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Cognitive Processes of Distributional Preferences: A Response Time Study[⊕]

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Abstract

There is ample evidence that people differ considerably in their preferences. We identify individual heterogeneity in type and strength of social preferences in a series of binary three-person dictator games. Based on this identification, we analyze response times in another series of games to investigate the cognitive processes of distributional preferences. We find that the response time increases with the number of conflicts between individually relevant motives and decreases with the utility difference between choice options. The selfish motive is more intuitive for subjects who are more selfish. The heterogeneity in preferences is reflected in the heterogeneity of the underlying cognitive processes. Our findings provide evidence for both, sequential sampling models and dual-process theories, and help to reconcile the mixed results on the correlations between response time and prosociality. Our results also show that it is important to take heterogeneity of preferences into account when investigating the cognitive processes of social decision making.

Key words: distributional preferences; cognitive process; response time; heterogeneity

JEL Classification: A12, C72, C91, D30, D87

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1. Introduction

A huge body of evidence indicates that people are willing to sacrifice their own material resources to benefit or hurt others. Empirical research has investigated the motives underlying this behavior and theoretical models have been developed to formalize these motives (Bolton and Ockenfels 2000, Charness and Rabin 2002, Dufwenberg and Kirchsteiger 2004, Falk and Fischbacher 2006, Fehr and Schmidt 1999, Rabin 1993). More recently, the cognitive processes which govern people's social behavior have come into focus: How are social decisions actually made? Social decisions are particularly interesting because they can be considered as compound goods satisfying different motives. Cognitive processes are about how we deal with these conflicting motives.

There has been considerable interest in exploring the cognitive processes of social decision making using dual-process approaches which assume the existence of two qualitatively distinct processes: One is relatively automatic and intuitive, and the other is relatively controlled and deliberative (Achtziger and Alós-Ferrer 2014, Alós-Ferrer and Strack 2014, Brocas and Carrillo 2014, Chaiken and Trope 1999, Frederick 2005, Fudenberg and Levine 2006, Hauge et al. 2016, Kahneman 2003, 2011, Sloman 1996, Strack and Deutsch 2004). Relative response times (RTs) are widely used to distinguish between the intuitive and the deliberative processes since the intuitive process are executed more quickly than the deliberative process (Krajbich, Bartling, et al. 2015). In the domain of social preferences, this raises the question whether specific motives are processed more automatically than others, in particular whether the selfish or the social motive is more intuitive. The evidence based on studies using RTs and the manipulation of cognitive process is mixed so far. Some studies find that prosocial decisions are quicker than selfish decisions and people tend to be more prosocial under time pressure or cognitive load, which indicates that the social motives are more intuitive (Cappelen et al. 2015, Cappelletti et al. 2011, Cornelissen et al. 2011, Lotito et al. 2013, Nielsen et al. 2014, Peysakhovich and Rand forthcoming, Rand et al. 2012, Rubinstein 2007, Schulz et al. 2014), while other studies find that selfish motives are more intuitive (Duffy and Smith 2014, Lohse et al. 2014, Piovesan and Wengström 2009, Tinghog et al. 2013, Verkoeijen and Bouwmeester 2014).

A different view regarding the cognitive processes of social decision making is taken by the sequential sampling models, which assume that a noisy relative decision value is integrated at each moment in time and a choice is made when this accumulated decision value crosses a threshold. The sequential sampling models were developed for perceptual decision making (Ratcliff 1978, Ratcliff and Smith 2004) and recently adapted to the analysis of economic and in particular social decisions (Cary and Nave 2015, Dickhaut et al. 2013, Hutcherson et al. 2015, Krajbich et al. 2010, Krajbich, Bartling, et al. 2015, Krajbich et al. 2014). These studies indicate that there exists a common computational mechanism underlying economic (social) decision making and perceptual decision making. Importantly,

sequential sampling models assume that there is only one single deliberative process governing social decisions but not competing processes. The strength of preference which is based on the utility difference between choice options determines RTs and stronger preference over one option requires shorter RTs. Moreover, the RT of selfish decisions is not significantly different from that of social decisions after controlling for the strength of preference (Krajbich, Bartling, et al. 2015).

Which explanation of the cognitive process is correct has major implications for understanding human nature, and from a practical point of view for modeling the cognitive process to predict human behavior or designing institutions to promote prosocial behavior (Bear and Rand 2016, Cone and Rand 2015, Krajbich, Hare, et al. 2015, Krajbich et al. 2014). Therefore, it is crucial to identify the cognitive processes of social decision making. This paper studies this topic in depth by taking the heterogeneity of preferences into account and analyzing RTs in distribution decisions. It is a well-established fact that people are heterogeneous in the relevant motives and in the strength of preferences (Andreoni and Miller 2002, Engelmann and Strobel 2004, Erlei 2008, Fisman et al. 2007, Kerschbamer 2015). For instance, some people care more about efficiency, while others care more about fairness (Murphy et al. 2011). We explicitly take individual heterogeneity into account, not only with respect to what kind of social motives people care about, but also with respect to the strength of people's selfish motives. Our experiment includes two types of binary three-person dictator games: the third-party (TP) dictator game and the second-party (SP) dictator game. In TP games, the dictator's payoffs are the same in the two allocations, while in SP games, the dictator's payoffs differ between the two allocations. Decisions in TP games allow us to identify subjects' social motives. Based on this identification, we can study how people with different social motives react to various decision situations in SP games using RT analysis. In addition, we can study which kind of motive, the selfish or the social motives, can be considered as more intuitive.

We classify subjects into three norm types which differ with respect to the relevant social motives based on the decisions for TP games. Based on this identification, a within-subject analysis on the SP games shows that the RT increases with the number of conflicts between individually relevant motives and decreases with the utility difference between choice options. These results are in line with the predictions of sequential sampling models. A between-subject analysis reveals the heterogeneity with respect to whether the selfish or the social motive is more intuitive. It turns out that the selfish motive is more intuitive for subjects who are more selfish. We also show that the heterogeneity in social motives and selfishness is reflected in process differences. Our findings demonstrate that the cognitive processes of social decision making comply with both, sequential sampling models and dual-process theories. And our findings also show that it is important to take the heterogeneity of preferences into account when investigating the cognitive processes of social decision making.

Our study contributes to the emerging and conflicting literature on the cognitive underpinnings of social decision making. The experiment allows identifying both the heterogeneity in social motives and

the strength of selfishness. Based on this identification, we are not only able to provide evidence for sequential sampling models, but we can also show the heterogeneity in whether the selfish or the social motive is related to the intuitive process. This could help to reconcile the mixed results on the correlations between RT and prosociality, and resolve the debate between the dual-process explanation and the sequential sampling explanation of the cognitive processes of social decision making. We argue that conflicts between individually relevant motives, the strength of preference, and the intuition or the deliberation of selfishness all contribute to the variations of RT. Thus, it is crucial to take these factors and the heterogeneity of preferences into account when investigate the cognitive processes of social decision making.

2. Experimental Design and Procedures

In this section, we first describe the game that we use in our experiment and then provide a detailed description of our experimental procedures.

2.1 Experimental Design

The experiment consists of a series of 64 binary three-person dictator games.[1] In each of these dictator games, a subject (dictator) decides between two predefined allocations (A_1, A_2, A_3) and (B_1, B_2, B_3), which determine how money is distributed between herself (player 2) and the other two subjects in her group. The other two subjects have no choice. 32 of the 64 games are third-party (TP) dictator games, in which the dictator's payoff does not differ between the two options. In TP games we can assess the importance of different social motives – unaffected by the selfish motive – and define a 'personal norm', which refers to a person's purely social motive. These social motives include efficiency, maximin, envy, disadvantageous inequality aversion (FS-α) and advantageous inequality aversion (FS-β). The social motives are defined as follows: Efficiency maximizes the total payoff of all subjects in the group. Maximin maximizes the minimum payoff of all subjects in the group, guaranteeing that no one is left in a very bad position. Envy is to minimize the difference between one's payoff and the highest payoff of others (Engelmann and Strobel 2004). The minimization of disadvantageous inequality corresponds to a high value of the α-term in the model by Fehr and Schmidt (1999) and the minimization of advantageous inequality corresponds to a high value of the β-term in the model by Fehr and Schmidt (1999). The conflict between the selfish and the social motives is studied in another 32 second-party (SP) dictator games in which the payoff of the dictator varies. Table 1 gives examples for the two types of the binary three-person dictator games.

[1] Appendix A lists the 64 games.

Table 1. Examples of the two types of games

Player	Third party (TP) game		Second party (SP) game	
	Option A	Option B	Option A	Option B
1	$A_1 = 5$	$15 = B_1$	$A_1 = 7$	$18 = B_1$
2 (Dictator)	$A_2 = 14$	$14 = B_2$	$A_2 = 14$	$13 = B_2$
3	$A_3 = 19$	$19 = B_3$	$A_3 = 13$	$20 = B_3$

We chose the 64 games systematically in such a way that different combinations of the previously suggested motives are represented in the games. We presented the six payoffs that describe each decision situation in a numeric form as well as a graphical form, in order to make them quickly accessible. The screen layout is shown in Figure F2 in Appendix F.

2.2 Procedural Details

The experiment was computerized and conducted with the software "z-Tree" (Fischbacher 2007). We conducted four sessions in October and November 2013 at the Lakelab of the University of Konstanz. 105 subjects participated in the experiment.[2] Subjects were recruited using the online recruitment system "ORSEE" (Greiner 2015). Each session lasted about 50 minutes and none of the subjects participated in more than one session. Upon entering the laboratory, subjects were randomly assigned to a PC terminal and were given a copy of instructions (Appendix F). A set of control questions was provided to ensure the understanding of the decision task. Questions were answered individually at subjects' own seats. The experiment did not start until all subjects had answered all questions correctly. At the end of a session, subjects were asked to fill out a socio-economic questionnaire.

To avoid order effects, we randomized the sequence of the 64 games for each subject. This means in particular that we also mixed the SP and TP games. In addition, Option A and Option B of each game were also randomly reshuffled. All subjects made their decisions as dictators by pressing key "F" or "J" on the keyboard. We recorded RTs on the server. The RT measured the time between when the allocation was sent to the client and when the server received the message that the key was pressed.[3] After each decision, subjects saw a waiting screen and were required to press the "Spacebar" to advance to the next decision. At the end of the experiment, the roles of the three players in each group were randomly determined. One of the 64 games was randomly selected and paid out according to their random roles. On average, each subject earned 9.92 Euros which included a show-up fee of 3 Euros.

[2] In order to address heterogeneity, our sample size is sufficiently larger than Hutcherson et al. (2015), who have 51 subjects actively making decisions.

[3] This causes some delay in comparison to the pure response time. However, the delay is completely uncorrelated to the decision situation because their sequence was randomized.

3. Main Results

In this section, we first characterize the heterogeneity in social preferences by conducting finite mixture analysis on subjects' decisions in TP games. Then, we analyze the RTs of SP decisions to investigate the cognitive processes of distributional preferences. Finally, we show that the heterogeneity in preferences is also reflected in the differences of cognitive processes.

3.1 Heterogeneity of Social Preferences

In order to deal with the heterogeneity and to determine individual social preferences, we analyze TP decisions using finite mixture analysis.[4] Moreover, in the finite mixture analysis we use four different structural models to check the robustness of our estimation. The results of the finite mixture analysis are robust. All four models show that the optimal number of types equals three according to the Normalized Entropy Criterion (Celeux and Soromenho 1996), and all four models create the same classification. In addition, all subjects can be assigned to one distinct type with high posterior probability. These clean classifications suggest that our analysis is able to capture the distinctive characteristics of each preference type. The results of the finite mixture analysis are shown in Appendix B. In the following, we will base our analysis on model IV in Table B1, which performs best according to the BIC criterion. However, the main results are robust with respect to the choice of the model. We identify subjects' social motives according to whether the coefficient of the motive is significant or not in Table B1. The relevant motives for each norm type in Model IV are summarized in Table 2.

Table 2. Pure social motives of each norm type

Norm type	Social motives	Number of subjects
I	Efficiency, Maximin	10
II	Envy, Maximin	16
III	Efficiency, Maximin, FS-β	79

3.2 Response Time Analysis

In this section we investigate the RTs of SP decisions based on the identification of heterogeneity in preferences[5]. We first show that the cognitive processes of distributional preferences comply with the sequential sampling models. Then we show that the selfish motive is more intuitive for subjects who are more selfish.

[4] We conducted the finite mixture analysis using R package flexmix (Grun and Leisch 2008).
[5] The evolution and the distributions of RTs are shown in Appendix C.1 and C.2.

3.2.1 Evidence for Sequential Sampling Models

In this section, we present evidence that the cognitive processes of distribution decisions comply with sequential sampling models (Ratcliff 1978, Ratcliff and Smith 2004). Sequential sampling models originate from psychology and neuroscience, and describe the dynamics of the decision process. These models assume that there is a value representing the collected evidence in favor of a particular decision. This value is stochastically sampled over time, and the choice is executed when the value hits one of two pre-specified boundaries. Sequential sampling models predict that the probability of choosing an option is a sigmoidal function of the value (utility) difference between the two options, and RT increases with the difficulty (measured by the value difference between the two options) of the decision.

In this part, we focus on the question that how cognitive conflicts and the utility difference between the two options affect RT. We use the relevant motives identified before and define decision situation as conflicting if there is a conflict between these motives. And we use the latent variable of choosing Option A assessed by regressions as a measure of the utility difference. The utility difference between choice options measures the strength of preferences.

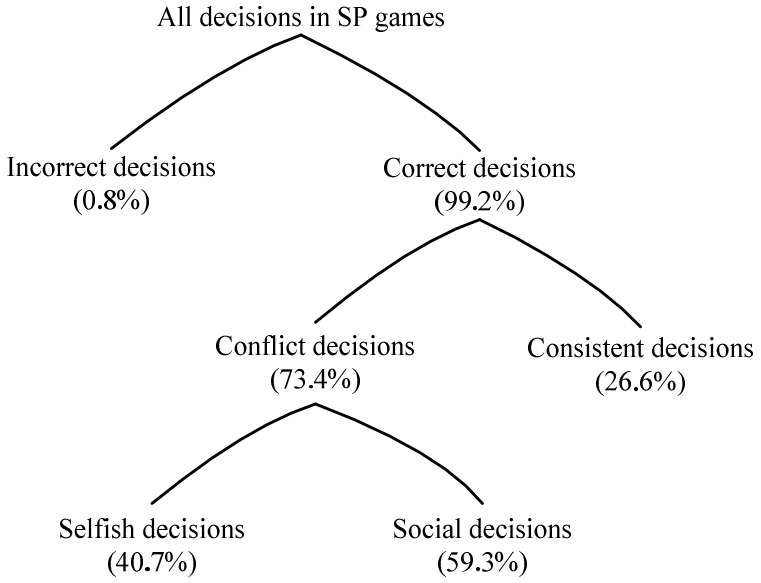

Fig.1 Classification of all decisions in the second-party dictator games. A decision is incorrect if it neither follow the personal norms nor the selfish motives. If the personal norms and the selfish motives are in line, it is considered as consistent otherwise as a conflict decision. The conflict decision is selfish or social decision depending on which motive people follow in that decision. More details about how the decisions are classified are shown in Tables C1.

First, we compare the RT of conflict and consistent decisions in SP games. Conflict and consistent decisions are defined according to whether the subject's behavior is consistent with all her own motives or not. *Conflict decisions* are decisions for the situation in which the subject's behavior is consistent with some of her motives but in conflict with the other motives. *Consistent decisions* are decisions for

the situation in which the subject's behavior is consistent with all her motives (Fig. 1). We expect that conflict decisions take longer than consistent decisions. First, the conflicts between individually relevant motives make the decision situation more complex. Second, the average utility difference between the two options in conflict situations is smaller than that in consistent situations. According to sequential sampling models, it takes more time to accumulate evidence to reach the threshold and make a decision if the utility difference is small. The left panel of Figure 2 displays the mean log(RT) of conflict and consistent decisions in SP games.[6] Each point represents one subject. Most of the data points are above the 45° line. That is, the RTs of conflict decisions are longer than the RTs of consistent decisions for most of the subjects (Wilcoxon sign-rank test, $p < 10^{-9}$).

Apart from the binary measure of decision conflict, we also use *the number of conflicts*. We get the number of conflicts by considering the pairwise comparisons of the individually relevant motives. The number of conflicts for each type of subjects in SP decisions are shown in Table C1. In conflict situations this number always equals one if two motives are involved, and always equals two if three motives are involved. Thus, the number of conflicts only varies for subjects of Type III, which is the largest group. In these decisions, the number of conflicts can be three or four. The right panel of Figure 2 displays the mean log(RT) of decisions with three conflicts and four conflicts for each subject. It shows that most of the subjects are above the 45° line. That is, the decisions with four conflicts take longer than the decisions with three conflicts (Wilcoxon sign-rank test, $p < 10^{-7}$).

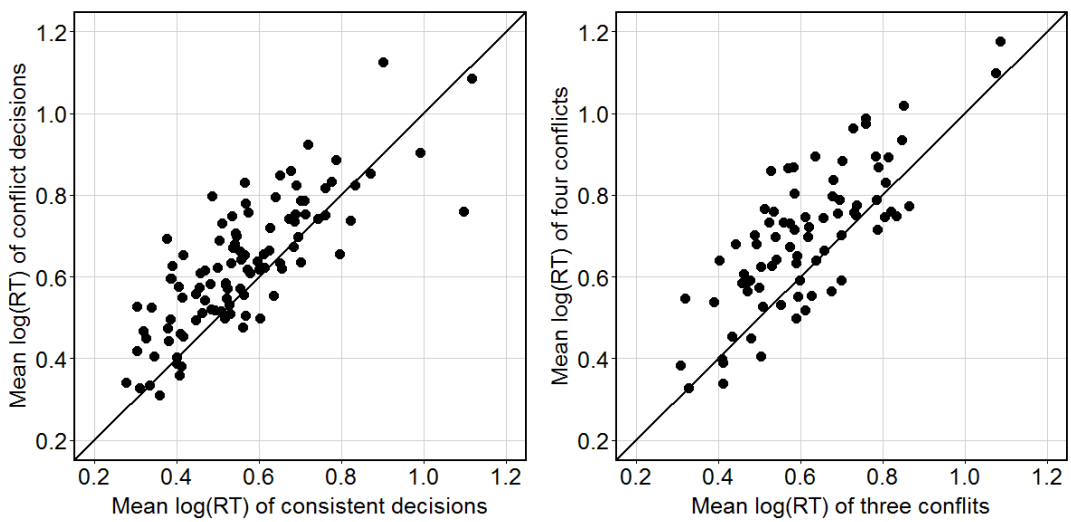

Fig. 2. The RT of decisions with different number of conflicts in the second-party dictator games

Turning to the utility difference between choice options, the sequential sampling models predict that the closer the utilities of the two options, the longer time subject needs to make a decision. We construct

[6] To test the robustness of our results, we also conducted the analysis using untransformed RT, which essentially leads to the same results.

a measure of utility difference by calculating the latent variable of choosing Option A. To do an out-of-sample analysis, we conducted regressions for the *even* trials of SP decisions with the dummy *Decision* as the dependent variable explained by variables reflecting the selfish incentive and the latent variables derived from TP decisions.[7] Then we use the coefficients of these regressions to calculate the latent variable of choosing Option A for the *odd* trials of SP decisions and take the latent variable as the measure of the utility difference between choice options. However, the results are similar if we use the data of the odd trials to predict the RT in the even trials, which are shown in Appendix D.

Figure 3 displays the relationship between the mean log(RT) and the utility difference in the odd trials of SP decisions. All the data in the odd trials of SP decisions is divided into 10 bins of equal size. Each dot represents one bin and the solid line is the standard error of the mean log(RT). Figure 3 shows that the mean log(RT) decreases as the utility difference increases. The curve peaks at the utility difference of around 0, and falls off steadily as the utility difference increases in either direction. The correlation is highly significant (Pearson's correlation test, $r = -0.205$, $p < 10^{-15}$). But since the observations are not independent we test the correlation at the individual level. The Pearson correlation coefficient between the mean log(RT) and the absolute value of the utility difference is positive for 77 of 105 subjects, which is significantly different from the chance level of 50% (two-sided binomial test $p < 10^{-5}$).

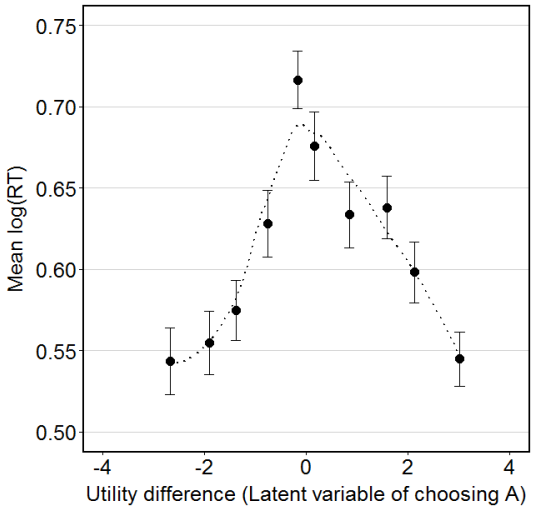

Fig. 3. The mean log(RT) and the utility difference in the odd trials of the second-party dictator games. The dotted line is the smoothing line using method "loess"

The dependence of RTs on the number of conflicts and the utility difference can also be confirmed by mixed-effects regressions. The regression results are shown in Table 3. The dependent variable is *log*(*RT*). The coefficient of the *conflict decision* dummy is positive and significant in regressions (1)

[7] The regression results are shown in Table C2.

and (3), and the coefficient of the *number of conflicts* is positive and significant in regressions (2) and (4). This indicates that the cognitive conflict between individually relevant motives has significantly positive effects on the RTs. With respect to the utility difference, the coefficients are negative and highly significant in regressions (3) and (4). That is, the RT decreases as the utility difference increases. All these results indicate that the RT of distribution decisions is in line with the predictions of sequential sampling models. We now summarize the evidence for sequential sampling models.

Table 3. Mixed-effects regressions of response times on the conflict and the utility difference

	All SP decisions		The odd trials of SP decisions	
	All subjects	Type III	All subjects	Type III
	(1)	(2)	(3)	(4)
Constant	0.659***	0.504***	0.772***	0.709***
	(0.017)	(0.038)	(0.023)	(0.059)
Conflict decision	0.076***		0.040***	
	(0.008)		(0.012)	
Decision number	-0.003***	-0.004***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of conflicts		0.076***		0.036**
		(0.010)		(0.014)
abs(Utility difference)			-0.052***	-0.047***
			(0.006)	(0.008)
AIC	-976.750	-427.512	-451.559	-205.120
BIC	-946.198	-399.982	-419.047	-176.279
Log Likelihood	493.375	218.756	231.780	108.560
Num. obs.	3332	1822	1671	908
Num. groups	105	79	105	79

Notes: The dependent variable is log(RT). ***p < 0.01, **p < 0.05, *p < 0.1.

RESULT 1. *The cognitive processes of distributional preferences comply with the sequential sampling models. Specifically, the response time increases with the number of conflicts between individually relevant motives and decreases with the utility difference between the choice options.*

3.2.2 The Intuition and Deliberation of Selfishness

Dual-process theories postulate that two interacting processes produce decisions. One of the processes is more automatic and intuitive, and the other is more controlled and deliberative. Thus, people's reasoning does not consistently conform to a rationality norm. This section studies the relevance of this model and tests whether selfishness or prosociality can be associated with the intuitive process when people decide in situations in which the selfish motive conflicts with their social motives.

According to dual-process theories, decisions which are more associated with the intuitive process should be quicker than decisions that are more associated with the deliberative process. However, evidence on which motive, the selfish or the social motive, is more related to the intuitive process is still disputed. Evans et al. (2015) and Krajbich, Bartling, et al. (2015) have shown that the identification of the process using RT is difficult because it interacts with the strength of conflicted and the utility

difference between choice options. Therefore, we will control for the strength of conflicted and the utility difference in our analysis. There is a second reason for the conflicting evidence on what is the intuitive process. People may differ with respect to what is the intuitive response to them. Our experimental design allows us to take into account both the heterogeneity in social motives and the heterogeneity in selfishness.

To compare the RTs of selfish and social decisions, we exclude all consistent decisions and focus only on decisions in which the selfish motive is in conflict with the social motive. We classify all conflict decisions in SP games into *selfish decisions* and *social decisions* according to whether the decision is consistent with the selfish motive or not (Fig. 1). According to dual-process theories, the selfish decisions should be quicker than the social decisions if the selfish motive is more intuitive and the social decisions should be quicker than the selfish decisions if the social motive is more intuitive. To test these predictions, we conducted a mixed-effects regression with *log*(*RT*) as the dependent variable. The regression result is shown in regression (1) of Table 4. *Decision number* controls for learning, and *Utility difference* as well as the variable *Conflict within norms* (dummy which indicates whether there is a conflict within the social motives) control for the strength of preference and the strength of conflict of the decision. The results show that the RT does not differ between selfish and social decisions across all subjects if we control for variables *Utility difference* and *Conflict within norms*. This indicates there is no evidence that the selfish or the social decision is more intuitive if we ignore the heterogeneity in selfishness.

In the next step we take the heterogeneity of selfishness into account and study whether the selfish motive is more intuitive for some people and deliberative for others. Specifically, we study how the strength of selfishness influences subject's intuition towards the selfish or the social motive. We calculate the proportion of selfish decisions in the *even* trials of conflict decisions for each subject, and take this proportion as the measure of the strength of selfishness. Then we study the relationship between the RTs of selfish and social decisions with the strength of selfishness in the *odd* trials of conflict decisions. Figure 4 shows the distribution of the strength of selfishness in the even trials of conflict decisions. We expect that the selfish motive is more intuitive for the subjects who are more selfish. More specifically, we expect that more selfish subjects are quicker in making selfish decisions than social decisions.

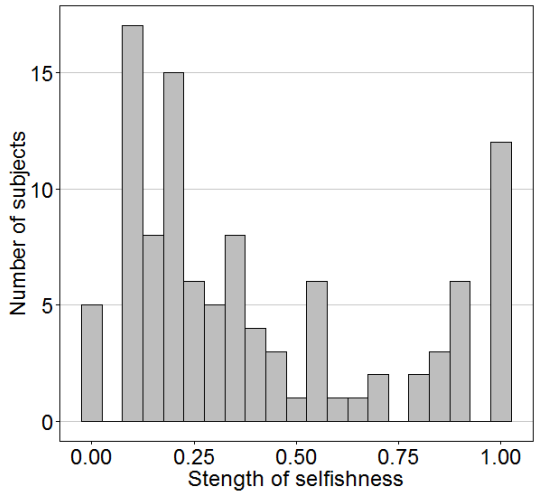

Fig. 4. The distribution of the strength-of-selfishness in the even trials of conflict decisions

The left panel of Figure 5 displays the relationship between the RTs of selfish (social) decisions and the strength of selfishness in the odd trials of conflict decisions. It shows that subjects who are more selfish are quicker in making selfish decisions (Pearson's correlation test, r = -0.391, $p < 10^{-15}$). But subjects who are more selfish are not significantly slower in making social decisions (Pearson's correlation test, r = 0.059, p = 0.117). The right panel of Figure 5 displays the time difference between selfish and social decisions. It shows that the selfish decisions are quicker than social decisions for subjects who are more selfish and the selfish decisions are slower than social decisions for subjects who are more prosocial (Pearson's correlation test, r = -0.450, $p < 10^{-5}$). These results suggest that the selfish motive is more intuitive for subjects who are more selfish, and the selfish motives are more deliberative for subjects who are more prosocial.

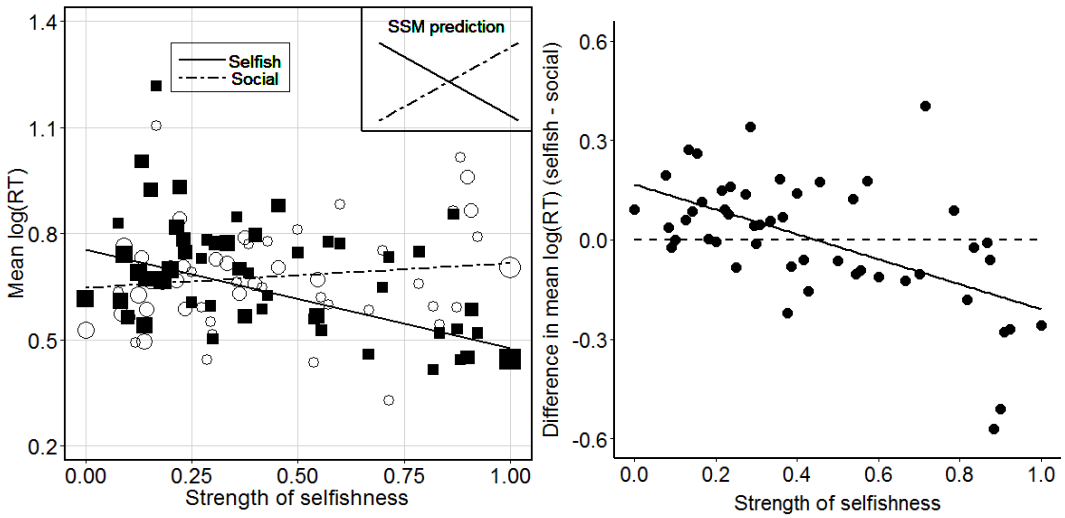

Fig. 5. The response time of selfish and social decisions in the odd trials of conflict decisions. The size of the point or the square indicates the number of subjects in that point or square. The solid and dotted lines are regression lines.

The econometric analysis in Table 4 corroborates these results. Regression (3) in Table 4 shows that the RTs of selfish decisions significantly decrease with the strength of selfishness. However, the coefficient of strength of selfishness is not significant in regression (3). That is, the strength of selfishness has no significant effects on the RTs of social decisions. In a recent study, Rand et al. (2016) show that the intuition favors prosociality for women but not for men. We also control the gender in our analysis. As shown in regressions (2) and (3), the RTs of selfish or social decisions of male are not significantly different from those of female.

Table 4. Regressions of response times on the decision type and the strength-of-selfishness (the odd trials in conflict decisions)

	Mixed-effects regression	OLS regressions	
	(1)	(2)	(3)
Constant	0.787***	0.825***	0.780***
	(0.021)	(0.031)	(0.034)
Selfish decision	-0.011	-0.018	0.127***
	(0.016)	(0.029)	(0.041)
Strength of selfishness		-0.134***	0.103
		(0.047)	(0.067)
abs(Utility difference)	-0.045***	-0.035***	-0.045***
	(0.007)	(0.010)	(0.010)
Conflict within norms	0.044***	0.055***	0.038***
	(0.013)	(0.016)	(0.016)
Male		0.029	0.025
		(0.033)	(0.031)
Decision number	-0.003***	-0.003***	-0.004***
	(0.000)	(0.000)	(0.000)
Selfish decision × Male		-0.057	0.041
		(0.039)	(0.035)
Selfish decision × Strength-of-selfishness			-0.373***
			(0.068)
Num. obs.	1207	1207	1207
Num. groups	105	105	105

Notes. The dependent variable is *log*(*RT*). *Selfish Decision* is a dummy variable which indicate the decision is a selfish decision or social decision. *Male* is a dummy variable which indicate the gender. The robust standard errors for regressions (2) and (3) are clustered on subjects and reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Our results show that selfishness interacts with the speed of selfish vs. social decisions. We control for the strength of the conflict and the strength of preference, which deals with the argument brought up by Krajbich, Bartling, et al. (2015) and Evans et al. (2015). On the other hand, sequential sampling models also predict that selfish decisions is quicker for subjects who are more selfish since more selfish people put higher weight on the selfish dimension (Cary and Nave 2015, Dickhaut et al. 2013, Hutcherson et al. 2015, Krajbich et al. 2010, Krajbich, Bartling, et al. 2015, Krajbich et al. 2014). However, sequential sampling models predict that social decisions are slower for subjects who are more selfish as well. That is, the relationship between the RTs of selfish decisions and the strength of selfishness should be symmetric with the relationship between the RTs of social decisions and the strength of selfishness, as shown in the upper right corner of the left panel of Fig. 5 (SSM prediction).

Obviously, the data is different from the prediction by the sequential sampling models. Of course, the control is incomplete because the utility difference and the strength of the conflict are constructed at the norm type level but not at the individual level. Eye tracking provides an independent method to assess what motive is more intuitive. Subject for which selfishness is intuitive should look at the own payoff. We do not have collected eye tracking data ourselves but we analyze the eye-tracking data from Fiedler et al. (2013) and the results show that at the beginning of the decision process, selfish subjects put more attention (80.1%) on their own payoffs compared to prosocial subjects (60.1%)(Fig. E1).[8] To look at each fixation individually, we also plot the proportion of subjects who fixate on their own payoffs in each fixation. It shows that 78.6% of selfish subject who fixate on their own payoffs in the first fixation, while 58.5% of prosocial subjects who fixate on their own payoffs in the first fixation. Over time people care about both payoffs equally. From the fifth fixation, the proportion of subjects who fixate on the own payoff is around 50% both for selfish and prosocial subjects (Fig. E2). We now summarize our evidence for the intuition and deliberation of selfish motives.

RESULT 2. *The direction and extent of the intuition towards selfishness depends on the selfishness of the subjects. The selfish motive is more intuitive for subjects who are more selfish and the selfish motive is more deliberative for subjects who are less selfish.*

3.3 Why Heterogeneity is Important

Individual heterogeneity in social preferences is not at all controversial. But data limitations have often forced us to assume homogeneity. We take into account both the heterogeneity in social motives and the heterogeneity in selfishness. In this section, we present evidence that the heterogeneity in preferences is reflected in the corresponding heterogeneity of cognitive processes. The results in the previous section show that the heterogeneity in selfishness explains different RT patterns. In Table 4, we have shown that if we assume homogeneity, selfish and social decisions seem to have similar RTs. However, the heterogeneity in selfishness is also reflected in the heterogeneity of the underlying decision processes – reflected in RT.

In the following, we show that taking heterogeneity into account improves process predictions. We compare the explanatory power of the variable *utility difference* on the RTs of the odd trials of SP decisions. The utility difference based on the standard Logit model is calculated using the coefficients in Table C4 and C5.[9] Since the standard Logit model neglects heterogeneity, we expect that the utility difference based on the finite mixture model has a higher explanatory power.

[8] The results are shown in Appendix E.
[9] The calculation is similar to the utility difference based on heterogeneity.

The results are shown in Table 5. Since there is only one parameter in regressions (1) and (2), the R^2 in regressions (1) and (2) can be compared directly. The explanatory power of the utility difference based on the finite mixture model (adjusted R^2 = 0.042) is higher than the explanatory power of the utility difference based on the standard Logit model (adjusted R^2 = 0.038). If the two variables are simultaneously included in the regression, the coefficient of the utility difference based on the finite mixture model is more robust than the coefficient based on the standard Logit model, and the utility difference based on the standard Logit model is not significant at all. We now summarize our third result.

RESULT 3. *The analysis based on the heterogeneity outperforms the analysis based on the homogeneity in explaining response times. The heterogeneity in preferences is reflected in the differences of cognitive processes.*

Table 5. OLS regressions of response time on the utility difference (the odd trials of the second-party decisions)

	(1)	(2)	(3)
(Intercept)	0.690***	0.693***	0.702***
	(0.021)	(0.018)	(0.019)
abs(Utility difference FMM)	-0.053***		-0.034*
	(0.009)		(0.018)
abs(Utility difference Logit)		-0.065***	-0.032
		(0.008)	(0.020)
R^2	0.042	0.039	0.046
Adj. R^2	0.042	0.038	0.045
Num. obs.	1683	1683	1683

Notes. The dependent variable is *log*(*RT*). *Utility difference based on FMM* is the utility difference based on finite mixture model. *Utility difference based on Logit* is the utility difference based on standard Logit model. The robust standard errors are clustered on subjects and reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

4. Conclusion

This paper studies the cognitive mechanism of distributional preferences by investigating subjects' RTs in a series of binary three-person dictator games. Our experiment takes into account, both, the heterogeneity in the relevant social motives as well as the heterogeneity in the strength of selfishness. We find evidence for both, sequential sampling models and dual-process theories. First, the results show that the RT increases with the number of conflicts between individually relevant motives and decreases with the strength of preferences, which is predicted by the sequential sampling models. Second, the more selfish subjects are quicker in making selfish decisions than the less selfish subjects. This is in line with a dual-process approach with heterogeneity in whether the selfish motive is intuitive or deliberative: the selfish motive is intuitive for subjects who are more selfish and deliberative for subjects who are more prosocial. Our study provides an explanation for the conflicting results concerning the automaticity of the selfish motive observed in the previous literature, as well as the debate between the

dual-process explanation and the sequential sampling explanation of the cognitive processes of social decision making.

It is undisputed that people are heterogeneous in their preferences but explicitly taking heterogeneity into account is still rare. Our study not only shows the analysis based on the heterogeneity outperforms the analysis based on the homogeneity, but also shows that the heterogeneity in preferences is reflected in the differences of the cognitive processes. In particular, people differ in what their automatic response is. Thus, in order to identify the correct process model, taking the heterogeneity into account can be indispensable. For example, if our data were analyzed assuming homogeneity, no evidence for a dual-process model could be detected. Thus, the heterogeneity is not only crucial for the determination of the parameters but even for the choice of the model.

We have to admit that the RT analysis does not allow to draw causal inference. However, the sequential sampling models make clear predictions that conflicts between motives increases RT and less utility difference between choice options need more time. This prediction could clearly be confirmed. The predictions of dual-process models are less clear, in particular if one assumes heterogeneity in the process. Nevertheless, it is reasonable to assume the motive that is more relevant behaviorally, is also more intuitive in the sense of a dual-process model. We indeed find evidence that the processing of the selfish motive is more intuitive for more selfish subjects. Nevertheless, causal tests of dual-process models have to rely on intervention methods like time pressure or cognitive load.

References

Achtziger, Anja, and Carlos Alós-Ferrer. 2014. "Fast or Rational? A Response-Times Study of Bayesian Updating." *Management Science* 60 (4):923-38.

Alós-Ferrer, Carlos, and Fritz Strack. 2014. "From Dual Processes to Multiple Selves: Implications for Economic Behavior." *Journal of Economic Psychology* 41:1-11.

Andreoni, James, and John Miller. 2002. "Giving According to Garp: An Experimental Test of the Consistency of Preferences for Altruism." *Econometrica* 70 (2):737-53.

Bear, Adam, and David G. Rand. 2016. "Intuition, Deliberation, and the Evolution of Cooperation." *Proceedings of the National Academy of Sciences* 113 (4):936-41.

Bolton, Gary E., and Axel Ockenfels. 2000. "Erc: A Theory of Equity, Reciprocity, and Competition." *American Economic Review* 90 (1):166-93.

Breitmoser, Yves. 2013. "Estimation of Social Preferences in Generalized Dictator Games." *Economics Letters* 121 (2):192-7.

Brocas, Isabelle, and Juan D. Carrillo. 2014. "Dual-Process Theories of Decision-Making: A Selective Survey." *Journal of Economic Psychology* 41:45-54.

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper. 2010. "Risk and Rationality: Uncovering Heterogeneity in Probability Distortion." *Econometrica* 78 (4):1375-412.

Cappelen, Alexander W., Ulrik H. Nielsen, Bertil Tungodden, Jean-Robert Tyran, and Erik Wengström. 2015. "Fairness Is Intuitive." *Experimental Economics*:1-14.

Cappelletti, Dominique, Werner Güth, and Matteo Ploner. 2011. "Being of Two Minds: Ultimatum Offers under Cognitive Constraints." *Journal of Economic Psychology* 32 (6):940-50.

Cary, Frydman, and Gideon Nave. 2015. "Extrapolative Beliefs in Perceptual and Economic Decisions: Evidence of a Common Mechanism." *Working Papaer*.

Celeux, Gilles, and Gilda Soromenho. 1996. "An Entropy Criterion for Assessing the Number of Clusters in a Mixture Model." *Journal of Classification* 13 (2):195-212.

Chaiken, Shelly, and Yaacov Trope. 1999. *Dual-Process Theories in Social Psychology*: Guilford Press.

Charness, Gary, and Matthew Rabin. 2002. "Understanding Social Preferences with Simple Tests." *Quarterly Journal of Economics* 117 (3):817-69.

Cone, Jeremy, and David G. Rand. 2015. "Time Pressure Increases Cooperation in Competitively Framed Social Dilemmas." *PLoS ONE* 9 (12):e115756.

Cornelissen, Gert, Siegfried Dewitte, and Luk Warlop. 2011. "Are Social Value Orientations Expressed Automatically? Decision Making in the Dictator Game." *Personality and Social Psychology Bulletin* 37 (8):1080-90.

Dickhaut, John, Vernon Smith, Baohua Xin, and Aldo Rustichini. 2013. "Human Economic Choice as Costly Information Processing." *Journal of Economic Behavior & Organization* 94:206-21.

Duffy, Sean, and John Smith. 2014. "Cognitive Load in the Multi-Player Prisoner's Dilemma Game: Are There Brains in Games." *Journal of Behavioral and Experimental Economics* 51:47-56.

Dufwenberg, Martin, and Georg Kirchsteiger. 2004. "A Theory of Sequential Reciprocity." *Games and Economic Behavior* 47 (2):268-98.

Engelmann, Dirk, and Martin Strobel. 2004. "Inequality Aversion, Efficiency, and Maximin Preferences in Simple Distribution Experiments." *American Economic Review* 94 (4):857-69.

Erlei, Mathias. 2008. "Heterogeneous Social Preferences." *Journal of Economic Behavior & Organization* 65 (3–4):436-57.

Evans, Anthony M, Kyle D Dillon, and David G Rand. 2015. "Fast but Not Intuitive, Slow but Not Reflective: Decision Conflict Drives Reaction Times in Social Dilemmas." *Journal of Experimental Psychology: General* 144 (5):951-66.

Falk, Armin, and Urs Fischbacher. 2006. "A Theory of Reciprocity." *Games and Economic Behavior* 54 (2):293-315.

Fehr, Ernst, and Klaus M. Schmidt. 1999. "A Theory of Fairness, Competition, and Cooperation." *Quarterly Journal of Economics* 114 (3):817-68.

Fiedler, Susann, Andreas Glöckner, Andreas Nicklisch, and Stephan Dickert. 2013. "Social Value Orientation and Information Search in Social Dilemmas: An Eye-Tracking Analysis." *Organizational Behavior and Human Decision Processes* 120 (2):272-84.

Fischbacher, Urs. 2007. "z-Tree: Zurich Toolbox for Ready-Made Economic Experiments." *Experimental Economics* 10 (2):171-8.

Fisman, Raymond, Shachar Kariv, and Daniel Markovits. 2007. "Individual Preferences for Giving." *American Economic Review* 97 (5):1858-76.

Frederick, Shane. 2005. "Cognitive Reflection and Decision Making." *Journal of Economic Perspectives* 19 (4):25-42.

Fudenberg, Drew, and David K. Levine. 2006. "A Dual-Self Model of Impulse Control." *American Economic Review* 96 (5):1449-76.

Greiner, Ben. 2015. "Subject Pool Recruitment Procedures: Organizing Experiments with ORSEE." *Journal of the Economic Science Association* 1 (1):114-25.

Grun, Bettina, and Friedrich Leisch. 2008. "Flexmix Version 2: Finite Mixtures with Concomitant Variables and Varying and Constant Parameters." *Journal of Statistical Software* 28 (4):1-35.

Hauge, Karen Evelyn, Kjell Arne Brekke, Lars-Olof Johansson, Olof Johansson-Stenman, and Henrik Svedsäter. 2016. "Keeping Others in Our Mind or in Our Heart? Distribution Games under Cognitive Load." *Experimental Economics* 19 (3):562-76.

Houser, Daniel, Michael Keane, and Kevin McCabe. 2004. "Behavior in a Dynamic Decision Problem: An Analysis of Experimental Evidence Using a Bayesian Type Classification Algorithm." *Econometrica* 72 (3):781-822.

Hutcherson, Cendri A., Benjamin Bushong, and Antonio Rangel. 2015. "A Neurocomputational Model of Altruistic Choice and Its Implications." *Neuron* 87 (2):451-62.

Kahneman, Daniel. 2003. "A Perspective on Judgment and Choice: Mapping Bounded Rationality." *American Psychologist* 58 (9):697-720.

Kahneman, Daniel. 2011. *Thinking, Fast and Slow*: Macmillan.

Kerschbamer, Rudolf. 2015. "The Geometry of Distributional Preferences and a Non-Parametric Identification Approach: The Equality Equivalence Test." *European Economic Review* 76:85-103.

Krajbich, Ian, Carrie Armel, and Antonio Rangel. 2010. "Visual Fixations and the Computation and Comparison of Value in Simple Choice." *Nature Neuroscience* 13 (10):1292-8.

Krajbich, Ian, Bjorn Bartling, Todd Hare, and Ernst Fehr. 2015. "Rethinking Fast and Slow Based on a Critique of Reaction-Time Reverse Inference." *Nature Communication* 6:7455.

Krajbich, Ian, Todd Hare, Bjoern Bartling, Yosuke Morishima, and Ernst Fehr. 2015. "A Common Mechanism Underlying Food Choice and Social Decisions." *PLoS Comput Biol* 11 (10):e1004371.

Krajbich, Ian, Bastiaan Oud, and Ernst Fehr. 2014. "Benefits of Neuroeconomic Modeling: New Policy Interventions and Predictors of Preference." *American Economic Review* 104 (5):501-6.

Lohse, Johannes, Timo Goeschl, and Johannes Diederich. 2014. "Giving Is a Question of Time: Response Times and Contributions to a Real World Public Good." *University of Heidelberg Department of Economics Discussion Paper Series*, (566).

Lotito, Gianna, Matteo Migheli, and Guido Ortona. 2013. "Is Cooperation Instinctive? Evidence from the Response Times in a Public Goods Game." *Journal of Bioeconomics* 15 (2):123-33.

Murphy, Ryan O., Kurt A. Ackermann, and Michel J. J. Handgraaf. 2011. "Measuring Social Value Orientation." *Judgment & Decision Making* 6 (8):771-81.

Nielsen, Ulrik H., Jean-Robert Tyran, and Erik Wengström. 2014. "Second Thoughts on Free Riding." *Economics Letters* 122 (2):136-9.

Peysakhovich, Alexander, and David G. Rand. forthcoming. "Habits of Virtue: Creating Norms of Cooperation and Defection in the Laboratory." *Management Science*.

Piovesan, Marco, and Erik Wengström. 2009. "Fast or Fair? A Study of Response Times." *Economics Letters* 105 (2):193-6.

Rabin, Matthew. 1993. "Incorporating Fairness into Game Theory and Economics." *American Economic Review* 83 (5):1281-302.

Rand, David G, Victoria Brescoll, Jim AC Everett, Valerio Capraro, and Helene Barcelo. 2016. "Social Heuristics and Social Roles: Intuition Favors Altruism for Women but Not for Men." *Forthcoming in Journal of Experimental Psychology: General*.

Rand, David G., Joshua D. Greene, and Martin A. Nowak. 2012. "Spontaneous Giving and Calculated Greed." *Nature* 489 (7416):427-30.

Ratcliff, Roger. 1978. "A Theory of Memory Retrieval." *Psychological Review* 85 (2):59-108.

Ratcliff, Roger, and Philip L. Smith. 2004. "A Comparison of Sequential Sampling Models for Two-Choice Reaction Time." *Psychological Review* 111 (2):333-67.

Rubinstein, Ariel. 2007. "Instinctive and Cognitive Reasoning: A Study of Response Times." *The Economic Journal* 117 (523):1243-59.

Schulz, Jonathan F., Urs Fischbacher, Christian Thöni, and Verena Utikal. 2014. "Affect and Fairness: Dictator Games under Cognitive Load." *Journal of Economic Psychology* 41:77-87.

Sloman, Steven A. 1996. "The Empirical Case for Two Systems of Reasoning." *Psychological Bulletin* 119 (1):3-22.

Strack, Fritz, and Roland Deutsch. 2004. "Reflective and Impulsive Determinants of Social Behavior." *Personality and Social Psychology Review* 8 (3):220-47.

Tinghog, Gustav, David Andersson, Caroline Bonn, Harald Bottiger, Camilla Josephson, Gustaf Lundgren, Daniel Vastfjall, Michael Kirchler, and Magnus Johannesson. 2013. "Intuition and Cooperation Reconsidered." *Nature* 498 (7452):E1-E2.

Verkoeijen, Peter P. J. L., and Samantha Bouwmeester. 2014. "Does Intuition Cause Cooperation?" *PLoS ONE* 9 (5):e96654.

Appendix A. The Games

Table A1. Sixty-Four Games in the Experiment

Type	Game ID	Option A			Option B			Signs					
		A1	A2	A3	B1	B2	B3	Selfishness	Efficiency	Maximin	Envy	FS-α	FS-β
TP	1	6	14	7	6	14	19	0	-1	0	1	1	-1
	2	7	18	9	7	18	20	0	-1	0	1	1	-1
	3	11	16	14	13	16	18	0	-1	-1	1	1	-1
	4	10	14	13	12	14	18	0	-1	-1	1	1	-1
	5	5	11	20	15	11	16	0	-1	-1	-1	0	-1
	6	6	13	19	16	13	16	0	-1	-1	-1	0	-1
	7	9	14	19	12	14	18	0	-1	-1	-1	-1	-1
	8	5	9	18	10	9	16	0	-1	-1	-1	-1	-1
	9	6	12	19	16	12	19	0	-1	-1	0	1	-1
	10	5	14	19	15	14	19	0	-1	-1	0	1	-1
	11	11	13	18	15	13	17	0	-1	-1	-1	1	-1
	12	8	9	19	15	9	17	0	-1	-1	-1	1	-1
	13	5	16	20	19	16	19	0	-1	-1	-1	1	-1
	14	5	15	18	17	15	17	0	-1	-1	-1	1	-1
	15	13	16	17	17	16	17	0	-1	-1	0	1	-1
	16	9	14	16	15	14	16	0	-1	-1	0	1	-1
	17	7	10	20	8	10	8	0	1	-1	-1	-1	1
	18	8	11	20	9	11	9	0	1	-1	-1	-1	1
	19	7	9	8	7	9	20	0	-1	0	1	1	-1
	20	14	15	14	14	15	19	0	-1	0	1	1	-1
	21	6	20	19	8	20	8	0	1	-1	0	0	1
	22	8	19	18	9	19	9	0	1	-1	0	0	1
	23	12	18	19	13	18	14	0	1	-1	-1	-1	1
	24	7	15	19	10	15	11	0	1	-1	-1	-1	1
	25	5	11	20	11	11	11	0	1	-1	-1	-1	-1
	26	6	11	19	7	11	14	0	1	-1	-1	-1	-1
	27	11	15	19	12	15	17	0	1	-1	-1	-1	-1
	28	6	13	20	12	13	12	0	1	-1	-1	-1	-1
	29	11	16	15	20	16	20	0	-1	-1	1	1	-1
	30	8	16	18	20	16	20	0	-1	-1	1	1	-1
	31	12	15	17	16	15	18	0	-1	-1	1	1	-1
	32	8	9	15	12	9	19	0	-1	-1	1	1	-1
SP	33	7	11	9	7	13	19	-1	-1	0	1	1	0
	34	10	15	11	10	17	19	-1	-1	0	1	1	-1
	35	9	16	14	11	17	19	-1	-1	-1	1	1	-1
	36	8	12	11	10	13	19	-1	-1	-1	1	1	-1
	37	3	14	20	15	12	15	1	-1	-1	-1	0	-1
	38	5	14	20	16	13	16	1	-1	-1	-1	0	-1
	39	7	13	18	13	12	15	1	-1	-1	-1	-1	-1
	40	2	13	20	13	11	15	1	-1	-1	-1	-1	-1
	41	7	8	16	17	10	18	-1	-1	-1	0	1	-1
	42	6	8	12	11	10	14	-1	-1	-1	0	1	-1
	43	12	13	19	17	14	18	-1	-1	-1	-1	1	-1
	44	6	7	15	15	8	15	-1	-1	-1	-1	1	-1
	45	5	17	20	17	15	17	1	-1	-1	-1	1	-1
	46	5	17	20	18	16	18	1	-1	-1	-1	1	-1
	47	6	13	16	13	12	15	1	-1	-1	0	1	-1
	48	5	16	20	15	14	18	1	-1	-1	0	1	-1
	49	12	19	20	13	16	14	1	1	-1	-1	-1	-1
	50	8	17	18	9	13	11	1	1	-1	-1	-1	-1
	51	10	12	11	10	16	17	-1	-1	0	1	1	1
	52	8	9	8	8	10	19	-1	-1	0	1	1	0
	53	5	18	17	6	20	6	-1	1	-1	0	0	1
	54	7	19	18	8	20	8	-1	1	-1	0	0	1
	55	10	17	18	11	18	12	-1	1	-1	-1	-1	1
	56	8	18	19	9	20	10	-1	1	-1	-1	-1	1
	57	3	14	20	12	12	12	1	1	-1	-1	-1	-1
	58	5	12	17	10	11	12	1	1	-1	-1	-1	-1
	59	6	13	20	11	12	14	1	1	-1	-1	-1	-1
	60	5	12	20	11	11	13	1	1	-1	-1	-1	-1
	61	10	13	10	16	12	16	1	-1	-1	1	1	-1
	62	7	14	13	18	13	20	1	-1	-1	1	1	-1
	63	5	16	19	19	14	20	1	-1	-1	1	1	-1
	64	5	16	20	18	14	19	1	-1	-1	1	1	-1

Notes. In the columns of signs, 1 indicates that the motive favors Option A, -1 indicates the motives favors Option B, and 0 means the two options are indifferent for that motive. For example, in the fourth game, the dictator could choose between allocations of Option A (10, 15, 11) and Option B (10, 17, 19), where the parameters in each option refers to the payoffs for the first players, the dictator and the third player. The *efficiency* motive favors Option B, the *envy* motive favors Option A, and the two options are indifferent for the *maximin* motive.

Appendix B. Finite Mixture Estimation

In this part, we first present the social motives that we use in the finite mixture model. Then, we introduce the estimation procedure for the finite mixture analysis.

B.1 The Decision Motives

People differ in the nature of their distributional preferences. The TP games allow to deal with the heterogeneity of distributional preferences, even for selfish subjects. In each situation of the experiment, the subject made a binary decision by choosing Option A or Option B according to her personal norm. We use a logit model to capture the importance of potential social motives in the estimation of the finite mixture model. The dependent variable of the logit model is the dummy variable *Decision* which indicates whether the subject chose Option A or not. The independent variables are the differences between the strength of different motives and the signs of these differences. The differences between Option A and Option B on each motive are calculated as follows:

$$DiffEfficiency = (A_1 + A_2 + A_3) - (B_1 + B_2 + B_3);$$

$$DiffEnvy = [\max(B_1, B_2, B_3) - B_2] - [\max(A_1, A_2, A_3) - A_2];$$

$$DiffMaximin = \min(A_1, A_2, A_3) - \min(B_1, B_2, B_3);$$

$$DiffFS\text{-}\beta = 1/2*\{[\max(B_2 - B_1, 0) + \max(B_2 - B_3, 0)] - [\max(A_2 - A_1,0) + \max(A_2 - A_3,0)]\};$$

$$DiffFS\text{-}\alpha = 1/2*\{[\max(B_1 - B_2, 0) + \max(B_3 - B_2, 0)] - [\max(A_1 - A_2,0) + \max(A_3 - A_2,0)]\};$$

$$DiffSelfish = A_2 - B_2.$$

A_i and B_i are the payoffs for Player i in Option A and Option B. We take the signs of these difference as the signs of motives. That is, the signs of motives are discrete variables (-1, 0, 1).

In order to check the robustness of our estimation, we use four different structural models in the finite mixture analysis:

Model I: $Decision \sim SignEfficiency + DiffEfficiency + SignEnvy + DiffEnvy + SignMaximin + DiffMaximin + SignFS\text{-}\alpha + SignFS\text{-}\beta + DiffFS\text{-}\beta;$

Model II: $Decision \sim SignEfficiency + SignEnvy + SignMaximin + SignFS\text{-}\alpha + SignFS\text{-}\beta;$

Model III: $Decision \sim SignEfficiency + DiffEnvy + SignMaximin + DiffMaximin + SignFS\text{-}\beta;$

Model IV: $Decision \sim SignEfficiency + DiffEnvy + SignMaximin + SignFS\text{-}\beta.$

In the first model, we include all the variables of signs and differences on social motives. However, we have to leave out the variable *DiffFS-α* in order to avoid the collinearity problem.[10] The second model includes the signs of all the social motives. The independent variables of the third model are the subset of all variables which fit the data best according to Akaike Information Criterion (AIC) at the aggregate level. And the independent variables of the fourth model are the subset of all variables which fit the data best according to Bayesian Information Criterion (BIC) at the aggregate level.

B.2 Finite Mixture Analysis

To explore the heterogeneity in distributional preferences in the sense that there may exist distinct type of subjects that differ in the their social motives, we estimate a finite mixture model (Breitmoser 2013, Bruhin et al. 2010, Houser et al. 2004). The finite mixture model assumes that the sample consists of C different preference types. The model consists of the estimation of the parameters of the C different types and the estimation of individual probabilities that a subject belongs to one of the C preference types. The finite mixture model's log likelihood,

$$\ln L(\Theta; X) \;=\; \sum_{i=1}^{N} \ln \sum_{c=1}^{C} \pi_c f(\theta_c; x_i)\,,$$

weights the individual type-specific likelihood contributions $f(\theta_c; x_i)$ - here, the densities of the structural decision model with preference type parameters θ_c - by the proportions π_c of the C different types in the sample. Maximizing $\ln L(\Theta; X)$ yields the maximum likelihood estimates for the preference type parameters $\widehat{\theta_c}$ and the corresponding relative type sizes $\widehat{\pi_c}$. Once we obtain the type-specific parameters, we can calculate the posterior probability that an individual i is of type c using Bayes' rule,

$$\tau_{ic} = \frac{\widehat{\pi_c} f(\widehat{\theta_c}; x_i)}{\sum_{m=1}^{C} \widehat{\pi_m} f(\widehat{\theta_c}; x_i)}.$$

Then we classify each individual into the preference type with the highest posterior probability.

We use Normalized Entropy Criterion (NEC) (Celeux and Soromenho 1996) to determine the optimal number of types C^* by estimating mixture models with varying C. NEC is based on the ex-post probabilities of type membership and directly reflects the model's ability to provide a clean classification:

[10] Due to the definitions of differences, there exists a linear relationship between *DiffFS-α*, *DiffFS-β* and *DiffEfficiency*, that is, *DiffEfficiency* = 2(*DiffFS-β* – *DiffFS-α*).

$$NEC(C) = \frac{E(C)}{L(C) - L(1)} \ ,$$

in which $L(C)$ is the log likelihood of the finite mixture model with C types, $L(1)$ is the log likelihood at the aggregate level, and $E(C)$ is the entropy which measures the ambiguity of the classification,

$$E(C) \ = \ - \sum_{c=1}^{C} \sum_{i=1}^{N} \tau_{ic} \ln \tau_{ic} \ .$$

The entropy is low if all τ_{ic} are either close to 1 or close to 0. And the entropy is high if many τ_{ic} are close to $1/C$, meaning that the classification of subjects into preference types is ambiguous. Thus, we determine the optimal number of types by minimizing NEC with respect to C.

B.3 Heterogeneity of Social Preferences

In order to deal with the heterogeneity and to determine individual distributional preferences, we analyze SP decisions using a finite mixture model. The results of the finite mixture analysis are robust. All four models show that the optimal number of types equals three according to NEC (Figure B1), and all four models create the same classification.

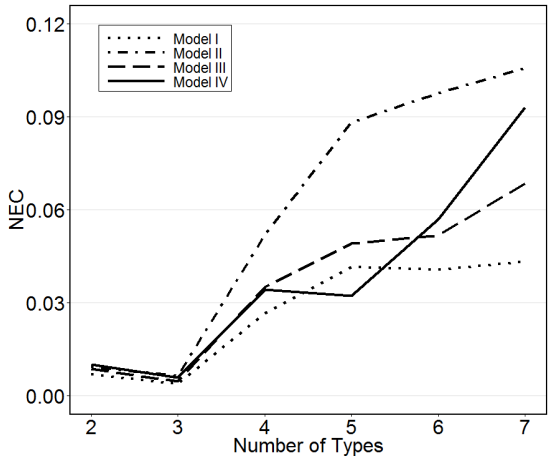

Fig. B1. The optimal number of types

In addition, all subjects can be assigned to one distinct type with high posterior probability. Figure B2 shows the posterior probabilities which are larger than 0.01. A peak at probability 1 indicates that a preference type is well separated from the other types, and no significant mass in the middle of the unit interval indicates clean classification.[11] These clean classifications suggest that our analysis is able to

[11] In Model I, all subjects can be classified into their types with the probabilities of greater than 0.93, and 93.3% of all subjects are classified into their types with the probabilities of greater than 0.99. In Model II, only one subject is classified into her type

capture the distinctive characteristics of each preference type. We call the type based on the classification of the personal norms 'Norm Type'.

The regression results of the finite mixture analysis are shown in Table B1. We identify subjects' social motives according to whether the coefficient of the motive is significant or not. One exception is the coefficient of *SignEnvy* for subjects of the first norm type in Model I.[12] The relevant motives for the personal norms of each type are summarized in Table B2. Apart from some minor differences, all four models identify almost identical norm types. In the paper, we base our analysis on model IV, which performs best according to the BIC criterion. However, the main results are robust with respect to the choice of the model.

with the posterior probability of less than 0.90 (0.895), and 91.4% of all subjects are classified into their types with the posterior probabilities of greater than 0.99. In Model III, only one subject is classified into her type with the probability of less than 0.90 (0.88), and 92.4% of all subjects are classified into their types with the probabilities of greater than 0.99. In Model IV, two subjects are classified into their types with the probabilities of less than 0.90 (0.79 and 0.86), and 95.2% of all subjects are classified into their types with the probabilities of greater than 0.99.

[12] Envy is inequality aversion toward the person with the highest income. If people care about efficiency, they might like situations that envious people dislike.

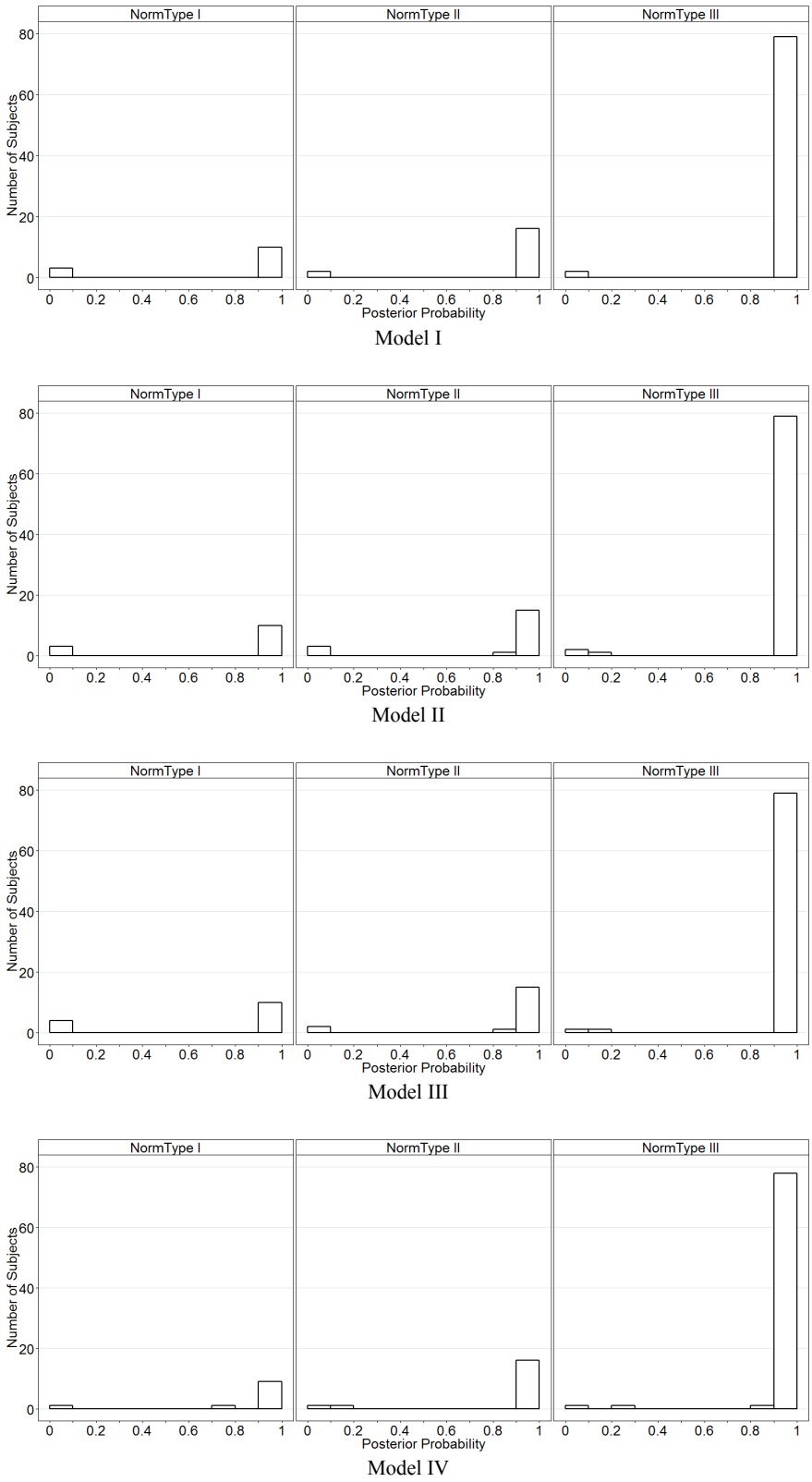

Fig. B2. The posterior probabilities for the four models ($p > 0.01$)

Table B1. Results of the finite mixture model

	Model I			Model II			Model III			Model IV		
Num. subjects	10	16	79	10	16	79	10	16	79	10	16	79
	NT I	NT II	NT III	NT I	NT II	NT III	NT I	NT II	NT III	NT I	NT II	NT III
SignEfficiency	0.588*	-4.960	1.581***	0.542**	-3.018	2.585***	0.639***	-5.185	2.627***	0.613***	-4.612	2.395***
	(0.312)	(47.541)	(0.302)	(0.270)	(11.103)	(0.319)	(0.235)	(55.662)	(0.220)	(0.237)	(28.857)	(0.176)
DiffEfficiency	0.091	0.014	0.084									
	(0.112)	(0.107)	(0.246)									
SignEnvy	-0.658**	-0.213	0.379	-0.327	0.972***	0.435						
	(0.291)	(0.335)	(0.636)	(0.214)	(0.246)	(0.502)						
DiffEnvy	0.152	0.342**	-0.077				-0.020	0.293***	-0.039	-0.010	0.286***	-0.048
	(0.118)	(0.134)	(0.248)				(0.040)	(0.053)	(0.032)	(0.040)	(0.050)	(0.033)
SignMaximin	0.193	0.396	0.829***	0.486***	1.330***	1.435***	0.273	0.454*	0.442**			
	(0.291)	(0.301)	(0.314)	(0.186)	(0.173)	(0.211)	(0.231)	(0.252)	(0.218)			
DiffMaximin	0.065	0.287***	0.345***				0.032	0.266***	0.493***	0.073*	0.383***	0.552***
	(0.077)	(0.091)	(0.070)				(0.053)	(0.079)	(0.056)	(0.041)	(0.055)	(0.050)
SignFS-α	0.113	0.114	-0.897	-0.013	0.070	-0.353						
	(0.302)	(0.352)	0.658	(0.270)	(0.377)	(0.555)						
SignFS-β	-0.044	5.547	-0.178	-0.057	3.532	0.940***	-0.117	5.620	0.521***	-0.089	5.024	0.539***
	(0.294)	(47.540)	(0.193)	(0.218)	(11.088)	(0.108)	(0.221)	(55.661)	(0.115)	(0.222)	(29.857)	(0.119)
DiffFS-β	-0.225	-0.083	0.414									
	(0.246)	(0.239)	(0.513)									
Constant	0.195	-0.258*	-0.093	0.205	-0.136	-0.034	0.163	-0.269**	-0.032	0.136	-0.297**	-0.058
	(0.133)	(0.139)	(0.110)	(0.129)	(0.127)	(0.103)	(0.129)	(0.137)	(0.108)	(0.127)	(0.135)	(0.108)
Num. obs	320	512	2528	320	512	2528	320	512	2528	320	512	2528
AIC		1793.316			1942.759			1798.439			1801.709	
BIC		1989.146			2065.153			1920.833			1905.743	
Log Likelihood		-864.658			-951.380			-879.219			-883.854	

Notes. The dependent variable is *Decision*. ***p < 0.01, **p < 0.05, *p < 0.1.

Table B2. The identified social motives for each norm type in the four models

Classification	Norm type I	Norm type II	Norm type III
Model I	Efficiency	Envy, Maximin	Efficiency, Maximin
Model II	Efficiency, Maximin	Envy, Maximin	Efficiency, Maximin, FS-β
Model III	Efficiency	Envy, Maximin	Efficiency, Maximin, FS-β
Model IV	Efficiency, Maximin	Envy, Maximin	Efficiency, Maximin, FS-β

Appendix C

C.1 The Evolution of Mean Response Time

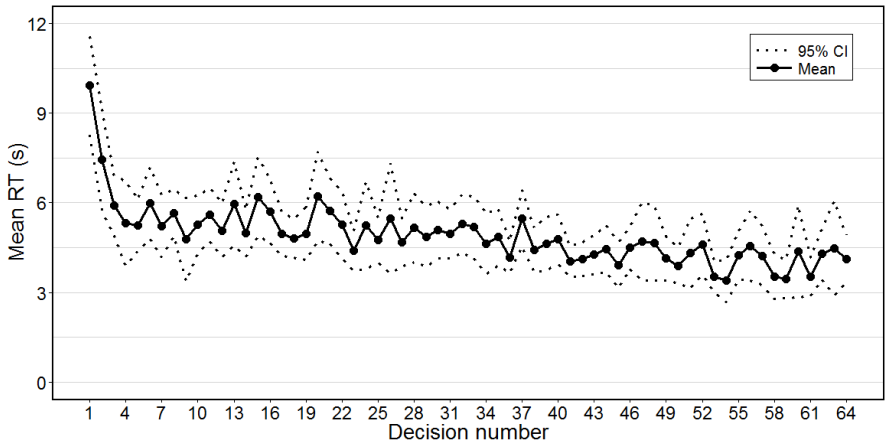

Fig. C.1. The evolution of the mean RT

C.2 The Distribution of Response Times in the Second-Party decisions

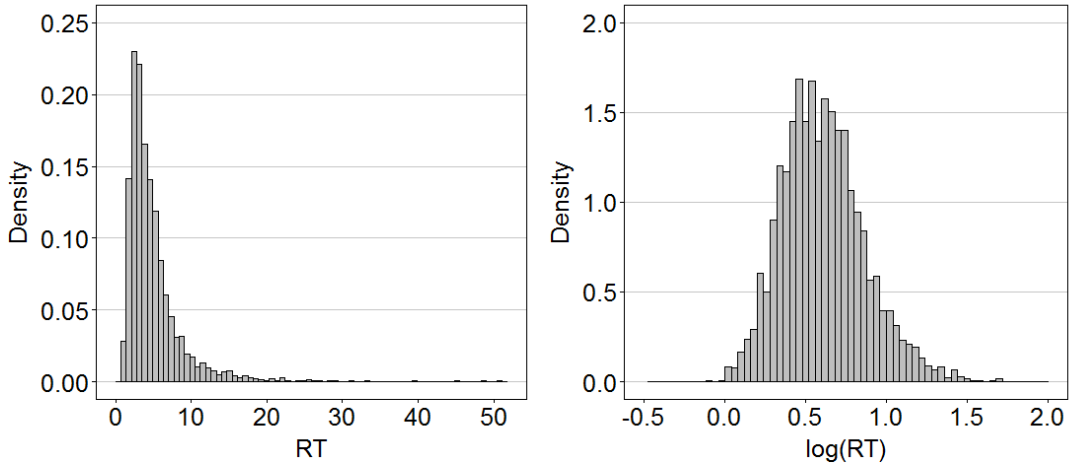

Fig. C.2. The distributions of RTs and log(RT) in the second-party decisions

C.3 Classification of the Second-Party decisions

Table C1. Classification of SP decisions

Norm type	Situation number	In line with					Decision type				Num. conflicts	Num. decisions
							Correct			Incorrect		
							Conflict		Consistent			
		Selfishness	Maximin	Envy	Efficiency	FS-β	Selfish	Social				
I	1	1	0		0		1				2	91
	2	1	1		0		1				2	30
	3	1	0		1		1				2	49
	4	1	1		1				1		0	88
	5	0	0		0					1		9
	6	0	1		0			1			2	14
	7	0	0		1			1			2	10
	8	0	1		1			1			2	29
II	1	1	0	0			1				2	53
	2	1	1	0			1				2	61
	3	1	0	1			1				2	24
	4	1	1	1					1		0	96
	5	0	0	0						1		15
	6	0	1	0				1			2	46
	7	0	0	1				1			2	25
	8	0	1	1				1			2	192
III	1	1	0		0	0	1				3	220
	2	1	0		1	0	1				4	287
	3	1	1		0	1	1				3	0
	4	1	1		0	0	1				4	101
	5	1	0		1	1	1				3	0
	6	1	0		0	1	1				4	0
	7	1	1		1	0	1				3	79
	8	1	1		1	1			1		0	702
	9	0	0		0	0				1		4
	10	0	0		1	0		1			3	0
	11	0	1		0	1		1			4	191
	12	0	1		0	0		1			3	1
	13	0	0		1	1		1			4	215
	14	0	0		0	1		1			3	0
	15	0	1		1	0		1			4	0
	16	0	1		1	1		1			3	728

Notes. In *Consistency* columns, 1 means the decision is consistent with the motive, 0 means the decision is not consistent with the motive. In *Decision type* columns, 1 indicates the decisions is classified into that type. *Number of conflicts* is the number of conflicts by pairwise comparisons between all the relevant social motives and selfish decisions.
For instance, for a subject of Norm type III, in situation No. 2, the decision that the subject made is in line with the selfishness and efficiency motives, but not in line with the maximin and FS-β motives. The decision is a conflict decision, since the efficiency and selfishness motives conflict with the maximin and FS-β motives when she made the decision. The number of conflicts is 4 (efficiency vs maximin, efficiency vs FS-β, selfishness vs maximin, selfishness vs FS-β).

C.4 Regressions for Calculating the Utility Difference based on FMM

Table C2. Logit regression for the even trials of the second-party decisions

	Norm type I	Norm type II	Norm type III
Constant	-0.101	0.119	0.232***
	(0.190)	(0.146)	(0.063)
Latent FMM based on TP decisions	0.577**	0.129***	0.359***
	(0.285)	(0.042)	(0.026)
DiffSelfish	0.298	0.338	0.620***
	(0.186)	(0.211)	(0.091)
SignSelfish	1.106*	-0.229	0.180
	(0.591)	(0.381)	(0.212)
AIC	166.139	350.757	1135.501
BIC	178.563	365.061	1156.018
Log Likelihood	-79.070	-171.378	-563.750
Deviance	158.139	342.757	1127.501
Num. obs.	165	264	1248

Notes. The dependent variable is *Decision*. The robust standard errors are clustered on subjects and reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table C3. Logit regression for the odd trials of the second-party decisions

	Norm type I	Norm type II	Norm type III
Constant	-0.037	0.065	0.254***
	(0.172)	(0.149)	(0.077)
Latent FMM based on TP decisions	0.272	0.147***	0.397***
	(0.278)	(0.041)	(0.033)
DiffSelfish	0.205	0.509***	1.039***
	(0.223)	(0.179)	(0.107)
SignSelfish	1.191*	-0.462	-0.502**
	(0.672)	(0.393)	(0.204)
AIC	155.546	324.700	1038.934
BIC	167.720	338.754	1059.552
Log Likelihood	-73.773	-158.350	-515.467
Pseudo R^2	0.310	0.079	0.419
Num. obs.	155	248	1280

Notes. The dependent variable is *Decision*. The robust standard errors are clustered on subjects and reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

C.5 Regressions for Calculating the Utility Difference based on Logit Model

Table C4. Logit regression of the third-party decisions

Constant	-0.095
	(0.069)
DiffEnvy	0.042***
	(0.013)
DiffMaximin	0.259***
	(0.036)
SignEfficiency	1.404***
	(0.143)
SignFS-β	0.380***
	(0.073)
AIC	2377.581
BIC	2408.179
Pseudo R^2	0.492
Log Likelihood	-1183.790
Num. obs.	3360

Notes. The dependent variable is *Decision*. The robust standard errors are clustered on subjects and reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table C5. Logit regression of the even trials of the second-party decisions

Constant	0.201***
	(0.053)
Latent variable based on TP decisions	0.527***
	(0.043)
DiffSelfish	0.383***
	(0.087)
SignSelfish	0.359**
	(0.176)
AIC	1760.487
BIC	1782.186
Log Likelihood	-876.243
Deviance	1752.487
Num. obs.	1677

Notes. The dependent variable is *Decision*. The robust standard errors are clustered on subjects and reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Table C6. Logit regression of the odd trials of the second-party decisions

Constant	0.227***
	(0.063)
Latent variable based on TP decisions	0.598***
	(0.047)
DiffSelfish	0.614***
	(0.110)
SignSelfish	0.029
	(0.175)
AIC	1610.849
BIC	1632.563
Pseudo R^2	0.313
Log Likelihood	-801.425
Num. obs.	1683

Notes. The dependent variable is *Decision*. The robust standard errors are clustered on subjects and reported in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

Appendix D (Using Data of Odd Trials to Predict the RT of Even Trials)

D.1 The RT and the Utility Difference

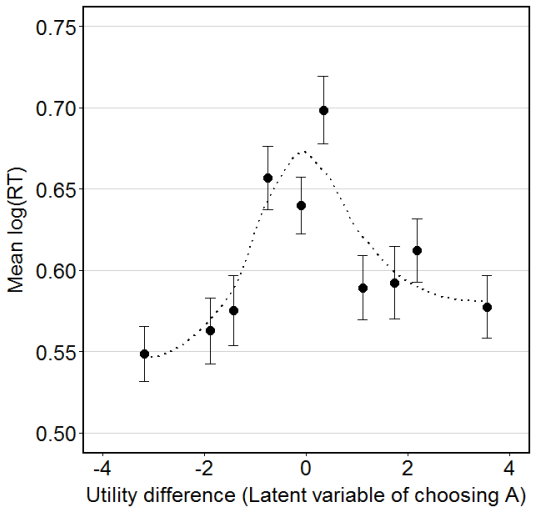

Fig. D1. The mean log(RT) and the utility difference in the even trials of the second-party decisions. The dotted line is the smoothing line using method "loess". The log(RT) is significantly negatively related to the absolute value of the utility difference (Pearson correlation test, r = -0.146. $p < 10^{-8}$). The log(RT) has negative relationship with the absolute value of the utility difference for 79 of 105 subjects, which is significantly different from the chance level of 50% (two-sided binomial test, $p < 10^{-6}$).

D.2 The Mixed-Effects Regressions of Response Times on the Conflict and the Utility Difference

Table D1. Mixed-effects regressions of response times on conflicts and utility difference

	All SP decisions		The even trials of SP decisions	
	All subjects	Norm type III	All subjects	Norm type III
	(1)	(2)	(3)	(4)
Constant	0.659***	0.504***	0.730***	0.608***
	(0.017)	(0.038)	(0.022)	(0.065)
Conflict decision	0.076***		0.035***	
	(0.008)		(0.012)	
Decision number	-0.003***	-0.004***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of conflicts		0.076***		0.053***
		(0.010)		(0.016)
abs(Utility difference)			-0.036***	-0.022***
			(0.005)	(0.007)
AIC	-976.750	-427.512	-424.249	-112.853
BIC	-946.198	-399.982	-391.772	-83.972
Log Likelihood	493.375	218.756	218.124	62.427
Num. obs.	3332	1822	1661	914
Num. groups	105	79	105	79

Notes. The dependent variable is *log*(*RT*). ***p < 0.01, **p < 0.05, *p < 0.1. The coefficients of the absolute value of the utility difference are significantly negatively in regressions (3) and (4).

D.3 The Strength of Selfishness

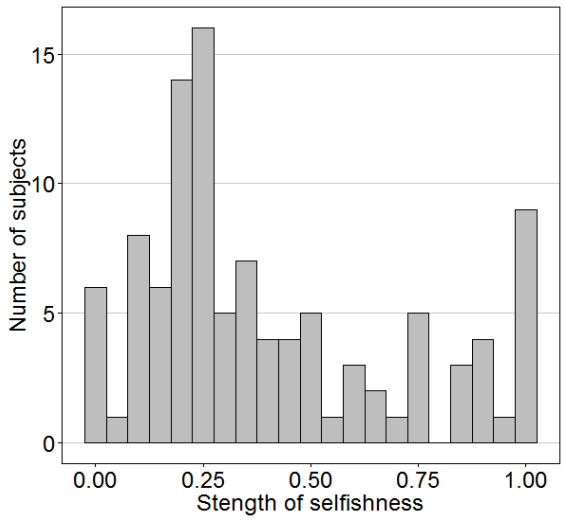

Fig. D2. The distribution of the strength of selfishness in the odd trials of conflict decisions

D.4 The Response Time of Selfish and Social Decisions

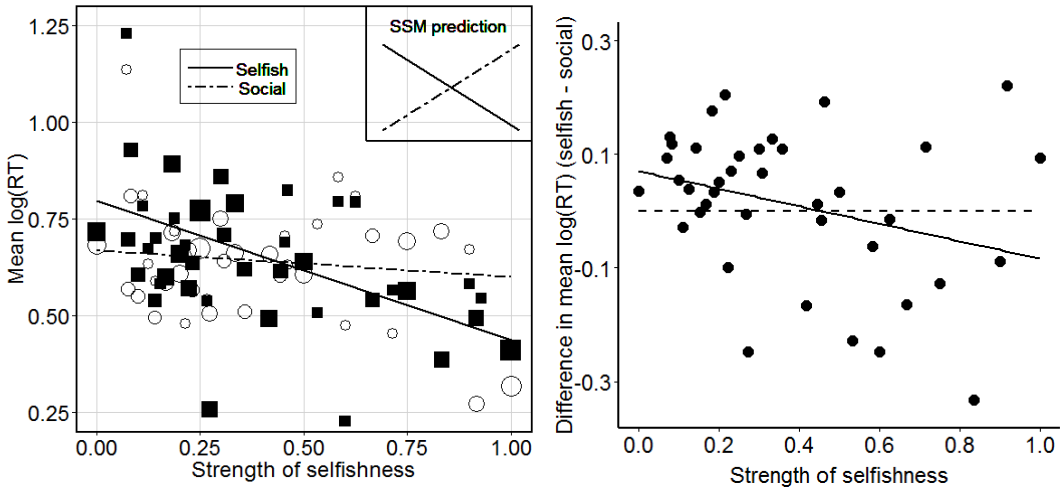

Fig. D3. The RT of selfish and social decisions in the even trials of conflict decisions. The size of the point or the square indicates the number of subjects in that point or square. The solid and dotted lines are regression lines. The left panel displays the relationship between the RTs of selfish (social) decisions and the strength of selfishness. Subjects who are more selfish are quicker in making selfish decisions (Pearson's correlation test, $r = -0.441$, $p < 10^{-15}$). But subjects who are more selfish are not significantly slower in making social decisions (Pearson's correlation test, $r = -0.048$, $p = 0.195$). The right panel shows that the time difference between selfish and social decisions is negatively related with the strength of selfishness (Pearson's correlation test, $r = -0.285$, $p < 0.007$).

D.5 Regressions of Response Times on the Decision Type and the Strength of Selfishness

Table D2. Regressions of response times on decision type and the strength of selfishness (the even trials of conflict decisions)

	Mixed-effects regression	OLS regressions	
	(1)	(2)	(3)
Constant	0.737***	0.826***	0.790***
	(0.022)	(0.036)	(0.037)
Selfish decision	0.011	0.023	0.122***
	(0.016)	(0.028)	(0.043)
Strength of selfishness		-0.287***	-0.090
		(0.048)	(0.079)
abs(Utility difference)	-0.028***	-0.023***	-0.029***
	(0.006)	(0.008)	(0.008)
Conflict within norms	0.049***	0.053***	0.042***
	(0.013)	(0.014)	(0.015)
Male		0.044	0.025
		(0.035)	(0.034)
Decision number	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Selfish decision × Male		-0.013	0.025
		(0.038)	(0.036)
Selfish decision × Strength of selfishness			-0.297***
			(0.085)
Num. obs.	1239	1239	1239
Num. groups	105	105	105

Notes. The dependent variable is *log*(*RT*). *Selfish Decision* is a dummy variable which indicate the decision is a selfish decision or social decision. *Male* is a dummy variable which indicate the gender. The robust standard errors for regressions (2) and (3) are clustered on subjects and reported in parentheses. Regression (1) and (2) show that the RTs of selfish decisions are not significantly different from the RTs of social decisions when we control the utility difference between choice options and the conflicts between norms. Regression (3) shows that the RTs of selfish decisions decrease with the strength of selfishness, but the strength of selfishness has no significant effect on the RTs of social decisions. Both regressions (2) and (3) show that there is no significant gender difference on the RTs of selfish and social decisions.
***p < 0.01, **p < 0.05, *p < 0.1.

D.6 The Explanatory Power of the Utility Differences based on FMM and Logit

Table D3. OLS regressions of response time on the utility difference (the odd trials of the second-party decisions)

	(1)	(2)	(3)
Constant	0.660***	0.664***	0.670***
	(0.020)	(0.019)	(0.019)
abs(Utility difference based on FMM)	-0.034***		-0.023*
	(0.008)		(0.014)
abs(Utility difference based on Logit)		-0.041***	-0.021
		(0.008)	(0.014)
R^2	0.021	0.019	0.024
Adj. R^2	0.021	0.019	0.023
Num. obs.	1677	1677	1677

Notes. The dependent variable is log(RT). The robust standard errors are clustered on subjects and reported in parentheses. Regressions (1) and (2) shows the utility difference based FMM has a higher explanatory power (adjusted $R^2 = 0.021$) than the utility difference based on the Logit model (adjusted $R^2 = 0.019$). Regression (3) shows that the coefficient of the utility difference based on FFM is more robust than the coefficient of the utility difference based on the Logit model, since the coefficient of the utility difference based on the Logit model is not significant at all if we simultaneously include the two variables in the regression.
***p < 0.01, **p < 0.05, *p < 0.1.

Appendix E (Analysis of Eye-Tracking Data from Fiedler et al, 2013)

In the paper of Fiedler et al. (2013), subjects make decision for both Social Value Orientation (SVO) Ring Measure Task and SVO Slider Task. To do an out-of-sample analysis, we access subjects' prosociality using their decisions for SVO Slider Task, and analyze their fixation behavior in the SVO Ring Measure Task.

Using decisions for SVO Slider Task, all subjects can be classified into three types: selfish, prosocial and competitive types. Since there is only one subject who is competitive type. In the following, we focus our analysis on selfish and prosocial subjects. Figure E1 displays the proportion of the fixation on own payoffs and how it changes with time. We divide each decision (process) into five bins with equal time period. It shows that the selfish subjects put more attention (80.117%) on their own payoffs at the beginning of the decision process compare to prosocial subjects (60.078%). The proportion of the fixation on own payoffs decreases with time for both selfish and prosocial subjects, and becomes stable at the end of the decision process.

Figure E2 displays the proportion of subjects who fixate on their own payoffs in each fixation. It shows that 78.571% of selfish subjects who fixate on their own payoffs in the first fixation, while 58.523% of prosocial subjects who fixate on their own payoffs in the first fixation. The proportion of subjects who fixate on own payoffs becomes stable and around 50% from the fifth fixation for both selfish and prosocial types.

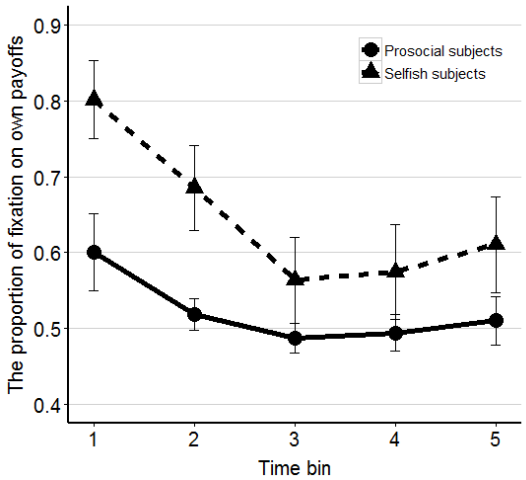

Fig. E1. The proportion of the fixation on own payoffs

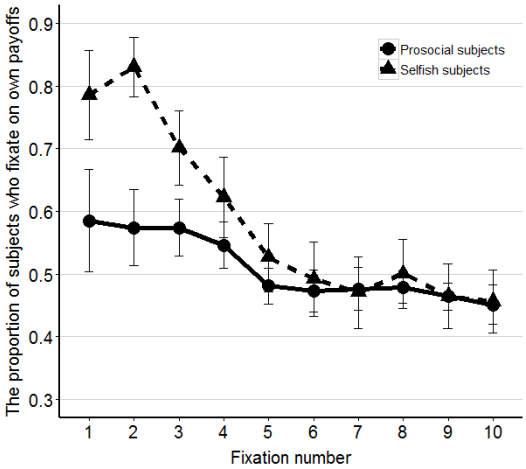

Fig. E2. The proportion of subjects who fixate on own payoffs in each fixation

Appendix F.

General Instructions

Today you are participating in an economic experiment. If you read the following instructions carefully, you can – depending on your decisions – earn money in addition to the show-up fee of 3 Euros. Therefore, it is important that you read these instructions carefully.

During the whole experiment, it is not allowed to communicate with other participants. We, therefore, ask you to turn off the cell phone and not to speak with each other. If you do not understand something, please consult the instructions again. If you still have questions, please raise your hand. We will come to you and answer your questions individually.

In this experiment, you will need to decide for different situations. At the end, one of the situations will be randomly drawn and paid out. You will receive your payment in accordance with the decisions in this relevant situation.

In the instructions we do not speak of Euro, but points. The points you earn during the experiment will be converted into Euros in the following rate:

1 Point = 50 Cents

That is, you get 50 cents per point in the relevant situation. Of course, you will also receive a show up fee of 3 Euros.

On the following pages we will explain the exact course of the experiment. First, we will familiarize you with the decision situation. When you finish reading the instructions, on your screen you will find control questions which will help you to understand the situations. The experiment only begins when all participants are completely familiar with the course of the experiment.

The Experiment

All the participants in the laboratory are randomly divided into groups of three. Each group consists of Participant I, Participant II and Participant III. In each situation, two point distributions which relate to the three members of the group are available. Participant II can decide which of the two distributions is selected. Since only Participant II makes decisions, in the following we explain the experiment from the perspective of Participant II (Important: Each participant can be Participant II). In the experiment, each participant makes decisions as Participant II. Which person is Participant I, II or III in the group will be randomly drawn at the end of the experiment. In addition, one of the decisions of Participant II will be randomly drawn to be implemented at the end of the experiment.

Display on the Screen

Figure F1. Keys, with which you make decisions

This experiment consists of a series of 64 decision situations in which you can choose one of two point distributions as Participant II. The following screen shot shows an example. In the left option, Participant I receives 9 points, you, as Participant II, receive 12 points and Participant III receives 16 points. The height of bars on the left corresponds to the corresponding amounts. “Your” bar is always shown in the middle and in white color. In the right option, Participant I receives 10 points, you, as Participant II, receive 17 points and Participant III receives 19 points. The height of the bars on the right also corresponds to these amounts. You make your decisions with the help of the keyboard. For the left option, you press the key “F” and for the right option you press the key “J” (see Figure 1). Which key to press is also displayed at the bottom of the screen. Therefore, in this example, if you press “F”, you receive 12 points, Participant I receives 9 points and Participant III received 16 points. If you press “J”, you receives 17 points, Participant I receives 10 points and Participant III receives 19 points. After each

decision you have to press the ‘Spacebar’ to continue.

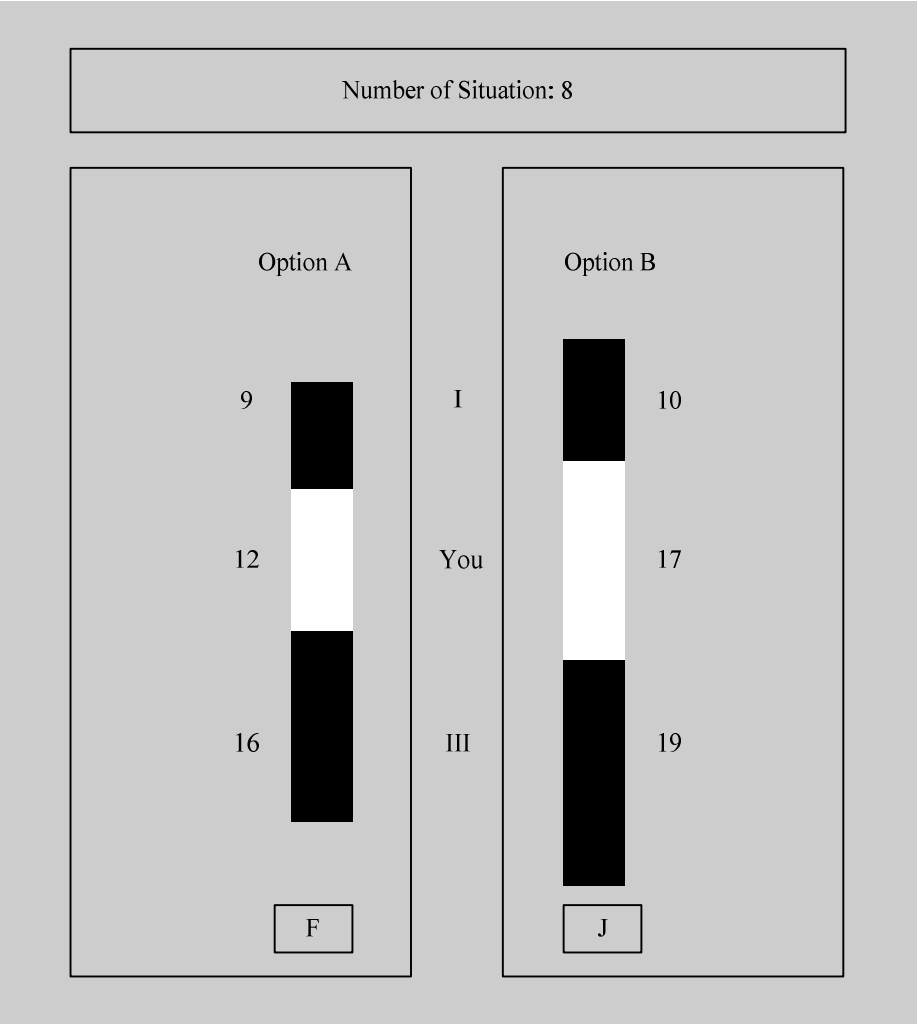

Figure F2. Screen layout

Payment

At the end of the experiment, it will be randomly drawn which one of the 64 situations will be paid and who is Participant I, II and III. The draw will be made with a die by the participant at the 13th place. Then it takes about one minute to display all your decision situations and your income in the experiment.

If you have understood the instructions, please answer the control questions on the screen.

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