separately considers the payoff for the self, disadvantageous inequality (self gets less than other), and advantageous inequality (other gets less than self). Here, beta represents disadvantageous inequality aversion and gamma represents advantageous inequality aversion. If the difference between $Other and $Self is a negative value, the term *max($Other - $Self,0)* sets the result to zero (and keeps the result if it is a positive value). The same holds for the difference between $Self and $Other ($Self - $Other). Both, disadvantageous and advantageous inequality aversion are supposed to affect the utility negatively. Parameters were not restricted to enable the possibility of altruistic and competitive motives. This model is equivalent to the model used by Haruno and Frith (2010) but has a different parameterization (i.e., this parameterization distinguishes between payoffs to self and other but collapses advantageous and disadvantageous inequality aversion into absolute inequality aversion; see Appendix in the Supplementary Material). The Fehr-Schmidt model is also equivalent to a formulation that includes a regressor for joint-gain (i.e., $\$Self + \$Other$) instead of a regressor for pure self-gain (i.e., $\$Self$).

(8) ERC (Equity, Reciprocity, Competition) model:

$$U = \alpha * \$Self + \frac{\beta}{2} * \left(\frac{\$Self}{\$Self + \$Other} - \frac{1}{2}\right)^2$$

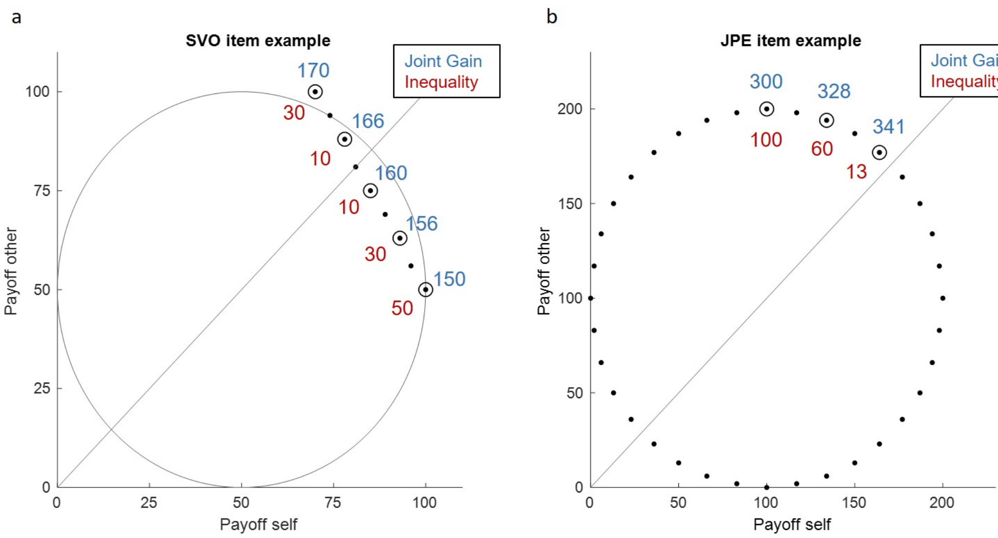
The ERC model (Bolton & Ockenfels, 2000) considers (quadratic and normalized) inequality (but does not explicitly distinguish between advantageous and disadvantageous inequality).

Model fitting and model selection. For model fitting, we excluded participants who showed no variance in the JPE task at all (i.e., they selected the same evaluation option on each trial; see Supplementary Table 1). Regression models were fitted using the MATLAB function *regress*, which minimizes the sum of squared errors (also known as residual sum of squares, RSS). Parameter estimates were unbounded.

For model selection, we used the Bayesian information criterion (BIC). BIC depends on model fit (calculated as RSS) and includes a penalty for model complexity (that depends on the number of parameters, k), according to the following standard formula (Burnham & Anderson, 2004; Hurvich & Tsai, 1990), where n is the number of trials per participant:

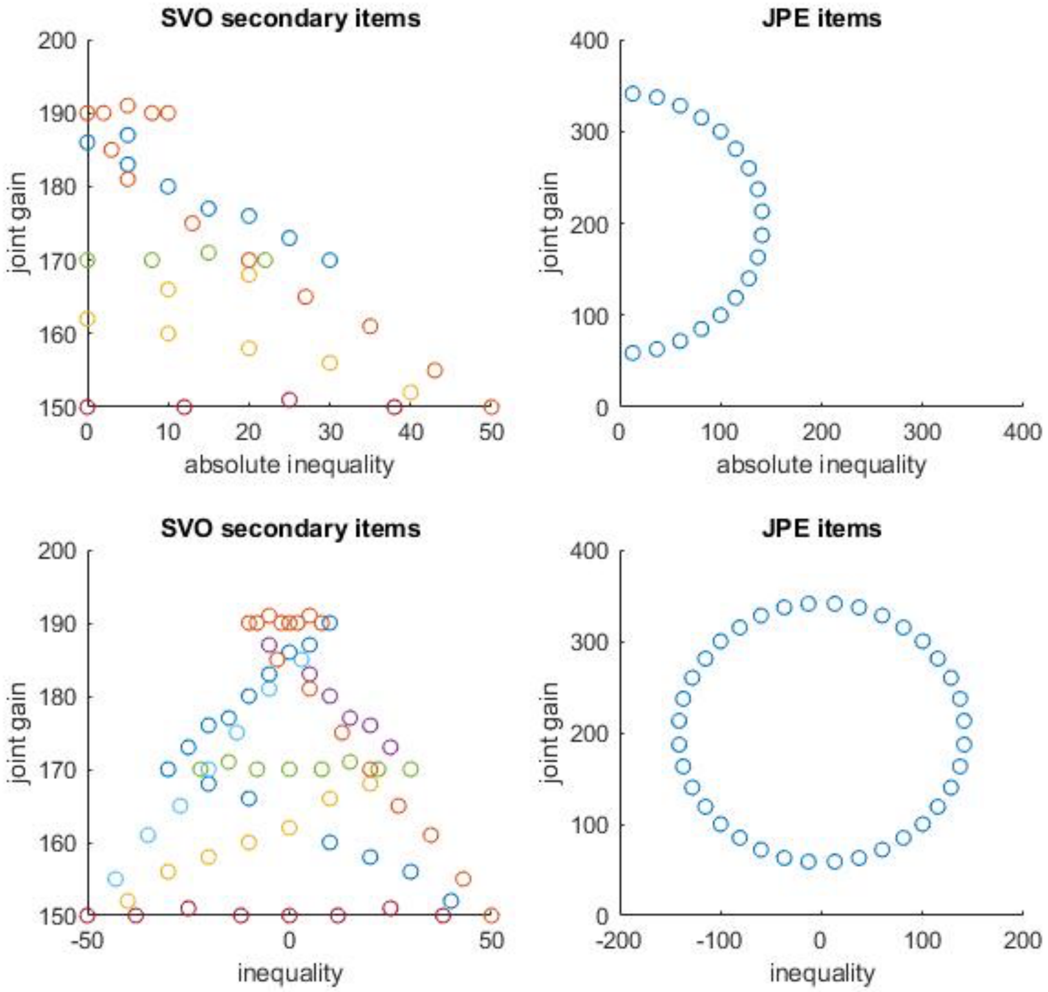
$$BIC = n * \ln\left(\frac{RSS}{n}\right) + k * \ln(n)$$

First, we performed fixed-effects analyses, under the assumption that every participant uses the same model: BIC values are summed over participants to obtain log-group Bayes factors. The model with the lowest log-group Bayes factors is preferred. Second, we performed random-effects analyses under the assumption that different participants may use different models. We used the function *spm_BMS* in the MATLAB toolbox SPM (https://www.fil.ion.ucl.ac.uk/spm/) to calculate protected exceedance probabilities, which measure how likely it is that any given model is more frequent than all other models in the population.



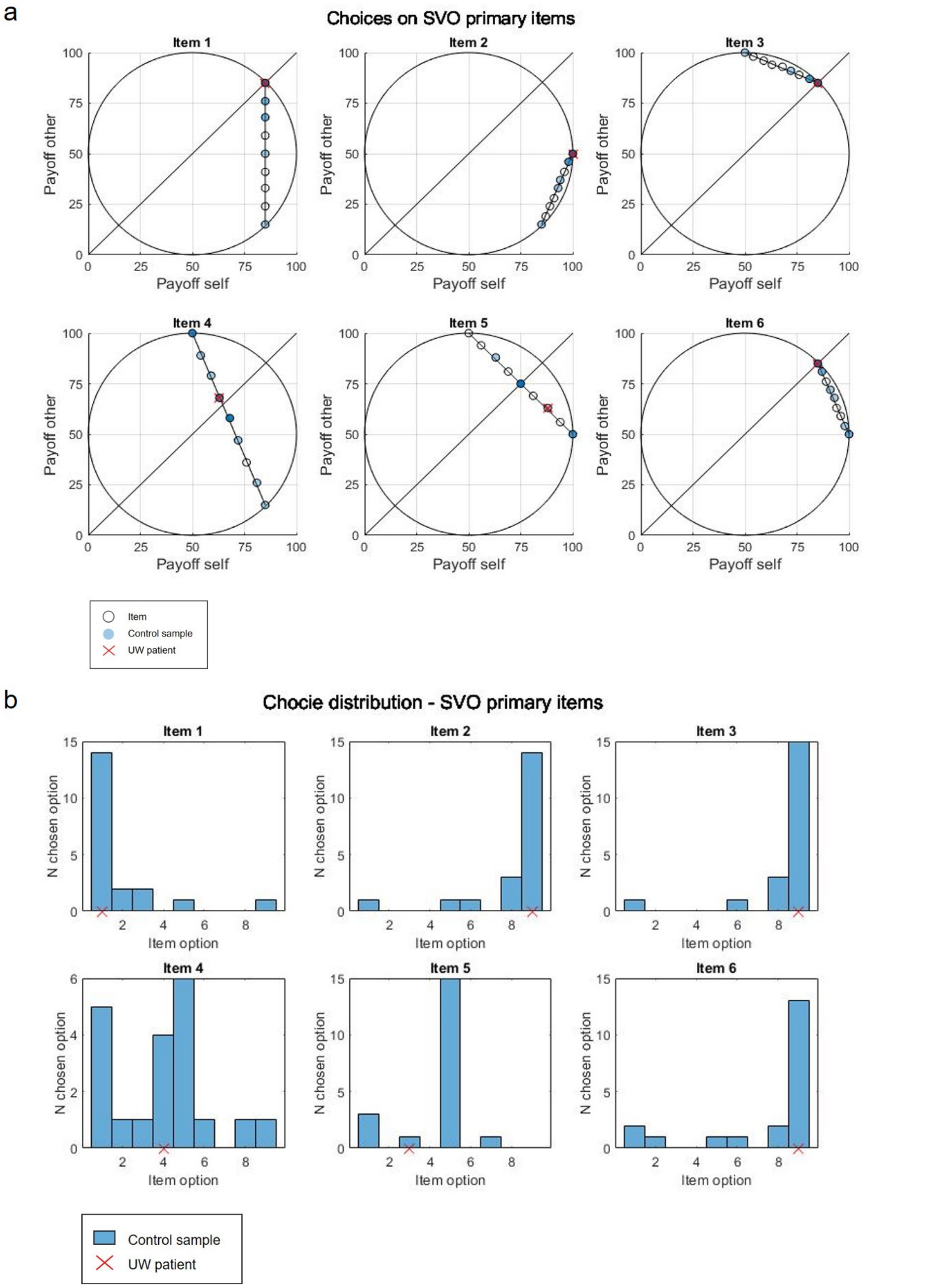
Supplementary Figure 1. Example items of the SVO task and the JPE task.

a. Example item of one of the secondary items of the SVO task and corresponding joint gain and inequality values. Black dots visualize the 9 options of the item. Circles around the dots indicate the example option corresponding to the numbers. **b.** Example items of the JPE task and corresponding joint gain and inequality values. Black dots display all 36 items of the JPE task (see Supplementary Table 2 for a list of these 36 items). Circles around the dots indicate the example item corresponding to the numbers **a. & b.** Blue values above the dots indicate the joint gain, red values below the dots indicate the inequality between payoffs for self and other for the corresponding option/item. Secondary items of the SVO comprise different combinations (higher/lower) of joint gain and inequality. See Figure 1 for a visualization of all SVO items. See Supplementary Figure 2 for the depiction of the SVO and JPE items in terms of (absolute) inequality and joint gain. See Supplementary Figures 3 & 4 for choice distributions across the SVO items.



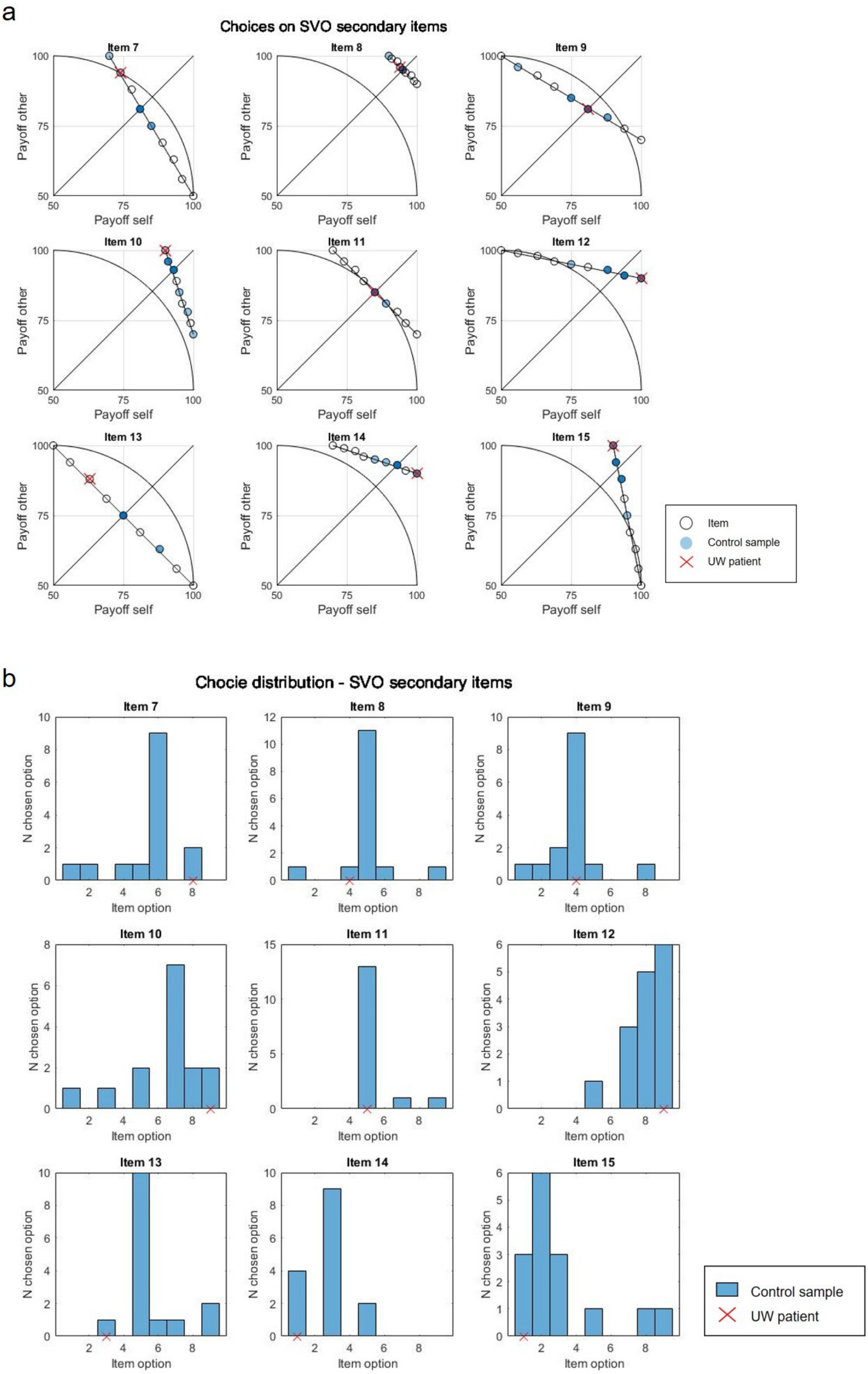
Supplementary Figure 2. Items of the SVO task and the JPE task in terms of (absolute) inequality and joint gain.

Left column: The nine options of each of the nine SVO secondary items are depicted. Right column: The 36 items of the JPE task are depicted. These 36 items are positioned on a circle in the coordinate system with payoff for self and payoff for other as axes (see Supplementary Figure 1). In the coordinate system of Supplementary Figure 1, the diagonal identity line (with a slope of 1 and an intercept of 0, i.e., at an angle of 45°) corresponds to inequality of 0 between payoffs for self and other (see also Figure 1c). The orthogonal diagonal line (with a slope of -1 and an intercept of 0, i.e., at an angle of 135°) corresponds to joint gain (see also Figure 1d). That is, the axes for the JPE items can be rotated by an angle of 45° to switch from axes in terms of self and other payoffs (Supplementary Figure 1) to axes in terms of inequality and joint gain.



Supplementary Figure 3. Choice distributions on the SVO primary items.

a. All nine options for the six primary items are depicted. The numbers of participants in the control sample who chose the respective options are color-coded. b. For better visualization, these numbers are shown as histograms.



Supplementary Figure 4. Choice distributions on the SVO secondary items.

Same logic as in Supplementary Figure 3 for the SVO secondary items.

Supplementary Table 1. Sample sizes according to the used exclusion criteria for different analyses.

Criteria	Descriptions of exclusion or inclusion criteria	Control	Online subgroup	Online sample	Student
(1) Tested participants	No participants excluded	23 (100)	97 (100)	628 (100)	41 (100)
(2) Transitive in SVO task primary items	Participants with intransitive choices in the primary items of SVO task excluded; this exclusion criterion was used for all analyses	20 (86.96)	91 (93.81)	603 (96.02)	40 (97.56)
(3) Not deterministic in JPE task	Participants with a choice variance of 0 in the JPE task were excluded because they made deterministic choices; this exclusion criterion was used for modeling the JPE data	19 (82.61)	86 (88.66)	586 (93.31)	40 (97.56)
(4) Prosocials in SVO primary items	Participants with a prosocial SVO scores according to primary items of SVO task; this inclusion criterion was used for calculating the proportion of prosocials in Table 1	16 (69.57)	74 (76.29)	474 (75.48)	32 (78.05)
(5) Prosocials in SVO primary and secondary items	Participants with prosocial SVO scores according to both the primary and the secondary items of the SVO task; this inclusion criterion was used for all analyses and plots that describe prosocial motivation; the numbers correspond to the proportion of prosocials in Table 2	15 (65.22)	66 (68.04)	432 (68.79)	26 (63.41)

Participants are given as N (% of tested participants)

Supplementary Table 2. Items of the JPE task

Item number	Payoff self	Payoff other
1	36	177
2	23	164
3	13	150
4	6	134
5	2	117
6	0	100
7	66	6
8	83	2
9	100	0
10	117	2
11	134	6
12	150	13
13	198	117
14	194	134
15	187	150
16	177	164
17	164	177
18	150	187
19	2	83
20	6	66
21	13	50
22	23	36
23	36	23
24	50	13
25	134	194
26	117	198
27	100	200
28	83	198
29	66	194
30	50	187
31	164	23
32	177	36
33	187	50
34	194	66
35	198	83
36	200	100

Supplementary Table 4. Model comparisons in the JPE task according to random-effects analyses

Model	Control sample	Online subgroup	Online sample	Student sample
Individualism	0	0	0	0
Prosocial	0.003	0	0	0
Altruism	0	0	0	0
Joint-gain	0	0	0	0
Inequality	0	0	0	0
Inequality & Joint-gain	0.984	0.931	1	0.806
Fehr-Schmidt	0.005	0.069	0	0.072
Equity, Reciprocity, Competition (ERC)	0.007	0	0	0.122

Higher protected exceedance probabilities indicate better model fit according to random-effects analyses, which assume that different participants may use different models. Protected exceedance probabilities are rounded to three decimal places.

Supplementary Table 5. Model comparisons in the JPE task according to number of participants for which the model performed best in terms of BIC

Model	UW patient	Control sample	Online subgroup	Online sample	Student sample
Individualism	0	0	7	51	0
Prosocial	0	2	10	81	2
Altruism	0	0	2	12	0
Joint-gain	0	0	2	18	0
Inequality	0	1	2	22	2
Inequality & Joint-gain	1	11	34	238	15
Fehr-Schmidt	0	2	21	109	9
Equity, Reciprocity, Competition (ERC)	0	3	8	55	12
Total N	1	19	86	586	40

Appendix

Here, we show that the Fehr-Schmidt model is equivalent to the model used by Haruno and Frith (2010) but with a different parameterization. Two regression models are equivalent if a linear combination of the regressors of the first model results in the regressors of the second model. Below, we first list the two models again:

Fehr-Schmidt model:

(1) $U_{FS} = \alpha_{FS} * \$Self + \beta_{FS} * \max(\$Other - \$Self, 0) + \gamma_{FS} * \max(\$Self - \$Other, 0)$

Haruno-Frith model:

(2) $U_{HF} = \alpha_{HF} * \$Self + \beta_{HF} * \$Other + \gamma_{HF} * \text{abs}(\$Self - \$Other)$

Now, we want to show that $U_{FS} = U_{HF}$ for any scalars $\$Self$ and $\$Other$. That is, we want to show that the parameters of the Fehr-Schmidt model can be expressed by the parameters of the Haruno-Frith model (without any dependence on the regressors). Because the models contain the "max" and the "abs" operators, we treat $\$Self \geq \$Other$ and $\$Self < \$Other$ separately.

For $\$Self \geq \$Other$, the Fehr-Schmidt model (1) is

$U_{FS} = \alpha_{FS} * \$Self + \beta_{FS} * 0 + \gamma_{FS} * (\$Self - \$Other)$

For $\$Self \geq \$Other$, the interior of the first "max" operator equates to zero. Rearranging gives

(3) $U_{FS} = (\alpha_{FS} + \gamma_{FS}) * \$Self - \gamma_{FS} * \$Other$

For $\$Self \geq \$Other$, the Haruno-Frith model (2) is

$U_{HF} = \alpha_{HF} * \$Self + \beta_{HF} * \$Other + \gamma_{HF} * (\$Self - \$Other)$

That is, the "abs" operator can be omitted (because $\$Self - \$Other \geq 0$). Rearranging gives

(4) $U_{HF} = (\alpha_{HF} + \gamma_{HF}) * \$Self + (\beta_{HF} - \gamma_{HF}) * \$Other$

Thus, the two models can be reduced to expressions that only contain $\$Self$ and $\$Other$ as regressors. Fitting a regression with these two regressors to the same data will result in identical parameter estimates regardless of the notation used in (3) or (4). Therefore, we can equate the parameter estimate for $\$Self$ in the two formulations (3) and (4).

(5) $\alpha_{FS} + \gamma_{FS} = \alpha_{HF} + \gamma_{HF}$

Analogously, we can equate the parameter estimate for $\$Other$ in the two formulations (3) and (4).

(6) $-\gamma_{FS} = \beta_{HF} - \gamma_{HF}$

Solving for the parameters of the Fehr-Schmidt model in (5) and (6) yields

$\alpha_{FS} = \alpha_{HF} + \beta_{HF}$ and

$\gamma_{FS} = -\beta_{HF} + \gamma_{HF}$

Now, we consider the other case in the same way. For $\$Self < \$Other$, the Fehr-Schmidt model (1) is

$U_{FS} = \alpha_{FS} * \$Self + \beta_{FS} * (\$Other - \$Self) + \gamma_{FS} * 0$

For $\$Self < \$Other$, the interior of the second "max" operator equates to zero. Rearranging gives

(7) $U_{FS} = (\alpha_{FS} - \beta_{FS}) * \$Self + \beta_{FS} * \$Other$

For $\$Self < \$Other$, the Haruno-Frith model is

$U_{HF} = \alpha_{HF} * \$Self + \beta_{HF} * \$Other + \gamma_{HF} * (\$Other - \$Self)$

For $\$Self < \$Other$, the interior of the "abs" operator has to be multiplied by -1 (because $\$Self - \$Other < 0$). Rearranging gives

(8) $U_{HF} = (\alpha_{HF} - \gamma_{HF}) * \$Self + (\beta_{HF} + \gamma_{HF}) * \$Other$

Again, the two models can be reduced to expressions that only contain $\$Self$ and $\$Other$ as regressors. We equate the parameter estimate for $\$Self$ in the two formulations (7) and (8).

(9) $\alpha_{FS} - \beta_{FS} = \alpha_{HF} - \gamma_{HF}$

We equate the parameter estimate for $\$Other$ in (7) and (8).

(10) $\beta_{FS} = \beta_{HF} + \gamma_{HF}$

Solving for the parameters of the Fehr-Schmidt model in (9) and (10) yields

$\alpha_{FS} = \alpha_{HF} + \beta_{HF}$ and

$\beta_{FS} = \beta_{HF} + \gamma_{HF}$

Thus, we can express the parameters of the Fehr-Schmidt model solely in terms of the Haruno-Frith model. For the two cases, we obtain the same equivalence for α_{FS} and unique equivalences for β_{FS} and γ_{FS}. The two models are equivalent.

An analogous derivation can be made for a model that includes a regressor for joint-gain (i.e., $\$Self + \$Other$) instead of a regressor for pure self-gain (i.e., $\$Self$).