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Cognitive Processes of Distributional Preferences: A Response Time Study

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Cognitive Processes of Distributional Preferences: A Response Time Study*

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Fadong Chen[a] Urs Fischbacher[b]

Abstract

There is ample evidence that people differ considerably in the strength of their social preferences. We identify individual heterogeneity in social motives and selfishness in a series of binary three-person dictator games. Based on this identification, we analyze response time to investigate the cognitive processes of distributional preferences. We find that response time increases with the number of conflicts between individually relevant motives and the difficulty of the decisions. The selfish motive is more intuitive for subjects who are more selfish. This is evidence for both, evidence accumulation models and dual-process theory, and we can show that heterogeneity in preferences is reflected in heterogeneity in the underlying cognitive processes. This shows 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: C72, C91, D03, D87

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1. Introduction

A considerable 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. For example, dual-process approaches 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, Kahneman 2003, 2011, Sloman 1996, Strack and Deutsch 2004). Relative response times (RTs) are widely used to distinguish between intuitive and deliberative processes since intuitive processes are executed more quickly than deliberative processes (Krajbich et al. forthcoming). In the domain of social preference, this raises the question whether specific motives are processed more automatic than others, in particular whether the selfish or the social motive is more intuitive. The evidence based on studies using RTs and cognitive load is mixed so far. Some studies find that people tend to be more pro-social under time pressure or cognitive load, indicating that the social motives are more intuitive (Cappelletti, Güth, and Ploner 2011, Cornelissen, Dewitte, and Warlop 2011, Lotito, Migheli, and Ortona 2013, Nielsen, Tyran, and Wengström 2014, Peysakhovich and Rand forthcoming, Rand, Greene, and Nowak 2012, Rubinstein 2007, Schulz et al. 2014), while other studies find that selfish motives are more intuitive (Duffy and Smith 2014, Piovesan and Wengström 2009, Tinghog et al. 2013, Verkoeijen and Bouwmeester 2014).

A different view regarding the interpretation of RTs is taken by evidence accumulation 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 evidence accumulation 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, Bushong, and Rangel 2015, Krajbich, Armel, and Rangel 2010, Krajbich et al. forthcoming, Krajbich, Oud, and Fehr 2014). These studies indicate that there exists a common computational mechanism underlying economic decision making and perceptual decision making. The difficulty of decisions which is based on the utility difference between options determines RTs and more difficult decisions require longer RTs.

We study the cognitive mechanisms of social decision making using RT analysis in distribution decisions. It is a well-established fact that people are heterogeneous in the relevant motives and in the strength of social preferences (Andreoni and Miller 2002, Engelmann and Strobel 2004, Erlei 2008, Fisman, Kariv, and Markovits 2007, Kerschbamer 2015). For instance, some people care more about efficiency, while others care more about fairness (Murphy, Ackermann, and Handgraaf 2011). We also explicitly take individual heterogeneity into account, not only with respect to the strength of people's social and selfish motives, but also with respect to what kind of social motives people care about. Our experiment includes two types of binary three-person dictator games. In the first type of games the dictator's payoff is the same in the two allocations, while in the second type the dictator's payoff differs between the two allocations. Decisions in the first type of games allow us to identify the subjects' social motives. Based on this identification, we can study how people with different social motives react to various decision situations using RT analysis. In addition, we can study which kind of motive, selfish or social motives, can be considered as more intuitive.

We classify subjects into three norm types, which differ with respect to the relevant social motives. A within-subject analysis shows that decisions with potential conflicts between individually relevant motives take longer than decisions without conflict, i.e., RT increases with the number of conflicts between the motives and with the difficulty of decisions. These results are in line with the predictions of evidence accumulation models. A between-subject analysis reveals 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. Thus, it is crucial taking heterogeneity into account. It increases predictive and explanatory power of behavior as well as of RT, and heterogeneity in social motives and selfishness is reflected in process differences.

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 the social motives and in the strength of social preferences. Based on this identification, we are not only able to provide evidence for evidence accumulation models, but we can also show heterogeneity in whether the selfish or the social motive is related to an intuitive process. This could help to reconcile the mixed results on the correlations between RT and pro-sociality. We argue that both the heterogeneity in the social motives and the heterogeneity in the strength of social preferences have effects on the RT.

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 two other subjects. The other two subjects have no choice. In 32 of the 64 games, the dictator's payoff does not differ between the two options. We call these games selfishness indifferent (SI) games. In SI 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 games in which the payoff of the dictator varies. We call these games selfishness different (SD) games. Table 1 gives examples for the two types of the binary three-person dictator games.

Table 1. Examples of the Two Types of Games

Player	SI Game		SD Game	
	Option A	Option B	Option A	Option B
1	$A_1 = 5$	$15 = B_1$	$A_1 = 10$	$10 = B_1$
2 (Dictator)	$A_2 = 11$	$11 = B_2$	$A_2 = 15$	$17 = B_2$
3	$A_3 = 20$	$16 = B_3$	$A_3 = 11$	$19 = B_3$

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 numeric form as well as in a graphical form, in order to make them quickly accessible. The screen layout is shown in Figure B2 in the Appendix.

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

[1] Table A1 in Appendix A lists the 64 games.

Konstanz. 105 subjects participated in the experiment. In order to address heterogeneity, our sample size is sufficiently larger than Hutcherson, Bushong, and Rangel (2015), who have 51 subjects actively making decisions. 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 B). 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 SD and SI games. In addition, Option A and Option B of each game were also randomly reshuffled. All subjects made their decisions as dictators by pressing buttons "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.[2] After each decision, subjects saw a waiting screen and were required to press the "SPACE" button to continue 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.

3. Finite Mixture Estimation

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

3.1 The Decision Motives

People differ in the nature of their distributional preferences. The SI games allow to deal with the heterogeneity of distributional preferences, even for selfish subjects. In this section, we present the motives that we take into account in our models.

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 motive and the signs of these

[2] 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.

differences. The difference takes always the sign that if a person has the corresponding motive, she chooses A. 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 ~ SignEfficiency + DiffEfficiency + SignEnvy + DiffEnvy + SignMaximin + DiffMaximin + SignFS-α + SignFS-β + DiffFS-β*;

Model II: *Decision ~ SignEfficiency + SignEnvy + SignMaximin + SignFS-α + SignFS-β*;

Model III: *Decision ~ SignEfficiency + DiffEnvy + SignMaximin + DiffMaximin + SignFS-β*;

Model IV: *Decision ~ SignEfficiency + DiffEnvy + SignMaximin + SignFS-β.*

In the first model, we include all the variables of signs and differences on social motives.[3] However, we have to leave out the variable *DiffFS-α* in order to avoid the collinearity problem.[4] 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.

3.2 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 strength of their social motives, we estimate a finite mixture model (Breitmoser 2013, Bruhin, Fehr-Duda, and Epper 2010, Houser, Keane, and McCabe 2004). The finite

[3] Selfish motive is not involved in SI decisions.

[4] 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).*

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:

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

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.

4. Results

In this section, we first present the results of the finite mixture estimation, which characterize the heterogeneity in distributional preferences. Then, we analyze RT in order to investigate the cognitive processes of decision making. Finally, we show that the heterogeneity in social preferences is also reflected in the differences of cognitive processes.

4.1 Behavioral Analysis

In order to deal with the heterogeneity and to determine individual distributional preferences, we analyze SI decisions using a finite mixture model.[5] 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 1), and all four models create the same classification.

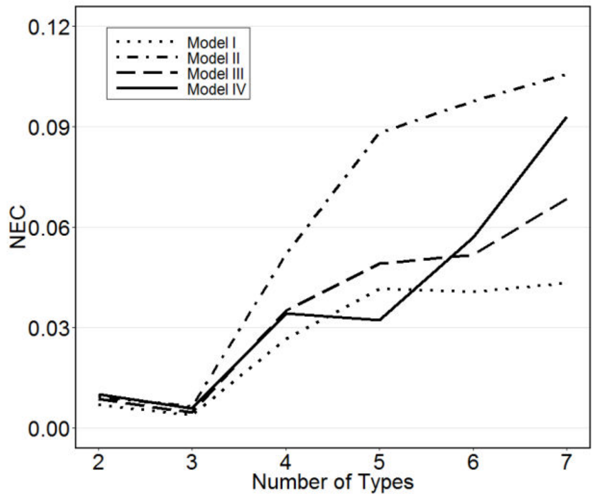
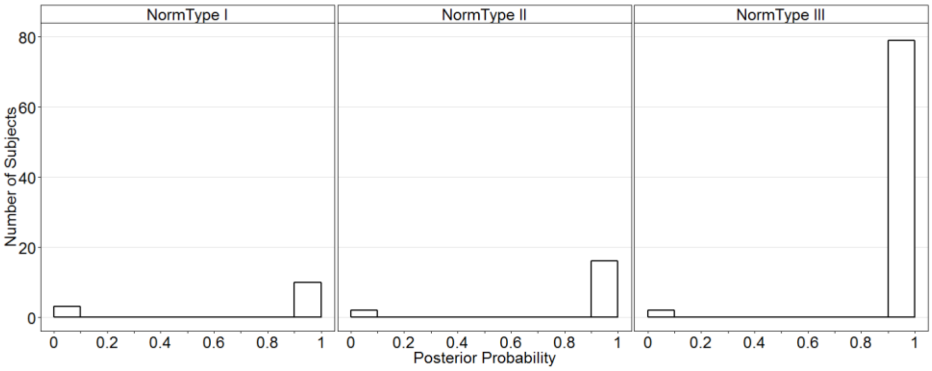


Fig. 1. The Optimal Number of Types

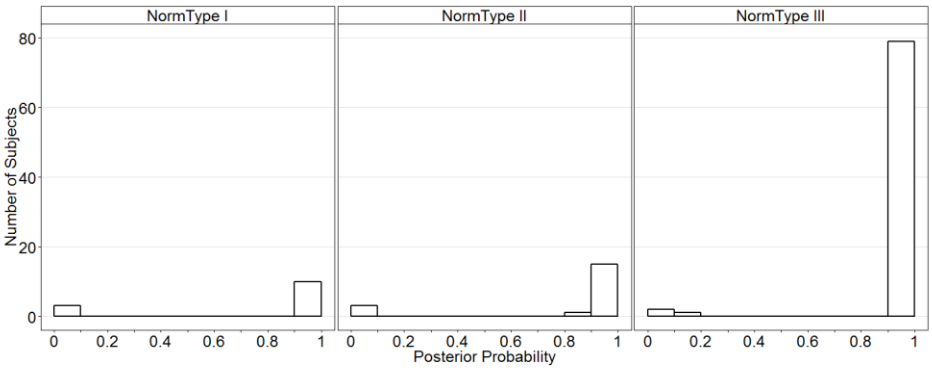
In addition, all subjects can be assigned to one distinct type with high posterior probability. Figure 2 shows the posterior probabilities which are larger than 0.01. A peak at probability 1 indicates that a preference type is well separated from the other types, and no significant mass in the middle of the unit interval indicates clean classification.[6] These clean classifications suggest that our analysis is able to capture the distinctive characteristics of each preference type. We call the type based on the classification of the personal norms 'Norm Type (NT)'.

[5] We do the finite mixture analysis using R package flexmix (Grun and Leisch 2008).

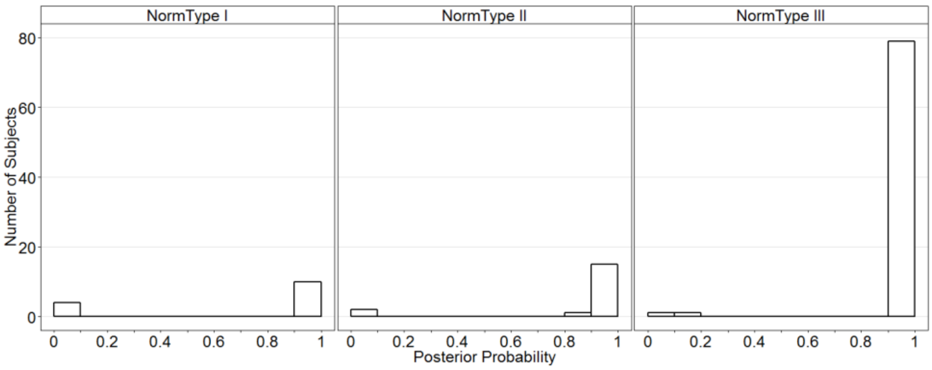
[6] In Model I, all subjects can be classified into their types with the probabilities of greater than 0.93, and 93.3% of all subjects are classified into their types with the probabilities of greater than 0.99. In Model II, only one subject is classified into her type with the posterior probability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



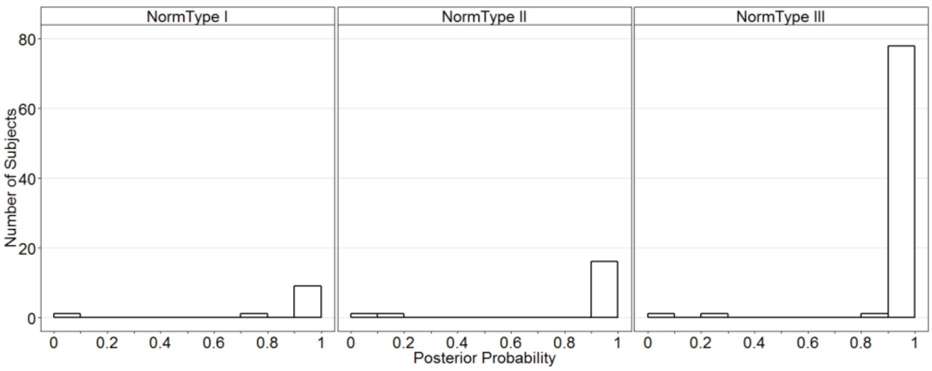
Model I



Model II



Model III



Model IV

Fig. 2. The Posterior Probabilities for the Four Models ($p > 0.01$)

Table 2. Results of 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.

The regression results of the finite mixture analysis are shown in Table 2. 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.[7] The relevant motives for the personal norms of each type are summarized in Table 3.

Table 3. Personal Norms of Each Type Identified by the Four Models

Classification	NT I	NT II	NT 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

Apart from some minor differences, all four models identify almost identical norm types. In the following, we will 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. In Model IV, subjects of Norm Type I (NT I) care about *efficiency* and *maximin*. Subjects of Norm Type II (NT II) care about *envy* and *maximin*. And subjects of Norm Type III (NT III) care about *efficiency*, *maximin* and *FS-β*. We summarize our main results based on the behavioral analysis.

RESULT 1. *People have heterogeneous distributional preferences. 9.5% (10) of the subjects care about maximin and efficiency, 15.2% (16) care about envy and maximin and 75.2% (79) care about efficiency, maximin and FS-β.*

4.2 Response Time Analysis

In this section we analyze RTs of the distribution decisions in our experiment. Before addressing specific questions, we first take a general look at the data of the RTs and report the statistical properties of the RTs. Figure 3 shows the evolution of the average response time (ART) and the 95% confidence interval over time. The ART decreases sharply in the beginning periods, especially the first four periods, followed by a rather stable level throughout the remaining periods. The ARTs of the first and last decisions are 10.35 and 4.34 seconds respectively. As subjects get familiar with the format of the decision task they need less time to make decisions.[8]

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

[8] In the following regression analysis, we usually remove the first four decisions if we study the RTs of both SI and SD decisions, and we remove the first two decisions if we only study the RTs of SD or SI decisions.

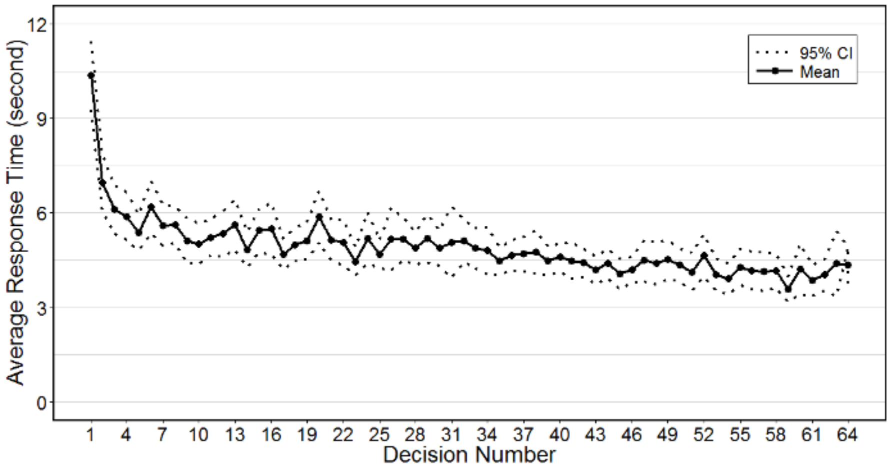


Fig. 3. Evolution of Average Response Times

Figure 4 shows the distributions of the RTs in SD and SI decisions, and Figure 5 shows the distributions of the logarithm of the RTs. Obviously, the distribution of the RTs are strongly right skewed, while the distribution of the logarithm of RTs follows more a normal distribution.[9] For this reason, we use the logarithm of RTs in the following analyses. More specifically, we report the logarithm with base 10 in Figures 4 and 5, because it is easier to translate into the actual time, but use the natural logarithm in the following regressions because a 1% change is approximated by a 0.01 difference in the natural logarithm.

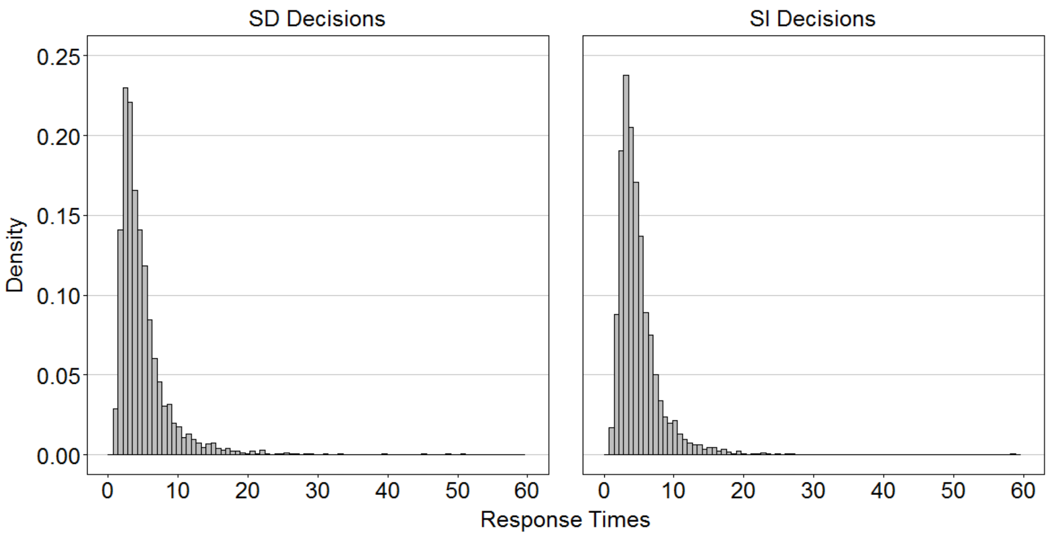


Fig. 4. Distributions of Response Times

[9] At the 0.05 level, the Shapiro-Wilk test rejects the normality of RTs of SI decisions for 85 of 105 subjects, and the Shapiro-Wilk test rejects the normality of RTs of SD decisions for 88 of 105 subjects. However, at the 0.05 level, the Shapiro-Wilk test rejects the normality of ln(RTs) of SI decisions for 17 of 105 subjects, and the Shapiro-Wilk test rejects the normality of ln(RTs) of SD decisions for 20 of 105 subjects.

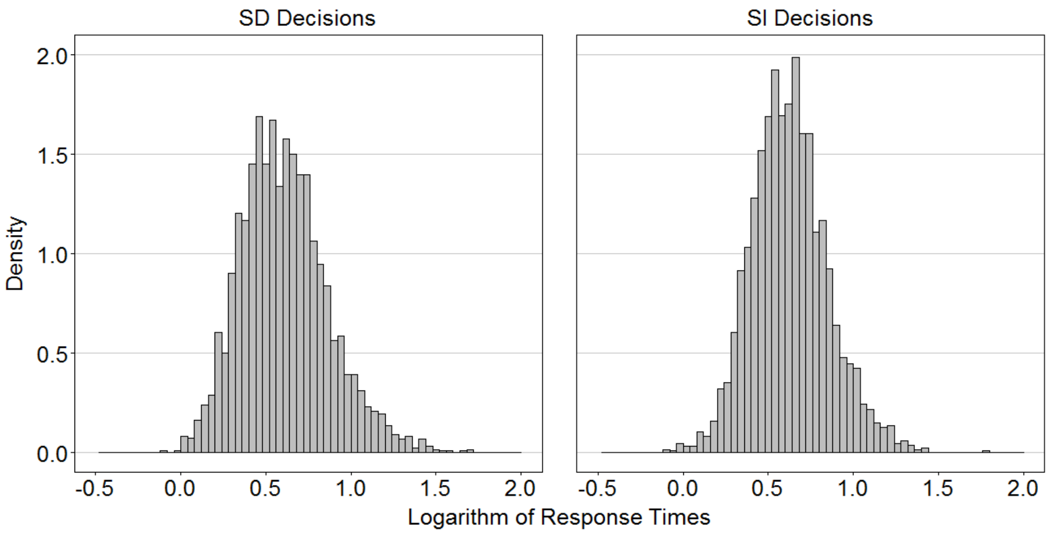


Fig. 5. Distributions of the Logarithm of Response Times

4.2.1 Evidence for Evidence Accumulation Models

In this section, we present evidence that the cognitive processes of distribution decisions comply with evidence accumulation models (Ratcliff 1978, Ratcliff and Smith 2004). Specifically, we focus on the question how cognitive conflicts and the difficulty of the decisions affect RTs. First, we use the relevant motives identified before and define decision situation as conflicting if there is a conflict between these motives. Second, we use the utility difference assessed by regressions as a measure of difficulty. As we will discuss below, the difficulty of a decision problem is given by how close the two options are to indifference.

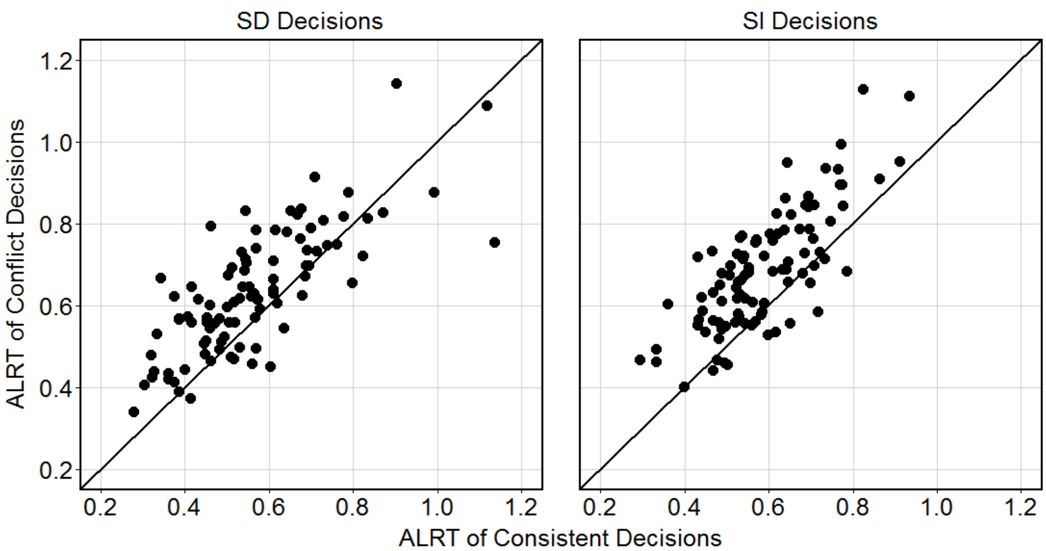


Fig. 6. ALRTs of Conflict and Consistent Decisions

First, we compare the RTs of conflict and consistent decisions. 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 in which the subject's behavior is consistent with some of her motives but in conflict with other motives. *Consistent decisions* are decisions in which the subject's behavior is consistent with all her motives.[10] We expect that conflict decisions take longer than consistent decisions. First, 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 evidence accumulation models, it takes more time to accumulate evidence to reach the threshold and make a decision if the utility difference is small. Figure 6 displays the average logarithm response times (ALRTs) of conflict and consistent decisions for each subject.[11] Most of the data points are above the 45° line in both SD and SI decisions. That is, the RTs of conflict decisions are longer than the RTs of consistent decisions for most of the subjects (Wilcoxon sign-rank test, $p < 0.001$ for both SI and SD decisions).

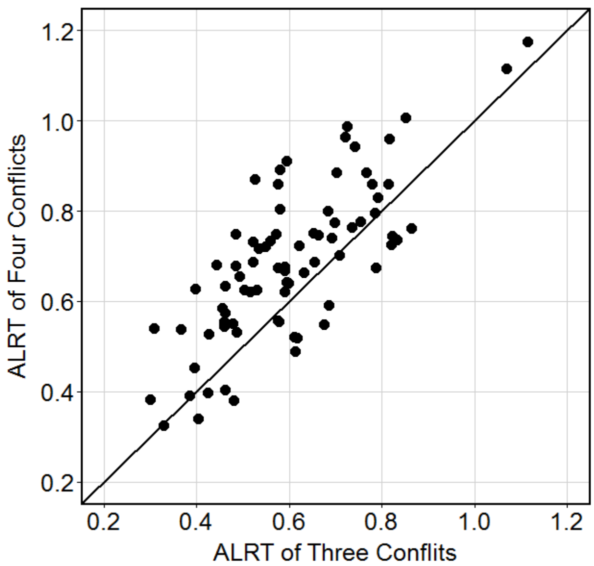


Fig. 7. ALRTs for Different Number of Conflicts

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 norm type are shown in Table A2 and A3. 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 NT III, which is the largest group. In these decisions, the number of conflicts can be three or four. Figure 7 displays the ALRTs of different

[10] Details about how the decisions are classified are shown in Tables A2 and A3. If the two options are indifferent on one motive, the behavior is seen as consistent with that motive no matter which option the subject has chosen. There are a few decisions (1.62% of all) in which subjects neither follow their personal norms nor selfish motives. We call these decisions 'incorrect decisions'. We exclude these incorrect decisions from our RT analysis.
[11] To test the robustness of our results, we also conducted the analysis using untransformed RTs, which essentially leads to the same results.

numbers of conflicts. It shows that decisions with four conflicts take longer than those with three conflicts (Wilcoxon sign-rank test, $p < 0.001$).

Turning to the difficulty of the decisions, the evidence accumulation models predicts that the closer the utilities of the two options, the longer subject needs to make a decision. We construct a measure of difficulty based on the utility difference between the two options. As a measure for the utility, we use the latent variable of the finite mixture model specified above. The latent variable of SI decisions is calculated using the coefficients in Table 2, and the latent variable of SD decisions is calculated using the coefficients in Table A4. We define the difficulty as the absolute value of the latent variable, and then normalized it to be between 0 and 1.[12] Figure 8 displays the relationship between the ALRTs and the difficulty of decisions. It shows that, in both SD and SI decisions, RT increases with the difficulty of decisions. The correlation is highly significant, but since the observations are not independent we consider the decisions at the individual level. The Pearson correlation coefficient between difficulty and ALRT is positive for 89.5% (94 of 105) of the subjects in SI decisions, and for 85.7% (90 of 105) of the subjects in SD decisions. Both numbers are highly significantly different from the chance level of 50% (binomial test $p<10^{-14}$).

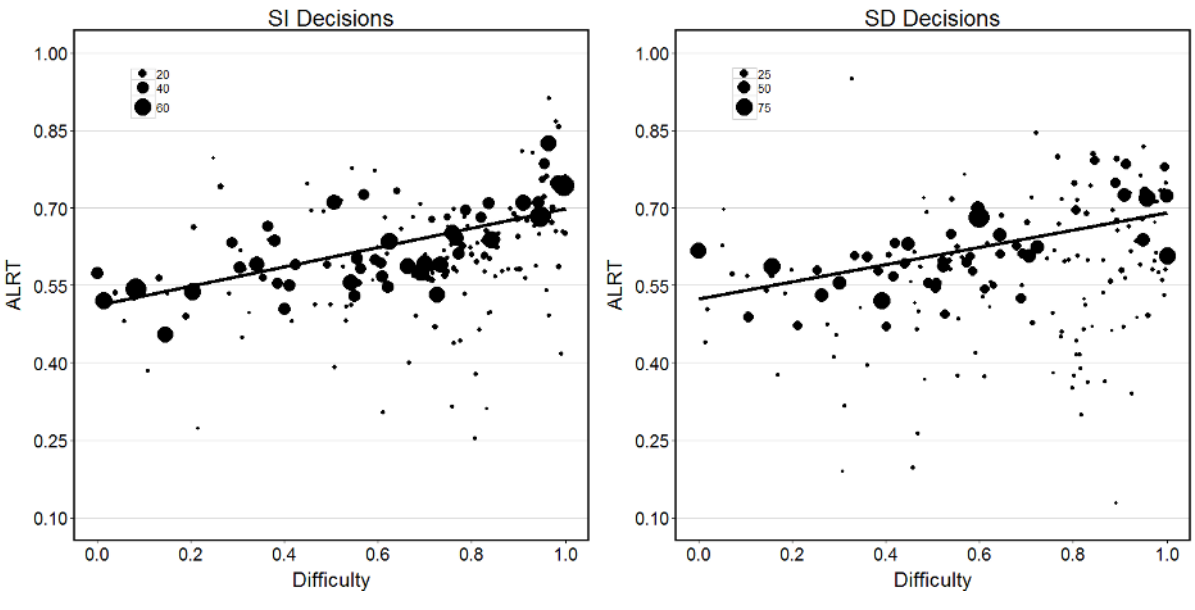


Fig. 8. The Average Logarithm Response Times and the Difficulty of the decisions

The dependence of RTs on the number of conflicts and the difficulty of decisions can also be confirmed using fixed effects regressions. The regression results are shown in Table 4. The dependent variable is $ln(RT)$. The coefficient of the conflict decision dummy is positive and significant, which indicates that the cognitive conflict between individually relevant motives has significantly positive effects on the RTs. In regression (6), the coefficient of the number of conflicts is positive and significant.

[12] The normalization is done for each norm type (NT) separately in both SD and SI decisions.

It indicates that, when the situation has one more conflict, the subjects need 8.6% more time to decide. With respect to the difficulty of decisions, the coefficients are positive and highly significant in all regressions. All these results indicate that the RT of distribution decisions is in line with the prediction of evidence accumulation models. We now summarize the evidence for evidence accumulation models.

RESULT 2. *There exist cognitive conflicts between individually relevant motives. The cognitive conflict leads to longer response times, and the response time increases with the number of conflicts and the difficulty of the decisions.*

Table 4. Fixed Effects Regressions on Response Times

	SD Decisions		SI Decisions		SD & SI Decisions	Conflict SD Decisions for NT III
	(1)	(2)	(3)	(4)	(5)	(6)
Conflict Decision	0.186***	0.106***	0.246***	0.140***	0.119***	
	(0.023)	(0.021)	(0.021)	(0.024)	(0.015)	
Difficulty		0.336***		0.277***	0.312***	0.381***
		(0.041)		(0.035)	(0.030)	(0.070)
Decision Number	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SD Decision					-0.064**	
					(0.016)	
Selfish Decision						0.056
						(0.042)
Num. Conflicts						0.086**
						(0.034)
R^2	0.094	0.123	0.144	0.162	0.137	0.139
Adj. R^2	0.091	0.119	0.139	0.156	0.135	0.132
Num. obs.	2883	2883	2860	2860	5743	1617

Notes. The dependent variable is $ln(RT)$. The robust standard errors are clustered on subjects and reported in parentheses. Always selfish subjects, incorrect decisions and the first two decisions of each subject in both SD and SI decisions are removed. ***p < 0.01, **p < 0.05, *p < 0.1.

4.2.2 Evidence for Dual-Process Theory

According to the dual-process theory, decisions which are more associated with intuitive processes should be quicker than those that are more associated with deliberative processes. In this section, we present evidence on which motive, the selfish or the social motive, is more related to intuitive processes by comparing the RTs. There is conflicting evidence on this question. Evans, Dillon, and Rand (forthcoming) and Krajbich et al. (forthcoming) have shown that the identification of the process using RT is difficult because it interacts with the conflictedness and the difficulty of the situation. Therefore, we will control for difficulty 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 heterogeneity in social motives and heterogeneity in selfishness.

To compare 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 SD games into *selfish decisions* and *social decisions* according to whether the decision is consistent with the selfish motive or not. The selfish decisions should be quicker than the social decisions if the selfish motive is more intuitive and social decisions should be quicker than the selfish decisions if the social motive is more intuitive. To test these predictions, we conducted a fixed effects regression with *ln*(*RT*) as the dependent variable. *Decision Number* controls for learning, and *Difficulty* (utility difference) as well as variable *Conflict within Norms* (dummy whether there is a conflict within the social motives) control for the difficulty of the decision. The regressions in Table 5 show that the RTs of selfish decisions appear to be longer than those of social decisions except for subjects of NT I (regressions (2) - (4)) – if we do not control for the variable *Conflict within Norms*. Using the available measures of difficulty (i.e. including *Conflict within Norms*), RT does not to differ between selfish and non-selfish decision –across all subjects (regressions (5) - (8)). This shows that there is no evidence that the selfish or social decision is more intuitive if we ignore the heterogeneity in selfishness.

Table 5. Fixed Effects Regression of Response Time on Selfish and Social Decisions in SD Games

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	NT I	NT II	NT III	All	NT I	NT II	NT III	All
Selfish Decision	-0.133	0.158***	0.106**	0.077**	-0.129	0.108	0.044	0.010
	(0.132)	(0.059)	(0.044)	(0.034)	(0.140)	(0.066)	(0.041)	(0.034)
Difficulty	-0.198	0.090	0.483***	0.349***	-0.005	0.009	0.403***	0.273***
	(0.171)	(0.079)	(0.059)	(0.049)	(0.178)	(0.071)	(0.062)	(0.049)
Decision Number	-0.008	-0.007***	-0.008***	-0.007***	-0.008	-0.006***	-0.007***	-0.007***
	(0.006)	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)	(0.001)
Conflict within Norms					0.128*	0.140**	0.094***	0.125***
					(0.067)	(0.067)	(0.031)	(0.027)
R^2	0.082	0.099	0.134	0.110	0.091	0.118	0.140	0.124
Adj. R^2	0.076	0.094	0.127	0.105	0.084	0.111	0.133	0.118
Num. obs.	146	352	1617	2115	146	352	1617	2115

Notes. The dependent variable is *ln*(*RT*). *Selfish Decision* is a dummy variable which indicates whether the decision is a selfish decision (1) or social decision (0). The robust standard errors are clustered on subjects and reported in parentheses. Incorrect decisions and the first two decisions of each subject are removed. ***p < 0.01, **p < 0.05, *p < 0.1.

In our next step we take heterogeneity into account and study whether the selfish motive is more intuitive for some people and the social motive is more intuitive for others. Specifically, we study how the strength of selfishness influences subject's intuition towards the selfish or social motive. We calculate the ratio of selfish decisions for each subject as the measure of the strength of selfishness. Figure 9 shows the distribution of the ratio of selfish decisions. It shows that eight subjects always choose the selfish option when the selfish motive conflicts with their social motives and many subjects have high proportions of social decisions.[13] We expect that the selfish motive is more intuitive for the

[13] In our experimental design, the differences on selfish motives are usually small. Thus, we make it "cheap" to make social decisions when the selfish motives conflict with the social motives. Table A2 shows the number of selfish and social decisions for subjects of each norm type.

subjects who have a higher ratio of selfish decisions. More specifically, we expect for subjects who have a higher ratio of selfish decisions, first, that the selfish decisions are quicker than social decisions, and second, that the SD decisions are quicker than SI decisions since the selfish motive is relevant in SD decisions.

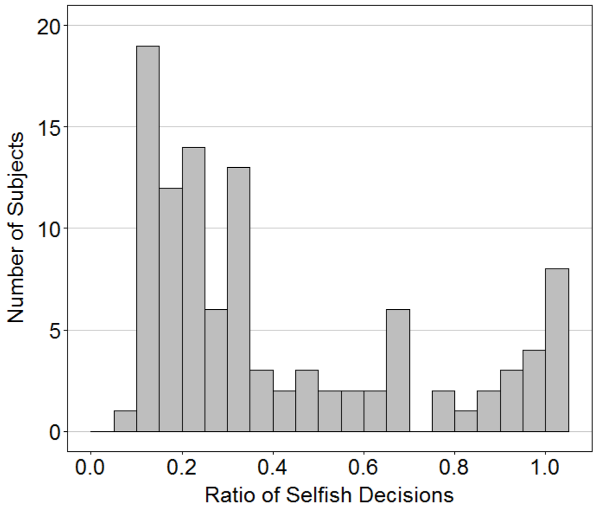


Fig. 9. The Distribution of the Ratio of Selfish Decisions in Conflict SD Decisions

The left panel of Figure 10 displays the relationship between the ratio of selfish decisions and the ALRTs of selfish and social decisions. It shows that subjects who are more selfish are quicker in making selfish decisions (Pearson's correlation test, $\rho = -0.534$, $p < 10^{-8}$). But subjects who are more selfish are not significantly slower in making social decisions (Pearson's correlation test, $\rho = 0.082$, $p = 0.277$). The right panel of Figure 10 displays the time difference of selfish and social decisions. It shows that the selfish decisions are quicker than social decisions for subjects who have a high ratio of selfish decisions and the selfish decisions are slower than social decisions for subjects who have a low ratio of selfish decisions. However, whether decisions are selfish is endogenous. For this reason, we also study whether RT differs between SD and SI decisions. Figure 11 displays the RTs of SD and SI decisions. The left panel shows that subjects who are more selfish are significantly quicker in SD decisions (Pearson's correlation test, $\rho = -0.459$, $p = 0.002$) as well as in SI decisions (Pearson's correlation two-sided test, $\rho = -0.204$, $p = 0.037$). However while subjects with fewer selfish decisions have similar RTs in SI and SD decisions, selfish subjects are quicker in SD decisions. This is most evident in the right panel of Figure 11. These results suggest that the selfish motive is more intuitive for subjects who have a high ratio of selfish decisions, and the selfish motives are more deliberative for subjects who have a low ratio of selfish decisions.

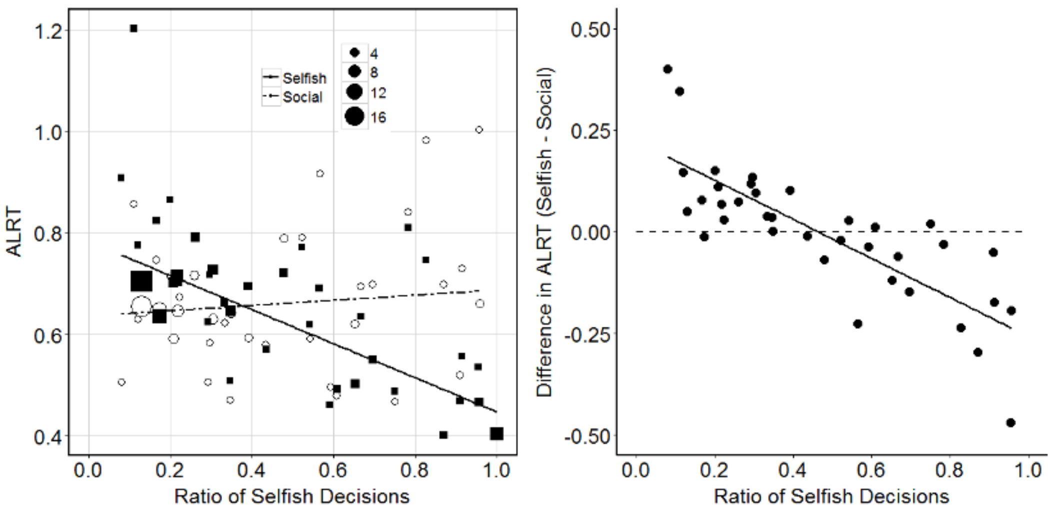


Fig. 10. The Response Times of Selfish and Social Decisions

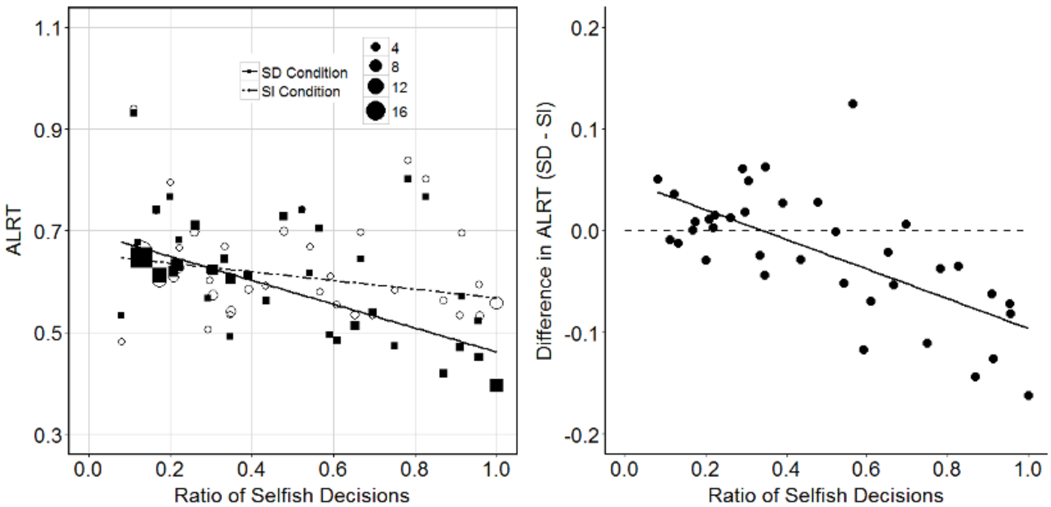


Fig. 11. The Response Times of SD and SI Decisions

The econometric analysis in Table 6 corroborates these results. Regression (2) in Table 6 indicates that the RTs of selfish decisions decrease with the ratio of selfish decisions. Subjects who are 1% more selfish need 0.847% less time to make selfish decisions. However, the coefficient of *ratio of selfish* is not significant in regression (2). Thus, the ratio of selfish decisions has no significant effects on the RTs of social decisions. Regression (4) shows that subjects who are more selfish are quicker in making SI decisions, and they are much quicker in making SD decisions.

Our results show that selfishness interacts with speed of selfish vs. non-selfish decisions. We control for difficulty, which deals with the argument brought up by Krajbich et al. (forthcoming). Of course, control is incomplete because difficulty is constructed at the norm type level and not at the individual level. Nevertheless, studies using cognitive load show the relevance of dual-process theories. Our results show that heterogeneity is a way to reconcile the conflicting evidence of these studies. These considerations support the following result.

RESULT 3. *The direction and extent of the intuition (deliberation) towards selfishness depends on how selfish the subjects is. The selfish motive is more intuitive (deliberative) for subjects who are more (less) selfish.*

Table 6. OLS Regressions of Response Times on the Ratio of Selfish Decisions

	Selfish and Social Decisions		SD and SI Decisions	
	(1)	(2)	(3)	(4)
Constant	1.653***	1.468***	1.525***	1.452***
	(0.070)	(0.087)	(0.061)	(0.059)
Selfish Decision	0.012	0.345***		
	(0.033)	(0.079)		
Ratio of Selfish Decisions	-0.564***	0.017	-0.357***	-0.181**
	(0.113)	(0.194)	(0.090)	(0.091)
Difficulty	0.241***	0.299***	0.403***	0.405***
	(0.049)	(0.052)	(0.038)	(0.038)
Conflict within Norms	0.126***	0.097***		
	(0.025)	(0.027)		
Decision Number	-0.007***	-0.007***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Selfish Decision * Ratio of Selfish Decisions		-0.847***		
		(0.200)		
SD Decision			-0.037**	0.107***
			(0.017)	(0.022)
SD Decision * Ratio of Selfish Decisions				-0.351***
				(0.055)
R^2	0.145	0.167	0.121	0.130
Adj. R^2	0.143	0.165	0.120	0.129
Num. obs.	2287	2287	6300	6300

Notes. The dependent variable is *ln*(*RT*). *Selfish Decision* is a dummy variable which indicate the decision is a selfish decision (1) or social decision. *SD Decision* is a dummy variable which indicate the decision is a SD decision or SI decision. The robust standard errors are clustered on subjects and reported in parentheses. The first two decisions of each subject in both SD and SI conditions are removed. ***p < 0.01, **p < 0.05, *p < 0.1.

4.3 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 the strength of selfishness. In this section, we present evidence that the analysis based on heterogeneity outperforms the analysis at the aggregate level, and the heterogeneity in social preferences is reflected in corresponding heterogeneity of cognitive processes. The results in the previous section show that heterogeneity in selfishness explains different RT patterns. In Table 5, we have shown that if we assume homogeneity, selfish and non-selfish decision seem to have similar RTs. However, the heterogeneity in selfishness is also reflected in heterogeneity in the underlying decision processes – reflected in RT.

In the following, we will study the relevance of heterogeneity in the relevant motives of social preferences. First, we show that taking heterogeneity into account improves out of sample predictions. We use the prediction in the SI decisions to predict behavior in the SD decision. We compare the prediction that is based on heterogeneity (the finite mixture model) with predictions that are based on homogeneity (standard logit regression).[14] We use the latent variables derived from the SI decision predictions and the variables reflecting the selfish incentive to estimate decision in the SD decisions. Since the standard logit model neglects heterogeneity, we expect that the latent variable based on the finite mixture model has a higher predictive power. The results in Table 7 show indeed that the prediction based on the finite mixture model outperforms the prediction based on the standard logit model. That is, the R^2 in regression (1) is higher than the R^2 in regression (2). And the coefficient of the latent variable based on the finite mixture model is more robust than the coefficient of the latent variable based on the standard logit model if we simultaneously put the two predictors in the regression (regression (3)).

Table 7. Logit Regression for Comparing Predictive Power

	(1)	(2)	(3)
Constant	0.180***	0.210***	0.202***
	(0.048)	(0.043)	(0.048)
Latent FMM	0.338***		0.226***
	(0.027)		(0.037)
Latent Standard Logit		0.560***	0.260***
		(0.040)	(0.054)
SignSelfish	-0.147	0.196	0.149
	(0.160)	(0.130)	(0.151)
DiffSelfish	0.767***	0.498***	0.643***
	(0.068)	(0.068)	(0.067)
AIC	3231.926	3370.512	3152.713
BIC	3256.405	3394.991	3183.311
Pseudo R^2	0.307	0.278	0.323
Num. obs.	3360	3360	3360

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

Heterogeneity also improves process predictions. We compare the explanatory power of the variable *difficulty* on the RTs. The difficulty based on the standard logit model is calculated using the coefficients in Table A5 and A6.[15] The results are shown in Table 8. Since there is only one parameter in regressions (1), (2), (4) and (5), the R^2 in regressions (1) and (2), and in regression (4) and (5) can be compared directly.

[14] The latent variable based on the standard logit models is calculated using the coefficients of the standard logit regression in Table A5.

[15] The calculation is similar to the difficulty based on heterogeneity. And it is also normalized between 0 and 1.

Table 8. The Explanatory Power of Difficulty on Response Time

	SI Decisions			SD Decisions		
	(1)	(2)	(3)	(4)	(5)	(6)
Difficulty based on FMM	0.428***		0.307***	0.408***		0.253***
	(0.032)		(0.045)	(0.045)		(0.057)
Difficulty based on Standard Logit		0.402***	0.160***		0.374***	0.198***
		(0.032)	(0.045)		(0.041)	(0.049)
R^2	0.075	0.064	0.079	0.051	0.049	0.058
Adj. R^2	0.073	0.062	0.077	0.050	0.047	0.056
Num. obs.	2860	2860	2860	2883	2883	2883

Notes. Fixed effects regressions. The dependent variable is *ln*(*RT*). *Difficulty based on FMM* is the difficulty based on finite mixture model. *Difficulty based on Standard Logit* is the difficulty based on standard logit model. The robust standard errors are clustered on subjects and reported in parentheses. Always selfish subjects, incorrect decisions and the first two decisions of each subject in both SD and SI decisions are removed. ***p < 0.01, **p < 0.05, *p < 0.1

The explanatory power of difficulty based on the finite mixture model (adjusted R^2 = 0.073 for SI decisions and adjusted R^2 = 0.050 for SD decisions) is higher than the explanatory power of difficulty based on the standard logit model (adjusted R^2 = 0.062 for SI decisions and adjusted R^2 = 0.047 for SD decisions). If the two variables are simultaneously included in the regression, the coefficients of difficulty based on the finite mixture model are more robust (0.428 to 0.307 for SI decisions and 0.408 to 0.253 for SD decisions) than the coefficients based on the standard logit model (0.402 to 0.160 for SI decisions and 0.374 to 0.198 for SD decisions). Interestingly, regressions (3) and (6) show that the difficulty based on the standard logit model adds almost no explanatory power on top of that based on the finite mixture model (the adjusted. R^2 is from 0.073 to 0.077 for SI decisions and from 0.050 to 0.056 for SD decisions). We now summarize our evidence that heterogeneity in preferences is reflected in the process differences.

RESULT 4. *The analysis based on heterogeneity outperforms the analysis at the aggregate level in both predictive and explanatory power on behavior and response times. The heterogeneity in the social preferences is reflected in the differences of cognitive processes.*

5. 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 evidence accumulation models and the dual-process theory. First, the results show that the potential conflict between individually relevant motives leads to longer RTs, and RT increases with the number of conflicts and the difficulty of the decisions, which is predicted by evidence accumulation models. Second, the more selfish subjects are the shorter their RT in decisions in which selfishness matters in comparison to decisions in which selfishness does not matter. This is in line with a dual-process approach with heterogeneity in what is the intuitive motive: it is the selfish motive for subjects who are more selfish and the social motive for less selfish subjects. Our study provides an explanation for the conflicting results concerning the automaticity of the selfish motive observed in the previous literature. This result also shows that the heterogeneity in preferences is reflected in the differences of cognitive processes, which implies that it is crucial to take heterogeneity in preferences into account when investigating 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 that heterogeneity helps to model behavior, also the processes underlying the behavior are heterogeneous. In particular, people differ in what is their automatic response. Thus, in order to identify the correct process model, taking 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, heterogeneity is not only crucial for the determination of the parameters but even for the choice of the model.

We have to admit that RT analysis does not allow to draw causal inference. However, evidence accumulation models make the clear prediction that more difficult decisions 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 the 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 cognitive load.

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E-Companion (Supplemental File)

Cognitiv Processes of Distributional Preferences: A Response Time Study

Appendix A.

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
SI	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
SD	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. *Efficiency* motive favors Option B, *envy* motive favors Option A, and the two options are indifferent for *maximin* motive.

Table A2. Classification of SD Decisions

NT	Situation Number	In line with					Decision Type				Num. Conflicts	Num. Decisions
		Selfishness	Maximin	Envy	Efficiency	FS-β	Correct			Incorrect		
							Conflict		Consistent			
							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 NT III, in situation No. 2, the decision that the subject made is in line with her selfishness and efficiency motives, but no in line with her 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).

Table A3. Classification of SI Decisions

NT	Situation Number	In line with				Decision Type			Num. Conflicts	Num. Decisions
						Correct		Incorrect		
		Maximin	Envy	Efficiency	FS-β	Conflict	Consistent			
I	1	0		0				1		51
	2	1		0		1			1	53
	3	0		1		1			1	60
	4	1		1			1		0	156
II	1	0	0					1		21
	2	1	0			1			1	86
	3	0	1			1			1	43
	4	1	1				1		0	362
III	1	0		0	0			1		9
	2	0		1	0	1			2	166
	3	1		0	1	1			2	150
	4	1		0	0	1			2	63
	5	0		1	1	1			2	418
	6	0		0	1	1			2	0
	7	1		1	0	1			2	0
	8	1		1	1		1		0	1722

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 NT II, in situation No. 3, the decision that the subject made is in line with her envy motive, but no in line with her maximin motive. The decision is a conflict decision, since the envy motive conflict with the maximin motive when she made the decision. The number of conflicts is 1 (envy vs maximin)

Table A4. Logit Regression of SD Decisions on the FMM Latent Variable

	NT I	NT II	NT III
Constant	-0.071	0.091	0.237***
	(0.080)	(0.122)	(0.056)
Latent FMM based on SI Decisions	0.430*	0.138***	0.375***
	(0.250)	(0.038)	(0.026)
DiffSelfish	0.247	0.424***	0.822***
	(0.156)	(0.127)	(0.061)
SignSelfish	1.146**	-0.344	-0.154
	(0.583)	(0.300)	(0.167)
AIC	314.501	668.078	2174.923
BIC	329.575	685.031	2198.264
Log Likelihood	-153.251	-330.039	-1083.462
Pseudo R^2	0.308	0.069	0.381
Num. obs.	320	512	2528

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 A5. Logit Regression of SI 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 A6. Logit Regression of SD Decisions on the Standard Logit Latent Variable

Constant	0.210***
	(0.043)
Latent Standard Logit based on SI Decisions	0.560***
	(0.040)
DiffSelfish	0.498***
	(0.068)
SignSelfish	0.196
	(0.130)
AIC	3370.512
BIC	3394.991
Pseudo R^2	0.278
Log Likelihood	-1681.256
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.

Appendix B.

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 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 explain the exact course of the experiment. First, we will familiarize you with the decision situation. When you are finished 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 B1. 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 'Space' key to continue.

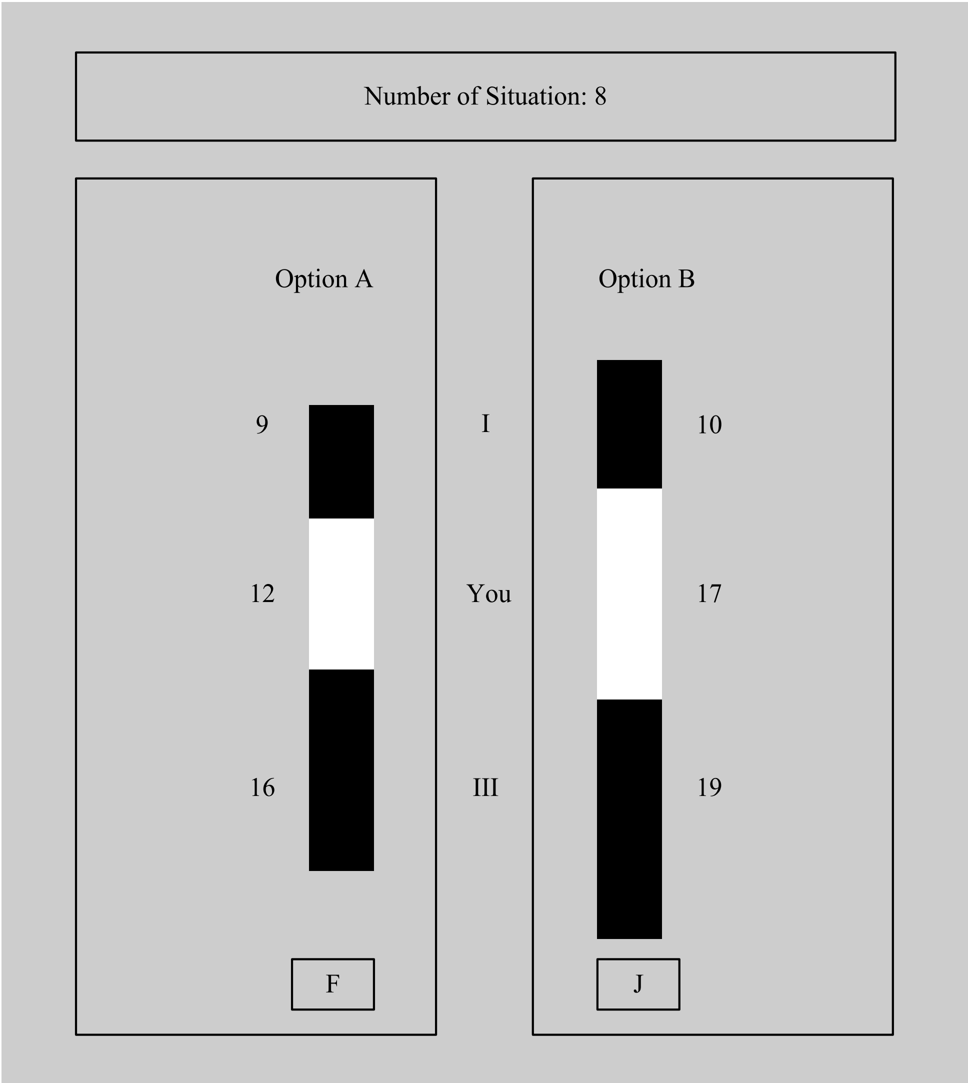

Figure B2. Screen layout

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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