Experiments on Individual Decision-making and Information

This thesis is composed by three experiments that explore the role of information in individual decision-making.

In Chapter 1 it is presented an experimental test of the contextual inference theory (Kamenica,2008). The experiment shows that the dimension of choice sets conveys payoff-relevant information in decision-making: even when options are not directly observable, the likelihood of finding an option that fits individual tastes can be inferred from the set size.
Information on the lenght of a product line is then shown to be relevant in individual decision making.

In Chapter 2 the decision-maker is presented with payoff irrelevant information: group-membership and others' behavior. The experiment test if and how these information affect individual decision of behaving ethically. The results provide evidence of the effectiveness of these information in shaping moral behavior.

Chapter 3 aims at going into the *black box* of information processing under uncertainty with an eye-tracking experiment. The aim of this last chapter is to contribute to the understanding of the choice process under different dimensions of the choice sets (small and large), and its relation with the response time.

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Choice Overload and contextual inference: an experimental test

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Abstract

The paradoxical finding of the preference for small sets of products (Iyengar and Lepper, 2000) has been explained with cognitive costs and regret. Instead, Kamenica (2008) suggests that the set size conveys a payoff relevant information: in small set there are the most popular product. The present experimental analysis aims to test if the contextual inference theory can explain the increased willingness to take a product from small sets. The design rules out alternative explanations, and find a support for the contextual inference hypothesis: the information about the set size conveys payoff relevant information in favor of small sets; however, the information seems not be about the popularity of the option according to the beliefs analysis.

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1 Introduction

The paradoxical finding that having extensive choice sets may have detrimental consequences for consumer welfare (Iyengar and Lepper, 2000) has opened a new strand of literature that aims at identifying the antecedences and consequences of large sets in decision making. The failure of some papers to replicate these paradoxical findings (Chernev (2003);Scheibehenne et al. (2009)), stresses the necessity to identify the circumstances that lead to the arise of this phenomenon. The cognitive overload that the processing of many options implies has been proposed as a possible explanation for this phenomenon, that is consequently often labelled as choice overload. Reutskaja and Hogarth (2009) show experimental evidence in favor of the moderating role that cognitive costs play in decreased satisfaction in small sets. Also, the emotional aspects of choices as regrets have been proposed as a moderator of the phenomenon (e.g. Sarver (2008)). An alternative explanation based on standard assumption of utility maximizing consumers has been suggested by Kamenica (2008): the dimension of the choice set (large vs small) conveys payoff-relevant information on the products. This model explains the preference for small sets assuming asymmetric information between firms and consumers on the distribution of tastes in the population and a fraction of consumer uninformed on their tastes. The uninformed consumers look for the most popular options since these are more likely to suit them. They can infer information on the popularity of the products from the length of the product line: the average popularity of the products in the small set is higher than in the large set. It follows that they are more willing to pick at random a product from a small set than from a large set because it is more likely that they pick a product that satisfies them. The present experimental analysis aims at testing if contextual inference can to some extent explain the preference for small sets. The design relies on the standard framework used to test willingness to purchase a product in large and small sets: a between-subjects study where the experimental groups are alternatively presented with a small or large set of products and have to decide to take a fixed monetary fee or a product from the set. This baseline design is modified implementing the assumption on consumers' information: uncertainty about preferences is introduced offering products that subjects cannot see, so that they do not know their subjective values. The only information given is on the dimension of the choice set. This design allows to rule out preference for small sets due to cognitive costs since participants do not have differential amounts of information to process in the small and large sets. They know that the offers in the sets is the real product line offered by a store in Rome. They can then rely on the length of the product line to infer the popularity. If they choose to take a product instead of money, it is randomly drawn from the set. The choice task is done on three products:

chocolate, yogurts and crisps.To preempt the results, in two of the three procuct categories the proportion of people that prefer to take whatever product from the small set is higher than from the large one. This evidence supports the contextual inference as an explanation of the preference for small sets, and this evidence cannot be explained by cognitive costs and regret since they are eliminated by the design itself. In section 2, the literature literature on preference for small set is reviewed and the reserch questions are introduced. In section 3 the experimental design is presented together with the hypotheses tested. In Section 4, the experimental procedure is presented in details. Results are reported in section 5, and section 6 concludes.

2 Literature Review and Reserch Questions

The experimental analysis of Iyengar and Lepper (2000) has highlighted the negative effect that an increasing number of options may have on consumer satisfaction and willingness to purchase a product. This phenomenon is a paradox in choice theory, since enlarging the choice set should not worsen consumers' welfare. These detrimental consequences have being explained in terms of cost-benefits analysis, where an increasing number of options raises both the opportunities of consumption and the costs of choices in terms of cognitive effort (e.g. Roberts and Lattin (1991); Reutskaja and Hogarth (2009)) and time (Botti and Hsee, 2010) rise. Regret has been shown to be a consequence of the increasing number of choices (e.g.Iyengar and Lepper (2000) ; Inbar et al. (2011)); As a consequence, an anticipatory regret could be an antecedent of choice overload (e.g. Sarver (2008)). Also, individual attitudes toward maximizing and satisficing (e.g. Schwartz (2004)) have been shown to have a role in satisfaction from different sized sets. Chernev et al. (2015) identifies the most relevant moderating factors of choice overload in a meta-analysis: decision task difficulty, choice set complexity, preference uncertainty, and effort-minimizing goal. Kamenica (2008) suggests that the preference for small choice sets may be due not to cognitive limitations or emotional factors, but to the rational inference of the consumers. When there is preference uncertainty and asymmetric information between consumers and firms on the distribution of tastes, the uninformed consumer infers the popularity of the options from the set size; this hypothesis relies on previous literature showing that the consumer may be uncertain on the subjetive value of the options. Instead, the consumer has less uncertainty on how his/her tastes compare with the tastes of the rest of the population. Hence, individual preferences are defined not absolutely, but relatively to others' preferences (Wernerfelt, 1995). According to this argument, the popularity of a product becomes a way to establish which option is more likely to fit the tastes of the consumer who is uncertain about his/her preferences (if one believes that his/her tastes are not different from the average of the population, that is, not atypical). Prelec et al. (1997) show that this kind of preference uncertainty implies that consumption choices are sensitive to the context, since different contexts may imply different inferences about other tastes. This argument is used by Kamenica (2008) in order to explain the choice overload phenomenon: the context (that is, small or large set) affects the inference on the popularity of the options available; in particular, small choice sets provide better information on the popularity of the options inside, and here arises the preference for choosing from small sets. Indeed, on the supply side, the model assumes that firms know the distribution of tastes in the population, and they build the product line according to these tastes in order to maximize their profit: they want to offer the most popular products; however, the average popularity of the products offered is decreasing in the breath of the product line: the first product introduced is the most popular, the second is the second most popular, an so on. Hence, products with lower popularity are sequencially introduced, and the larger the product line the more products are introduced with relatively lower popularity.[1] From the demand side, the model assumes that there is a fraction of consumers that is uninformed about its tastes and about the distribution of tastes in the population. Since there is asymmetric information between consumers and firms, and it is assumed that consumers know this asymmetry, the uninformed consumer can infer the distribution of tastes from the production choices of the firms. In particular, they can infer the average popularity of the products from the number of products offered: since they cannot do better than choose randomly[2], they are more willing to pick whatever product when the product line is limited than when it is large. Indeed, they have more chances to take a product that is likely to suit them from a small set. Therefore, the model predicts the preference for small sets as an inference of payoff-relevant information from the set size. Under the preference uncertainty and information asymmetry, it is payoff maximizing choosing from the small set even in absence of cognitve limitations and emotional factors in decision-making. Hence, the following desing aim to test experimentally if the preference for taking products from small sets can be explained by the inference-based mechanism proposed by the model of Kamenica (2008).

[1] It has to be noticed that the small sets contains the most popular options because this behaviour is profit maximizing for the firms. If the small sets were a random selection from a larger sets, the small sets would not have this property. For example, in Reutskaja and Nagel (2011), the small sets are chosen randomlt from the small sets. It follows that the large sets contains a greater amount of (approximately similar) good options than small sets, and this increases th efficiency of choice from large sets.

[2] because they have uncertain preferences

3 Experimental Design and Hypotheses Testing

The present experiment relies on the standard framework in experiments on over-choices: it is a between-subjects experiment where the willingness to purchase a product rather than accept a fixed monetary payment is compared in the two experimental conditions, that is when an extensive or a small choice set are provided to the participants. The new element with respect to previous studies on this topic is that the participants do not see the options in the set: the items are presented inside bags . The subjects choose to take one product at random from the set or a the monetary fee. Hence, the partcipants are put on the same condition of preference uncertainty assumed by the contextual-inference theory, since no one has the possibility to observe the products and evaluate their subjective values, and they are forced to choose at random in case they decide to pick one product from the set; this condition (preference uncertainty) should imply the necessity to infer the popularity of the products, since they cannot do best than choose at random from the choice set. They were told that in case they chose to take a product, they would receive one of the products of the set randomly drawn; it was explicitly stated that they would be allowed to see only the drawn product, and not the whole content of the set. Instead, if they took the monetary payment, the would receive an amount of money equal to the average value of the products in the set. Since it is not possibile to see the products in the set before the choices, cognitive costs cannot account for a preference for the small set in this design. Further, since the whole product line cannot be seen after the choices, anticipated regret cannot explain the preference for taking a product from the small set as well.

Another elements of the design that is fundamental to test contextual inference theory is that the participants know that the products offered are the entire product line of a store: they know that the options within a set are of the same brand and they are the actual and whole assortment of that product offered by a store in Rome. The name of the brand and of the store was not told to them. Since the product offered are a real assortment offered by a supplier, they may consider the assortment as informative on population tastes. For this reason real products have been used, instead of abstract induced value objects[3]. The two experimental conditions, small and large sets, are implemented as follow: to the group of subjects in the small set condition, the number of items offered is taken from a store with a limited product line; to the group of subjects in the large set

[3]since these products do not have an induced-value, individual homegrown preferences are taken into account asking for a non-incentivized liking-rating score from 0 to 10 and frequency of consumption.
Note that the theory may be tested with value induced objects creating experimentally the supply side of the market and inducing preference over objects with an asymmetry of information. However, using real products the inference process may be elicited more unconsiuosly. Further,is the standard way in which choice overload has been studied.Therefore, keeping this framework is more helpful for a comparison with previous findings.

condition, the offer is taken from stores with a large product line. In each session the choice is done for three products: chocolate, yoghurts and chips.

The prediction of the theory is that uninformed subjects prefer to take whatever product from the small set than whatever product from the large set because the context (small vs large set) conveys the information about the likelihood of receiving a product that suits their preference: the smaller is the product line the more it is probable to take a product that they may like. Hence, the present experiment tests the following hypothesis:

Hypothesis 1: The probability of taking a product in small sets is graeter than in large sets.

According to this hypothesis, subjects should choose to take a product rather than money from the small sets more ofter in the large sets. Preference for small sets in such an experimental setting cannot be explained by cognitive costs since the costs of processing information are eliminated not allowing to see and compare the products and choose among them. Neither by regret, because the product line offered is not observable after the choice. Instead, in line with the contextual inference argument, the participants may expect that more popular products are in the small sets (for example, traditional flavors of chocolate: dark, milk..), since the shops offering few flavors select the most standard (usually liked) ones; instead, in the large set they may pick an unsual product that is less likely to suit their tastes,as spiced chocolate. To add further evidence to the contextual inference theory, the partcipants' beliefs on the popularity of the products in the sets are elicited. Through a survey before the experiment, there were collecte the liking-ratings over the products offered in the experiment by a sample of 15 potencial consumers. Products were rated them from 0 to 10, and the partcipants were incetivized knowing that would have received one of the products that they rated at least 7. The subjects in the experiment knew this information, and they have to guess how many products in the offered set recevived an average rating equal to 7 or higher. According to the contextual inference theory, one should choose more likely to take a product if he/she believes that there is a higher percentage of high rated, that is popular, products. Furthermore, extending the argument of Kamenica (2008), one may prefer the small set if he/ she believes that in the large set there is a higher proportion of niche products that are then unlikely to suit the tastes of the average consumer. The guessing on the number of products that received a rating equal or lower than 4 is then introduced. From the third class session also the guessing on the number of products that received a rating equal or lower than 4 is introduced. Further, The following hypotheses are then tested:

Hypothesis 2a: The choice of acceptance is positively associated with the beliefs of a greater proportion of high-rate products and negatively associated with the beliefs of a lower proportion of low-rated products is the choice set.

Hypothesis 2b: In small sets it is expected to be a greater proportion of high-rated products and a lower proportion of low rated products

4 Experimental Protocol

The experimental sessions were run in May and June 2017 at the University of Rome "La Sapienza", in the faculty of economics. They were five in total. The first three sessions were run in classes and the other two sessions in the EXE LAB, the experimental laboratory of the faculty.[4]

Class Sessions In the first session (the 18th of May) 22 subjects were assigned to the small set condition and 18 to the large set one. In the second session (the 25th of May) 31 subjects were assigned to the small set condition and 31 to the large set one. In the third session (the 26th of May) 18 subjects were assigned to the small set condition and 16 to the large set one. The products used in the first session were chocolate and yogurt; in the second and third sessions the products were chocolate, yogurt and crisps. In the small set condition the subjects chose among 6 types of chocolate and 8 yogurts, and 5 types of crisps. In the large set condition they choose among 25 chocolates and 30 yogurts and 27 crisps. Beliefs on each of these products were elicited only on the number of products rated higher than 7. All sessions were run with pencil and paper and subjects in the different experimental conditions were possibily not sitting near to each other. The participants were bachelor students. The tasks were six in total (three choice tasks and three belief tasks) and one was randomly chosen for payment. In the case one of the choice tasks was chosen for payment, the students would have received the product or the monetary payment, according to their choices; the monetary payment was 2 euros for chocolate and crisps and 1.5 euros for the yogurt, but they were not explicitly told the amount of the payment they would have received during the session. They just knew that the fixed moentary payment was equal to the average value of the products in

[4]All the sessions were managed by me in Italian.Instructions and English translation are in the appendix.

the set. In the case one belief tasks was chosen for payment, they would have received 5 euros if the guessing was correct , and 5 minus the quadratic error if not correct without the possibility of negative payoffs. The experiment lasted 20 minutes; the instructions were read aloud sequencially: the participants were instructed to complete each task of the experiment after it was read aloud by the experimenter, and they were not allowed to look at the following tasks before being authorized, that is before the tasks were read aloud. No show-up fee was provided for these class sessions, and one third of the subjects was randomly chosen for payment, except for the last class session where they were all paid. In the first two sessions, a belief task was drawn for payment in front of the class and the students received the payment at the beginning of the following lesson. The average payment was 2 euros. In the last session the crisps choice task was drawn for payment; the subject received the products after few days.

Laboratory Sessions Two laboratory sessions were run on the 15th of June with 60 students. The sessions were computerized and programed in ztree (Fischbacher, 2007). The participants were recruited by the didactic manager who sent an email to the institutional email address of all the students of the faculty of economics, and they registered replying to it. They received a show-up fee of 5 euros. The large set treatment was run in the first session, and small set treatment in the second one with 30 participants in each. Control variables about sex, age and education (university year) were collected. In the small set condition they chose among 6 types of chocolate, 8 yogurts and 5 crisps. In the large set condition they chose among 38 types of chocolate, 30 yogurts and 22 crisps. Beliefs about the number of products rated 7 or more and 4 or less were elicited. In the case one of the belief sessions was drawn for payment, they were paid for one of the two beliefs chosen randomly. Differently from the class sessions, the amount of the fixed monetary payment that partcipants would have received in the case they did not choose a product was explicitly declared in the instructions. The payment rule for guessing tasks was different from the class sessions: 5 euros for the correct guessing, and 5 minus the error in case of incorrect guessing. The experiment lasted 30 minutes and payment was administered individually after each session. The instructions were on the screen and they were read aloud at the beginning of each of the six tasks of the experiment. They knew that in case one of the tasks with products was chosen estraction with replacement was possible: the set contained the same products for all the subjects. The products were physically in the laboratory when the sessions were run: products were inside bags so that they could not be seen. One subject was recruited at the beginning of each session among the participants to look inside these bags and guarantee the other participants that there really was the variety of different

Table 1: Summary Statistics on Class Sessions

Rating is a variable that assumes integer values from 0 to 10 and it is the self-reported liking of each product. *Frequency* takes values from 1 (every day) to 5 (never), and represents the frequency of consumption of the product.
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	Mean	SD	Min	Max
Rating Chocolate	7.5	1.7	3	10
Rating Yoghurt	5.5	2.3	0	10
Rating Crips	7.4	2	0	10
Frequency Chocolate	2.1	0.9	1	5
Frequency Yoghurt	2.7	1.14	1	5
Frequency Crisps	2.7	0.8	2	5
N	135 (Chocolate and Yoghurt)			95 (Chips)

Table 2: Summary Statistics on Laboratory Sessions

	Mean	SD	Min	Max
Rating Chocolate	7.75	1.5	3	10
Rating Yoghurt	6.3	2.1	0	10
Rating Crisps	6.7	2.4	0	10
Frequency Chocolate	2	0.85	1	4
Frequency Yoghurt	2.5	1.1	0	5
Frequency Crisps	2.8	1	1	5
N	59			

products declared; this subject did not complete the tasks and received a fixed payment equal to 7 euros. One of the six tasks was randomly chosen for payment. In the first session the product task with crisps was paid giving the show-up fee plus 2 euros to those who did not choose the product and one random product to the others[5]. In the second session the belief task with chocolate was paid and the average payment was approximately 8 euros including the show-up fee.

5 Results

The summary statistics of the data from class sessions and laboratory sessions are reported in table 1 and 2. A summary of the finding of this section is in table 3.

The results of the regression analyses on Class session data (5.1) and laboratory session data (5.2) are first presented separately. Then, the data are analyzed pooled (5.3). Finally, the beliefs analysis is presented.

[5]It was possibile to replace all products after the random estraction, and the subjects was made aware of it.

Table 3: Summary of the Findings

This table shows the percetages of accpected products in small (*% products Small Set*) and large sets (*% products Large Set*). *N obs* is the number of observations. *P-Value* is the significance level of the set size in the regression analyses below.
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	% Products Small Set	%Products Large Set	N obs	P-value
Class Chocolate	36%	17%	135	0.07
Class Yoghurt	15%	15%	135	not significant
Class Crips	48%	30%	94	0.04
All Class Products	30%	19%	364	0.01
Laboratory Chocolate	29%	21%	59	not significant
Laboratory Yoghurt	20%	15%	59	not significant
Laboratory Crisps	33%	33%	59	0.06
All Laboratory Products	27%	24%	177	0.03
All Session Products	29%	21%	541	0.006

5.1 Class Sessions

Firts, the data from class session are analyzed product by product type through logistic regressions. Then, all data from class sessions are analyzed using a mixed-effects logistic regression with random intercept that account for the repeated measurement. The results of the regression analyses are reported in table 4.

Chocolate Class The dimension of the set significantly (p-value=0.07) affects the decision to take the chocolate or not: the predicted probability of taking chocolate is 15% in the large set and 29% in the small set.

Yoghurt Class The decision whether to take the yogurt or not was not significantly affected neither by the set size nor by other covariates.

Crisps Class The dimension of the set significantly (p-value=0.04) affects the decision to take the crisps or not: the predicted probability of taking crisps is 25% in the large set and 48% in the small set.

Table 4: Regression Analysis on Class Sessions' data

This table displays the results of the logistic regression analysis on data from class sessions. Regressions 1, 2 and 3 are run for single products. Regression 4 is run on all class data using a mixed-effects logit with random intercept. The values in the table are the *Odds Ratios*.
The dependent variable of the regression is *Acceptance*: a dummy variable equal to 1 when the product is accepted and equal to 0 when the product is not accepted.
*Treatment*is a dummy variable equal to 1 in the small set condition and equal to 0 in the large set condition.
Guessing 7 is the proportion of products that, according to their guessings, received a rating equal or higher than 7.
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	(1) Acceptance Chocolate	(2) Acceptance Yoghurt	(3) Acceptance Crisps	(4) Acceptance All Class Sessions
Treatment	2.2* (0.95)	1.15 (0.57)	2.59** (1.22)	0.671** (0.262)
Rating	1.45** (0.25)	1.17 (0.19)	1.17 (0.2)	0.258*** (0.0932)
Frequency	0.74 (0.21)	0.73 (0.22)	0.38*** (0.14)	-0.396** (0.184)
Guessing 7	0.55 (0.56)	0.66 (0.76)	0.95 (1.03)	-0.181 (0.607)
Constant	0.03** (0.05)	2.95 (0.3)	0.17 (2.95)	-2.231** (1.044)
N	135	135	94	364 (number of groups: 3)
$P(LRchi2)$	0.001	0.18	0.001	0.0001
		Standard errors in parentheses	*** p<0.01, ** p<0.05, * p<0.1	

All Class Sessions Considering the data in all class session, the dimension of the set significantly (p-value=0.011) affects the decision to take one of the products from the set. Also, Rating and Frequency positively affect the choice to take the product. The predicted probability of taking crisps is 16% in the large set and 28% in the small set.

5.2 Lab Sessions

Firts, the data from laboratory sessions are analyzed product by product type through logistic regressions. Then, all data from lab sessions are analyzed using a mixed-effects logistic regression with random intercept that account for the repeated measurement. The results of the regression analyses are reported in table 5.

Note that the significance of the set dimension is lower in the lab sessions than in the class ones. This may be because the subjects in the laboratory were explicitly told the amount of the monetary payment in case they did not choose the product. This may have decreased the difference in the acceptance rate in the two sets since the average value of the set was homogenized across the experimental conditions. This evidence is in line with previous findings on the moderating role of an ideal point in choice overload phenomenon (Chernev, 2003).

Chocolate Laboratory None of the covariates significantly affect the decision of taking the chocolate or not. Even if the treatment variable does not reach the significance level, the results slightly go in the predicted direction: in the large set condition 23 persons chose money and 6 chose chocolate. In the small set condition 21 persons chose money and 9 chocolate.

Yoghurt Laboratory None of the covariates significantly affect the decision of taking the product or not, except for the guessing on the number of products that were rated equal or lower than 4. Even if the treatment variable does not reach the statistical significance, the results slightly go in the predicted direction: in the large set condition 24 persons chose money and 5 yoghurt. In the small set condition 24 persons chose money and 6 yoghurt.

Crisps Laboratory The dimension of the set significantly (p-value=0.06) affects the decision to take crisps or not: the predicted probability of taking crisps is 4% in the large set and 30% in the small one. The evaluation of the crisps significantly (p-value=0.01) increases the willingness to take them as well as the beliefs about the number of high rated crisps (p-value=0.09).

Table 5: Regression Analysis on Laboratory Sessions' data

This table shows the results of the logistic regression on data from class sessions.Regressions 1, 2 and 3 are run for single products. Regression 4 is run on all class data using a mixed-effects logit with random intercept. The values in the table are the *Odds Ratios*. *Treatment*is a dummy variable equal to 1 in the small set condition and 0 in the large set one. The dependent variable of the regression is *Acceptance*: a dummy variable equal to 1 when the product is accepted and equal to 0 when the product is not accepted.
Guessing 7 and 4 is the proportion of products that, according to the guessing, received a rating equal or higher than 7 and equal or lower than 4 respectively. *Education* ranges from 1 to 6: it is equal to 1 at the first year of the bachelor, 5 at the last year of the master, otherwise 6.
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	(1) Acceptance Chocolate	(2) Acceptance Yoghurt	(3) Acceptance Chips	(4) Acceptance All Lab Products
Treatment	1.8	2.4	8.8*	0.945**
	(1.35)	(2.12)	(10.3)	(0.457)
Rating	2.02	2.5	3.38***	0.827***
	(0.73)	(0.92)	(1.6)	(0.179)
Frequency	1.18	1.6	0.05	0.158
	(0.68)	(0.83)	(0.25)	(0.281)
Guessing 7	42.7	0.05	0.006*	-0.257
	(109)	(0.15)	(0.37)	(1.277)
Guessing 4	6.63	0.001**	0.12	-2.414*
	(15.6)	(0.005)	(0.4)	(1.394)
Education	1.35	1.2	1.5	0.194
	(0.41)	(0.38)	(0.51)	(0.163)
Male	0.62	2	4.8	0.307
	(0.45)	(1.9)	(4.8)	(0.426)
Age	-0.04	0.93	1.1	-0.125
	(0.02)	(0.21)	(0.32)	(0.112)
Constant	0.81	0.002	0.0001	-5.532**
	(4.7)	(0.01)	(0.0002)	(2.695)
N	59	59	59	177 (n. of groups 3)
$P(LRchi2)$	0.06	0.04	0.0001	0.0006
		Standard errors in parentheses	*** p<0.01, ** p<0.05, * p<0.1	

All Lab Sessions Pooling all laboratory data, the dimension of the set significantly (p-value=0.03) affects the decision to take a product or not: the predicted probability of taking a product is 10% in the large set and 23% in the small one. The evaluation of the products significantly (p-value=0.001) increases the willingness to take them; further, the beliefs about the number of low rated products has a negative relation with the decision of acceptance (p-value=0.08).

Table 6: Regression Analysis on All Sessions' data

This table shows the results of the logistic regression on data from all sessions. The values in the table are the *Odds Ratios*. Regressions 1, 2 and 3 are run for single products. Regression 4 is run on all class data using a mixed-effects logit with random intercept. *Session* is a dummy variable equal to 1 in class sessions, and 0 in laboratory sessions.
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	(1) Acceptance Chocolate	(2) Acceptance Yoghurt	(3) Acceptance Chips	(4) Acceptance Products
Treatment	2.02**	1.32	2.2**	0.590***
	(0.72)	(0.53)	(0.87)	(0.215)
Rating	1.5***	1.14***	1.52***	0.438***
	(0.22)	(0.19)	(0.22)	(0.0763)
Frequency	0.81	0.94	0.41***	-0.173
	(0.20)	(0.23)	(0.12)	(0.138)
Guessing 7	1.17	0.48	0.6	0.107
	(1.05)	(0.48)	(0.55)	(0.519)
Session	0.91	1	1	
	(0.34)	(0.43)	(0.4)	
Constant	0.009***	0.03**	0.22	-4.233***
	(0.01)	(0.05)	(0.36)	(0.802)
N	194	195	154	541
$P(LRchi2)$	0.0003	0.02	0.0001	0.0001
		Standard errors in parentheses	*** p<0.01, ** p<0.05, * p<0.1	

5.3 All Sessions

Considering the data collected both in class and laboratory sessions product by product, the size of the set affects the decision to take the product ($p - value = 0.04$) for chocolate and crisps. The choice to take the yoghurt is not significantly affected by set size. This latter result about yogurt may depend on the fact that it is a less liked product: on average yoghurt received the lower liking-rating. It is plausible to think that if a product is not liked, it will not be chosen, whatever is the dimension of the set. Indeed, yoghurt was chosen very infrequently, considering the choices in both experimental conditions: 32 out of 195 participants chose to take a yogurt. Instead: 57 out of 154 chose to take crisps, and 50 out of 194 chose to take chocolate. This then may imply that there is no difference between the set dimension conditions. In addition, this finding about yogurt is in line with previous literature showing the moderating role of options' attractiveness in preference for small sets (e.g. Chernev and Hamilton (2009)).

Considering the data pooled for all products and all sessions (lab and class) the set size signficantly affects (p-value=0.006) the decision to take a product: the predicted probability of taking crisps is

16% in the large set and 26% in the small one. Also, the rating of the products affets positively the choice (p-value=0.0001).

***Conclusion1*: At product level, there is a milde evidence that small sets increases the probability of taking chocolate and chips. Yoghurt shows a low rate of acceptance both in small and large sets. The statistical significance is decreased in laboratory sessions, where the amount of the monetary fee is known. Pooling the data for all products and sessions (class and lab), there is a significant greater probability of taking one product from a small set than from a large set. Hence, Hypothesis 1 is supported by the current findings.**.

5.4 Beliefs' Analysis

The regression analyses do not show a relation between the choice to take a product and the belief on the number of high-rated products (rating over 7[6]).

In Lab sessions there were collected the guessing on the number of low-rated products in the sets. Pooled for all products, there is a marginally significant of evidence that decision of taking a product or not from a set is (negatively) associated with the beliefs that there are low-rated products in the set for crisps and yogurts, and not for chocolate. Although this latter finding has a low statistical significance, it has to be considered the low number of observations and the general decreased statistical significance in lab sessions; this result provides a first explicit evidence of the link between popularity of options and choices in such an ambiguos[7] consumption experimental context, suggesting that the willingness to avoid niche (that is, not popular) products may be a more relevant factor than the willingness to find the best product in such context. Hence, Hypothesis 2a is confirmed by these data just for low-rated products.

However, hypothesis 2b is not confirmed: there is not evidence that in small sets people expect a greater proportion of high-rated products (t-test, P-value=0.49) and a lower proportion of low-rated products (t-test, P-value=0.12)[8]. It may be that the beliefs elicitation task was not clear to the subjects.

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[6]In the regression analyses the variables that refer to the guessing are worked out computing the proportion of product high or low rated in each set.

[7]this might be considered an atypical ambiguos context: a lottery where the probabilities are known and the value of the outcomes is unknown.

[8]Regression analyses (not reported) on beliefs confirm these results.

***Conclusion 2*: The choice of acceptance of a product rather than the money is inversely related to the beliefs on the proportion of not popular products in the set. However, there is not support for the hypothesis that people expect the most popular products to be in the small sets.**

6 Discussion and Conclusion

Previous studies show that preference for small sets is related with cognitive costs and regret. The present evidence suggests that the length of the product line plays a role as well in determining the preference for small sets. The experiment carried out in this work shows that the information on the length of a product line significantly affects the decision to pick up a product from the set. Since the product lines were not observable neither ex-ante nor ex-post choices, cognitive costs and anticipatory regret cannot explain the preference for taking products from the small set observed in this experiment. Contextual inference can instead explain such behavior: payoff relevant features of the product in the set can be inferred by the information on the length of the product line. In particular, the participants may infer that in small product lines the most popular and standard flavors are offered, and then it is more likely to find a product that suits their tastes, as a bar of simple dark chocolate or a classic flavor of crisps. Instead, in the extensive product lines, they may expect to find niche products too (for example, coco and turmeric crisps or salty chocolate), and since these products are liked only by a small fraction of the consumers, it is less likely that they may like them. However, the analysis of their guesses on the number of high and low rated product in small and large set fails to provide direct evidence of this mechanism mediating the preference for small sets.

More data should be collected in this experimetal setting in order to confirm the robustness of the results, and to test the mediating role of popularity or of other mediating mechanisms that may be at work in such a context. According to the evidence collected, the a follow-up experiment should consider product specific effects, i.e. the yoghurt has been show to be not very suitable for these tasks. Further, knowing the monetary fee amount, as in lab sessions, may confound the effect of the treatment.

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Appendix

Translated instructions

WRITE HERE THE ID NUMBER THAT YOU HAVE RECEIVED........

Instruction: In this experiment there are 6 sections. [X] people will be randomly selected for payment; they will be paid according to their own choices in one of the sections. The section chosen for payment is randomly drawn at the end of the experiment.
At the beginning of each section the experimenter will read the instructions, that are also written in the paper sheets. Please, go on with the experiment according to the order indicated by the experimenter: it is important to finish one section before continuing with the following one. If you read one section before the experimenter allows you to do it, you will be excluded from the experiment and its payment.

DO NOT TURN THE PAGE BEFORE THE OFFICIAL START!

[In lab sessions socio-demografic variables were asked at the beginning of the experiment]
(in the following page or screen)
SECTION 1 - Chocolate

- How much do you like chocolate from 0 to 10?
  Write a number between 0 and 10 that represents your liking of chocolate in general.....

- How often do you consume chocolate?
  Put an "X" near the frequency that better represents your usual consumption of chocolate.
  1 Once a day.....
  2.Once a week....
  3.Once a month....
  4. Less than once a month/infrequently......
  5. Never.....

A store in Rome offers 6 (25) different flavors of chocolate of the same brand. Indicate with an "X" the option that you prefer between receiving one of the 6 (25) types of chocolate chosen at random or a monetary payment equal to the average value of the 6 (25) products [2 euros in the lab sessions]:

1. I prefer one of the 6 (25) types of chocolate chosen at random....

2. I prefer the monetary compensation...

(in the following page or screen)

SECTION 2 - Chocolate

The 6 (25) products offered by the store were observed by a group of potential consumers. They were asked to rate each product from 0 to 10 according to their liking. They knew that they would have received a product among those rated higher or equal to 7.

- How many products received an average rating higher or equal to 7?
  Write a number bewtween 0 and 6 (25) that represents your opinion...

- How many products received an average rating lower or equal to 4?
  Write a number bewtween 0 and 6 (25) that represents your opinion...

Note that if your guessing is exactly equal to the true average you will receive 5 euros. If your guessing is different from the true average, you will receive 5 euros minus the square of the difference between the true average and the guessed one: $5-(trueaverage-guessedaverage)^2$ [5-true average in the lab sessions]. If this value is negative, you will receive nothing. *(in the following page or screen)*

SECTION 3 - Yogurt

- How much do you like yogurt from 0 to 10?
  Write a number between 0 and 10 that represents your liking of yogurt in general.....

- How often do you consume yogurt?

  Put an "X" near the frequency that better represents your usual consumption of yogurt.

  1 Once a day.....

  2.Once a week....

  3.Once a month....

  4. Less than once a month/ /infrequently......

  5. Never.....

A store in Rome offers 8 (30) different flavors of yogurt of the same brand. Indicate with an "X" the option that you would prefer between receiving one of the 8 (30) yogurts chosen at random or a monetary payment equal to the average value of the 8 (30) products [1.5 euros in the lab sessions]:
1. I prefer one of the 8 (30) yogurts chosen at random....
2. I prefer the monetary compensation...

(in the following page or screen)

SECTION 4 - Yogurt

The eight (30) products offered by the store were observed by a group of potential consumers. They were asked to rate each product from 0 to 10 according to their liking. They knew that they would have received a product among those that were rated higher or equal to 7.

- How many products received an average rating higher or equal to 7?

  Write a number bewtween 0 and 8 (30) that represents your opinion...

- How many products received an average rating lower or equal to 4?

  Write a number bewtween 0 and 8 (30) that represents your opinion...

Note that if your guessing is exactly equal to the true average you will receive 5 euros. If your guessing is different from the true average, you will receive 5 euros minus the square of the difference between the true average and the guessed one: $5-(trueaverage-guessedaverage)^2$ [5-true average in the lab sessions]. If this value is negative, you will receive nothing. *(in the following page or screen)*

SECTION 5 - Crisps

- How much do you like crisps from 0 to 10?

  Write a number between 0 and 10 that represents you liking of crisps in general.....

- How often do you consume crisps?

  Put an "X" near the frequency that better represents your usual consumption of crisps.

  1 Once a day.....

  2.Once a week....

  3.Once a month....

  4. Less than once a month/infrequently......

  5. Never.....

A firm offers 5 (27) different flavors of crisps. Indicate with an "X" the option that you would prefer between receiving one of the 5(27) crisps chosen at random or a monetary payment equal to the average value of the 5 (27) products[2 euros in the lab sessions]:

1. I prefer one of the 8 (30) crisps chosen at random....

2. I prefer the monetary compensation...

(in the following page or screen)

SECTION 6 - Crisps

The 5 (27) crisps offered by the store were observed by a group of potential consumers. They were asked to rate each product from 0 to 10 according to their preferences. They knew that they would have received a product among those that were rated higher than or equal to 7.

- How many products received an average rating higher than or equal to 7?

  Write a number bewtween 0 and 5 (27) that represents your opinion..

- How many products received an average rating lower than or equal to 4?

  Write a number bewtween 0 and 5 (27) that represents your opinion...

Note that if your guessing is exactly equal to the true average you will receive 5 euros. If your guessing is different from the true average, you will receive 5 euros minus the square of the difference between the true average and the guessed one: $5 - (trueaverage - guessedaverage)^2[5 - trueaverageinthelabsessions]$. If this value is negative, you will receive nothing.

Esperimento in classe

Univeristá di Roma La Sapienza

SCIVETE QUI IL NUMERO IDENTIFICATIVO CHE VI E' STATO CONSEGNATO: ....

Conservate il foglietto con il numero per il pagamento

Xbigletti verranno estratti casualmente per il pagamento

Istruzioni In questo esperimento ci sono 6 sezioni. Le [X] persone estratte per il pagamento verranno remunerate per le loro scelte in una delle sei sezioni, la quale verrá estratta casualmente. All'inizio di ogni sezione lo sperimentatore leggerá le istruzioni della relativa sezione che troverete scritte anche sul foglio. Procedere nell'esperimento secondo l'ordine indicato dallo sperimentatore: é importante completare una sezione prima di passare a quella successiva. Chi legge una sezione prima che lo sperimentatore l'abbia autorizzato sará escluso dell'esperimento e dal relativo pagamento.

NON GIRARE LA PAGINA PRIMA DELL'INIZIO UFFICIALE!

- **SEZIONE 1 - Cioccolata**
  - Quanto ti piace la cioccolata da 0 a 10?
    Scrivi un numero tra 0 e 10 che rappresenti il tuo gradimento della cioccolata in generale . .
  - Quanto spesso consumi la cioccolata? Metti una "X" vicino alla frequenza che meglio rappresenta il tuo consumo abituale di cioccolata.
    1. una volta al giorno....
    2. una volta alla settimana....
    3. una volta al mese....
    4. meno di una volta al mese/infrequentemente......
    5. mai......
  - Un negozio a Roma offre 25 diversi gusti della stessa marca di cioccolata. Indica con una X nell'apposita opzione se preferisci ricevere uno dei 25 prodotti (che verrá estratto casualmente tra questi 25) o una compensazione monetaria di un valore pari al valore medio dei 25 prodotti.
    1. Preferisco una delle 25 cioccolate estratta casualmente....
    2. Preferisco la compensazione monetaria...

- **SEZIONE 2 - Cioccolata**

  I 25 prodotti offerti da questo negozio sono stati osservati e valutati da un gruppo di potenziali consumatori. E' stato chiesto a queste persone di dare una valutazione da 0 a 10 sul loro gradimento di ciascuno dei 25 prodotti. Sono stati inoltre avvisati che avrebbero ricevuto uno dei prodotti tra quelli a cui avevano attribuito una voto maggiore o uguale a 7.

  - Secondo te quanti dei 25 prodotti hanno ricevuto in media un voto maggiore o uguale a 7?
    Scrivi qui un numero tra 0 e 25 che rispecchi la tua opinione......
  - Secondo te quanti dei 25 prodotti hanno ricevuto in media un voto minore o uguale a 4?
    Scrivi qui un numero tra 0 e 25 che rispecchi la tua opinione......
  - **Nota Bene** Se indovinerai esattamente quanti gusti sono stati valutati con un numero maggiore o uguale a 7 riceverai 5 euro. Se ti discosterai da tale valore riceverai 5 euro meno il quadrato della differenza tra il vero valore e quello da te espresso: $5-(veramedia-mediadateipotizzata)^2$. Se il valore del pagamento sará negativo, non riceverai nulla.

- **SEZIONE 3 - Yogurt**
  - Quanto ti piace lo yogurt da 0 a 10?
    Scrivi un numero tra 0 e 10 che rappresenti il tuo gradimento dello yogurt in generale .....
  - Quanto spesso consumi lo yogurt? Metti una "X" vicino alla frequenza che meglio rappresenta il tuo consumo abituale di yogurt.
    1. una volta al giorno
    2. una volta alla settimana
    3. una volta al mese
    4. meno di una volta al mese/infrequentemente
    5. mai
  - Un negozio a Roma offre 30 diversi gusti della stessa marca di yogurt. Indica con una X nell'apposita opzione se preferisci ricevere uno degli 30 prodotti (che verrá estratto casualmente tra questi 30) o una compensazione monetaria di un valore medio pari a quello dei 30 prodotti.
    1. Preferisco uno degli 30 yogurt estratto casualmente....
    2. Preferisco la compensazione monetaria....

- **SEZIONE 4 - Yogurt**

  Gli 30 prodotti offerti da questo negozio sono stati osservati e valutati da un gruppo di potenziali consumatori. E' stato chiesto a queste persone di dare una valutazione da 0 a 10 sul loro gradimento di ciascuno degli 30 prodotti. Sono stati inoltre avvisati che avrebbero ricevuto uno dei prodotti tra quelli a cui avevano attribuito una voto maggiore o uguale a 7.

  - Secondo te quanti degli 30 yogurt hanno ricevuto in media un voto maggiore o uguale a 7?
    Scrivi qui un numero tra 0 e 30 che rispecchi la tua opinione...
  - Secondo te quanti degli 30 yogurt hanno ricevuto in media un voto minore o uguale a 4?
    Scrivi qui un numero tra 0 e 30 che rispecchi la tua opinione...
  - **Nota Bene** Se indovinerai esattamente quanti gusti sono stati valutati con un numero maggiore o uguale a 7 riceverai 5 euro. Se ti discosterai da tale valore riceverai 5 euro meno il quadrato della differenza tra il vero valore e quello da te espresso:
    $5 - (veramedia - mediadateipotizzata)^2$. Se il valore del pagamento sará negativo, non riceverai nulla.

- **SEZIONE 5 - Patatine**

  – Quanto ti piacciono le patatine in busta da 0 a 10?

  Scrivi un numero tra 0 e 10 che rappresenti il tuo gradimento delle patatine in busta in generale

  – Quanto spesso consumi le patatine in busta? Metti una ”X” vicino alla frequenza che meglio rappresenta il tuo consumo abituale di patatine in busta.

    1. una volta al giorno
    2. una volta alla settimana
    3. una volta al mese
    4. meno di una volta al mese/infrequentemente
    5. mai

  – Un’azienda offre complessivamente 27 tipi diversi di patatine in busta. Indica con una X nell’apposita opzione se preferisci ricevere una confezione di patatine in busta tra i 27 tipi offerti da questa azienda (che verrá estratto casualmente tra questi 27) o una compensazione monetaria di un valore pari alla media dei 27 prodotti.

    1. Preferisco uno dei 27 tipi di patatine estratto casualmente....
    2. Preferisco la compensazione monetaria....

- **SEZIONE 6 - Patatine**

  I 27 tipi di patatine offerte da questa azienda sono stati osservati e valutati da un gruppo di potenziali consumatori. E' stato chiesto a queste persone di dare una valutazione da 0 a 10 sul loro gradimento di ciascuno degli 27 prodotti. Sono stati inoltre avvisati che avrebbero ricevuto uno dei prodotti tra quelli a cui avevano attribuito una voto maggiore o uguale a 7.

  - Secondo te quante delle 27 patatine hanno ricevuto in media un voto maggiore o uguale a 7?
    Scrivi qui un numero tra 0 e 27 che rispecchi la tua opinione...
  - Secondo te quante delle 27 patatine hanno ricevuto in media un voto minore o uguale a 4?
    Scrivi qui un numero tra 0 e 27 che rispecchi la tua opinione...
  - **Nota Bene** Se indovinerai esattamente quanti gusti sono stati valutati con un numero maggiore o uguale a 7 riceverai 5 euro. Se ti discosterai da tale valore riceverai 5 euro meno il quadrato della differenza tra il vero valore e quello da te espresso:
    $5-(veramedia-mediadateipotizzata)^2$. Se il valore del pagamento sará negativo, non riceverai nulla.

Who Deceives More - Winners or Losers? Experimental Analysis of Cheating and Social Interaction

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Abstract

Previous research highlights the important role of social interaction for individual dishonesty. This paper enhances the understanding of how group identity in this context determines whether or not people decide to cheat. We test the impact of a membership to a winning team versus a losing team on individual cheating levels as well as participants' conformity to feedback about the cheating behavior of in-group and out-group members in a laboratory experiment. The experimental setting consists of a tournament and a computerized cheating task. First, our results show that, if not provided with any feedback, winners cheat significantly less than losers ("honor effect"). Second, we find that feedback about whether others cheat or not, influences participants' subsequent cheating levels. Third, we provide first empirical indication of winners and losers reacting differently to in-group and out-group feedback.

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1 Introduction

Previous research shows that, although people frequently cheat or lie[1], on average they do not cheat to the full extent, even when honesty may mean losing money (Fischbacher and Föllmi-Heusi; 2013; Gneezy; 2005; Gneezy et al.; 2013; Sutter; 2009). This is in contrast to the standard economic model of rational and self-interested human behavior, which assumes that people trade off the expected benefits and costs of their behavior, regardless of whether maximizing the expected utility requires dishonesty (Becker; 1968). Reasons for deviation are abundant and varied. Introducing self-concept maintenance, Mazar et al. (2008) suggest that people weigh the motivation to gain from cheating and the motivation to maintain a positive self-image. People behave dishonestly enough to profit, but also behave honestly enough to not harm their positive self-image. Furthermore, people appear to restrain from cheating to avoid negative emotions, such as guilt (Battigalli et al.; 2013). However, high levels of cheating are observable in decision-making contexts involving social interaction, especially when others' dishonest behavior can be directly observed (Gino et al.; 2009). Previous studies have found evidence for a tendency of social conformity to the observed behavior, in the form of contagiousness and spread of norm violations (Diekmann et al.; 2015; Rauhut; 2013). Yet, there is also experimental evidence for anti-conformity behavior in a cheating task with social interaction (Fortin et al.; 2007). In this vein, differences in conformity seem to be influenced by social comparison processes and group identity (Gino et al.; 2009).

This paper builds on this strand of literature and enhances the understanding of how group identity impacts individual cheating behavior in a social environment. We study the impact of group identity for members of a winning team versus a losing team on individual cheating levels as well as their conformity to observed cheating behavior of in- and out-group members by means of a controlled laboratory experiment. By providing participants with feedback about other participants' (mis)reporting, our experimental design allows us to test differences in cheating of groups with different group status (winners and losers) and, importantly, to investigate how individual cheating levels are influenced by in-group and out-group feedback.

Our experiment consists of two parts: a tournament and a computerized cheating task. The tournament is used to create experimental groups comprised of winning and losing teams. It is similar to a minimal-effort game with asymmetric endowments. Afterwards, participants engaged

[1] Lying and cheating are both forms of dishonest behavior. The definitions of lying and cheating do not provide a precise delineation. According to Grolleau et al. (2016), lying is associated with sending intentionally false signals, whereas cheating is associated with a dishonest act. In this article we refer to cheating. In our experiment, participants can cheat to earn a higher payoff at expense of the experimenter, comparable to insurance fraud or underreporting of one's income or wealth in order to reduce tax payments.

in a cheating task using the "die throw"- paradigm (e.g. Fischbacher and Föllmi-Heusi (2013)). Participants were asked to repeatedly report the outcome of a random die roll, which determined their payoff at the end of the experiment. In total, the cheating task is composed of three rounds. In contrast to previous studies, we did not guarantee anonymity of individual misreporting[2] and provided participants with feedback about the reporting behavior of another participant from the experimental session after the second round. The feedback presented differed on whether participants were provided with information about the reporting behavior of another in-group member or an out-group member.

We first found that group identity for members of a winning team versus a losing team influences individual cheating levels. Our results are in accordance with the "honor effect" hypothesis and show that, if not provided with any feedback, winners cheat significantly less than losers. Second, we provide evidence for how people react to observed cheating behavior of in-group and out-group members. The experimental results show that feedback about whether others cheat or not, influences participants' subsequent cheating levels. We find that participants' cheating levels in the first and second round of the cheating task were not significantly different; yet, participants' cheating levels significantly increased in the third round with the participant feedback. Furthermore, we document that winners were more sensitive to an honesty feedback, i.e. observing that another participant reported the true outcome. Winners decreased their level of cheating in the third round compared to the second round when they received honesty feedback; however, losers did not. Third, we do not find any difference in individual cheating when observing the behavior of in-group versus out-group members. However, we find a tendency for different behavioral reactions to in-group and out-group feedback for winners and losers.

This paper makes several contributions to the extant literature. First, we provide controlled laboratory evidence on the important role of group status for group identity impacting individual cheating behavior, which is disentangled from personal determinants such as coordination or solidarity preferences. Second, by introducing feedback about other participants' (mis)reporting, we add a new perspective to previous research on imitation of and conformity to dishonest behavior. Being a winner or loser seems to determine people's social comparison processes and in turn the decision to conform or not with the observed cheating behavior of others.

The remainder of this paper proceeds as follows: In Section 2, we review related literature. The experimental design and our hypotheses are presented in Section 3. The results are provided in

[2]We clearly admitted that misreporting is experimentally controlled and retrievable, however, we ensured the anonymity of participants.

Section 4. We conclude in Section 5.

2 Related Literature and Research Questions

The social environment seems to matter for individual cheating behavior. Cheating increases when the benefits of cheating are shared with others (Wiltermuth; 2011) and collaborative settings provide a basis for cheating (Weisel and Shalvi; 2015). Social context may affect behavior by reason of several factors and thus previous literature provides a broad range of identified channels. Social information can, for example, influence the estimated probability of being detected and punished in a cost-benefit analysis of cheating (Allingham and Sandmo; 1972). Moreover, Falk and Fischbacher (2002) find support for the importance of social interaction with respect to criminal activities in the lab and interpret this finding in terms of reciprocity.

This study is mainly related to research on individual cheating behavior and the impact of social interaction hereon. We briefly review experimental studies examining individual cheating behavior using competition tasks (Section 2.1) and social feedback (Section 2.2).

2.1 Competition and Cheating Behavior

In social psychology, team or group competition tasks are widely used to study inter-group behavior. For example, studies provide experimental evidence for in-group favoring and out-group discrimination as well as that confronting an out-group enhances in-group solidarity and cooperation (Halevy et al.; 2008, 2012). In economics, an extensive strand of experimental research investigates the behavioral effects of contests, auctions, and tournaments (see Dechenaux et al. (2015) for a review). Team competition is particularly examined with respect to levels of effort (Gneezy et al.; 2003; Sutter and Strassmair; 2009) and group coordination (Bornstein et al.; 2002), and it is shown that competition may have positive effects increasing effort and improving coordination. However, coordination may have detrimental effects. Shleifer (2004) suggests that competition favors unethical behavior such as corruption. Indeed, experimental studies provide evidence for individual cheating behavior being associated with competition. Schwieren and Weichselbaumer (2010) find that competing for a desired reward influences levels of cheating in the way that poor performers significantly increase their cheating behavior under competition. Faravelli et al. (2015) show that competition increases dishonesty when the reward scheme is exogenously determined. In addition, participants with a higher propensity to be dishonest seem to be more likely to select into competition in the first place (Faravelli et al.; 2015). Further, it has been shown that competition can reduce trust (Rode,2010) and have negative consequence in terms of emotion and well-beign (Brands et al., 2004).

In our experiment, a competition task is introduced in order to test the effect of group membership on a subsequent cheating task, making use of the fact that letting participants compete creates winners and losers (Hayek; 1982). Jauernig et al. (2016), for example, use a tournament design to elicit punishment and aggressive behavior from winners and losers. Our hypothesis is that winning and losing elicit different levels of ethicality. On one side, winners would feel entitled with an honor state: winning increases self-esteem and self-concept and the feeling of group affiliation (Cialdini et al.; 1976; Tajfel and Turner; 1979). As self-concept maintenance and social concerns are strong drivers of ethical behaviors, the highlighted self-concept and group affiliation may decrease winners' cheating. According to this argument, they would be more sensitive to feedback stressing the ethicality of others members. On the other side, losers may be instead more prone to cheat according to the "frustration aggression hypothesis" (Berkowitz; 1989). Further, self-esteem and feeling of belonging to a group would be weakened by the bad performance. Aronson and Mettee (1968) show that low level of self-esteem is correlated with dishonest behavior; additionally, the other drivers of ethicality as concern for social norms and self-concept maintenance would be weakened by the bad performance of the group. These conditions would contribute to increase the level of cheating of losers relative to winners and to lower sensitivity to social feedback about honest behaviors of other subjects. Indeed, the feedback about others' behavior introduced a further element of social interaction among subjects and it is examined as an additional research question in our work. The related literature and specification of research questions are in the following paragraph.

2.2 Social Feedback and Individual Cheating Levels

Observing (un)ethical behavior of another person seems to influence one's own tendency to engage in (un)ethical behavior as it seems to convey information on the appropriateness of specific activities, especially when it is performed by similar others (Cialdini et al.; 1991; Cialdini and Trost; 1998). Even when this observed behavior is in conflict with normative prescriptions existing in the society, it may exert a very powerful influence on own activities: Bicchieri and Xiao (2009) show that in a dictator game when expectations of others' behavior (descriptive beliefs) and expectation of the behavior accepted by others (normative beliefs) are in contrast, the giving behavior complies more with the descriptive norm inferred. As a consequence, studies find evidence for a tendency of social conformity in unethical behavior. Diekmann et al. (2015) provide evidence for the contagiousness of norm violations and Rauhut (2013) demonstrates the crucial role of expectations of others' behavior for the spreading of norm violation. With respect to cheating, research shows that cheating levels increase when people observe others cheat (Gino et al.; 2009). Further, Mann et al. (2014) examine whether lying tendencies might be transmitted through social networks and find that a person's lying tendencies can be predicted by the lying tendencies of his or her friends and family members. Yet, social conformity to the respective observed behavior is not an universal rule when it comes to cheating. For example, Fortin et al. (2007) document anti-conformity behavior in an experimental cheating task with social interaction. In addition, Gino et al. (2009) explore differences in dishonest behavior when observing cheating behavior of others. They show that social identity plays a crucial role in determining the decision to conform or to not conform to dishonest behavior of others. Using exogenous assigned group identity in the laboratory, Gino et al. (2009) find that people tend to conform to cheating behavior of in-group members and to be anti-conformist with respect to cheating behavior of out-group members. Moreover, Cadsby et al. (2016) find in-group dynamics leading to increased cheating levels as people seem to be willing to cheat in order to favor an in-group member; even if this does not impact their own payoff positively.

Hence, group identity seems to influence individual cheating levels. In this vein, group status and social comparison processes among in-group and out-group members might have a strong impact on cheating behavior. General findings on cheating support this notion. John et al. (2014) show that social comparison processes may encourage to cheat and Pettit et al. (2016) indicate that people are willing to cheat to achieve a social status as well as an even stronger propensity to cheat in order to not lose this status.

We refer to this literature to add an additional purpose to our experiment: investigate the effect of social interaction introducing a feedback about others' participant behavior at the beginning of the third round of the cheating task. We want to see if cheating level changes respect to previous round when the feedback is given. This information is payoff irrelevant, but it may suggest which is the norms in the group and then affecting the behavior. Further, the effect may be differentiated according to the group affiliation: as already pointed out at the end of previous paragraph, winners may be more sensitive to social appraisal and then be more reactive to feedback especially when showing honest behavior. This would reinforce evidence in favor of an honor effect for winners. Instead, losers may be less reactive to feedback, and in particular to honesty feedback. Also, we introduced two different between-subjects treatments in relation to the feedback: in-group and out-group feedback. The feedback is in-group when cheating of a loser is shown to another loser,and winner's cheating to another winner. Out-group feedback is from a loser to a winner or vice versa. According to social identity theory, the in-group feedback should have a stronger impact on behavior than out-group feedback. The out-group feedback may even lead to anti-conformity reactions, according to the tendency to discriminate out-group members. However, members of low-status groups may show out-group favoritism conforming to high status members' behavior (Reichl,1977).

3 Experimental Design and Hypotheses

The experiment was conducted as follows: first, participants were organized into two teams comprised of two participants per team. The teams first engaged in a tournament awarding a financial bonus only to the members of the winning team. Participants were informed of the results of the tournament, i.e. whether their team won or lost, before starting a computerized cheating task.

The experiment was programmed in ztree, and run at Luiss in CESARE laboratory in September 2017. Participants were recruited with ORSEE and were paid a show-up fee of 5 euros. Six sessions were run, with a total of 136 participants. Anonymity was guaranteed to the participants regarding their choices during the experiment. The payment was administered individually by an external assistant. This external assistant did not know the contents of the experiment (this was also disclosed to participants) and simply paid the appropriate amounts according to the participants' receipts.

3.1 Tournament

At the beginning of the experiment, each participant was randomly assigned to a group of 4.[3] Within each group were two teams, "E" and "O", that competed against each other. Participants were informed that throughout the duration of the experiment they will remain in the same group of 4 as well as the same team, E or O. The game used in the tournament resembles the minimal-effort game's structure (Van Huyck et al.; 1990); however, to ensure that there would always be a winning and a losing group, we introduced asymmetric endowments. E-teams had an initial endowment equal to 8 euros, and their members were able to choose what effort level to use in the competition among the following: e=1,3,5,7. O-teams have an initial endowment equal to 9 euros, and their members were able to choose what effort level to use in the competition among the following: o=2,4,6,8. The team whose lowest effort level is larger than that of the other team wins. As a result, both team members received 4 euros each in addition to their endowment. All four interacting participants were required to pay their effort costs, which was measured by their respective effort levels.

Thus, in total a member of the O-team earns 8 euros own effort level in euros + 5 euros (+4 euros) and a member of the O-team 9 euros - own effort level in euros + 5 euros (+4 euros) when his team lost (won) in the tournament.

[3] We are grateful to Werner Güth for suggesting us tournament to induce status differences and for his help in developing the design and related hypotheses.

After the tournament, participants were informed which team won, but were not given information regarding their teammates effort choice or effort choices from other teams. It is important to note that participants are not informed about the different endowment and effort levels of the opposing team: the initial instructions were read aloud and explained the mechanism of the tournament without specifying the amount of initial endowment and effort levels available for each respective team. Later, they received detailed instructions, which specified these amounts on the screen during the experiment. The members also answered comprehension questions on the tournament after reading the instructions on the screen, to make sure that they understood the rules. Few subjects (on average, less than one per session) asked about the eventuality of a tie. The assistant then informed the teams that there is no winner in that case[4].

Contrary to previous work using tournaments, our focus was not on the theoretical predictions generated from this game and the resulting effects. Rather, we used this tool to create different experimental groups. Further, this structure minimizes the possibility of selecting winning and losing group participants with systematically different attitudes in terms of coordination and solidarity in a way that well-defined games usually used in tournaments would not ensure.

3.2 Cheating Task

After learning about the tournament results, each participant engaged in a three-round reporting task: a computerized die throw generated the actual numbers, n=1, 2, 3, 4, 5, 6. Once the participants knew n, they were able to report any number, n"=1, 2, 3, 4, 5, 6 on the following screen. Each participant received n" units irrespective of n. We refer to $\Delta = n - n"$ as the size of misreporting among participants. The only information gained by participants was that all n-numbers have positive probability: the participant were not explicetly told thatthe numbers n=1, 2, 3 were five times as likely to occur compared to n=4, 5, 6. This is to present participants with more frequent cheating incentives (the probability of n is 5/18 in the range n=1,2,3 and only 1/18 in the range n=4,5,6). The assistant in the laboratory was not asked by any participants if the probabilities were the same for each number. Hence, participants were aware that each number from 1 to 6 may be drawn, i.e. they have positive probabilities, but the bias in the die was not made explicit.

We aknowledge that in the dice tasks the harmed person by cheating is the experimenter and not the other subjects; Gneezy (2005) suggests that the identity of the harmed person may affect the decision making. However, in the present experiment the goal is to look at the effect of misreporting

[4]However, tie was not possibile by design. Since the subjects were not informed about the asymmetry in endowments, they may expect a tie and, when asked, the assistant relied to questions about a tie suggesting that there would be no winners and losers in that case.

on winners vs losers behavior, and not to the level of cheating *per se'*, this element of the design should not affect the conclusions. Further, if the identity of the victim of cheating affects differently winners and losers, this effect should be considered part of the treatment.

The experimental control on misreporting was made explicit from the beginning of the first round, even if it was not sanctioned. Further, in the first round participants were unaware that they would receive feedback. The awareness of experimental control from the first round avoids the eventual surprise in undertanding that (mis)reporting is experimentally controlled once they receive the feedback: the surprise of control may confound the effect of the feedback on cheating.

After the first and before the second round, participants were told that they would receive information regarding the difference between reported and drawn numbers of other participants after the second round[5]. This pre-feedback is given to test if knowledge about the possibility that their behavior would be shown to other participants affecs their own cheating level. Between rounds two and three, the difference between reported and drawn numbers, Δ, of one of the orther participants is shown to each participant. In the in-group treatment, all participants learned the difference in reporting of one of their teammate. In the out-group treatment, all participants learned the difference of one member of the opposing team. Participants were not informed how the member of the other team has been selected: the member shown in the out-group treatment is the one that is behaving most differently compared to the participant that receive the feedback: the members of the winning team with the larger (smaller) difference learn about the smaller (larger) or equal difference in the losing team, and vice versa.

3.3 Hypotheses

Hypothesis H1 (Effect of Honor):

Members of the winning team misreport significantly less than members of the losing team. The reason for the Effect of Honor is that winning (losing) enhances (questions) team solidarity and thereby enhances (weakens) one's ethical obligation. We test it comparing cheating levels of winners and losers in the first round in the regression analysis.

Hypothesis H2 (Weakening of Honor):

The difference in cheating of the winning and losing team members is smaller for the second (mis)reporting task compared to the first one. We test it comparing cheating levels of winners and losers in the second round in the regression analysis.

[5]the information was about the second round behavior.

Hypothesis H3 (Effect of Feedback):
Social interaction via the feedback affects cheating behavior: it increases the average cheating when greater than zero and decreases the average cheating when equal to zero. We test it comparing cheating levels in the second and third round with a parametric and non-parametric tests, and conditioning cheating in the third round to the level of feedback in the regression analysis.

Hypothesis H4 (Higer sensitivity of winners to honesty feedback):
Winners react more strongly to the feedback showing honest behavior than losers, decreasing their cheating. We test it with parametric and non-parametric tests comparing cheating levels of winners and losers in the third round, conditional to receiving a feedback equal to zero.

Hypothesis H5 (In-group vs Out-group feedback): The in-group feedback more strongly affects behavior than the out-group. Also, out-group feedback may lead to anti-conformist reactions. We test it with parametric and non-parametric tests comparing cheating levels in the third round, conditional to the type of feedback, that is in-group or out-group.

4 Results

4.1 Descriptive Results

Winners and losers behaved in the same way in the team competition: the average effort level in winners and losers group is not significantly different (p-value=0.18). Indeed, the difference in the endowment after the team competition is approximately equal to the prize. This implies that the game in the tournament created groups of winners and losers composed by persons that do not behave differently in a systematic way, on average.

4.2 Individual Cheating Levels

Table 2 show the summary statistics for cheating in the three rounds. In Figure 1, the average cheating in each round is shown. The results of the t-test shown in the table confirm that the cheating level in the first and second round is not significantly different. Instead, cheating significantly increases in the third round.

Table 1: Summary Statistics

This table displays the summary statistics. *Effort* is a discrete variable from 1 to 4. It indicates the level of effort: effort level 1 is equal to 1 euro for team E and 2 euros for team O; effort level 2 is equal to 3 euro for team E and 4 euros for team O; effort level 3 is equal to 5 euro for team E and 6 euros for team O; effort level 4 is equal to 7 euro for team E and 8 euros for team O;. *Endowment* is the endowment after the team competition. Winners and losers have significantly different endowment at the beginning of the cheating task. The difference being around 4 euros, the amount of the prize for winning.

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	Mean	SD	Min	Max
Male	0.56	0.50	0.00	1.00
Age	22.63	2.22	18.00	34.00
Effort	1.74	0.69	1.00	3.00
Effort Losers	1.67	0.76	1.00	3.00
Effort Winners	1.79	0.61	1.00	3.00
Profit	17.88	2.74	9.00	22.00
Endowment Losers	5.7	1.49	3.00	7.00
Endowment Winners	9.4	1.22	7.00	11.00
Risk	5.45	2.09	0.00	9.00
Living Standard	2.59	1.14	1.00	7.00
N	136		(68 winners and 68 losers)	

Table 2: Summary Statistics and Regression Analysis

This table displays the summary statistics of the three rounds of the cheating task. *Cheating 1/2/3* is the average difference between the number reported and the actual drawn number in rounds 1/2/3.

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	Mean	SD	Min	Max	Average Winners	Average Losers
Cheating_1	2.71	1.77	0	5	2.44	2.98
Cheating_2	2.72	1.8	-3	6	2.36	3.07
Cheating_3	3.16	1.6	0	5	2.75	3.58
N	68					

4.2.1 Cheating Levels of Winners and Losers

Regression analysis in Table 3 and Figure 2 show that winners cheat significantly less than losers in the first round, even when controlling for endowment at the beginning of the cheating task and effort spent, according to Hypothesis 1; this result provide evidence in favor of hypothesis 1 on an honor effect for winners, and a weakened moral obligation for losers.

According to hypothesis 2 regarding weakening of honor, the difference in the second round between winners and losers is no more significant. The actual draw number n, has a negative effect on cheating: the higher is the drawn number, the lower is the incentive to cheat. This confirms that different probabilities for high and low numbers was a useful tool to get more interesting data.

In regression 3 we can see that the dummy variable for being in the in-group or out-group treatment is not significant.

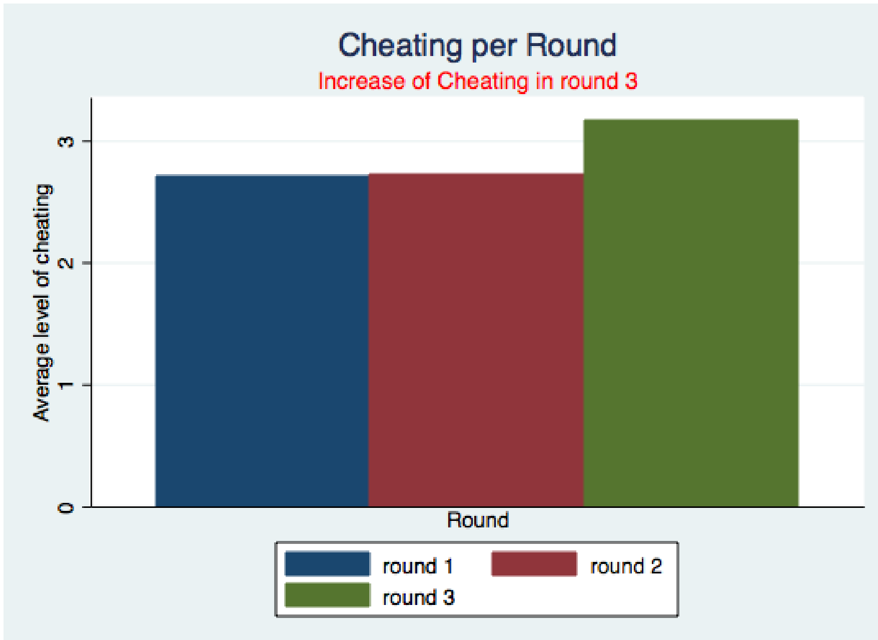

Figure 1

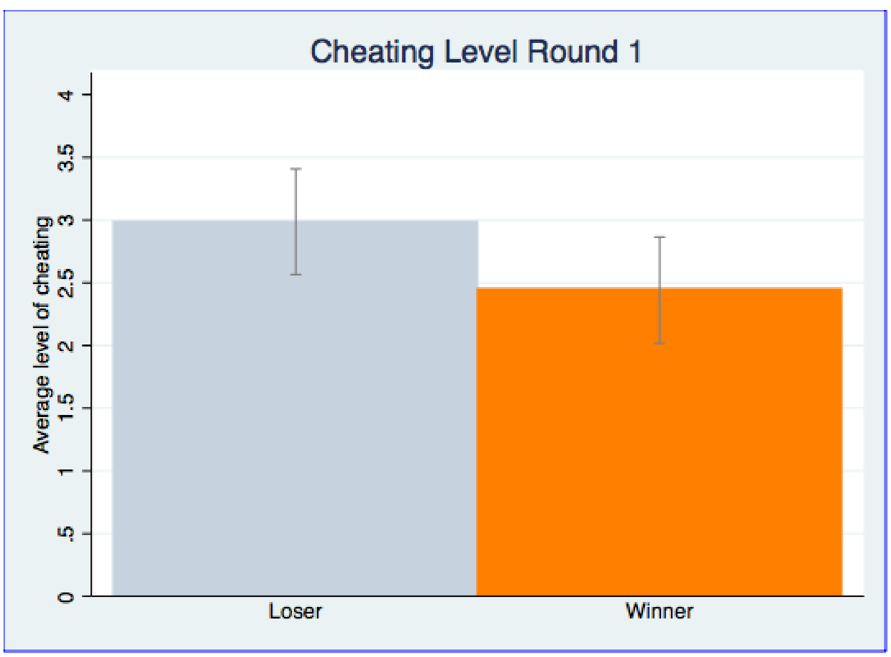

Figure 2

Table 3: Regression Analysis

	(1) Cheating Level R1	(2) Cheating Level R2	(3) Cheating Level R3
Loser	2.3*	0.96	0.59
	(1.3)	(1.2)	(1.05)
In-Group Feedback			0.16
			(0.18)
Level of Feedback			0.05
			(0.08)
Dummy Feedback			-0.61*
			(0.37)
Endowment	0.3	0.21	0.11
	(.32)	(0.3)	(0.26)
First drawn number	-.89***		
	(.08)		
Second drawn number		-0.93***	
		(0.07)	
Third drawn number			-0.98***
			(0.07)
Effort	.53	0.18	0.15
	(0.65)	(0.60)	(0.51)
Cheating round 1		0.28***	
		(0.06)	
Cheating round 2			0.13***
			(0.05)
Age	-0.03	-0.07	-0.13***
	(0.06)	(0.06)	(0.05)
Sex	-0.52**	-0.20	-0.10
	(0.24)	(0.22)	(0.2)
Type of study	yes	yes	yes
Years of study	yes	yes	yes
Risk	yes	yes	yes
Living Standards	yes	yes	yes
Statistics	yes	yes	yes
Constant	-0.61	2.95	6.36
	(4.5)	(4.2)	(3.5)
N	136	136	136
$R^2 - Adj$	0.5	0.58	0.53

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.2.2 Impact of (Mis)Reporting Feedback

According to hypothesis 3, social interactions matter: in the regression on the level of cheating in the third round, the level of feedback is not significant. However, the dummy variable *Dummy Feedback* is significant: this variable is 0 when feedback is equal to 0 and it is 1 when feedback is greater than zero. Participants then react to honest or dishonest behavior.

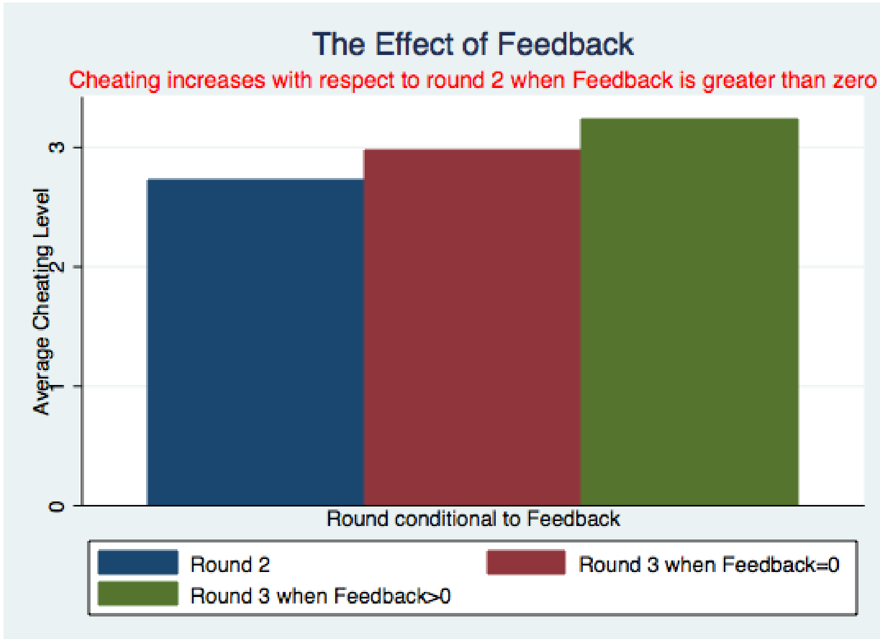

Figure 3

winners are more sensitive than the losers to an honesty feedback, that is feedback equal to zero. Indeed, winners decrease their level of cheating in round 3 compared to round 2 when feedback is equal to zero (t-test, p-value=0.05)[6]. This may still be an effect of the honor status of winners that increases their sensitivity to honesty feedback according to Hypothesis 4.

This is not true instead for losers: when they receive a feedback equal to zero, they neither increase nor decrease their level of cheating[7]. This result confirms hypothesis 4 and is shown in Figures 4 and 5. When losers and winners receive a feedback greater than zero they both significantly increase their cheating[8].

[6]The t-test compares the cheating levels of round 2 and 3 of the winners when feedback is equal to zero. There are 15 winners receiving the *honesty* feedback, and they decrease the average cheating level from 3 to 2.1

[7]The t-test compares the cheating levels of round 2 and 3 of the losers when feedback is equal to zero. There are 18 winners receiving the *honesty* feedback, and they increase the average cheating level from 3.44 to 3.6, and this difference is not significant (p-value=0.29)

[8]ttest winners p-value=0.006. ttest losers p-value=0.04

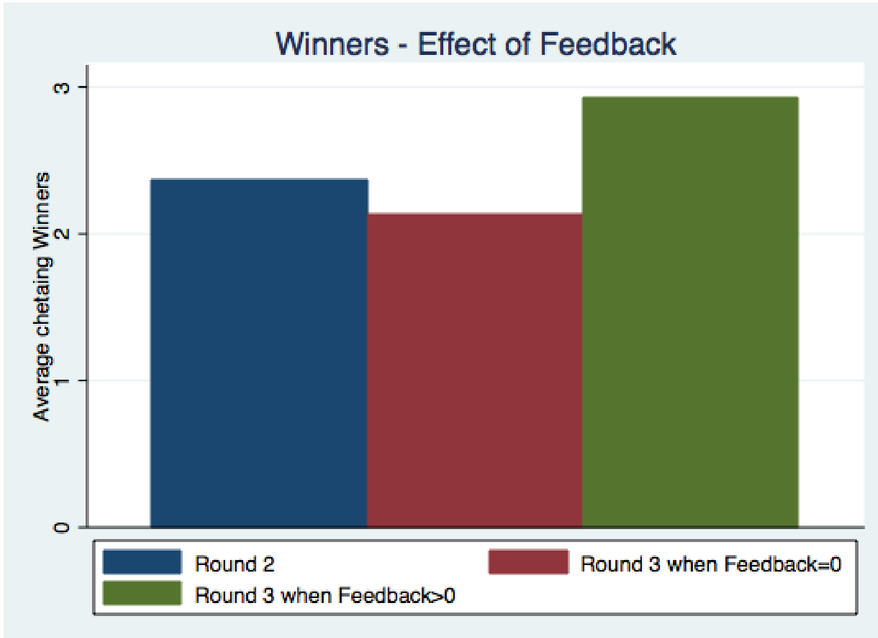

Figure 4

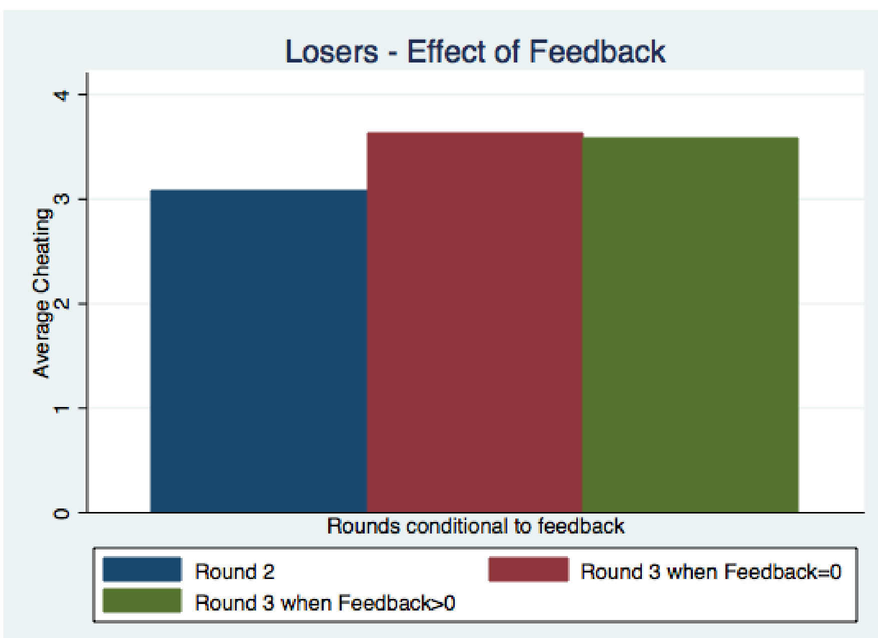

Figure 5

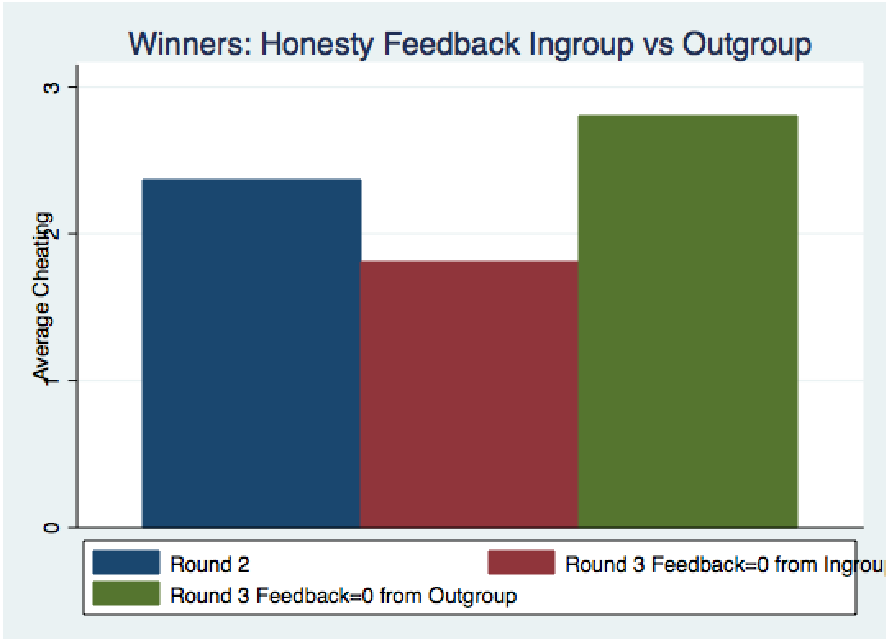

Figure 6

4.2.3 Behavioral Responses to In-Group and Out-Group Feedback

The regression analysis does not confirm hypothesis 5: there is not a differentiated effect when receiving in-group vs out-group feedback in general. Both losers and winners tend to increase cheting when they receive a feedback greater than zero, both from ingroup and outgroup. However, looking at the reaction of winners and losers(Figures 6 and 7) to an honesty feedback from in-group *versus* out-group, when winner receive an honesty feedback from in-group there is the tendency to behave more in line to the in-group (cheating less) and less in line to the out-group (cheating more). Interestingly, losers seems anticonformist to both in-group and out-group honest behavior. However, all these differnece between in-group and out-group honesty feedback are not significant because there are two few observations. This work then provide just a first evidence on the differenciated effect of in-group and out-group behavior of winners and losers that need further deepening in future experimental analysis.

5 Conclusion

This paper sheds light on how group identity impacts individual cheating behavior in a social environment. Based on an incentivized laboratory experiment, we find that group identity of members of a winning and of a losing team influences individual cheating levels differently. In line with a "honor effect" hypothesis, we show that winners cheat significantly less than losers in a subsequent

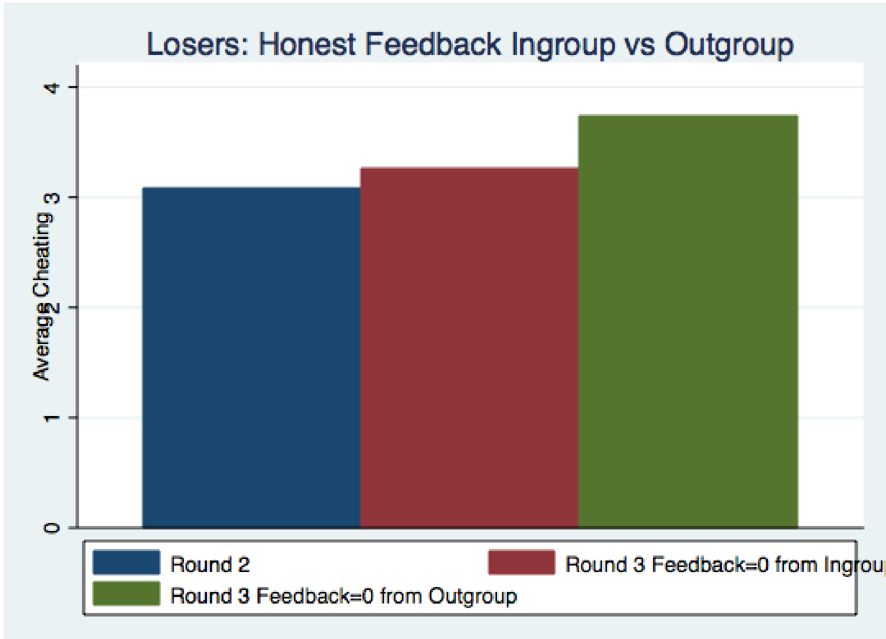

Figure 7

cheating task. Thereby, we contribute to existing literature by providing evidence for heterogeneity in group identity affecting cheating behavior, depending on the groups' status. Importantly, given our tournament structure, the observed heterogeneity should not be driven by systematic differences in participants' coordination or solidarity preferences.

Moreover, we provide causal evidence on people's reaction to observed cheating behavior of in-group and out-group members. Feedback about other participants' (mis)reporting influences participants' subsequent cheating levels significantly. Importantly, we uncover that winners are more sensitive to an honesty feedback than losers, i.e they decreased their level of cheating in round 3 compared to round 2 when they received an honesty feedback. This adds a new perspective to previous research on conformity. Group status seems to determine people's social comparison processes and in turn the decision to conform or to not conform to observed cheating behavior of others. Further, we provide first empirical indication of winners and losers reacting differently to in-group and out-group feedback. Whereby winners tend to conform to both observed in-group and out-group honesty, losers conform to observed in-group honesty but show anti-conformity to observed in-group honesty.

Our results offer various avenues for future research. While this experiment focuses on (mis)reporting, future experimental studies might additionally look at dishonest behavior towards others, for example in-group and out-group members, to test whether this fact might be even strengthened. Moreover, it might be interesting to examine whether the observed difference in cheating behavior based on group status exists for "natural" status groups in society, such as rich and poor.

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Appendices

A Translated instructions and control questions

A.1 Read aloud

Welcome to the Experimental Laboratory. You will be taking part in an economics related experiment.

For the duration of the experiment, we ask you to observe a few rules: starting from now refrain from any sort of communication. If at any point you have a question, please notify us by raising your hand to be visible outside of the cubicle. We will then come to you to answer any questions.

We also ask you to turn off your cell phones and other devices, or at least to put them on silent, and to pack them away with your bag or belongings.

If you do not adhere to these rules, this will lead to an automatic exclusion from the experiment and from payment.

The experiment is composed by two phases. At beginning of each phase detailed introductions will be displayed on your screen, and you will read it individually. Please read those instructions carefully, since it will be not possible to going back after you proceed in the experiment. You have enough time to read through the instructions and therefore do not need to hurry.

Now you will receive general information on the content of the experiment. In this experiment you will be randomly assigned to groups with four participants. Also, two participants of the group are randomly assigned by the computer to team O, the other two to team E. The assignment to team E or O is random and it is shown on your screen at the beginning of the experiment. The identity of the other members of the group will remain anonymous.

A.1.1 Phase 1

In the first phase of the experiment the two teams E and O engage in a tournament to win a monetary prize. Each partcipant will have an initial endowment and has to decide how much of it he/she wants to use in the competition. This amount will be subtracted to the initial endowment in the final payment.

In order to establish the winnng group in the competition, in each team the lower value chosen in the competition by the members will be taken into account. The team where the lower value is higher win. Each member of the winning team will receive 4 euros that will be added to the final payment.

At the beginning of the first phase you will read individually on the screen detailed instruction on the competition and a few examples to understand the mechanism. Also, before doing your choice, you will be asked to answer some questions to be sure of your comprehension. Once the competition finishes, you will see on the screen if your team won or lost.

A.1.2 Phase 2

Phase 2 is composed by three rounds. In each round the computer will randomly select an integer number from 1 to 6, and it will be shown to you on the screen. You will be then asked to report the drawn number in the following screen. Your payment in this phase of the experiment will depend only on the reported number and not on the drawn number (1 = 1 euro, 2 = 2 euro, 3 = 3 euro, 4 = 4 euro, 5 = 5 euro, 6 = 6 euro). Detailed instructions will be shown to you at the beginning of the phase, and you will answer to control questions before starting the rounds. At the end of the second phase one round will be randomly selected for payment and shown to you on the screen.

A.1.3 Questionnaire

At the of the experiment you will be asked to answer to a questionnaire on the screen where you have to give some information about you, but not your name. Indeed, the data analysis of the experiment will be absolutely anonymous: the experimenters will not able to connect your choices to you.

A.1.4 Payment

The final payment will depend on the amount you earn in the first and second phase of the experiment. To this amount 5 euros will be added for your participation. The total amount earned will be shown to you on the final screen at the end of the second phase: you have to write this amount on the receipt in your cubicle. The payment will be done after the questionnaire: you will go individually out of the laboratory. In another room an assistant who is not aware about the content of the experiment will pay you according to the amount reported on the receipt.

We start now with the experiment.

Please note that you will receive the instruction for the different parts of the experiment sequentially; that means you will see instructions for the respective part only when the previous one is over

A.2 On screen

Welcome and thank you for your participation. Please, remember that the experiment has two phases , and you will receive the instruction for the different phases sequentially; i.e. you will see instructions for the respective phase only when the previous one is over.

Before starting the experiment klick "NEXT" for your team assignment.

— Next screen —

You belong to team O[E].

Please klick NEXT to proceed.

— Next screen —

A.2.1 Phase 1: Tournament

First, you and and your teammate engage in a tournament with team E [O]. At the end of the competition the winning and loosing team will be announced. You and the other O[E]-member are endowed with 8[9] euros each which you can use to win the tournament. Each member has to decide which of these possible values use in the competition: 1,3,5 or 7 [2,4,6 or 8]. The chosen value will be subtracted to your initial endowment in the final payment.

To establish the winner of the competition, it will be considered the lower value chosen in your team, and it will be compared with the lower value chosen in the opposing team. The winning team will be the one which lowest value exceeds the lowest value of the other team. Each member of the winning team will receive a prize equal to 4 euros that will be added to the final payment.

Thus, if your team wins, you earn: initial endowment minus the value chosen in the competition plus bonus (8[9] euro value chosen + 4 euro).

If your team loses, you earn: initial endowment minus the value chosen in the competition (8[9] euro value chosen).

Now there are two examples that help you to understand the mechanism of the competition:

1. Suppose that you chose 5 [6] as value in the competition and your teammate chose 3 [4]. Also, suppose that your team lost since the lowest value in the opposing team is higher than 3 [4]. The final payment for this phase of the experiment will be 8[9]-5[6] euros.

2. Suppose that you chose 5 [6] as value in the competition and your teammate chose 3 [4]. Also, suppose that your team won since the lowest value in the opposing team is lower than 3 [4]. The final payment for this phase of the experiment will be 8[9]-5[6] + 4 euros.

Please klick NEXT to proceed.

— Next screen —

We kindly ask you to answer few control questions before continuing the experiment:

1. Remember that your endowment is 8[9]. Suppose that you chose 7 [8] as value in the competition, and your teammate chose 3[4]. Then, the lower value in your team is 3 [4]. Also, suppose that you team won because the lower value in the opposing team is lower than 3 [4]. How many euros you will earn in this phase of the experiment?

2. Suppose that you chose 7 [8] as value in the competition, and your teammate chose 5[6]. Then, the lower value in your team is 5 [6]. Also, suppose that you team won because the lower value in the opposing team is lower than 5 [6]. How many euros you will earn in this phase of the experiment?

Please klick "NEXT" to proceed

— Next screen —

Your endowment is 8[9]. Please, choose the value you want to use in the competition: I choose value: 1[2] 3[4] 5[6] 7[8]

Please klick OK to confirm your entry.

— Next screen —

Your team won [lost].

Please klick NEXT to proceed.

— Next screen —

The first phase of the experiment is finished.

Please klick NEXT to start the second phase.

— Next screen —

A.2.2 Part 2: Decision Task

Instruction Phase 2 In this second phase of the experiment you will be shown on the screen an integer number ranging from 0 to 6 selected by the computer. The number will be then 1, 2, 3, 4, 5 or 6. Every number might be drawn. After seeing the number, you will be asked to report it in the following screen. Your earnings from phase 2 of the experiment will depend on your reported number, and not on the drawn number. You earn the exact amount of the reported number in euro (1 = 1 euro, 2 = 2 euro, 3 = 3 euro, 4 = 4 euro, 5 = 5 euro 6 = 6 euro).

Note that the computer automatically collect the drawn number. However, your payment for the experiment depend only on the reported number and the data analysis of the experiment is anonymous: your choices cannot be associated with you.

Remember that the second phase of the experiment is composed by three rounds: a number will be drawn three times and you are asked to report it. One of the three reported numbers will be randomly drawn for payment. The selected round and the reported number will be shown to you on the screen at the end of the experiment.

Please klick NEXT to proceed.

— Next screen —

We kindly ask you to answer few control questions before continuing the experiment:

1. Suppose that in one round the drawn number is 3 and you report 5. How much would you earn if this round was selected for payment?

2. Suppose that in one round the drawn number is 3 and you report 3. How much would you earn if this round was selected for payment?

3. Suppose that in one round the drawn number is 3 and you report 1. How much would you earn if this round was selected for payment?

Please klick NEXT to proceed.

— Next screen —

(Phase 2 round 1)

The computer drawn the number: x . Please, keep in mind this number klick NEXT to proceed

— Next screen —

Please report the number drawn in the first round, that is, 1,2,3,4,5 or 6.

Please klick OK to confirm your entry.

— Next screen —

Before continuing the experiment note that after this the second round and before the third round of this phase you will receive a feedback about the behavior of one other participant in the second round, that is the eventual difference between the drawn number and reported number. The information will be displayed on your computer screen.

Please klick NEXT to draw the second number.

— Next screen —

The computer drawn the number: x . Please, keep in mind this number klick NEXT to proceed

— Next screen —

Please report the number drawn in the second round, that is, 1,2,3,4,5 or 6.

Please klick OK to confirm your entry.

— Next screen —

(In-group treatment) Before drawing the third number, please, note that your teammate has chosen the reported number such that the difference between the drawn number and the reported number is: x.

(Out-group treatment) Before drawing the third number, please, note that one member of the winning[losing] team has cho-sen the reported number such that the difference between the drawn number and the reported number is: x.

Please klick NEXT to draw the third number.

The computer drawn the number: x . Please, keep in mind this number klick NEXT to proceed

— Next screen —

Please report the number drawn in the third round, that is, 1,2,3,4,5 or 6.

Please klick OK to confirm your entry.

— Next screen —

Phase 2 has finished.

Please klick NEXT to drawn one round of phase 2 for payment.

— Next screen — The round chosen randomly for payment is: y

— Next screen —

Your initial endowment was 8 [9] euro and in the competition you choose value [e].

Your team has a prize equal to 4[0]. In round y of phase 2 you reported [x]. Also, you have 5 euros for your participation.

Please, now write the amount of the payment in the receipt. Before starting the payment, please answer the questionnaire.

A.2.3 Part 3: Final Questions

This part of the experiment is not relevant for your payout. Please answer each of the following questions as accurately as possible. Of course your responses will be treated completely confidentially. Your answers will be of immense value for our scientific investigation. If you have any questions, do not hesitate to contact the experimenter. Thank you in advance for your cooperation.

1 Personal questions

1.1 What is your gender?

☐ Male

☐ Female

1.2. How old are you in years? Age in years:

1.3. If you are a student, what is you major?

- Economics and Business
- Management
- Political Science
- Law
- Other

1.4. What is the level of the highest degree you are currently studying?

- Qualification for university entrance
- Bachelor
- Master
- Doctor/PhD
- Other

1.5. What best describes your standard of living?

- Very well off
- Very satisfying
- Rather satisfying
- Mediocre
- Almost poor
- Poor
- Prefer not to say

2 Risk Preferences

How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?

- 0 (avoid taking risks)
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 (take risks)
- Refusal

3 Statistical knowledge

How do you rate your statistical knowledge?

- Basic knowledge (from school)
- Advanced knowledge (basic courses, e.g. at the University)
- Deeper knowledge (specialized courses, e.g. at the University)

4 Questions about the experiment

Using the following scale, please indicate how much you agree or disagree with the following statements about the experimental tasks you performed:

- 0 (strongly agree)
- 1

- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10 (strongly disagree)

5 Additional questions about the experiment

- After I knew that I will get information about the reporting behavior of one other participant in the second round, I was concerned about the fact that other subjects may also see information about my choice.
- In the competition the two teams had equal chances to win.
- In my opinion, the information about the reporting behavior of one other participant in the second round was truthful.
- In my opinion, the competition was fair since both teams had the same chance to win.
- In the decision task every number (from 1 to 6) had the same probability to be drawn.

6 Problems and Comments

6.1 Did you ever make a mistake during the tasks? If so, please tell us exactly what went wrong and in what phase/round: 6.2 Did you find the instructions of the experiment transparent, clear, and understandable? What if anything was unclear?

Thank you for your participation. Please remain seated until the assistant in the laboratory calls you to receive the payment.

Choice Process under uncertainty: an eye-tracking analysis

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Abstract

This work explores the features of the choice process under uncertainty through an eye-tracking experiment: the research questions on which the experiment focuses are 1) the process model that fits better the process data both in small and large choice sets; 2) the differences in the choice process of fast and slow subjects, and the relation between the response time and the final choice.

Subjects are sequencially presented with 14 choices between 2 gambles and 14 choices between 10 gambles. The data both in small and large sets fit the predictions of automatic integration models as Decision Field Theory and Parallel Constraint Satisfaction. Instead, data do not support Priority Heuristic and the standard maximization process assumed by the Expected Utility theory and Cumulative Prospect theory. In small and large sets there are similar eye-movements, but in large sets subjects seem to simplify the choice process restricting the consideration set. In two gamble sets, the slow responders do not rely on a deeper cognitive process than fast subjects according to the fixation duration analysis, but the two groups use different search strategies: slow subjects search information in a more systematic manner than fast ones. This evidence is against Rubinstein (2007,2013,2016) classification of slow subjects as *deliberative* and fast subjects as *intuitive* because they both rely on the automatic integration of information.

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1 Introduction

Economic theories of choice under risk mainly focus on the modelization of choice outcomes (e.g. Von Neumann and Morgenstern (1947); Tversky and Kahneman (1992)). These models assume that decision makers behave *as-if* they maximize a well-defined objective function. Most of the effort in order to add psychological realism to economic models has been directed towards the elements and form of the this function, keeping the assumption on its maximization. The prospect theory and its advances (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) merge economic theory with descriptive psychological features and it is able to explain a great proportion of choices. Nonetheless, new paradoxes have emerged in relation to this theory (Birnbaum; 2008) and statistical analyses with mixture models have shown that the current choice models fails to capture a significant part of heterogeneity in behavior taken singurlaly (e.g. Harrison and Rutström (2009); Conte et al. (2011))[1]. These findings claim for more flexible and integrated theories of decision making in order to account for new paradoxes and individual heterogeneity. In order to add explanatory power to decision theories, the study of the choice process has been proposed as a useful element to be integrated, as Benhabib and Bisin (2007) pointed out: *"..even if we agree that our objective as economists is to explain choice per se, not process, nonetheless the study of choice processes has in principle additional explanatory power for decision theory"*. The process of maximization assumed in standard theories of risky choices implies a deliberate integration of information,that is, a thought multiplication of probabilities and outcomes. This process has been assumed without empirical evidence on it, and it may be significantly different from the natural one. Cognitive limitations and contingent situations may imply an actual process far from that postulated in economic theories (Simon; 1955). Reutskaja and Nagel (2011) found that the actual process of choice among consumption products fits better with a search model that relies on satisficing and optimization than with a pure standard optimal search model. Procedural elements of decision making have been rarely integrated in theory of decision under risk in economics, although this aspect of human behavior has been extensively studied in other disciplines such as psychology and neuroscience. Rubinstein (1988) has proposed a formal model of choice under risk that explicitly refers to the natural decision-making process; his model of choice under risk is based on similarity relations on both the probability and prize dimensions, and relies on psychological studies on the use of such similarity relations in learning

[1] I am grateful to one of the referees that clarified that mixture models analyses have taken into consideration models of choices tha relies on standard maximization process, and that these studies show just that people are different. The reference to mixture models in this chapter aims to highlight the limits of the current choice models in accounting for heterogeneity. This observation fits the line of reasoning of this introductive section since the point it is to stress the need for more flexible theories of decision making under uncertainty. As discussed later in this section, the introduction of procedural elements has been proposed as a useful tool to achieve this goal.

processes (Tversky; 1977). Research in psychology and neuroscience provides an extensive amount of findings and models on the choice process. Process models can be distinguished in three main categories: Heuristics, Automatic Integration Models, Deliberate Integration Models. These three classes of models may be distinguished according to two features of the process: the degree of integration of information and the degree of deliberation in such an integration. Heuristic models are based on non-compensatory rules. Automatic integration models rely on the quick and efficient automatic integration of all the pieces of information. Deliberate integration models are instead based on the thought integration of probabilities and outcomes, as postulated by standard choice models[2]. This chapter looks at the choice process under risk and its relation with choices in an experimental analysis where eye-tracking technology allows to go into the *black box* of decision-making. This works refers to two strands of literature on choice under risk: the first is the one of the studies on choice process under uncertainty introducing measures of process variables (as eye-movements and response time) in the experimental analyses on choices under risk in order to test alternative process models. The second strand of literature is the one on choice overload, that studies the choice process and final decision in context where there is a proliferation of the choice options (e.g. Reutskaja and Nagel (2011);Iyengar and Kamenica (2010)). The experiment presented in this chapter aims to contribute to the literature studying the choice process under risk in two experimental conditions: small and large sets. The goal is to test if the choice process in large sets shows different features from the one in small sets. In particular, it is hypothesized that as the set size increases the choice process increasingly relies on simple and fast non-compensatory choice strategies that lead to choose the simplest option, that is the risk-free.

Additionally, this chapter aims to contribute to the literature on choice process under uncertainty exploring the relation between the choice process and the response time, and the final choice. Indeed, the data on the fixation duration gathered with the eye-tracking offer the oppurtunity to deepen the knowledge on the relation between short *versus* long response time and the use of intuitive *versus* deliberative modes of thinking, that is a paradigm on which relies many experimental studies on uncertainty (e.g. Rubinstein, 2007,2013; Butler et al., 2014). The present work aim then to deepen the procedural antecetents of short/long response time and the behavioral consequence in terms of risk-taking.

[2]Standard choice models, as the expected utility theory and prospect theory, assume this deliberate integration process, but they are not process models. In the rest of this chapter the reference to EU and CPT models as deliberate integration process models means that the kind of process that they assume is tested in order to see if it is plausible. Although, I aknowledge that these models do not aims at describing the actual choice process, in previous eye-tracking studies (e.g.Glöckner and Herbold (2011)) these models have been considered as a *Weighted Additive Compensatory Process*(**?**).

In Section 2, the literature on choice process in decision under uncertainty is briefly reviewed presenting the main models on the choice process. Section 3 introduces the research questions about the choice process under choice overload (3.1) and on the relation between the choice process and the response time (3.2). In Section 4, the experimental design and protocol is presented. In Section 5 the hypotheses testing on process variables and choices is analytically developed. In Section 6, the results of the experimental analysis are presented. Section 7 concludes summarizing the main findings and the directions for future research.

2 Choice Process in decisions under uncertainty

Several economic analyses studied the choice process under uncertainty using a simple measure of choice process: the response time. Rubinstein (2007,2013,2016) explored the role of the decision time in both strategic and individual decision-making stressing the relation between the respose time and the level of cognitive reasoning. Other studies that collected response times found a positive relation of the response time with the sophistication of the choice strategy (Conte et al.; 2014) and with risk and ambiguity aversion (Butler et al.; 2014).

The eye-tracking technique allows to study more deeply the choice process than the response time: this technology collects process measures as the direction of information search, the distribution of attention over outcomes and probabilities, and the fixation duration. Another toolthat has been used to measure variables related to the search process is MouseLab (Johnson et al.; 1989): this technique traces the search through mouse clicking on boxes containing information. However, this latter tracking method collects data in a less unconscious way than eye-tracking: Glöckner and Herbold (2011) suggested that MouseLab may affect the decision making process, since hiding information may prevent from relying on automatic processes. Furthermore, eye-tracking permits to collect data that more clearly show the level of cognitive reasoning: pupil dilatation and fixation duration. Several eye-tracking studies (e.g. Glöckner and Herbold (2011); Arieli et al. (2011); Fiedler and Glöckner (2012); Stewart et al. (2016)) have investigated with eye-tracking the decision-making process in choices among two gambles. The evidence provided by these analyses of eye-movements supports automatic integration processes rather than deliberate integration processes or non-compensatory strategies as priority heuritsics (Brandstätter et al.; 2006): the substantial amount of transitions both within and between gambles provides evidence against non-compensatory strategies that would predict a greater amount of transition between gambles. The short fixation duration provides evidence against serial integration of outcomes and probabilities as it should be expected according to the expected utility and cumulative prospect theory[3], and support instead an automatic integration of outcomes and probabilities. The main automatic integration models that have been adapted to choices under uncertainty are Decision Field Theory (Busemeyer and Townsend (1993); Busemeyer and Johnson (2004)) and Parallel Constraint Satisfaction (Glöckner and Betsch (2008); Glöckner and Herbold (2011)). Furthermore, differences in the response time depending on the similarity of the options cannot be accounted by standard static models of choices under risk, as expected utility and cumulative prospect theory, and can instead be expalined by dynamic models as Decision Field Theory and Parallel Constrain Satisfaction. A brief description of the models taken into consideration in this chapter is proposed in the remaing part of this section, before presenting the research questions. In section 5 on hypotheses testing, these models will be analytically classified according the decision-making features into three categories: Non-compesatory, Automatic and Deliberate Integration. This classification will be useful to proceed to the hypothesis testing on the features of the decision process.

Priotity Heuristic Brandstätter et al. (2006) proposed the Priority Heuristics (PH) as a model that can explain both choices and process under uncertainty. This process models relies on non-compensatory decision rules. According to the PH, first there is a stage of information screening where expected values are approximately computed. If expected values are similar[4], the PH is applied. In the second stage information is inspected without integrating information, but instead using non-compesatory strategies, that is, comparing minimum outcomes, probability of the minimum outcomes and the maximum outcomes between gambles. These three *reasons* are sequencially looked up, until one satisfies the aspiration level. Brandstätter et al. (2006) provided evidence in favor of the PH as a choice and process model. However, many studies questioned PH as both choice model (Birnbaum (2008); Birnbaum and LaCroix (2008)) and process model (Johnson et al. (2008); Ayal and Hochman (2009); Fiedler and Glöckner (2012); Franco-Watkins and Johnson (2011); Stewart et al. (2016)). Pachur et al. (2013) provided new evidence in favor of PH with MouseLab. In an eye-traking analysis Brandstätter and Körner (2014) found evidence against the PH, but in favor of

[3]As pointed out in a previous footnote, the Expected Utility Theory, the Cumulative Prospect Theory and the other as-if models are not process models: they do not make predictions on the process. However, they assume a maximization process. These findings speak against the maximization process assumed by these models.

[4]The expected values have to be such that one is not greater than the double of the other, otherwise the choice would be very simple. This argument is applied in two lottery choices.

a dimensional heuristic-like search of information.

Decision Field Theory and Parallel Constraint Satisfaction The two main models of process under uncertainty based on automatic integration are the Decision Field Theory and the Parallel Constraint Satisfaction models; automatic integration means that probabilities and subjective values of the outcomes are integrated through efficient and quick automatic processes, and not through an effortful and deliberate calculation of weighted sums.

Decision Field Theory (DFT) is a dynamic-stochastic theory that aims at modelizing the decision-making process unconscioulsy (that is, automatically) carried out by the neural system; this process model does not rely on the implementation of a deliberate weighted average of probabilities and outcomes, but instead on an integration of information through an automatic sequencial sampling of the outcomes. The probability of the outcome determines the frequency of its sampling and the value of the outcome causes a positive (*attraction*) or negative (*avoidance*) reaction in the affective system. The affective reactions determines the *valence* of the gamble at that moment of time, and it is automatically compared with the *valences* accumulated for the alternative actions. The evidence from affective system is accumulated along the sampling process in favor of the gamble with the best valence in that moment. The motor system is inhibited to take an action (that is, choose a gamble) until the evidence accumulated for one of the actions (that is the preference state of one of the gambles) gets over a threshold, and then the decision-maker chooses it. DFT then predicts that outcomes are fixated proportionally to their probabilities, and that the number of fixations is independent from the value of the outcome; further, since it is a dynamic theory, the response time is predicted too: it increases as the options become more similar. Rieskamp (2008) showed that DFT predicts choices better than the priority heuristic.

Another process model based on automatic integration of information that has been used to explain the choice process between pairs of gambles is Parallel Constraint Satisfaction (Glöckner and Herbold (2011);Fiedler and Glöckner (2012);Stewart et al. (2016)). This model is based on the idea that the cognitive system engages in an automatic consistency-maximizing process, that is a process that aims to create a coerent mental representation of the information provided in the task .[5]. This coherence formation mechanism is essetial to reach a decision: the decision-maker activelly interprets the

[5] The coherence creation mechanism is a concept inherited by Gestalt psychology: a theory of mind where the cognitive processes interact with perception and experience in order to create a coherent mental representation of the reality. According to this approach, the elimination of the dissonance among different pieces of information about a decision is not a post-choice phenomenon, but it is the process that leads to the decision.

information so that one option looks better than the other. The PCS is a connectionist model that formalize the coherence formation mechanism through a network structure (Glöckner and Betsch; 2008). In this network the nodes are the outcomes and the final options (gambles); outcomes are connected to the options with links more or less strong depending on the probability of the outcome. The work in the network starts from an *a priori* evaluation (that may be for example due to past experience), which is linked to outcomes with inhibitory and excitatory link. The activation of the outcomes in the network changes in order to achieve a coherent choice: the information in favor of the a priori-preferred option are highlighted through excitatory activation of nodes, and information in contrast to the preferred option is inhibited[6]. Then, this process predicts an automatic compesatory integration of probability and outcomes in decision under unceratinty through the network work. Although this process of information integration and option selection is carried out automatically, deliberation may play a role in shaping the network: the deliberate activity in this framework is the decision of adding new information to the network and search for this information. Active search and adding new information to the network restructure the problem space. However, this activity is just functional to the network activity of coherence creation: the activity of the network, that is an automatic process of information integration and option selection, is the choice rule. The search strategy is not by itself the process of choice. The stragegy of search may show individual heterogeneity: it can be based on a compensatory or non-compensatory mechanism. Although there may be then differences in the attitude to scrutiny information, direct attention, and in the direction of search (within vs between gambles) that can be detected, the choice rule is based on the automatic integration of the information.

Expected-Utility-Like Models The last class of models contains those models that assume a deliberate integration of probabilities and outcomes, that is, Expected utility theory and Cumulative prospect theory. Contrary to automatic process models, these models assumes a deliberate calculation of weighted sums. Further, such a maximization process has implication for how the information is searched: all pieces of information are inspected before reaching a decision and equal attention is given to each outcome. Further, this process is static: it cannot take into account differences in response times due to the difficulty or conflict experienced in the task when option are similar.

[6]This model predicts rutine choices.However, the choices break the routine when new information is introduced in the network.

3 Research Questions

This section presents the research questions and the related literature on the choice process under uncertainty that this work aims to explore. The focus of the experimental analysis carried out is to test the alternative models of process reviewed in the literature section gathering evidence from the eye-tracking on the features of decision-making process.

First, the choice process will be analyzed and compared in small and large sets, in order to test if the features of the choice process change based on the number of options in the sets, i.e. which of the process models fits better the data in small sets and in large ones, and if it is the same one in both conditions.

Second, it is analyzed the response time both in small and large sets: it is explored its relation with *intuitive* and *deliberative* modes of thinking, and the arising of the violation of standard axioms of rationality, as the Allais Paradox.

These two groups of research questions have the common aim to investigate process variables in order to sheld light on the features of the decision process. Although the two sets of research questions may seem independent and unrelated in their presentation and in the hypotheses testing, they complement each other in the analysis of the choiche process under uncertainty.

3.1 Choice Overload and Choice Process under uncertainty

This experiment collects data on the features of the choice process under uncertainty in two experimental conditions: small choice sets and large ones; first, the subjects are present with 14 binary choices, and then with 14 choices with sets containing 10 gambles. The aim is to test if the choice process under uncertainty changes when the set size increases and if risky choices are influenced by these contexts, that is, small and large choice sets.

Overall, until now evidence on eye movements has sustained automatic processes of integration of information rather than heuristic processes or deliberate processes in two-gambles choices. However, Arieli et al. (2011) showed in an eye-tracking study that when the multiplication of probabilities and outcomes becomes more difficult, the decision maker tends to compare probabilities and prizes separately, that is a non-compesatory strategy. Then, the use of an heuristic decision strategy may be plausible when the task becomes more difficult because of the increasing number of options. Payne and Braunstein (1978) showed evidence in favor of the change of the decision strategy from compensatory to non-compensatory when the number of options increases. Payne et al. (1992) suggested that when the number of options increases the switch to non-compensatory strategies may be motivated by the lower effort required by these strategies. It is then possible that when many options are available the choice process tends to rely mostly on non-compensatory stategies or at least in a greater proportion than in small choice set. The first hypothesis that this experiment tests is then:

***Hypothesis 1*: The choice in small set is mainly based on the integration of information strategy. As the set size increses, the choice is mainly based on the use of non-compesatory strategies, or al least there is an increased tendency to use such strategies.**

In section 4 hypothesis 1 is specified analytically in terms of process variables (hypotheses from 1a to 1e), which allows to test the class of process models that fits better the data: heuristic models (non-compensatory stategies), automatic integration models or deliberate integration models (integration of information).

Also, Iyengar and Kamenica (2010) found a choice pattern consistent with the simplification of the choice strategy when many gambles are available: their experimental analysis show in large set there is a greater propoption of people that choose the risk-free option than in small sets, and they argue that this choice behavior is due to a simplicity-seeking strategy in large sets. Hence, according to the findings of Iyengar and Kamenica (2010), this simplity-seeking motivation in large sets, not only affect the process switching to non-compensatory strategies, but it affects as well the final outcome leading to choose the risk-free. The second hypothesis tested is then:

***Hypothesis 2*: The use of simpler non-compensatory strategies in larger set leads to choose more frequently the risk-free option.**

3.2 Response Time and Choice Process under uncertainty

The response time is a simple and useful measure of the choice process, and it has been often associated with the depth of cognitive reasoning in experimental analysis on choice process. In this vein, Rubinstein (2007,2008,2013,2016) proposes two typologies of players, intuitive *versus* deliberative identified through the response time: fast responders are suppposted to rely on simplified and intuitive decision rules, instead slow responders are supposed to engage in a deeper cognitive reasoning. This classification is rooted in dual-process models (e.g.Kahneman and Frederick (2002)) which suggest that decisions are influenced by two kinds of cognitive process: automatic processes that are carried out quickly and in parallels and without effort at inconscious level, and controlled processes which imply a deliberative and effortful processing, and may be perceived as conscious. Indeed, Rubinstein (2007) found that choices that are clearly a mistake are associated with quick responses. Several studies use response time to measure process exploring its relation with behavioral outcomes. In the field of behavior under uncertainty Butler et al. (2014) found that fast responders are more prone to take risk. However, the distinction between fast and slow individuals fails to account for violation of standard rationality as the Allais Paradox (Rubinstein, 2007, 2013) and decision bias (Alós-Ferrer et al.; 2016): fast and slow subjects are evenly likely to show inconsistent behavior in the Allais paradox; furthermore, the response time data fails to explain behavior in conjunction-fallacy and ratio bias in terms of automatic and deliberate processes. On one side, these findings cast doubt on the correspondence of fast and slow decisors with intuitive and deliberative modes of thinking; on the other side, the relation between differences in choice process and the violation of rationality axioms are not clear according to these results. The present experiment allows for a deeper understanding of the relation between response time and choice process; indeed, at the best of my knowledge, the relation between the response time and the mode of thinking (automatic vs deliberative) in decision under uncertainty have not been directly tested measuring other process variables related to cognitive load. The fixation duration collected with eye-tracking is a measure of the cognitive process that can be used to clarify this relation. Indeed, the short-medium fixation duration indicates the use of automatic processing; instead, long fixations indicate a deliberate and effurtful cognitive processing. The hypothesis tested is then:

***Hypothesis 3*: Slow responders show long fixations; Fast responders show short fixations.**

4 Experimental Design and Protocol

Three sessions were run in October 2017 in the WISO experimental laboratory at the University of Hamburg. The laboratory has 30 cubicles equipped with Tobii eye-trackers. Eye movements were collected at 60 Hz by the eye-trackers mounted on the desktop. 97 students of the university were recruited with hroot; 80 showed up and participated to the experiment. The eye-trackers succeeded in tracking 70 subjects[7]. The first session was run the 16th of October, and the other ones the following day. The experiment lasted one hour considering the initial alignment and calibration phases of the eye-trackers and the final payment. The participant earned on average of 12 euros including the show-up fee equal to 5 euros. [8] The experiment has 28 choices: 14 choices between 2 gambles[9] and 14 choices between 10 gambles. Participants were paid according to the gamble chosen in one of the 28 rounds chosen at random. Before the first 14 choices they had a trial round and another trial round before starting the 15th choice among 10 lotteries. All the gambles have two outcomes: one outcome is strictly positive and the other is zero. As in other eye-tracking studies with two gambles (Arieli et al. (2011); Stewart et al. (2016)), only the positive outcome and its probability were presented. The probability was presented as a percentage with its symbol "%". The monetary outcome was presented with te symbol "$"[10]

The sets with 10 gambles were constructed so that subjects were first presented with 7 *simple* gambles: the probability of each positive outcome decreased by 10% every time the positive outcome increased. The relation between probabilities and outcomes was such that a clear risk ordering was generated among lotteries, and subjects could easily choose their favourite gamble according to their own risk preferences. The second 7 gambles presented were *difficult*: the expected utility of a risk averse agent was approximately the same for all gambles and the probabilities were more similar (the probabilities may have less than a 10% difference). In each of the three sessions an exchange was proposed to the subjects: in the first session they could change the first 14 choices with a fixed monetary payment equal to 6.5 euros in case one of these rounds was drawn for payment; in the second session they could exchange the simple choices (rounds from 15 to 21) with a fixed monetary

[7] The subjects analyzed are 65, since the recording quality of a few subjects is not high.

[8] The sessions were run in English. The participants were required to be able to understand it in the invitation. The instructions were printed and put into each cubicle; the assistant read the instructions aloud at the beginning of the session, before the alignment and the calibration of the eye-trackers. The experiment was conduced by the laboratory assistant. I was in the laboratory during all sessions. The payment was carried out individually immediately after each session by the assistant.

[9] 10 out of 14 choices between pairs of lotteries were such that the Allais paradox could be tested with 5 repetitions. These 10 lotteries were taken from the work on learning in the Allais paradox by Van de Kuilen and Wakker (2006) where they showed a limited learning without feedback in 15 repetitions.

[10] it was clarified in the instructions that the 1$=1 euro

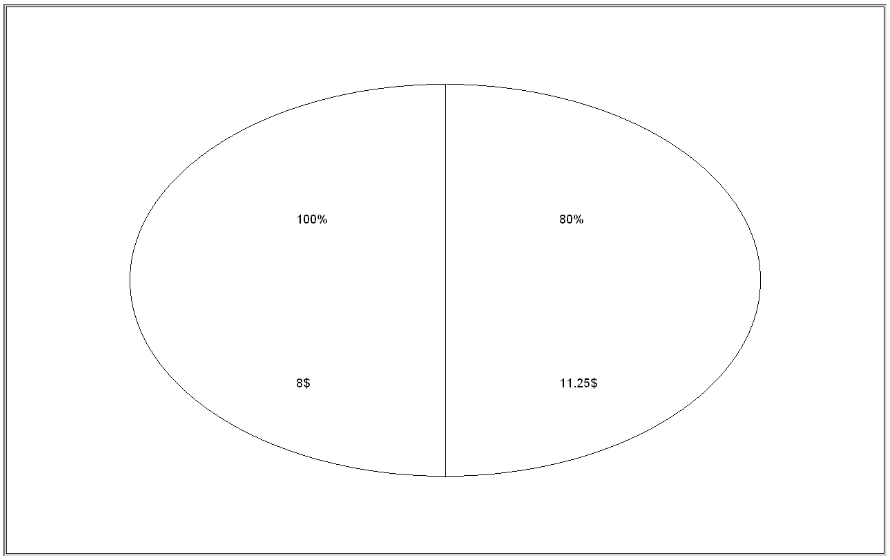

Figure 1

payment equal to 6.5 euros; in the third session they could change rounds from 15 to 27 with a fixed monetary payment equal to 6.5 euros. This between-subjects treatment was introduced to test if subjects were more convinced about their choices when they were simple, and then less willing to exchange such gambles (round from 15 to 21) than when difficult choice were included in the exchange. The pairs of gambles were presented in a ellipse as in Figure 1 and 2.

Previous studies (e.g. Fiedler and Glockner, 2012) used the ellipsoid format. The average distance among items is approximately equal across the two and ten gambles conditions. The order of presentation of the sets and the order in which information in shown in each set is random and fixed between subjects. The mouse is used to make choices (the buttons are placed around the ellipse in the area corrisponding to each lottery). At the beginning of each round subjects see a blank screen for few seconds and then a red dot appears in the center of the screen: they have to click on the dot to start the new round. This dot ensures that attention and cursor at the beginning of the round are in the center of the screen, that is approximately at the same distance from all pieces of information. The experiment was programmed in ztree(Fischbacher; 2007)[11], and subjects proceeded through rounds at their own speed [12].

[11]Response times are collected with Tobii Studio.

[12]The ztree programming was carried out by me. Using different channels between the server and the computers, the subjects were able to perform the experiment witout waiting for the other subjects during the experiment. However, once they completed all tasks, they had to wait in the cubicles until the lab assistant declared the experiment finished.

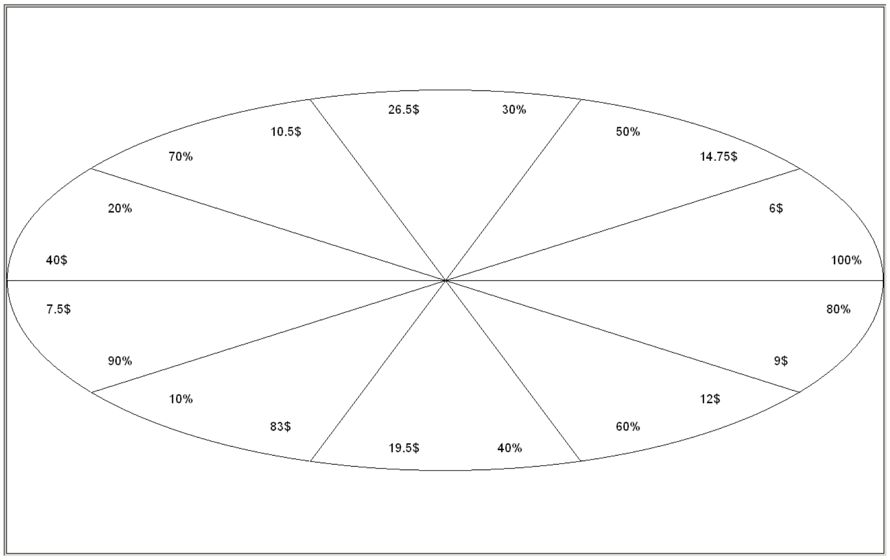

Figure 2

Table 1: Simple Lotteries' Structure

Probability	Outcome	EV	VAR	EU ($x^{\frac{1}{2}}$)	CPT-value
1	6	6	0	2.44	4.83
0.9	7.5	6.75	5	2.46	4.19
0.8	9	7.2	12.95	2.4	4.19
0.7	10.5	7.35	23.15	2.26	4.22
0.6	12	7.2	34.5	2.07	4.22
0.5	14.75	7.3	54.3	1.92	4.49
0.4	19.5	7.8	91	1.76	5
0.3	26.5	7.95	147	1.54	5.69
0.2	40	8	256	1.26	6.69
0.1	83	8.3	620	0.91	9

Table 2: Difficult Lotteries' Structure

Probability	Outcome	EU ($x^{\frac{1}{2}}$)	EV	VAR	CPT-value
1	9	3	9	0	6.9
0.95	10.25	3.04	9.7	14.47	6.14
0.9	11.75	3.08	10.5	29.2	6.22
0.85	13	3.06	11.05	45.968	6.24
0.8	15.5	3.15	12.4	76.88	6.7
0.75	18	3.2	13.5	115.4	7.23
0.65	23	3.2	14.95	187	7.9
0.5	34	2.91	17	361.25	9.36
0.45	37	2.7	16.65	421.99425	9.5
0.25	55	1.85	13.75	605	9.8

5 Hypotheses' Testing on process variables

In this section the hypotheses on the choice process are presented. As anticipated in Section 3.1, a part of the literature suggests that there is a tendency to switch to simplified non-compensatory strategies as the set size increases (Hypothesis 1), and this semplicity-seeking in choice strategy could have an effect on final choices, that is the choice of the risk-free options as a consequence of the simplicication of the strategy (Hypothesis 2).

In order to test hypothesis 1, the pricipal process models in the literature, presented in section 2, are classified in three classes: Automatic Integration[13], Deliberative Integration and Non-compensatory. The models in each class share similar features in the decision-making: table 3 summarizes the process features that characterize each class. According to hypothesis 1, we should find that process data from small sets fit one of the two classes of integration models (automatic or deliberative); and that process data from large set fit the class of non-compesatory model. The hypotheses from 1a to 1f inspect the main process variables (direction of search, fixation duration, response time, distribution of attention) and choices to test which of the different classes of process models (non-compensatory, automatic or deliberate integration) fits better the choice process in small and large sets of gambles. In the paragraph about the choices the hypotheses 2a and 2b are introduced to test the content of the hypothesis 2 outlined above. Hypothesis 3 is already specified in terms of process varables, and it will just briefly recalled.

- **Direction of Search**

  Hypothesis 1a:

  According to non-compensatory models, as Priority Heuristic, we should observe a dimensional search of information. This kind of search implies that there should be a greater number of transitions between gambles than within gambles. Further, Priority Heuristic suggests that there may be two stages of search, i.e. an initial inspection of all information before starting the between gambles search[14]. According to this hypothesis, there should be an increase of between gamble transitions along the round.

  Deliberate integration models have a clear implication for the search of strategy: since the probabilities and outcomes are integrated via a conscious calculation, the transitions within

[13]DFT and PCS are labelled as automatic integration models rather than automatic compensatory models: in these models the information is integrated, and this occurs at incounscious level since it is automatic. However, the terms "compensatory" is not overlapping with "integration" in these models; indeed, compensatory refers to the strategy of information search: in these models the way in which information is searched is not equal to the way in which is processed. In the hypothesis on the "information search" there is a more detailed explanation of the implication of the various models for information search.

[14]In many heuristics there are two stages of search; for example, in the Priority Heuristic model there is an initial inspection of all information before starting the between gambles search. However, the PH does not specify the direction of search in the first stage; it only describes the second stage search. Glöckner and Herbold (2011) tested the two stages hypothesis assuming a random search and a mainly within gamble search in the first stage. The hypothesis of two stages was rejected in both cases in the study of Glöckner and Herbold (2011). Also, Fiedler and Glöckner (2012) and Stewart et al. (2016) did not find evidence that support two stages of search

Table 3: Classification of Process Models according to Process's Features

Classes	Automatic Integration	Deliberate Integration	Non-Compensatory
Models	Decision Field Theory Parallel Constaint Satisfatction	Expected Utility Cumulative Prospect Theory	Priority Heuristic
Direction of Search **Hypothesis 1a**	Equal within and between gambles transitions/ No predictions	Mainly Within Gambles	Mainly Between Gambles
Fixation Duration **Hypothesis 1b**	Short/Medium	Long	No predictions
Response Time **Hypothesis 1c and 1d**	Not all info serched Depend on Similarity	all info serched Independent by similarity	not all info serched Independent by similariry
Distribution of Attention **Hupothesis 1e**	Not equally distrubuted	Equally distributed	Not equally distributed
Choices **Hupothesis 1f and 2**	No clear prediction	No Safe Outcome	Safe Outcome

gambles should be a greater proportion than within gambles transitions.

In the PCS model the information search shapes the network, that then integrates automatically the information: one may apply a compensatory or a non-compensatory strategy to search information, but then the information will be integrated into the network. It follows that PCS model has not a clear prediction for the direction of search, since the model allows it to occur both in a compensatory or a non-compensatory manner.

DFT is an automatic integration model: the information is sampled through a stocastic process. The implication for the direction of search is that there should be the same amount of transitions within and between gambles[15].

[15]Glockner and Herbold (2011) tested the same hypothesis on the Decision Field Theory (Hypothesis 5c in the paper): "*Information is sought according to a random sampling process which leads to an equal number of within- and between-gamble transitions.*"; however, Fiedler and Glöckner (2012) states that there is not clear predictions on the direction of search in DFT.

- **Fixation Duration**

  Hypothesis 1b :

  The mean fixation duration should be short or medium [16] if the choice process relies on automatic processes; instead, long fixations would indicate a thought and deliberate cognitive activity.

- **Response time**

  Hypothesis 1c:

  If people rely on a deliberate integration process as expected utility and CPT assume, the response time should increase proportionally to the number of options since all information have to be inspected.

  According to DFT and PCS,the formation of a preference state does not require the inspection of all information. Further, Priority heuristic does not require that all the information is searched to reach a decision, but just the relevant one according to the *reasons*. The response time may then increase less than proportionally when the number of options increases.

  Hypothesis 1d: Expected-utility-like processes and Priority-heuristic-like processes[17] predict the same average decision time for similar and dissimilar options.

  Instead, DFT and PCS predict that when options become similar it takes longer to form a preference state.

- **Distibution of attention (number of fixations) over attributes**

  Hypothesis 1e: According to an Expected-utility-like process, attention is equally distibuted over outcomes and probabilities. Further, the number of fixations on each outcome is independent from its own value and its probability.

  According to DFT, attention is distibuted on outcomes proportionally to their probabilities and independently from outcomes' values.

  According to PCS, distribution of attention over outcomes depends both on probability and outcome values.

[16] According to Glockner and Herbold(2011), fixations are categorized as short if lower than 250 milliseconds; instead, long fixations are greater than 500 milliseconds. Instead, Fiedler and Glockner (2012) categorize short fixation as lower than 150 milliseconds.

[17] PH does not predict an increasing response time in similariry, but instead in the number of reason that have to be inspected.

- **Choices**

Hypothesis 1f: The PH predicts that sure outcome is chosen. CPT-values of the sure gambles are never the highest in the sets shown. This allows to disentangle if the data fit better the choice prediction of deliberate compensatory process as CPT or an heuristic model. Automatic integration models do not make clear prediction on choices.

The hypothesis 2, presented in 3.1 is tested with two sub-hypotheses:

Hypothesis 2a:The proportion of risk-free choices is greater in large sets than in small ones. This Hypothesis is in line with the hypothesis 1, that predicts that the majority of subjects switch to non-compensatory strategies in large sets, and this imply that people choose the risk-free choice. However, it may happen that the switch for this simplicity seeking-motivation does not affect the majority of subjects. It is then test in hypothesis 2b if the subjects choosing the risk-free in the large sets are motivated by simplicity-seeking:

Hypothesis 2b: The subjects that choose the risk-free option in large sets are motivated by simplicty seeking, that is, subjects that choose the risk-free option rely more on fast non-compesatory strategies than other subjects.

The **Hypothesis 3** has been already specified in terms of process variables in 3.2: in order to test the relation between response time and the cognitive reasoning, the fixation duration of the fast and slow subjects is compared.

Table 4: Summary of findings on process variables

	Small Sets	**Large Sets**
Direction of Search	46% within gambles transitions	45% within gambles transitions
Fixation Duration	short (0.19s)	short (0.2s)
Response Time	5.8s	17.9s decreasing in similarity
Distribution of Attention	More fixation to probabilities	More fixations to outcomes
Choices	50% risk-free	15% risk-free

6 Results

6.1 Findings on Choice Process in small and Large Sets

The evidence on Hypothesis 1 is summarized by the following result:

***Result 1*: The choice process in small and large sets has the same features; automatic integration models as PCS and DFT are the ones that fit better the data.**

The hypothesis 1 seems then disconfirmed by the data, since the majority of the decision makers do not adopt non-compensatory strategies in larger sets to simplify the decision process, and there is not even a tendency to increase the use of non-compensatory strategies. Instead, they show the same eye-movements in small and large sets: a substancial amount of within and between gambles transitions (*Result 1a*) and short fixations (*Result 1b*). However, they seem to simplify the choice problem through the restriction of the set of considered items (*Result 1c*), that is, they rectrict the percentage of information inspected in large sets. Overall, these findings suggest that people apply an automanic integration of information both in small and large sets, and they simplify the choice process by resticting the amount of information considered as the set size increases. The hypotheses tested on the process variables (hypotheses 1 from a to f) conduce to *Result 1*. The evidence on the hypotheses on each process variable and on choices is summarized in table 4 and is analytically described in the rest of this section[18].

- **Direction of search**

[18] In the appendix it is explained how the metrics for the data analysis were worked out.

***Result 1a*: There is a substancial amount of both within and between gambles transition both in small and large sets. This evidence sustains the class of automatic integration models.**

There is a substancial amount of transition within and between gambles in both two and ten option sets.
In two gamble sets the total amount of transition is 6821 [19]. Subjects do on average 47% of within gamble transitions and 53% of between one. Between gambles transitions are significantly more frequent than within gambles one according to a T-test (p-value=0.005).[20].

In ten gamble sets the total amount of transitions is 2814.Subjects on average do 45% of within gamble transitions and 55% of between gamble transitions; according to a T-test, this difference is significant (p-value=0.0002). Further, there is approximately same proportion of within and between gamble transitions in small and large sets: a T-test finds no significant difference in the mean proportion of the within gamble transitions in small and large sets. Altough the differences between are significant, the process seems characterized by a substancial amount of both types of transitions. Condidering Hypothesis 1a, these findings are in line nor with a pure compensatory model (as the expected utility theory and cumulative prospect theory) that would predict a substancial dominance of within gambles transitions neither with a pure non-compensatory model (as Priority heuristic) that would instead predict a substancial dominance of between gambles respectively. Indeed, altough there is a statistical significant difference between the amount of between and within gambles transitions, none of the two types of transition seems to dominate the process. This finding is then in line with the class of automatic integration models. Indeed, Decision Field Theory predicts an equal amount of within and between gamble transitions. This evidence suggests then that the findings on

[19]The transitions between Areas of Interest (AOIs) of the same gamble are classified as a *within* gamble transition. The transitions between AOIs of different gambles are classified as *between* gambles transitions. Fixations outside the areas of interest are not condidered. Sequencial fixations to the same AOIs and fixations that cannot be attributed only to one area are not considered in the analysis. Further explanations on how the between and within tranistion metric was computed in the appendix.

[20]The variable used for this analysis is a dummy variable that assume value 1 if the subject do a within gamble transition and 0 if the subject do a between gamble transition. A subject cannot do a within and a between transition in the same moment obviously, but he/she can do a certain amount of both type of transition in the same decision. For each subject it is computed the proportion of within gamble transition in each round. For the statistical test, the T-test, it is considered the mean proportion across round for each subject- taking the average proportion, there is no need to account for the repeated measurement. The test has as a null hypothesis that the mean proportion is equal to 0.5

the direction of search supports the class of automatic integration models. This finding on transitions is at the extreme of the literature: Stewart et al., Glockner and Herbold (2011), and Fielder and Glockner (2012), find a dominance of within gambles transitions, ranging from 61% to 83% of the total amount in two gambles choices. The present findings are closer to Arieli et al. (2011) that find an amount of within gamble transitions that ranges from 55% to 43% depending on the difficulty of the choice task.

In order to explore if the search stategy changes over the decision process, the dynamic along the round of different types of trasitions is explored[21], dividing the fixations in two blocks: the first half of the fixations belongs to block one the the second half to block two. The frequency of within and between gamble transitions in compared in each fixation block. In two gamble choices, there is a significantly lower proportion (46%, p-value=0.0003 in the binomial test) of within gambles transitions in the first fixation block. In the second fixation block there is instead the same proportion of within and between gambles transitions. Differently from previous findings (Stewart et al. 2016, Glockner and Hebold 2011, Fiedler and Glocker 2012), there is then a significant difference along the decision process. However, this difference is small, and there is still a substancial amount of both kinds of tranistions. In ten gambles choices, there is a significantly lower proportion (48%, p-value=0.0002 in the binomial test on the first fixation block, p-value=0.0001 in the second fixation block) of within gambles tranistions in the both the first and the second fixations blocks. Overall, this findings show that there is a substancial amount of between and within gambles transition both in the first part and in the second part of the choice process, but there is a tendency to decrease the between gamble transitions. A better understanding of the existence of stages would require a division of fixation is smaller blocks or a time bins analysis as in Fiedler and Glockner (2012).

- **Fixation Duration**

***Result 1b*: Fixations are short both in small and large sets. This sustains automatic integration models**

[21]The original version of the prospect theory (Kahneman and Tversky, 1979) suggests that there is an ediding phase where there is a screening of information before starting the integration of probabilities and outcomes. Also, Priority Heuristic considers the possibility of an initial integration of information computing approximate expected values before staring the search between gambles.

The average fixation duration is 190 milliseconds (SD=2ms) in two gamble choice, and 200 milliseconds (SD=1ms) in ten gamble choices[22]. According to the literature, these fixations are categorized at the border between short and medium. Considering hypothesis 2, the choice process is then based on the automatic processes rather than on deliberative ones; this average fixation duration support DFT and PCS.

- **Response time**

***Result 1c*: The response time increases less than proportionally to the number of options: the consideration set is smaller in large choice sets, where not all the information is inspected. This evidence supports automatic integration models and Priority Heuristic.**

The average response time in two gambles choice is 5.8 seconds and in ten gamble choices is 17.9 seconds. Since the fixation duration is approximately unchanged (0.19 versus 0.2 milliseconds), and the time spent on the decision increases less than proportionally to the number of choices, the subject inspected a lower amount of information in ten gamble choices than in two gamble choices. Further, since the average number of fixations on each item is 2 (SD=0.05) in two gambles choices and 3 (SD=0.02) in ten gamble choices: the considered gambles are inspected more carefully.

This evidence suggests that as the number of gambles increases the consideration set becomes smaller: considering hypothesys 1c, this evidence does not support a Expected utility and Cumulative Prospect theory, where all the expected utilities/porspect values should be computed. This evidence is in line instead with PCS, DFT and PH.

***Result 1d*: There is positive relation between similarity of the options and the increase in the response time. This evidence support automatic integration models.**

Considering Hypothesis 1d, the response times in simple (round 15 to 21) and difficult choices (round 22 to 28) is compared. This categorization (simple vs difficult) relies on the assumption that the similarity among choices increases the conflict experienced in decision and then it increasse the average response time. Fieldler and Glockner (2012) show that the similarity of the expected values of the gambles in the set leads to an increase in response times. Janowski

[22]These averages are computed taking the average fixation duration in probability and outcome AOIs of each subject across rounds in small and large sets.

and Rangel (2012) find fewer fixations for less similar gambles. Stewart et al. (2016) show that the lower is the difference between probabilities the greater is the response time. In the present study, the increased similarity is achieved in terms of more similar expected utilities for risk-adverse subjects and closer values of the probabilities among gambles. The average response time in simple (less similar) choices is greater than in difficult (more similar) ones: on average 21 seconds in simple choices and 17 seconds in difficult choices. The hypothesis that increased similariry should make the choice more difficult and then the response time should increase seems not confirmed by the data. In order to explain the difference of the present result from predictions and past evidence on two gamble choices, the response time is regressed on the round number. The regression, reported in Table 5, shows a negative time trend: the response time in the two gamble choice sets is regressed on the round number with controls (age, education and sex); the trial number has a negative coefficient equal to 252 milliseconds (p-value=0.0001). The same regression in the 10 gamble choice set shows that the trial number has a negative coefficient equal to 1225 millisecods (p-value=0.0001). Hence, the response time decreases over the course of the experiment probably due to learning. This learning effect may confound the effect of the similarity of the options in the set since dissimilar and similar choices are presented sequencially instead of being randomized. Also, in the regression on response time in large choice sets it is introduced a dummy variable equal to one for difficult choices (rounds 22 to 28) and zero for simple choices (rounds 15 to 21): this variable has a positive and significant coefficient equal to 5963 (p-value=0.001). Hence, there is the tendency to increase the response time in round from 22 to 28, that is in difficult choices, but this increase is offset by the learning effect. Further, the data on the acceptance of the exchange offer show that in session 2 where the exchange was proposed for simple options (rounds 15 to 21), the exchange was accepted just by one subject out of 29; instead in session 3 where the exchange included difficult choices (rounds 15 to 27), 4 subjects out of 29 accepted. Although the acceptance rate is not statistically different in session 2 and 3 according to the Wilcoxon-Mann-Whitney Test (p-value=0.16), this evidence suggests that the subjects are less convinced of their choices when difficult choices are introduce and they are then more willing to accept the exchange. The exchange effect might have been significant if in session 3 the exchange would have been proposed only on difficult choices (round 22 to 28) rather then on the whole set of 10 gambles choices. According to hypothesis 1d this evidence fits DFT and PCS predictions, and instead such a result cannot be explained by expected utility-like models and Priority Heuristic that predict the same respose time for similar and dissimilar choices.

Table 5: Response time in small and large sets

This table displays the results of two regressions of the response time measured in milliseconds on the round number. *Difficult* is a dummy variable equal to 1 in round from 22 to 28, otherwise 0.
Demographic controls are: *Sex* equal to 1 if Male; *Age* equal to 1 if lower than or equal to 25 years, otherwise 2. *Education* equal to 1 if bachelor student, otherwise 2. In the second column the number of fixations to AOIs where are placed probabilities is regressed on the same variables.
.

VARIABLES	(1) Response Time Small Sets	(2) Response Time Large Sets
Round	-252.7***	-1,225***
	(28.20)	(230.1)
Sex	244.5	1,346
	(244.6)	(978.4)
Age	693.2***	326.1
	(247.1)	(1,003)
Education	388.0	1,560
	(259.0)	(1,040)
Difficult		5,963***
		(1,861)
Constant	6,187***	22,626***
	(472.5)	(1,981)
Observations	877	845
R-squared	0.098	0.047

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

- **Distribution of attention**

***Result 1e*: The distribution of attention is different is small and large sets: probabilities are fixated more often than outcomes in small sets; and outcomes are fixated more often than probabilities in large sets. This evidence is in contrast with Expected-Utility-like models, where attention should be equally distributed on probabilities and outcomes.**
Both in small and large choice set the attention to probabilities and outcomes is influenced in a small but significant way by probabilities' values. However, overall the effect of items values on fixation is negligible.
This evidence fits automatic integration models.

In two gamble choices the mean number of fixations on each outcome item is 2.5 and the mean number of fixations on each probability item is 3. This difference is significant (p-value=0.0001, number of observations=66) according to a t-test[23] that compares the average number of fixation of each subject on outcome items and on probabilities items. Subjects looked more frequently to probability than to outcomes. The average duration of fixation on outcomes (0.18 seconds) is slightly lower than the one on probabilities (0.19 seconds), and this difference is significant (p-value=0.007, t-test, number of observations=66)[24]. Considering hypothesis 1e, this evidence is not in line with the expected-value-like models that would predict that the same amount of attention is given to outcomes and probabilities. In order to explore the factors that drives attention to outcomes [probabilities], the number of fixations on outcomes [probabilities] are regressed on outcomes' and probabilities' values. In order to account for the repeated measurement on the same subjects, the regression is a mixed model with random intercept and slopes for outcome and probability values. The round number is introduced to control learning, and the display position to capture biases in attention toward specific areas of the screen. Also, demographic variables are controlled (sex, age and education). Regression result on small choice set are reported in table 6 and on large choice sets are reported in table 7.

[23]Since for each participant is taken the average over all the two gamble rounds of the number of fixations to outcomes and to probabilities, the statistical test does not need to take into account correlation among observations because of the repeated measurement on the same subject.The Number of fixation on each item is the number of fixation within the AOIs containing it, and this metrics is taken directly from Tobii-Studio.

[24]SAs in the fixation number, for each participant is taken the average ficxation duration over all the two gamble rounds to outcomes and to probabilities.The average fixation duration on each item is duration of fixation on the AOIs containing it, and it is taken directly from Tobii-Studio.

Table 6: Distribution of Attention in two gamble sets

This table displays the results of two regressions with mixed effect: random intercept and random effects for outcome and probability values; In the first column the number of fixations to AOIs where are placed outcomes is regressed on the values of the outcome fixated , *Outcome Values*, and on the values of the probability associated to .that outcome, *Probability Values*. The *Display* is a dicotomical variable that assume value equal to 1 when the gamble considered is placed on the right, and equal to 2 when on the left; it controls for attention biases. *Round* ranges from 1 to 14, according to the round number where the outcome where shown; it controls for learning.*Session* is a discrete variables that ranges from 1 to 3 according to the number of the session. Demographic controls are: *Sex* equal to 1 if Male; *Age* equal to 1 if lower than or equal to 25 years, otherwise 2. *Education* equal to 1 if bachelor student, otherwise 2. In the second column the number of fixations to AOIs where are placed probabilities is regressed on the same variables.
.

	(1) Fixations to Outcomes	(2) Fixations to Probabilities
Outcome Values	0.06 (0.05)	-0.01 (0.04)
Probability Values	-0.01* (0.001)	-0.02*** (0.001)
oV*pV	0.001 (0.0008)	0.001** (0.0008)
Display	-0.007 (0.11)	0.16 (0.10)
Round	-0.15*** (0.11)	-0.18*** (0.01)
Session	0.32 (0.25)	0.38 (0.25)
Sex	0.15 (0.39)	0.01 (0.37)
Age	0.14 (0.39)	-0.2 (0.37)
Education	-0.03 (0.41)	0.17 (0.39)
Constant	2.45** (1.0)	4.33*** (1.02)
Number of observation: 1792; Number of Subjects:64		
LRtest	chi2(3)= 691 p-value=0.0001	chi2(3)= 486 p-value=0.0001

Table 6 show that in small sets the number of fixations to an outcome depends on the value of its probability and not on its own value. According to hypothesis 1e, this evidence supports DFT, where the number of fixations to an outcome are proportional to the probability and independent from outcome value. Instead, PCS predicts that the number of fixations to the outcome depends both by outcome and probability values[25] The fixations to probabilities is influenced negatively by probability's value (low probability are fixated more frequently) and

[25]This latter result is different from Fiedler and Glöckner (2012) that instead find evidence in favor of PCS.

Table 7: Distribution of Attention in ten gamble sets

This table displays the results of two regressions with mixed effect: random intercept and random effects for outcome and probability values and their interaction;
Difficult is a dummy variable equal to 1 in when in the choice sets there are similar options; otherwise 0
.

	(1) Fixations to Outcomes	(2) Fixations to Probabilities
Outcome Values	0.00110	0.00539*
	(0.00350)	(0.00279)
Probability Values	0.00678***	0.00656***
	(0.00261)	(0.00194)
round	-0.146***	-0.118***
	(0.0144)	(0.0121)
display	-0.103***	-0.0564***
	(0.0102)	(0.00855)
OV*PV	-0.000120	-0.000179***
	(7.45e-05)	(6.22e-05)
difficulty	0.768***	0.688***
	(0.119)	(0.0999)
session	0.705***	0.445**
	(0.271)	(0.182)
Sex	0.297	0.0956
	(0.404)	(0.272)
Education	-0.0178	-0.0513
	(0.427)	(0.287)
Age	-0.647	-0.374
	(0.408)	(0.274)
Constant	4.670***	3.810***
	(0.962)	(0.664)
Observations	8880	8880
Number of groups	64	64

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

positively by outcome's value.

The analysis of the distribution of attention in 10 gambles sets shows that the distribution of attention is different from small sets: differently from small sets, probabilities are fixated significantly less often than outcomes (2 average fixation to each probability and 2.4 average fixations to each probability; t-test, p-value=0.0001, 66 observations). As in small sets, the fixations to probabilities are slightly longer than those to outcomes (average fixation duration to probabilities is 0.2s and to outcome is 0.19s, t test, p-value=0.0001, 66 observations). The regression analysis in tables 7 shows the drivers of attention in large sets: the main difference with respect to small sets is that in large set the fixation to probabilities are positively related to probabilities as well as outcome values[26]. The outcomes seems to gather increased attention in larger sets.

Additionally, in *difficult* choices in large sets the number of fixations is higher both on outcomes and on probabilities. This latter finding is in line with the argument of previous paragraph about the increased difficulty of choices in the rounds from 22 to 28.

- **Choices**

In two gamble sets the risk-free option is chosen 203 times out of 397[27], that is approximately 50% of times. In ten gamble sets the risk-free option is chosen 154 times out of 1066 (14 choices with ten gambles and 76 subjects)[28] choices, that is 15% of times. These percetanges show an opposing finding with respect to the one of Iyengar and Kamenica (2010). Indeed, in their work, they find that the risk-free choice is chosen by 16% of subjects in the small set, and by 60% of subjects in the large set. These first result seems then to disconfirm hypothesis 2 in terms of final choices:

***Result 2a*: The risk-free option is chosen more frequently in the small sets, than in large sets**

However, the gamble sets have partially a different structure from the ones of Iyengar and Kamenica (2010). In the present experiment the small sets have two options instead of three. Further, the lotteries in the large sets have have different CPT-values, and in particular the risk-free option never have the higher CPT-value;instead in Iyengar and Kamenica (2010) the CPT-vales are approximately the same for all gambles. This feature about CPT-value was chosen in the present experiment in order to disentangle the predictions of CPT from those of Priority Heuristic that always predicts that the risk-free option is chosen[29]. Even if we extend the prediction of the PH to the case in which the gamble with the highest outcome is chosen,

[26] Overall the effects of the probabilities' values on the number of fixations are very small even when significant both in small and large sets. Also Stewart et al. (2016) reached a similar conclusion on the relevance of probabilities and outcomes values on attention.

[27] There were considered only the rounds where the risk-free option was available, that is rounds 1,4,8,10,11,13

[28] There were collected the choices of 76 persons, even if just 66 were succesfully tracked by eye-tracking

[29] According to the Priority Heuritic the sure gambles should be chosen at least by the majority of subjects following the *reason* of the highest probability

the number of choices that in large sets fits the maximum outcome or the maximum probability predictions from Priority Heuristics are 268, which is still far from the 50% of choices. Furthermore, in order to test if the gambles that have the highest prospect values were chosen more frequently, an index based on the cumulative prospect value of the gambles is considered; the index on CPT-value is constructed in this way: in each choice set the gamble with the highest CPT-value is the number one, the gamble with the second highest CPT-value is the number two, and so on until the tenth gamble. The median of this index for all choice sets is 6. Hence, the CPT-value is not a good predictor of choices in ten gamble sets according to this simple index. Overall, choices in large sets show a tendency of the subjects to be risk averse; a simple index where the lotteries in each large set are ordered from the less risky to the most risky shows that the 4th less risky choice is the median in these sets.

***Result 1f*: CPT and Priority Heuristic do not predict accurately choices in large sets.**
The subjctes show risk aversion both in large and small sets.

6.2 Findings on the process underlying the risk-free choice in small and large sets

As we see in previous section of the results, hypothesis 2 was partially disconfirmed (result 2a) because there is not an increased tendency to choose the risk-free choice in large sets. However, the majority of people do not switch to simpler non-compensatory strategies, as shown in Resul 1, and this may explain why the majority also did not choose the risk-free option as predicted. In order to test if in larger sets those who choose the risk-free option are motivated by simplicity seeking, the choice process of subjects that chose the risk-free option in large sets is analyzed in order to test if they use non-compesatory stategies in an increased proportion than the subjects that did not choose the risk-free option in large sets.

In ten gamble choices those who chose the risk-free option show the same rate of within gamble transitions as those that chose the risky option according to the regression reported in Table 8. Further, in Table 9 the regression show that those who choose the risk-free are not slower or faster than the others.

Table 8: Transitions in Large Sets and Risk-taking

This table displays the results of a regression with mixed effect: random intercept and random slopes for *Response Time* and *Riskfree* variables. The dependent variable is the *Proportion of within gamble transitions* of a subject in a round. *Response Time* is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round. The regression controls for Sex, Age, Education, Session and Round. The regression with the control is in the appendix.
.

	Proportion of within Gamble Transitions
Riskfree	-0.0125
	(0.0145)
Response Time	-0.0228***
	(0.00866)
Constant	0.638***
	(0.103)
Observations	824
Number of groups	61

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Response Time and Risk in Large Sets

This table displays the results of a regression with mixed effect: random intercept and random slope for *Riskfree* variables. The dependent variable is the *Response Time* of a subject in a round, and it is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round. The regression controls for Sex, Age, Education, Session and Round. The regression with the control is in the appendix.
.

	Response Time height
Riskfree	-0.0796
	(0.0682)
Constant	9.861***
	(0.259)
Observations	824
Number of groups	61

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In two gamble choices, the choice process of invididuals who chose the risk free options (or the less risky one) has almost the the same feature of those who chose the risk-free in the ten gamble sets: the regression in table 10 they do not relies more on between gamble transitions with respect to those who did not choose the risk-free options; additionally, as in large sets, table 11 shows that they are neither slower nor faster than the other subjects.

This latter result is not in line with the findings of Rubinstein (2013) and Butler et al. (2014) that show that the slower decision makers are more prone to avoid risk. Hence, the choice of the low risky option, both in small and large sets seems not guided by a simplicity-seeking motivation rooted in the strategy of choice: there are not different process associated with

Table 10: Transitions In Small Sets and Risk Taking

This table displays the results of a regression with mixed effect: random intercept and random slopes for *Response Time* and *Riskfree* variables. The dependent variable is the *Proportion of within gamble transitions* of a subject in a round. *Response Time* is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round. The regression controls for Sex, Age, Education, Session and Round. The regression with the control is in the appendix.
.

	Proportion of within Gamble Transitions
Response Time	0.0660***
	(0.0248)
Riskfree	0.0145
	(0.0205)
Constant	-0.0129
	(0.234)
Observations	416
Number of groups	32

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Response Time and Risk in Small Sets

This table displays the results of a regression with mixed effect: random intercept and random slope for *Riskfree* variables. The dependent variable is the *Response Time* of a subject in a round, and it is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round. The regression controls for Sex, Age, Education, Session and Round. The regression with the control is in the appendix.
.

	Response Time
Riskfree	-0.0460
	(0.0369)
Constant	8.482***
	(0.269)
Observations	416
Number of groups	32

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

different types of choices, that is risky *versus* not risky.

***Result 2*: Both in small and large sets the subjects who chose the risk-free options do not rely more on non-compensatory strategies, are not faster than the subjects who did not choose the risk-free.**

6.3 Discussion on choice process in small and large sets

The findings on process and choices reported in this section show that the automatic integration models as PCS and DFT, fit the data from both small and large sets. Hence, these findings do not confirm the hypothesized simplification of the choice problem in large set through switching to non-compensatory strategies for the majority of the subjects (Result 1). The majority of subjects relies on automatic integration processes. Also, subjects restrict the consideration set. Hauser (2013) suggests that the formation of consideration sets is rational according to the cost-benefit trade-offs faced by consumers in large sets. Also, PCS suggests that deliberate strategies can be used to affect the information that goes to the automatic network. The deliberate strategies that decides which information will be processed have the purpose of easing the work in the network. According to the framework of PCS, the restriction of the information search may be a deliberate strategy to deal with the increased complexity of the environment, even if the information collected is then automatically integrated.

There is not heterogeity in the choice process in term of search strategy and response time between the subjects that choose a risky option and a risk-free (or low rirsk) one both in small and large set. It is the disconfirmed the hypothesis that non-compensatory strategies play a major role in large sets and lead to simpler choices as choosing the least risky options (Results 2).

6.4 Findings on Choice Process and Response Time

Fixation duration The average fixation duration of fast and slow subjects is not statistically different (T-test test, p-value=0.15): 0.18 for fast subjects and 0.19 for slow subjects. Although different response times may suggest that subjects are using different level of reasoning (Rubinstein,2013), the fixation duration, that is an indicator of the depth of reasoning, is not different. Hence, this evidence does not confirm hypothesis 3. In order to explore if there are differences in the choice process of fast and slow subjects, the other process variables are analyzed.

Direction of Search The direction of search in terms of types (within vs between gambles) of transitions is different for fast and slow subjects: fast subjects rely more on between gambles transitions than on within ones: Table 8 and 10 show that when the response time increases subjects rely more on within gamble comparisons. The slow subjects seems then to apply a more systematic information search.

Overall these findings on fast and slow subjects' process show that they apply the same decision process based on automatic integration of information, since the fixations are short for both categories. Instead, they are different in the search strategy applied: fast subjects rely more on a non-compensatory search than slow subjects. According to PCS, the search strategy is a deliberate rule that subjects decide to apply, and hence the fast and slow subjects seem to implement different strategies at this level. Instead, DFT cannot easily accont for this difference in search strategies since every subjects should follow the same stocastic process. In relation to hypothesis 3 on fast ans slow subjects the result is:
***Result 3*: Both fast and slow subjects rely on automatic processes of information integration; The main difference is in how they search information to process: slow subjects apply a more systemtic search strategy than fast subjects.**

Choices Even if in the choice process fast subject search information differently, these feature seems to have not an effect on final choices since slow and fast subjects choose equally often risky options both in small and large sets (Table 9 and 11).

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7 Conclusions and Directions for Future Research

According to the evidence provided by this experiment, the choice process in small and large sets show the same characteristics: short fixations, a substancial amount of both within and between gambles transitions and sensitivity of the response time to the difficulty of choices. These features of the choice process fit with dynamic models of choices based on sequencial sampling (Decision Field Theory) or a network connections (Parallel Constraint Satisfaction) that automatically integrate and compares gambles. This results confirms findings on choice process under risk in sets with two gamble sets(e.g.Fiedler and Glöckner (2012);Stewart, Hermens and Matthews (2016);) and add to previous findings the evidence on large sets. There is the tendency in large sets to simplify the decision making process resticting the consideration sets. Future reseaches on which options are included in the consideration set in large choice sets may give useful insight on the choice process when many options are available.

Analyzing the choice process conditional to choices, it seems that those who choose a risk-free and a risky option do not have different features of the decision process; in future research it could be interesting to explore the relation between process models and choice with a more sophisticated analysis than the present one: classifying the typologies of decision makers according to choice models using mixture models and looking at their process features. Also, even if the increased dimension of the set did not lead to adopt non-compensatory strategies,a topic for future reserch could be the analysis of choice process in large set where the simple risk-free option is not available and under time pressure. These settings may lead to an increased use of non-compensatory strategies.

Finally, the analysis of the fast and slow subjects show that they rely both on automatic processing of information, and the are instead different in the search strategy: slow subjects serch information in a more systemtic manner. This heterogenity in the search strategy, although both types of subjects rely on automatic integration, can be explained in the framework of PCS theory. Since the response time it is a useful and easy tool to study the choice process, its relation with the search strategy and the implication for the final choice it is a promising topic for future research.

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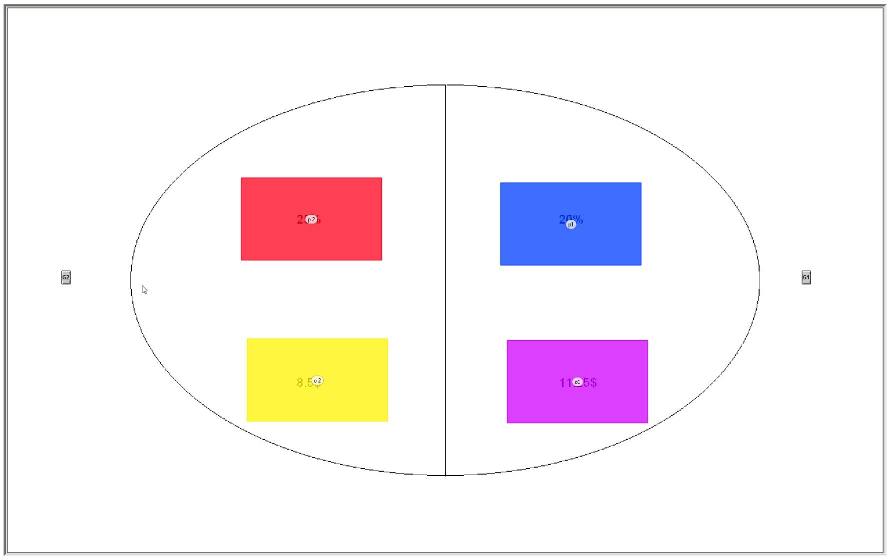

Figure 3: AOIs Small Sets

Appendices

1. **Process Variables from eye-tracking**
   In this section of the appendix it is explained how the process variable used in the data analysis are worked out from raw data. Most of the metrics used are taken directly from Tobii Studio, a software implemented by the provider of the eye-trackers.
   The *Area of Interests (AOIs)* were defined manually on Tobii-Studio on the media shown during experiment, that is, the images with 2 or 10 gambles.Each AOI include one item, that is, one of the outcomes or of the probabilities. There are few AOIs that have a small overlapping, then it may happen that one fixation belongs to two AOIs, but it is very infrequent. The following pictures show the AOIs drawn in small and large sets' in figure 3 and 4:
   In order to calculate the *Fixation Duration* and the *Number of fixations* on each outcome and on each probability it is used the command "Fixation Duration - seconds" in Tobii-Studio: this metrics measures the duration of each individual fixation within an AOI. I used this metric with the option "MEAN" that provides the average fixation duration in each AOIs and "N" that provides the number of fixations in each AOIs.
   The *Response Time* in each round is collected by Tobii-Studio with the command "SceneSegmentDuration" which measures in millisecond the duration of each scene, that in the experiment is the duration of the round: each scene starts when the lotteries appears on the screen and it ends when the subject press the botton to go on.
   The *Transitions* are computed in the following way: data are exported from Tobii-Studio with the command "FixationIndex" and "AOI[Name of AOI]Hit". "FixationIndex" gives the fixations of each participant in order, from the first to the last. In every fixation it is reported the value of each AOIs: the value is equal to 1 if the fixation is in the AOIs and zero if it is outside. Hence, each fixation can be attributed to one AOIs. Since the fixations are in sequencial order, it is posible to infer how the attention moved: between two AOIs of the same gamble (within-gamble transition) or between two AOIs of different gambles (between-gamble transistion). When two sequencial fixations belongs to the same AOIs it is not considered as a transition. Further, when one fixation does not belong to any of the AOIs or it belongs to more than one AOIs , that fixation is not considered. The count of fixations was programmed with Excel so that is was done automatically.

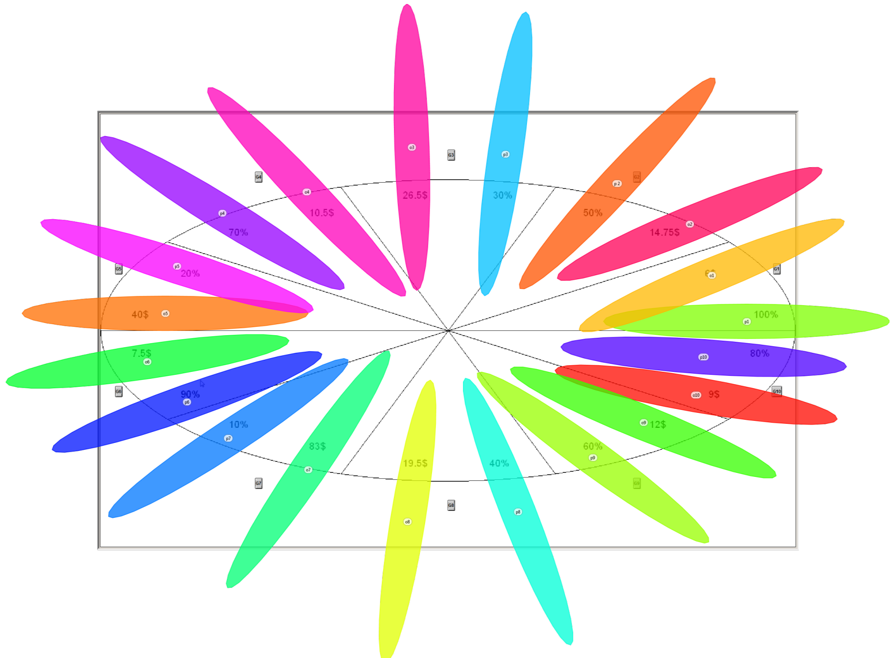

Figure 4: AOIs Large Sets

2. **Instruction**

This experiment has 28 rounds. In each round you will be presented with gambles, and you should decide which of the gambles you would prefer to play. In the end of the experiment, one round will be randomly selected for payment. The gamble that you chose in the selected round will be automatically played by the computer and your earning will be shown to you on the final screen. In each gamble you have a chance to win a positive monetary prize, and the complementary chances to receive nothing. Then, the chances to get the positive prize and to get nothing have to sum up to 100.

Each lottery that you will face will have the same structure of this example:

Gamble : $(80\%, 7\$)$

The number with the percentage "%" indicates the chances you have to win the prize, and the number with the dollar "$" indicates the amount of the monetary prize, where 1=1euro,2= $2euros$ an so on. In this example you would have 80 chances out of 100 of receiving 7 euros, and 20 chances out of 100 of receiving 0 euros. Now there are two examples of gambles to let you familiar with this structure of the gambles:

Example 1

Gamble: $(100\%, 10\$)$

In this gamble you have 100 chances out of 100 to win 10 euros: if you chose this lottery, you would earn 10 euros for sure.

Example 2

Gamble: $(10\%, 50\$)$

In this gamble you have 10 chances out of 100 to win 50 euros, and 90 chances out of 100 of receiving 0 euros.

At the beginning of each round you will see a blank screen for a few seconds and then a red point in the center will appear. You have to press the red point to start that round.

In the first 14 rounds you will choose between 2 gambles which one you would play. In the last 14 rounds you will choose among 10 gambles. At the beginning of the experiment you will be asked to answer to two questions on the screen to control that you correctly understood the

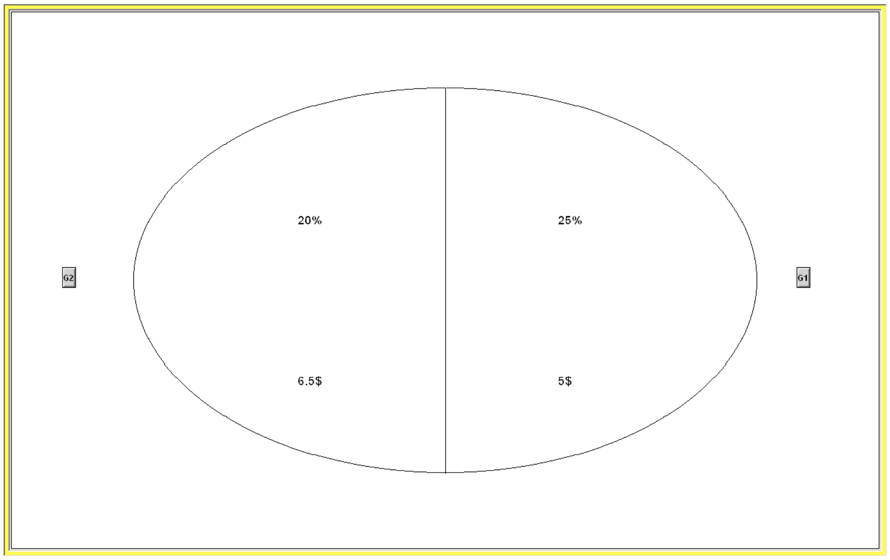

Figure 5

gambles' structure. You will be then see detailed instruction for choosing between two lotteries. You will play a trial round before starting the actual experiment: your choice in the trial round will not be part of the round that may be drew for the final payment. After the first 14 rounds, you will see on your screen detailed instruction for choosing among ten lotteries, and you will play a trail round. At the end of the experiment, you will be asked some questions about you that will note affect the final payment Please note that all the data collected during the experiment and the final questionnaire will treated anonymously.
Please remember that you are not allow to take notes, use phones or other devices during the experiment.

Control questions

(On the screen)

Consider the gamble (40%, 20$). If this gamble would be played, how many chances out of 100 you had to obtain 0$?
Consider the gamble (100%, 7$). If this gamble would be played, how many chances out of 100 you had to obtain 0$?

Instruction rounds with 2 gambles

(On the screen)

In the first 14 rounds you will be presented with pairs of gambles plotted in a circle like the ones in the picture. The right part of the circle is one gamble, and the left part is the other one. For each gamble, you are shown the chances you have of winning the prize (%) and the amount of the prize ($). If you want to select the gamble on the right, click the button on right side "G1". If you want to select the left gamble click the button on the left side "G2". Once you press one of the two buttons your choice is collected and you go to the next round. In the next sceen, you will play a trial round, then the experiment start. Remember that the trial round is not part of the rounds that can be used to determine your final payment.

Exchange offer

(Session 1)

In case one of the last 7 choices that you have done in this first section of the experiment is randomly drew for your final payment, would you exchange the monetary outcome that you obtained in this section for a fixed monetary payment of 6.5 euros? If you accept the exchange,

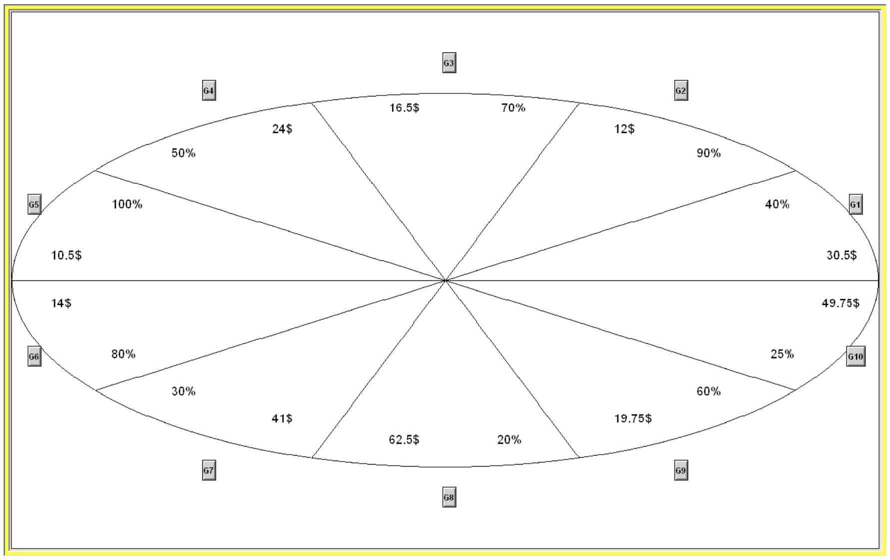

Figure 6

in case one of the rounds from 15 to 11 is selected for payment, you will receive 6.5 euros whatever is the outcome of the lottery.
Please click "YES" if you are willing to accept the exchange. Otherwise, click "NO".
(Next Screen)
Please, note that, indipendently by the fact that you accepted or not the exchange, you will no more receive this kind of offer for the following rounds.
Instruction rounds with 10 gambles
(On the screen)
In the following 14 rounds you will be presented with 10 gambles plotted in a ellipse like in the picture. The ellipse is divided into parts, and each part correspond to a gamble. For each gamble, you are shown the chances you have to win the prize (%) and the amount of the prize ($). Click the button next to the gamble that you want to select.
For example, if you want to select the gamble where the chances to win are 30 out of 100 and the prize is 41$, click on the button "G7".
Once you click one button, you leave the round. Now you play one trial round before starting.

Table 12: Transitions In Small Sets

This table displays the results of a regression with mixed effect: random intercept and random slopes for *Response Time* and *Riskfree* variables. The dependent variable is the *Proportion of within gamble transitions* of a subject in a round. *Response Time* is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round.

.

	Proportion of within Gamble Transitions
Response Time	0.0660***
	(0.0248)
Riskfree	0.0145
	(0.0205)
sex	-0.0183
	(0.0420)
education	0.0325
	(0.0458)
age	-0.0472
	(0.0428)
SESSION	-0.0451
	(0.0475)
round	-0.00131
	(0.00243)
Constant	-0.0129
	(0.234)
Observations	416
Number of groups	32

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Gambles in order of presentation													
2 gambles' sets													
1		2		3		4		5		6		7	
1	8	0.25	8.5	0.25	6	1	6.5	0.25	7.5	0.25	7	0.25	6.5
0.8	11.25	0.2	11.25	0.2	7.75	0.8	9	0.2	9.5	0.2	9.25	0.2	9
8		9		10		11		12		13		14	
1	7.5	1	8	1	7	1	8	0.2	8	1	9	0.25	9
0.8	9.5	0.8	11	0.8	9.25	0.8	11	0.25	11	0.8	11.5	0.2	11.5

Figure 7: Lotteries in Small Sets

10 gambles' sets													
simple1		simple2		simple3		simple4		simple5		simple6		simple7	
probability	outcome	p	o	p	o	p	o	p	o	p	o	p	o
1	6	1	5	1	7.5	1	8	1	7	1	5.5	1	9
0.9	7.5	0.9	6.75	0.9	8.5	0.9	9.5	0.9	8	0.9	7	0.9	10
0.8	9	0.8	7.75	0.8	10.25	0.8	11	0.8	9.5	0.8	8.5	0.8	11.5
0.7	10.5	0.7	9	0.7	11	0.7	13	0.7	10.75	0.7	9.25	0.7	13.5
0.6	12	0.6	10.5	0.6	12.5	0.6	15.25	0.6	13	0.6	10	0.6	16
0.5	14.75	0.5	13	0.5	14.75	0.5	18.5	0.5	15	0.5	12.75	0.5	19.5
0.4	19.5	0.4	16.5	0.4	18	0.4	23.5	0.4	19.75	0.4	15.25	0.4	25
0.3	26.5	0.3	22.5	0.3	25	0.3	31.5	0.3	26.5	0.3	20	0.3	34
0.2	40	0.2	28	0.2	38	0.2	40	0.2	40.25	0.2	24	0.2	41.5
0.1	83	0.1	41	0.1	70	0.1	76	0.1	82	0.1	35	0.1	52
difficult1		difficult2		difficult3		difficult4		difficult5		difficult6		difficult7	
1	8	1	9	1	6	1	5	1	5	1	7	1	7.5
0.95	9.25	0.95	10.25	0.95	7.25	0.85	8.25	0.95	8	0.9	8.25	0.9	10
0.9	10.75	0.9	11.75	0.85	9.5	0.7	10	0.9	8.75	0.85	9.75	0.85	10.75
0.8	13.5	0.85	13	0.7	11.5	0.6	13	0.7	12.25	0.8	11	0.8	11
0.75	15.25	0.8	15.5	0.65	13	0.65	10.75	0.6	16.5	0.75	13.25	0.75	14.75
0.7	17.5	0.75	18	0.55	16.25	0.5	18.5	0.5	23.75	0.7	15.75	0.65	17.5
0.6	23.5	0.65	23	0.5	21	0.4	27	0.4	33	0.55	21	0.6	21
0.5	31.5	0.5	34	0.4	30	0.3	45	0.3	42	0.45	28.5	0.5	28
0.4	35	0.45	37	0.3	47	0.25	55	0.25	50	0.3	50	0.45	33
0.3	50	0.25	55	0.1	80	0.1	80	0.1	70	0.2	75	0.2	53

Figure 8: Lotteries in Large Sets

Table 13: Response Time and Risk in Small Sets

This table displays the results of a regression with mixed effect: random intercept and random slope for *Riskfree* variables. The dependent variable is the *Response Time* of a subject in a round, and it is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round. The regression controls for Sex, Age, Education, Session and Round. The regression with the control is in the appendix.
.

	Response Time
Riskfree	-0.0460
	(0.0369)
sex	-0.114
	(0.113)
edu	-0.0750
	(0.123)
age	0.226**
	(0.114)
SESSION	0.129
	(0.127)
round	-0.0385***
	(0.00425)
Constant	8.482***
	(0.269)
Observations	416
Number of groups	32

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Transitions in Large Sets and Risk-taking

This table displays the results of a regression with mixed effect: random intercept and random slopes for *Response Time* and *Riskfree* variables. The dependent variable is the *Proportion of within gamble transitions* of a subject in a round. *Response Time* is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round. The regression controls for Sex, Age, Education, Session and Round. The regression with the control is in the appendix.
.

	propANEW
riskfree	-0.0125
	(0.0145)
lnTime	-0.0228***
	(0.00866)
sex	-0.0170
	(0.0242)
edu	0.00180
	(0.0261)
age	-0.0157
	(0.0250)
SESSION	0.0472***
	(0.0163)
round	-0.00189*
	(0.00103)
Constant	0.638***
	(0.103)
Observations	824
Number of groups	61

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Response Time and Risk in Large Sets

This table displays the results of a regression with mixed effect: random intercept and random slope for *Riskfree* variables. The dependent variable is the *Response Time* of a subject in a round, and it is the natural logarithm of the response time in milliseconds. *RiskFree* is a dummy variable that is equal to 1 if the subject chooses the least risky option in that round. The regression controls for Sex, Age, Education, Session and Round. The regression with the control is in the appendix.
.

	Response Time height
Riskfree	-0.0796
	(0.0682)
sex	0.0240
	(0.107)
edu	0.0187
	(0.115)
age	0.107
	(0.110)
SESSION	0.0990
	(0.0726)
round	-0.0248***
	(0.00401)
Constant	9.861***
	(0.259)
Observations	824
Number of groups	61

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1