THE INFLUENCE OF GROUP DECISION MAKING ON SEARCH BEHAVIOR

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THE INFLUENCE OF GROUP DECISION MAKING ON SEARCH BEHAVIOR

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The Influence of Group Decision Making on Search Behavior

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DECLARATION OF ORIGINALITY

I, Cavit Görkem Destan, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
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ABSTRACT

The Influence of Group Decision Making

on Search Behavior

We study a multi-agent search problem within an experimental framework. Two agents search separately with their own search costs for a reward that is common for both which can create a free-rider problem. In general, we found that behavior of the agents are consistent with the predictions of the theory. Even though the results slightly moved away from the optimal compared to individual search problem, in group search problem strategies of subjects are still substantially close to the best-response. Moreover, we controlled for the personality traits, gender, risk attitude and background in economics. However, we did not find any significant effect of these on optimal decision rate or free-ride.

ÖZET

Grup Halinde Karar Almanın

Arama Davranışı Üzerine Etkisi

Deneysel bir çerçevede çok kişili bir arama problemi üzerinde çalıştık. İki kişi, ikisi için ortak olacak bir ödül için, ayrı olarak, kendi arama maliyetleriyle arama yapıyor. Bu durumun bedavacılık sorununa yol açması beklenebilirdi. Genel olarak, ajanların davranışlarının teorinin tahminleriyle tutarlı olduğunu tespit ettik. Sonuçlar, bireysel arama problemine kıyasla optimalden biraz uzaklaşsa da; grup arama probleminde, deneklerin stratejileri hala en iyi cevaba oldukça yakın seviyededir. Ayrıca deneklerin kişilik özellikleri, cinsiyetleri, risk tutumları ve iktisat eğitimleri de kontrol değişkeni olarak kullanılmıştır; ancak, bu değişkenlerin optimum karar oranı veya bedavacılık üzerinde istatistiksel olarak anlamlı bir etkisi bulunamamıştır.

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TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION 1
CHAPTER 2: MODEL 3
2.1 Optimal individual search 3
2.2 Optimal group search 5
CHAPTER 3: EXPERIMENTAL DESIGN 6
3.1 Individual search treatment 6
3.2 Group search treatment 8
CHAPTER 4: EXPERIMENTAL RESULTS 10
4.1 Individual search results 10
4.2 Group search results 17
CHAPTER 5: WELFARE EFFECT 24
CHAPTER 6: CONCLUSION 26
APPENDIX A: INSTRUCTIONS FOR INDIVIDUAL SEARCH TREATMENT . 28
APPENDIX B: INSTRUCTIONS FOR GROUP SEARCH TREATMENT 30
REFERENCES 33

LIST OF TABLES

Table 1. Different Intervals for Offers and Search Costs 7

Table 2. An Example of the Calculation for Earnings in Group Search 9

Table 3. Means and Standard Deviations of Number of Searches by Distribution and Search Cost in Individual Search 11

Table 4. Regression of Number of Searches on Distribution and Cost in Individual Search 11

Table 5. Minimum Acceptable Offers for 12 Parameter Combinations in Individual Search 12

Table 6. Regression of Estimated Threshold on Distribution and Cost in Individual Search 14

Table 7. Probit Regression of Optimal Play on Personality Characteristics in Individual Search 16

Table 8. Probit Regression of Waiting on Distribution and Cost 18

Table 9. Regression of Number of Searches on Distribution and Cost in Group Search 18

Table 10. Minimum Acceptable Offers for 12 Parameter Combinations in Group Search (Assuming ρ=2) 19

Table 11. Regression of Estimated Threshold on Distribution and Cost in Group Search 20

Table 12. Probit Regression of Optimal Play on Personality Characteristics in Group Search 23

LIST OF FIGURES

Figure 1. Stopping decision screen on both treatments 7
Figure 2. Intro screen of group search treatment 8
Figure 3. Distribution of number of searches in individual search 10
Figure 4. Scatter of accepted and highest rejected offers and optimal thresholds by distribution and cost in individual search 13
Figure 5. Optimal and estimated thresholds by distribution and cost in individual search 14
Figure 6. Distribution of five personality traits in individual search 15
Figure 7. Distribution of number of searches in group search 17
Figure 8. Estimated and optimal thresholds with constant ρ=2 and with real distribution of ρ by distribution and cost 20
Figure 9. Scatter of accepted and highest rejected offers and optimal thresholds by distribution and cost in group search 22
Figure 10. Distribution of five personality traits in group search 22

CHAPTER 1

INTRODUCTION

Search problems are investigated widely in the discipline of Economics. One reason behind the popularity of these problems is that many everyday decisions involve some type of sequential search. As common examples, we can mention the job search of a fresh graduate or the price search of a buyer. However, sequential search problems are not limited to those cases. Even trying different Italian restaurants in your city until finding a good one is a sequential search problem.

In this area of research, the first studies were pure theoretical. In the canonical papers of information economics Stigler (1961) and Stigler (1962), marginal cost-benefit analysis is used firstly in search models. According to Stigler's model, an agent compares the life-time benefit of an additional search to its costs. Later, similar models are developed and theoretical research reached a saturation point with Kohn and Shavell (1974) in which authors investigate the optimal search strategies in all situations such as perfect, partial or imperfect information; with or without possibility of recall; with or without constraint on number of searches etc.

Afterwards, the research on search problems shifted mostly to an empirical area. In the first experimental study, Schotter and Braunstein (1981) showed that agents act surprisingly optimal in a very complex situation which is almost impossible to solve without computer. Although optimal stopping rule is not trivially easy to find, most of the subjects act as if they not the optimal rule. Therefore this result led to a natural question of "How can they manage to find the optimal strategy?". Further studies like Hey (1982), Hey (1987), Cox and Oaxaca (1989), Sonnemans (2000) and Schunk and Winter (2009) focused on the effects of individual characteristics such as risk attitude

or underlying heuristics that can result in the same outcome with optimal decision rule since agents following the optimal strategy was unlikely and implausible.

As an alternative framework to individual search, there are many recent studies that analyze search behavior within a group. Ibanez, Czermak, and Sutter (2009) conducted a search experiment where two agents talk and decide together in front of a computer screen but their results were not different than individual search. The authors interpret this similarity as a result of already high optimality of individual search and lack of room for improvement. Albrecht, Anderson, and Vroman (2010) investigated the case where stopping decision is made by a voting procedure in a committee and Güler, Güvenen, and Violante (2012) provided a theoretical framework for two agents (as in husband&wife) search where they decide collectively and share their income.

In this paper, we analyze a different 2-agent search problem where agents search separately with their own search costs for a reward that is common for both. As a clarifying example we can look at two partners searching for a potential buyer for their land. They individually collect offers and at the end of the search procedure they sell the land to the buyer with the highest offer. This framework is promising since it reveals both agents' beliefs about others and strategies (or possibly heuristics) used in a different setup than individual search.

By making the problem interactive with another person, we can first check whether optimal strategy is followed in a more complex problem and secondly find out a person's belief about the other people's search behavior which could help us in explaining the surprisingly optimal strategy of subjects.

CHAPTER 2

MODEL

Search is a sequential decision making with imperfect information. A decision maker faces the same choice, which is to stop or to continue, at every decision point. Therefore, a search problem can be seen as dynamic optimization. An expected utility maximizer would have the following value function

$$V(\hat{x}, \hat{C}) = \max_{\{stop, continue\}} \{\hat{x} - \hat{C}, E_x[V(x, \hat{C} + c)|\hat{x}]\}$$

where $\hat{x}$ is the maximum reward she has, $\hat{C}$ is the cost she spent until that time and c is the cost of an additional search. If the agent stops she gets $\hat{x} - \hat{C}$ and if she continues she faces the same decision with an additional search cost c and a new offer. In the following subsections we will look at the optimal strategies of agents for individual and group search. While doing so we will assume that the individual can always recall a past reward. Hence, her effective reward at each decision point becomes the maximum of the rewards she has so far. This assumption is both realistic in many circumstances and do not change our results compared to no-recall case.

2.1 Optimal individual search

First, we look at the individual case to clarify the basics of the optimal search strategy. In an individual search, an agent compares the net benefit of an extra draw and its cost at each decision point and continues as long as the net benefit exceeds its cost. Suppose individual's maximum reward until that moment is $\hat{x}$ and rewards are identically and independently distributed over $[\underline{x}, \bar{x}]$ with a probability distribution

function $f(x)$. Then, the net benefit of an extra draw can be calculated as below.

$$b(\hat{x}) = \int_{\hat{x}}^{\bar{x}} (x - \hat{x}) f(x) dx$$

When we have $\hat{x}$ as our maximum offer, we can have a benefit only if we draw an offer above it. Therefore, we integrate aver the values of x higher then $\hat{x}$. Moreover, our net benefit is the difference between our new offer and $\hat{x}$ that is how much extra earning we will get compared to $\hat{x}$.

Therefore, we know that an optimal decision rule would be a cutoff strategy. According to this strategy, an individual should stop if she draws a reward higher than some threshold R and continue if she draws a reward below it. The optimality of this strategy can be shown in two steps:

(i) If stopping is optimal at a reward $\hat{x}$, it is also optimal at $x' > \hat{x}$.

(ii) If continuing is optimal at a reward $\hat{x}$, it is also optimal at $x' < \hat{x}$.

The proof is trivial using $b(\hat{x})$. First, note that $b(\cdot)$ is a decreasing function since an increase in the input both restricts the integral limits and decreases integrated function at every point. Then,

For (i): $x' > \hat{x}$ and $b(\hat{x}) \leq c$ imply $b(x') \leq c$

For (ii): $x' < \hat{x}$ and $b(\hat{x}) \geq c$ imply $b(x') \geq c$

Hence, we can calculate the optimal threshold R. At R, the individual should be indifferent between stopping and continuing. Therefore, we can look at the point where the expected net benefit of an extra draw is equal to its cost. Then, at the threshold R, we have

$$\int_{R}^{\bar{x}} (x - R) f(x) dx = c$$

Note that the value of R does not depend on the number of past draws or the cost spent already since they are sunk costs and not relevant to present decision.

2.2 Optimal group search

The key factor in group search is the belief about other players search intensity. If a player believes that the other player searches too much and so gets a very high offer, then the net benefit of additional search would be very low. To gain a net benefit from a draw, new offer should be bigger than all offers of the individual and her partner. Let's say the agent believes that the other player searches ρ times. Given that maximum offer she has is $\hat{x}$, we can calculate the net benefit of an extra draw as

$$b(\hat{x}) = \int_{\hat{x}}^{\bar{x}} (x - \hat{x}) F(x)^{\rho} f(x) dx$$

where $F(x)^{\rho}$ is the probability that all ρ offers of the partner is lower than x, so it is the probability of gaining a net benefit from an offer x. Again, an optimal strategy would be a cutoff strategy using the same reasoning as in the individual search. Therefore, at the threshold we should have

$$\int_{R}^{\bar{x}} (x - R) F(x)^{\rho} f(x) dx = c$$

Note that for any non-degenerated distribution function and $\rho \geq 1$, $F(x)^{\rho}$ is strictly less than 1, so the term inside the integral is lower compared to individual search. Therefore, for the same search cost c, we should integrate over a larger domain to equate the integral to c. Thus, for the same distribution and cost structure, optimal threshold is lower in group search.

CHAPTER 3

EXPERIMENTAL DESIGN

3.1 Individual search treatment

We conducted two treatments in Bogazici University, Istanbul using university students as subjects. Treatment I measures the search behavior at the individual level and Treatment II measures the search behavior in a group. In Treatment I, we replicated the standard search model as a benchmark. We had 52 subjects and each subject confronted with a search problem. First she draws an offer from a discrete uniform distribution between $\underline{x}$ and $\bar{x}$ (including boundaries) with a cost c. After this draw and all future draws, she can stop and get the highest offer she has (perfect recall condition) or ask a new offer with the same cost c. When she stops, she earns the maximum offer minus total search cost. We did not introduce any discounting between periods since it is not our main interest and has no systematic effect on our findings.

We used 3 different intervals for offers and 4 different values for search costs (see Table 1 below). Each subject played 12 rounds (one for each parameter combination) in a random order. At the beginning of each round and at each decision screen these parameters are reminded to the subjects. Payments are determined as the earning of a random period out of 12 periods converted to real money with the exchange rate 0.5 TL/Experimental Currency in addition to 10 TL participation fee (10 TL $\approx$ 3 USD at the time of the experiment). You can find the instructions for this treatment in Appendix A.



Figure 1. Stopping decision screen on both treatments

Table 1. Different Intervals for Offers and Search Costs

Distributions	Costs
0-100	2
15-85	4
30-70	6
	8

Additionally, after the experiment each participant completed a short survey that includes demographic questions such as age,gender and TIPI items as a measure of the Big-Five personality dimensions as suggested by Gosling, Rentfrow, and Swann (2003). The validity of TIPI-scale measure for young people in Turkey is shown by Atak (2013).

3.2 Group search treatment

In this treatment, in the first round we randomly matched subjects in pairs and they are matched with the same partner at each other round. This treatment consisted of 12 rounds as well and the same 12 parameter combinations is played in a random order.

At the beginning of each round, after learning the parameter combinations, each subject decides to start searching or wait (see Figure 2 for decision screen). If she chooses to wait, she is considered to have zero maximum offer and zero total cost. If she searches, she can stop after any offer as in Treatment I. When both players in a group stop searching, individual earnings are calculated as the maximum offer in the group minus individual total cost (see Table 2 as an example). Therefore, we can think that offers are common goods in a group but costs are paid individually.



Figure 2. Intro screen of group search treatment

Table 2. An Example of the Calculation for Earnings in Group Search

	Maximum Offer	Total Cost	Earning
Player A	51	12	65-12=53
Player B	65	4	65-4=61

Again, the same payment scheme is applied as in Treatment I to this treatment and each participant completed the same survey. You can find the instructions for this treatment in Appendix B.

CHAPTER 4

EXPERIMENTAL RESULTS

4.1 Individual search results

In this treatment, mean earning was 57.89 and the mean number of search was 2.98 with 88.94% of them were less than or equal to 4. In Figure 3 you can see the overall distribution of the number of searches and in Table 3 you can see the distribution statistics of number of searches by distribution and search cost. As we expected, number of searches decreased by search cost. However, dispersion did not increase search intensity. As you can see in Table 4, the coefficients of distribution dummies do not have statistical significance. This might be the result of increased threshold with dispersion so that the expected number of draw to find an offer above threshold remained the same as a potential expectation from the theory.

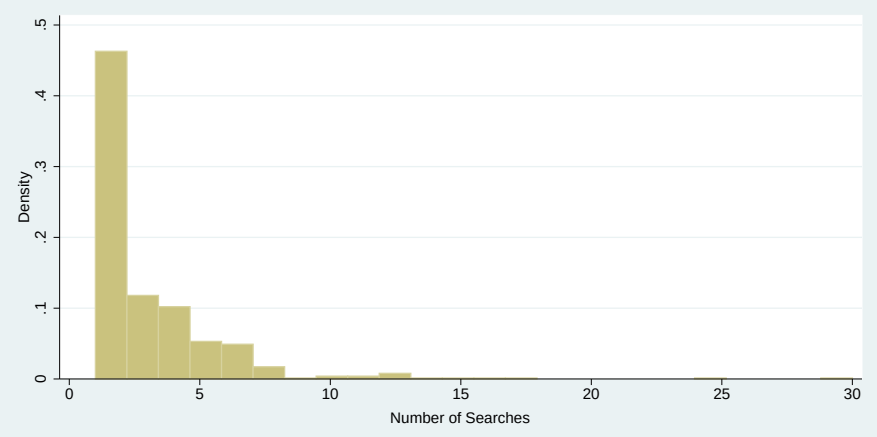


Figure 3. Distribution of number of searches in individual search

Table 3. Means and Standard Deviations of Number of Searches by Distribution and Search Cost in Individual Search

Distribution\Cost	2	4	6	8	Total
0-100	3.60 (2.86)	3.77 (3.36)	2.96 (2.34)	2.79 (2.16)	3.28 (2.73)
15-85	3 (1.96)	3.33 (2.83)	2.29 (1.6)	2.54 (1.64)	2.79 (2.09)
30-70	3.31 (2.84)	3.5 (5.16)	2.12 (2.06)	2.56 (2.06)	2.87 (3.31)
Total	3.3 (2.58)	3.53 (3.89)	2.46 (2.05)	2.63 (1.96)	2.98 (2.76)

Note: Standard errors in parentheses

Table 4. Regression of Number of Searches on Distribution and Cost in Individual Search

	Number of Searches	
Distribution: 15-85	-0.0817	(0.761)
Distribution: 0-100	0.409	(0.128)
Search Cost	-0.155**	(0.002)
Constant	3.644***	(0.000)
Observations	624	
R^2	0.022	

Notes:*p*-values in parentheses. * p $<$ 0.10, ** p $<$ 0.05, *** p $<$ 0.01.

To better understand the behaviors of the agents we should look at the thresholds. Using the model explained in Chapter 2.2, we can calculate optimal thresholds in experiment setup as

$$\sum_{R+1}^{\bar{x}}(x-R)\frac{1}{\bar{x}-\underline{x}+1}=c$$

where R represents the optimal threshold and $\frac{1}{\bar{x}-\underline{x}+1}$ is the probability of drawing any value x in discrete uniform distribution between $\underline{x}$ and $\bar{x}$ including boundary points. Optimal thresholds calculated for all parameter combinations are listed in Table 5.

Table 5. Minimum Acceptable Offers for 12 Parameter Combinations in Individual Search

Distribution\Cost	2	4	6	8
0-100	81	73	66	61
15-85	69	62	57	52
30-70	58	53	49	45

For example, when distribution domain is 15-85 and cost is 6, a risk-neutral expected utility maximizer agent should stop as soon as she gets an offer greater than or equal to 57. As it is shown in Chapter 2.2, recalling a past offer is never optimal.

Out of 624 observations (52 individuals $\times$ 12 periods) recall is seen only 49 times (7.85%) . Hence, we can think that most subjects used a strategy similar to threshold strategy. Moreover, results show that if individuals followed a threshold strategy, their cutoff points are very close to optimal threshold. Out of observations without recall, individuals stopped 86.76% of the time when they get an offer above the optimal threshold and continued 93.44% of the time when they get an offer below the optimal threshold. Therefore, it seems like they act as if they roughly know the optimal strategy. You can see the scatter of accepted and highest rejected offers in Figure 4.

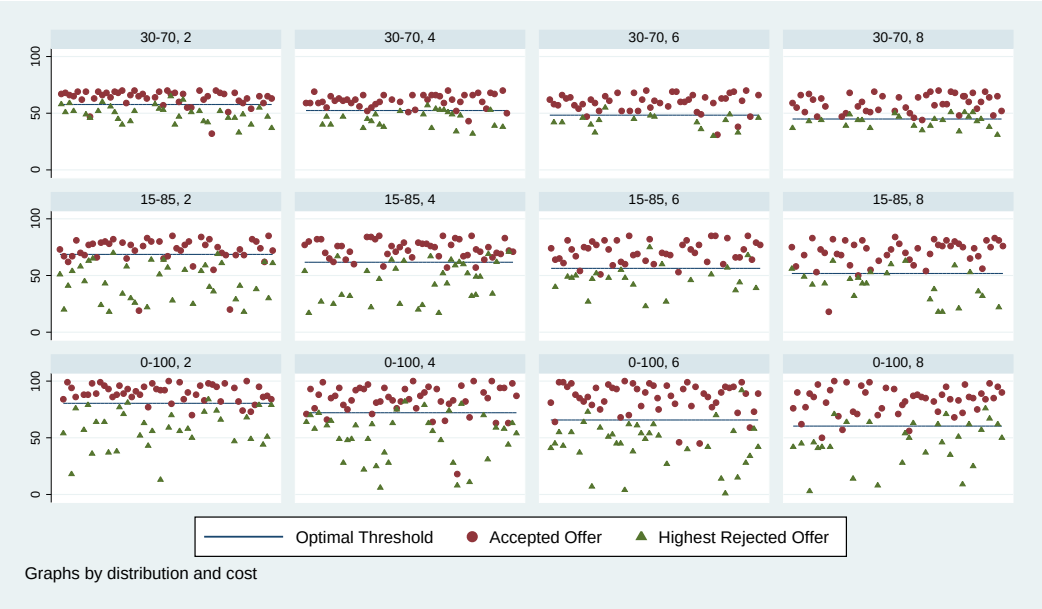


Figure 4. Scatter of accepted and highest rejected offers and optimal thresholds by distribution and cost in individual search

Furthermore, we used a maximum-likelihood estimation similar to Caplin, Dean, and Martin (2011) to understand the thresholds that individuals are using. Estimated cutoff points are very close to optimal thresholds and most of them are not statistically different than the optimal thresholds (see Figure 5). Both Wilcoxon matched-pairs signed-ranks test and paired t-test results cannot reject the null hypothesis that optimal and estimated thresholds have the same distribution with any confidence level less than or equal to 10%. Hence, we can deduce that if people use cutoff strategies they have highly similar threshold levels to optimal ones. As expected from the theory reservation levels increased with dispersion and decreased with search cost (see Table 6).

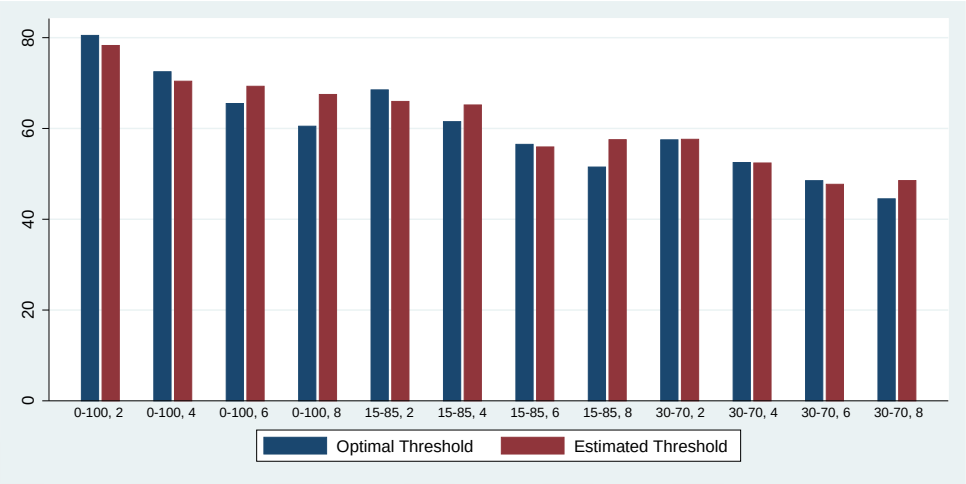


Figure 5. Optimal and estimated thresholds by distribution and cost in individual search

Table 6. Regression of Estimated Threshold on Distribution and Cost in Individual Search

	Estimated Threshold	
Distribution: 15-85	9.590***	(0.000)
Distribution: 0-100	19.81***	(0.000)
Search Cost	-1.667***	(0.001)
Constant	59.90***	(0.000)
Observations	12	
R^2	0.957	

p-values in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Lastly, we controlled for the effect of personality characteristics on the behavior using survey data. In Figure 4, you can see the distribution of five personality traits. We did not find any significant effect from any personal characteristics on the probability of the optimal behavior (see Table 7 for probit regression results). Similarly, there is no significant effect when we use probability of recall as dependent variable.

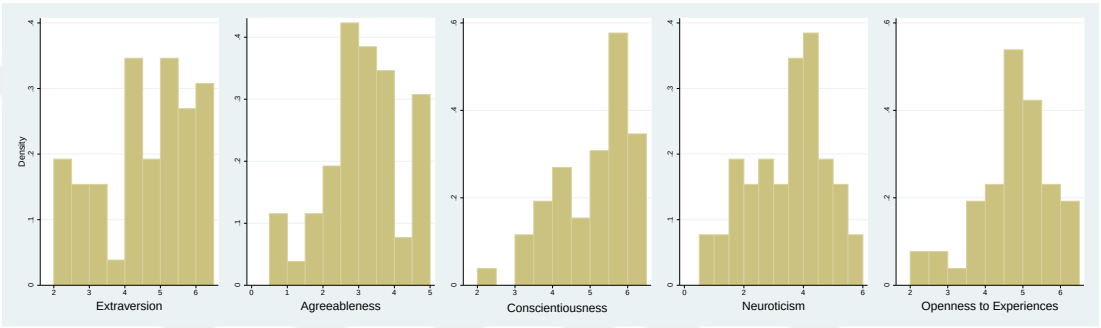


Figure 6. Distribution of five personality traits in group search

Table 7. Probit Regression of Optimal Play on Personality Characteristics in Individual Search

	Probability of Optimal Play	
Age	0.0142	(0.609)
Male	0.201	(0.169)
Number of Siblings	0.0768	(0.235)
Can we trust the others (=1 if Yes)	0.121	(0.460)
How willing are you to take risk (0 to 10)	-0.00600	(0.888)
How many economics courses did you take	-0.0455	(0.453)
Is your data reliable (=1 if Yes)	0.0744	(0.239)
Extraversion	-0.00905	(0.826)
Agreeableness	-0.0101	(0.878)
Conscientiousness	0.143	(0.076)
Neuroticism	0.0885	(0.127)
Openness to Experiences	-0.0165	(0.808)
Constant	-1.223	(0.291)
Observations	624	
Pseudo R^2	0.015	

p-values in parentheses

4.2 Group search results

In this treatment, mean earning was 62.67 and the mean number of search is 2.23 with 90.06% of them are less than or equal to 4 (see Figure 7 for distribution). Out of 624 observations (52 individuals $\times$ 12 periods) not-searching is chosen only 48 (7.69%) times. The agent who waited the most, waited 5 times in 12 periods. This statistics show us that individuals generally do not believe that the other agent searches deeply, so free-ride does occur very rarely. Additionally, Table 8 shows the probit regression results in which probability of waiting decreased in distributions 15-85 and 0-100 compared to 30-70 as the coefficient of distribution dummies are negative and statistically significant. However, the coefficients of distributions 15-85 and 0-100 are not statistically different than each other. Additionally, probability of waiting increased with search cost but did not significantly increase or decrease with periods. Hence, we can clearly say that there is a very slow convergence to not searching (if ever exists) contrary to convergence to not contributing in public good games.

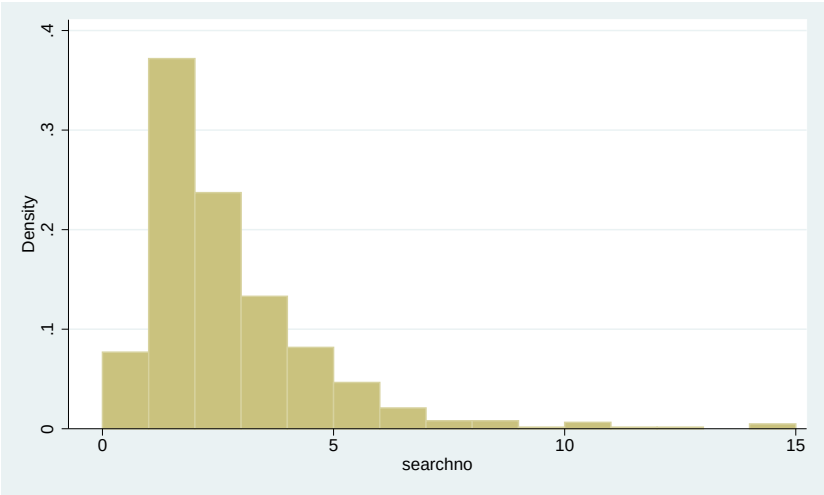


Figure 7. Distribution of number of searches in group search

Table 8. Probit Regression of Waiting on Distribution and Cost

	Probability of Waiting	
Period	0.0351	(0.179)
Distribution: 15-85	-0.544**	(0.010)
Distribution: 0-100	-0.478*	(0.012)
Search Cost	0.176***	(0.000)
Constant	-2.381***	(0.000)
Observations	624	
pseudo R^2	0.126	

p-values in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

We found that the number of searches increased by dispersion of rewards and declined with search cost (see Table 9).

Table 9. Regression of Number of Searches on Distribution and Cost in Group Search

	Number of Searches	
Distribution: 15-85	0.370*	(0.043)
Distribution: 0-100	0.923***	(0.000)
Search Cost	-0.223***	(0.000)
Constant	2.918***	(0.000)
Observations	624	
R^2	0.102	

p-values in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Again, we use thresholds to analyze the behaviors of agents. To find the optimal thresholds in Group Search Treatment we can use the model in Chapter 2.3 as

$$\sum_{R+1}^{\bar{x}}(x-R)\Big(\frac{x-\underline{x}}{\bar{x}-\underline{x}+1}\Big)^{\rho}\frac{1}{\bar{x}-\underline{x}+1}=c$$

where R represents the threshold, ρ represents the partner's number of search (or belief about it), $\left(\frac{x-\underline{x}}{\bar{x}-\underline{x}+1}\right)^{\rho}$ is the probability of partner's all offers being less than x and $\frac{1}{\bar{x}-\underline{x}+1}$ is the probability of drawing any value x in discrete uniform distribution between $\underline{x}$ and $\bar{x}$ including boundary points. Assuming agents believe that their partner will have 2 draws (since the mean is 2.23), minimum acceptable offers for 12 parameter combinations is shown below in Table 10.

Table 10. Minimum Acceptable Offers for 12 Parameter Combinations in Group Search (Assuming $\rho = 2$)

Distribution\Cost	2	4	6	8
0-100	79	69	61	53
15-85	67	59	51	44
30-70	56	49	42	36

Since certain belief of 2 about partner's number of draws seems restrictive, we calculated optimal thresholds with real distribution of search numbers as expected benefit of an extra draw should be equal to its cost at the threshold, which is

$$E_{\rho}\Big[\sum_{R+1}^{\bar{x}}(x-R)\Big(\frac{x-\underline{x}}{\bar{x}-\underline{x}+1}\Big)^{\rho}\frac{1}{\bar{x}-\underline{x}+1}\Big]=c$$

In Figure 8, you can see the optimal thresholds with certain belief $\rho = 2$, with true belief equals to real distribution and estimated thresholds similar to previous section. Since optimal thresholds with two different beliefs are almost identical and one does not outperform the other, we cannot conclude about the beliefs of the agents. Again, both Wilcoxon matched-pairs signed-ranks test and paired t-test results cannot reject the null hypothesis that optimal and estimated thresholds have the same distribution with any confidence level less than or equal to 10%. On the other hand,

the same tests indicates that estimated thresholds in group search treatment are lower compared to the individual search treatment. Moreover, as in previous section, we found that reservation levels increased with dispersion and decreased with search cost (see Table 11). Cutoff point is 16.64 lower in distribution 30-70 compared to distribution 0-100 (omitted in the regression as a baseline).

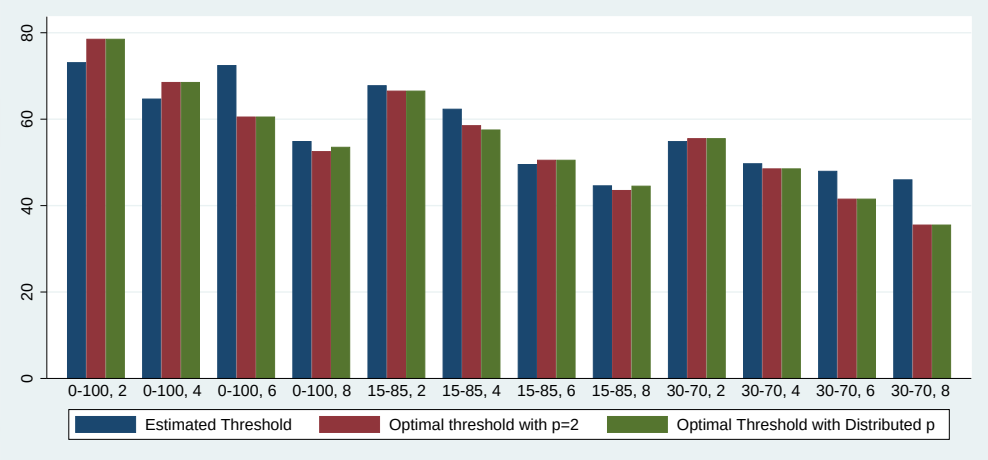


Figure 8. Estimated and optimal thresholds with constant $\rho = 2$ and with real distribution of ρ by distribution and cost

Table 11. Regression of Estimated Threshold on Distribution and Cost in Group Search

	Estimated Threshold	
Distribution: 30-70	-16.64**	(0.001)
Distribution: 15-85	-10.21*	(0.020)
Search Cost	-2.627**	(0.003)
Constant	79.38***	(0.000)
Observations	12	
R^2	0.832	

p-values in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Out of 576 observations including search, recall is seen 88 (15.28%) times. This rate is almost double of the rate in individual search. Hence, we can see that the fraction of cutoff strategy declined in group search. Looking at the 488 observations without recall (potentially using cutoff strategy) using optimal thresholds with correct belief (equals to real empirical distribution), agents stopped 85.5% of the time when they get an offer above optimal threshold and continued 86.48% of the time when they get an offer below the optimal threshold. Hence, agents still have a very good sense for the optimal threshold. You can see the scatter of accepted and highest rejected offers in Figure 9 where optimal threshold is calculated with real distribution of ρ.

Similar to Individual Search Treatment, we did not find any significant effect of personality traits on the probability of not searching and the probability of optimal play when agent searches. You can see the distribution of five personal traits in Figure 8 and the results of probit regression in Table 12.



Figure 9. Scatter of accepted and highest rejected offers and optimal thresholds by distribution and cost in group search

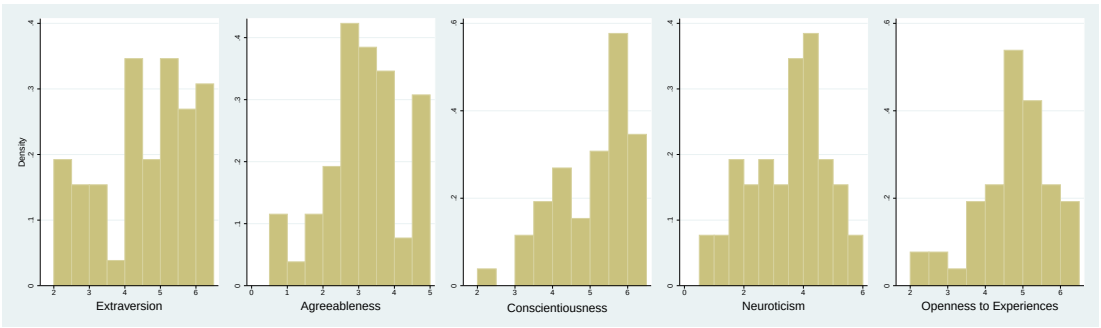


Figure 10. Distribution of five personality traits in group search

Table 12. Probit Regression of Optimal Play on Personality Characteristics in Group Search

	Probability of Optimal Play	
Age	0.0124	(0.768)
Male	-0.189	(0.158)
Can we generally trust the others (=1 if Yes)	-0.0402	(0.811)
How willing are you to take risk (0 to 10)	0.0133	(0.772)
How many economics courses did you take	0.0196	(0.675)
Is your data reliable (=1 if Yes)	0.00103	(0.986)
Extraversioon	-0.00743	(0.889)
Agreeableness	0.0246	(0.683)
Conscientiousness	-0.0579	(0.390)
Neuroticism	-0.00972	(0.857)
Openness to Experiences	0.0381	(0.560)
Constant	0.249	(0.832)
Observations	576	
Pseudo R^2	0.006	

p-values in parentheses

CHAPTER 5

WELFARE EFFECT

Another interesting dimension of the group search is its welfare effect. By the nature of the group search problem offers are public good so that each agent potentially benefits from an additional search. Therefore, searching in groups is more advantageous for agents compared to individual search. More formally, the search problem in individual search is

$$\max_{R_i} E(\Pi_i) = E(x|x \geq R_i) - \frac{c}{1 - F(R_i)}$$

where agent chooses optimal threshold R_i to maximize its expected payoff Π_i. In the calculation, $E(x|x \geq R_i)$ represents the expected accepted offer when agent accepts any offer above the threshold and $\frac{c}{1-F(R_i)}$ represents the expected total search cost where agents rejects any offer below the threshold. On the other hand, in group search, problem is transformed to

$$\max_{R_g} E(\Pi_g) = E(max\{x_1, x_2\}|x_1 \geq R_g) - \frac{c}{1 - F(R_g)}$$

where R_g is the optimal threshold in group search.

Note that, even by choosing the same threshold with individual search ($R_g = R_i$), agent earns an expected payoff in group search that is greater than or equal to the expected payoff from individual search since the objective function contains $max\{x_1, x_2\}$ instead of only x. Moreover, the agent can choose a better threshold R_g that would even increase the expected payoff.

Experimental results are also in line with the predictions of the theory. Subjects on average earned 57.89 in individual search treatment whereas mean earning was 62.67 in group search treatment. Even though the higher rate of optimal behavior in individual search, subjects could not reach the earnings of the group search on average. Hence, we can conclude that the if two agents have two search problem, searching in groups for both problems Pareto dominates two separate individual search.

CHAPTER 6

CONCLUSION

In Individual Search Treatment we get very similar results to previous studies. The behavior of the agents are highly consistent with cutoff strategy and they played predominantly optimal as expected. We get even higher frequency of optimal play then most previous researches. Estimated thresholds are increased with dispersion and decreased with search cost as theory suggests. This creates a solid base for the results of the second treatment.

In the Group Search Treatment we saw that agents slightly moved away from the optimality. However, we do not see any evidence for convergence to free-ride. The usage of non-optimal strategies that contradicts with cutoff strategy (namely recall or not searching) increased from 8% to 22% and correct decision rates of the rest marginally declined from 90.93% to 86.05%. In group search, agents generally decreased their thresholds and as a result searched less intensely as the model predicted. Considering the complexity of the problem, optimal decision rates are still surprisingly high. Hence, presumably agents either modified their heuristics that they use in individual search or found the new ones to cope with the problem. The old rule of thumbs that they potentially use in individual search is not valid here. However, if they find a new heuristic, it is still surprising that subjects with no special training in search problems can find brilliant heuristics for different types of problems within seconds.

Additionally, we showed that searching in groups for two problems Pareto dominates two separate individual search. For example, if two people want to sell their cars, they can earn more in total by searching for buyers together for both cars

compared to searching individually by their own cars. We can also say that even bigger groups sizes Pareto dominates smaller groups.

Moreover, we found that personal characteristics and even the number of economics courses taken do not effect the probability of optimal decision. Hence, optimal behavior may be determined by other factors or perhaps randomly. The next step of research could be analyzing the rule of thumbs that individuals are using in the context of group search. Additionally, the comparison of different education levels and occupations might be a fruitful study which we could not have a chance to examine in understanding the effects of education and experience.

APPENDIX A

INSTRUCTIONS FOR INDIVIDUAL SEARCH TREATMENT

Welcome!

Thank you for your participation. The aim of this study is to understand how people make decisions in certain situations. The experiment consists of 12 rounds and in each round you are going to make some individual decisions. As a result of the decisions you make in the experiment, you will receive a cash prize. Your earnings will depend on your decisions and your luck. Your gain and the participation fee will be paid in cash at the end of the experiment. The decisions you make and the amount you win will not be known by anyone except you. During the test, the decisions you make will be recorded by a participant number attached to you randomly by computer and will not be synchronized with your identity at any time. From now on the participants are not allowed to talk to each other. In case of any speech, we must end the experiment. If you have any questions raise your hand and ask out loud. Then everyone will hear the questions and answers.

We now begin to explain the game you will play.

The Game:

First, the system will provide you with a random offer from a specific range. After you get the offer, you will need to make a choice. You can either press the ”New Offer” button to take a new offer by paying a certain fee or the ”Finish” button to finish that period. After each offer received you will be given the same choice and if you press the ”Finish” button you will earn **the highest bid you have received** in that period.

The range of the offers and the cost of getting a new offer will change at each period and you will be notified about the values at the beginning of that period. The probabilities of encountering the numbers within an interval are the same. That is if the offer is in the range of 1 to 10, you will encounter 1 with probability 1/10, 2 with 1/10,....., 10 with 1/10.

Your earnings from a period will be determined by subtracting the total amount you paid for bids in that round from the highest bid that you have received in that round when you press the ”Finish” button.

Earnings:

Every single unit gain is worth 0.5 TL in the experiment. Your actual earnings in each period will be calculated as: ”*your gain in that period x 0.5 TL*”. Your actual earnings in the entire experiment will be determined by selecting one of the 12 periods randomly. All of the periods have the same probability of being selected, so it would be wise to think equally carefully at each round. Your actual earnings will be paid in cash in the end of the experiment, with an additional 5 TL participation fee.

APPENDIX B

INSTRUCTIONS FOR GROUP SEARCH TREATMENT

Welcome!

Thank you for your participation. The aim of this study is to understand how people make decisions in certain situations. The experiment consists of 12 rounds and in each round you are going to make some individual decisions. As a result of the decisions you make in the experiment, you will receive a cash prize. Your earnings will depend on your decisions, your partners decision and luck. Your gain and the participation fee will be paid in cash at the end of the experiment. The decisions you make and the amount you win will not be known by anyone except you. During the test, the decisions you make will be recorded by a participant number attached to you randomly by computer and will not be synchronized with your identity at any time. From now on the participants are not allowed to talk to each other. In case of any speech, we must end the experiment. If you have any questions raise your hand and ask out loud. Then everyone will hear the questions and answers.

We now begin to explain the game you will play.

The Game:

First, the system will ask you whether you want to have offer. You can press the Get Offer button and get an offer by paying a certain fee. If you press the Get Offer button, the system provide you with a random offer from a specific range. After you get the offer, you will need to make a choice. You can either press the ”New Offer” button to take a new offer by paying a certain fee or the ”Finish” button to finish that period. After each offer received you will be given the same choice and if you press the ”Finish” button you will earn **the highest bid you have received** in that period.

The range of the offers and the cost of getting a new offer will change at each period and you will be notified about the values at the beginning of that period. The probabilities of encountering the numbers within an interval are the same. That is if the offer is in the range of 1 to 10, you will encounter 1 with probability 1/10, 2 with 1/10,....., 10 with 1/10.

Your earnings from a period will be determined by subtracting the total amount you paid for bids in that round from the highest bid that you have received in that round when you press the ”Finish” button.

If you press the Wait button at the beginning of the round, your reward and cost will be zero.

Earnings:

The reward at each period is determined as the maximum of the offers that the partners have received. Individual earnings are calculated by subtracting individual total cost from that reward.

Example 1:

Your highest offer: 42

Your partner’s highest offer: 50

Your total cost: 10

Your earning: 50-10=40

Example 2:

Your highest offer: 62

Your partner's highest offer: 35

Your total cost: 18

Your earning: 62-18=44

Every single unit gain is worth 0.5 TL in the experiment. Your actual earnings in each period will be calculated as: "*your gain in that period x 0.5 TL*". Your actual earnings in the entire experiment will be determined by selecting one of the 12 periods randomly. All of the periods have the same probability of being selected, so it would be wise to think equally carefully at each round. Your actual earnings will be paid in cash in the end of the experiment, with an additional 5 TL participation fee.

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