Active Participation Bias

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Abstract

A common pattern observed in diverse contexts is that individuals take actions even if staying passive is optimal according to the standard economic theory. Using an online experiment, we demonstrate that people have an intrinsic tendency to become active even when the payoff maximizing action is to stay passive and even when other factors, such as cognitive mistakes or risk aversion, are ruled out. This tendency can explain a large set of findings in a unified way. Moreover, once participants become active (which is not optimal in the game), they play the optimal strategy in the off-the-path subgame that they entered by becoming active. In other words, participants ignore the supergame, and they myopically keep focusing on the task at hand. This can create vast inefficiencies in numerous domains.

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1 Introduction

Imagine being in Las Vegas where there is a world-class casino on every corner. Your return flight is the next day and you have nothing to do. In that case, you may be tempted to try your chance in one of the casinos even if you believe gambling is wrong and would never gamble in your daily life. Once you start gambling, you may even lose yourself to the excitement and bet sizeable amounts. Whether you start and even continue an activity can strongly depend on the environment you are in. Yet, we still lack a more general understanding of which circumstances generate which type of behaviors. In this study, we provide a new conceptual tool to explain how people start some activities and why they continue.

There is a common pattern in various experiments in diverse contexts such as auctions, contests, or double-sided markets. Whenever the equilibrium prediction is choosing zero bid, zero effort, or no action in general, we see a systematic deviation from the equilibrium[1]. Participants seem to deliberately avoid strategies that involve staying passive even if it is costly for them.

While each study proposes different mechanisms that drive this type of active behavior, we conjecture there is a common mechanism that causes this widespread phenomenon: a general preference to become active. This preference can explain the large body of evidence on non-optimal activity in the contexts where passivity is payoff maximizing.

We conduct a set of experiments to investigate the active participation behavior. Specifically, we set out to answer three questions: Is becoming active the prevalent choice, even in environments, in which the payoff maximizing strategy is staying passive? If so, what are the mechanisms that drive this type of behavior? Lastly, what are the possible impacts of this tendency? By answering these questions we hope to shed a light on numerous behavioral patterns in a unified way. We also aim for better choice architecture and potential debiasing strategies.

Lei, Noussair, and Plott (2001) use the term *active participation bias* to describe behavior in their double-sided asset market experiments that are designed to understand the formation of financial

[1]See Dechenaux, Kovenock, and Sheremeta (2015) for the detailed investigation of contests, all-pay auctions, and tournament experiments.

bubbles. In all of the experimental conditions, they observe an excess trading activity. Only in one condition, in which they provide an alternative task for participants, bubbles are less likely to occur as trading activity is reduced to optimal levels since some of the individuals do not participate in the asset market. As a result, they conjectured that people engage in trading since there is no other activity available and they called this behavior *Active Participation Bias*. Since then, the active participation bias has been proposed as an explanation for several experimental results. However, non of these studies rigorously scrutinized the various mechanism that might drive active participation.

In our experiments, participants play a sequential search game in groups of two players. During the search phase, they separately draw offers by paying a fixed marginal cost for each draw and do not know the actions of their partners. At the end of the search phase, the highest offer received in the group is rewarded to both players whereas search costs are paid individually. The potential draws of one group member (high-type) are much higher compared to the potential draws of the other member (low-type). Hence, in the unique equilibrium of the game, high-type players search until finding a high enough offer, and low-types do not search. Nonetheless, active participation bias can drive low-types to search. Therefore, we can understand the causes and impacts of the active participation bias by investigating the search behavior of low-type players. We have three main results.

Firstly, active participation bias exists and it is very widespread. Notably, 97% of the low-types in our baseline treatment become active, i.e. draw at least one offer even though this reduces their payoffs. Moreover, we ask participants what the optimal strategy for the low-type players is and 95% of the low-types with the correct answer (which is zero searches) searched nonetheless. This strongly suggests that participants intentionally chose to be active even if it is costly.

Secondly, active participation bias is caused mainly by the internal value of being active and it is independent of other preferences or biases. In one treatment, we replace high-type players with a computer algorithm that plays the optimal strategy. Despite knowing this, 85% of the low-type players draw at least one offer. Comparing it to the 97% active search in the baseline, we can deduce that the motives that may derive from human interaction, such as social image concerns or trust in other group members can only account for a 12% difference in the search activity while 85% remain unexplained by social motives. Moreover, we collect measures of cognitive ability, creativity, personality traits, time and risk preferences. None of these character traits and preferences are correlated with the active participation choice in any of the treatments. Thus, the tendency to be active seems to be a distinct character trait.

The consequences of the active participation bias can be immense, in particular when combined with narrow framing. As Barberis, Huang, and Thaler (2006) suggest, people generally evaluate small decisions in isolation without considering other related outcomes. We also observe a variant of narrow framing in our experiment: Participants who exhibit active participation bias, seem to ignore the overall structure of the game, in which it would be best to stop searching immediately, and instead search in line with a strategy that would be optimal if they were confronted with the search game in isolation.

Hence, active participation bias and narrow framing might jointly cause people to be trapped in the subgame. This will have substantial negative consequences if the optimal behavior in the subgame, if it was played in isolation, leads to even further deviation from the optimal outcome that would result from staying passive. For example, a person can start a new project when there are not any alternative projects available even if the project is not promising. Furthermore, the situation is aggravated if that person ignores the possibility of quitting the project and keeps investing more time and energy.

Besides, we conduct three additional treatments to measure the scope of the active participation bias. In one treatment, we change the search parameters to allow higher potential draws for low-types while still preserving the unique equilibrium of only high-types searching. In this treatment, participants search with a higher intensity once they become active. Moreover, their behavior is again in line with the optimal strategy of the alone subgame with the new parameters, confirming the narrow framing.

Contrary to the first additional treatment, the second additional treatment has a new payoff structure to reduce the search activity after becoming active. We first take the minimum draw of each member as their personal outcome in the intermediate step. Then, the maximum of the two personal outcomes (i.e., the maximum of minimums) becomes the group reward. In this case, it is optimal for the high-types to draw once and low-types to stay passive. However, almost all of the low-types start searching and half of them draw exactly once as parallel to our narrow framing result. Hence, low-types play again as if they are alone. Both first and the second additional treatments clearly show that individuals tend to focus entirely on their task and forget about the other players and different options once they start playing a game.

In the third additional treatment, we offer participants a free outside option that is higher than the expected payoff of the alone search subgame. Thus, they cannot achieve a higher (expected) outcome if they reject the option. Only 31% of the participants accept the outside option and the remaining 69% reject the option to play the game themselves. These results show that people receive an intrinsic utility from being active apart from the outcome.

This treatment can also be seen as a counter evidence against experimenter demand effects since some people might believe that researchers expect participants to accept their offer. However, we do not see a considerable effect as the vast majority rejects the offer.

We believe that we can design experiments more effectively by taking this pervasive tendency to be active into consideration. For instance, one can reduce the noise and increase the precision of the experimental results by providing subjects with more than one way of becoming active. Alternatively, we can frame alternative options such that they do not have connotations of passivity.

Similarly, we can design work environments in a more efficient way thanks to our insights from active participation bias. For example, we can remind decision makers of other related factors and alternative strategies after they begin to engage in a task. Hence, vast and unnecessary costs can be avoided if managers and workers are aware of this bias and act accordingly.

In Section 2 of the paper, we summarize the related literature and explain connections to our research. In section 3, we discuss the potential mechanisms of the bias and describe our hypotheses. The experimental design is explained in Section 4 and the results are presented in Section 5. We demonstrate additional treatments and robustness checks in Section 6. Our conclusion is in Section 7.

2 Literature

Active participation bias was observed in a lab experiment by Lei, Noussair, and Plott (2001) in which participants make investments in the stock market too often, thereby generating bubbles. While Lei et al. coined the term active participation bias, they did not investigate the mechanism further. Active participation bias is also observed in other contexts.

For example, in all-pay auction experiments, it is often observed that participants bid positive amounts even when the Nash equilibrium prediction is zero. Lugovskyy, Puzzello, and Tucker (2010) show that almost all of the bids are positive which leads to overdissipation. The overdissipation is eventually eliminated only in the treatment where negative bids are possible. They argue that active participation bias is effective in this context since individuals do not need to bid positive amounts to feel active in the negative-bid setting.

Similarly, in contest experiments, participants exert positive costly effort even when the optimal strategy is zero effort. Sheremeta (2010) shows that 40% of subjects exerted costly effort in contests for a prize of zero. Moreover, in the group contest framework, Abbink et al. (2010) and Sheremeta (2011) show that almost all players exert positive effort where the theoretical prediction is zero.

Likewise, Goerg, Kube, and Radbruch (2019) run an experiment in which participants perform a real-effort task under different payment schemes. In all settings, people exert more effort if they cannot leave the lab when they finish. Moreover, the prohibition of internet usage while waiting further increases the effort level.

Additionally, Carpenter, Liati, and Vickery (2010) show that many people send positive amounts in a two-way dictator game experiment in which two players simultaneously choose how much to donate the other player out of their endowments. They argue that altruism motives are not relevant since both players start with the same endowment, and participants donate because they are "ready to play". They also show that impulsivity (measured by an ADHD questionnaire) is positively correlated with donating positive amounts.

We also see active participation bias in the war of attrition experiments. Under full information, theoretical prediction is stopping immediately. Both Bilodeau, Childs, and Mestelman (2004), and

Hörisch and Kirchkamp (2010) show that stopping at time zero is rarely observed, contrary to the standard theory. Individuals tend to avoid choosing null actions in general.

Furthermore, some field behavior is also in line with active participation bias. Bar-Eli et al. (2007) point out that elite goalkeepers in Israel's professional football league do not stay in the middle during the penalty kicks as frequently as the shooter aims in the middle. They could have saved more penalties by increasing their probability of staying passive. In-depth interviews reveal that goalkeepers are aware of this imbalance but still choose to jump to a corner since staying in the middle is seen as incompetent by fans.

Another related domain might be the fear of missing out (FOMO). Recent studies show that people are more likely to engage in an activity when many other people are engaged as well. Moreover, they feel lonely and depressed when they cannot join popular endeavors. For instance, Zeelenberg and Pieters (2004) show that using a postcode-style lottery (where everyone with a ticket in a postcode area wins the lottery) instead of a state-wide lottery increases participation drastically. Likewise, Kuhn et al. (2011) present that neighbors of car winners in a lottery are more likely to buy a new car. Hence, people tend to take an action when it is prevalent in society.

In addition, the excessive literature on the demand for agency can be seen as related to active participation bias. *Agency* or *authority* is generally described as the ability to change the outcome. Although people who exhibit active participation bias in the studies listed above do not always affect the outcome (e.g., by low bids in auctions or small efforts in contests), they alter their individual payoffs. Possibly, they are willing to incur some cost to have a personal impact on the game.

Lastly, we can mention the literature on boredom as it can be one of the main variables in active participation decisions. The alternative to active participation is often waiting and it may provoke boredom. Killingsworth and Gilbert (2010) show that being idle causes unhappiness since people tend to think about what potential activities they could be involved in. Likewise, Wilson et al. (2014) conduct an experiment where subjects have to wait for 15 minutes in an empty room and can choose to give electric shocks to themselves. During the 15-minutes "just thinking" phase, 43% of the participants give themselves at least one electric shock.

All the findings mentioned above suggest that people are inclined to be active instead of staying passive in numerous domains. This study provides a common explanation that can clarify and connect the diverse evidence.

3 Possible Mechanisms

Several factors might drive the active participation bias, i.e. cause people to be active even when it is not payoff maximizing.

Firstly, social image concerns can be at play. In situations in which multiple players interact, costly actions might be used to signal to others that one is willing to actively contribute to group members' payoff. Such kind of signalling is particular relevant in situations in which free-riding or laziness would lead to inactivity.

A second potential channel is fairness concerns. If the reward of a group task is shared by everyone but some players do not pay any cost, that naturally causes some inequality among group members. The fairness literature documents (e.g., Forsythe et al. (1994)) that many people are willing to sacrifice some of their earnings to reduce the inequality in their group. Similarly, some individuals can engage in a costly activity to achieve a fairer distribution of payoffs. Naturally, fairness can also be a virtue that agents want to signal to other parties. That part of fairness concern can be seen as a form of the social image concerns described above.

Thirdly, beliefs and risk preferences can potentially lead to active participation bias. One player might understand that she must stay passive in the equilibrium play. However, she might act differently if she believes that her partner would make a mistake and not follow his optimal strategy. Thus, active participation can arise from insurance motives.

The fourth reason behind active participation can be simple mistakes in decision-making or in implementation. Since negative activity is not possible in many games by definition, we would observe any error as active participation. For example, in most of the auction or trade experiments you can either bid zero or a positive amount. In those cases, even small incidents such as clicking a button would be an indication of activity. Therefore, one-sided errors can be perceived as an overall tendency to be active.

Lastly, intrinsic utility from playing the game can be a source of active participation. Participants may be aware of the optimal strategies but still, deliberately play actively for pleasure or fun. Similarly, curiosity can cause them to take costly action to discover the potential outcomes of their actions.

Potentially, one or more of these channels can result in active participation bias. We use an experiment to analyze the effectiveness of each factor on activity. Lab experiments provide an ideal setting to investigate a behavioral pattern by strategically manipulating each component and observing the impact. We simply eliminate some factors by simplifying the game further and observing the impact.

3.1 Hypotheses

We test two hypotheses using the data from our experiment. The first one is about the existence of active participation bias. We conjecture that people have a tendency to become active instead of doing nothing even when the payoff maximizing action is staying passive.

The second hypothesis is about one mechanism that drives active participation. We conjecture that social image and fairness concerns are two of the main channels that drive active participation bias. We will test whether people take costly actions to signal their merit to other players and to reduce inequality within their group. More formally:

H1: People choose to be active even when it is costly and does not increase payoffs.

H2: Fairness and social image concerns increase the tendency to become active.

4 Experimental Design

The experiment is programmed in oTree (see Chen, Schonger, and Wickens (2016)) conducted online using a Zoom meeting. We use an online procedure instead of an offline lab procedure because of COVID-19 restrictions at the time of implementation. In order to mimic a setting as similar to the lab experiments as possible, and to ensure data quality, we used the Zoom procedure. Li et al. (2021) show that using Zoom for online experiments improves data quality at the lab level and generates comparable data.

The procedure of the experiment: Subjects are invited to a Zoom meeting and they enter the waiting room when they arrive. Later, each participant is sequentially admitted to the main room of the meeting, where she is instructed to keep her camera turned on during the whole experiment and informed briefly about the experimental procedure on Zoom. Then, she is moved to a breakout room alone before the next participant is admitted to the main room. After all participants have been transferred to their personal waiting room, the link to the experiment is shared and the experiment begins. Being in separate breakout rooms mimics the cubicles in a lab while preserving anonymity among participants. They use the "ask for help" button when they have a question or a problem.

Main Search Task: Two players are randomly matched to form a group. Each of the two group members separately plays a sequential search game in which each group member can search for a number that is uniformly distributed on a closed interval. The search result with the highest number of any of the two group members becomes relevant for payoffs. Searching entails drawing a number from a known distribution by paying a fee of 1 point. After learning the result of the draw, she can either draw another offer by paying the search cost again or she can stop searching. The search phase lasts for 10 minutes and each draw takes 10 seconds. During this phase, each player can draw as many offers as she wants and as time permits. It is also possible not to draw any offers. However, it is not possible to end the search phase earlier. Players would have to wait for the search phase to finish when they stop searching.

At the end of the search phase, the highest offer each player received determines their individual performance. This value is announced to the other group member and the highest individual performance in a group determines group performance. The payoff for each group member equals the group performance, i.e. the highest number drawn by any of the two group members, minus the individual search costs. In other words, the highest offer in a group is treated as a public good whereas search costs are paid individually.

Each group consists of one high-type and one low-type player. The offers of high-type players are drawn uniformly from the interval $[35, 100]$ and the offers of low-type players are drawn uniformly from $[0, 65]$. In equilibrium, the high-type player searches until reaching the threshold of 89 and the low-type player does not search at all. The proof of the equilibrium and the analysis under different utility structures are provided in Section A1 in Appendix. Our main focus will be on low-type players since their optimal choice is staying inactive. Becoming active reveals active participation bias.

We use a version of a sequential group search game to assess active participation bias and its underlying mechanism because this game has three major advantages for testing our hypotheses. Firstly, the task does not preclude factors that have been conjectured to explain active participation when staying passive is optimal. For example, the group setting could trigger social motives, such as social image or equity concerns. Also, the potential risk about the partner's performance and the random nature of a draw make risk preferences relevant.

Secondly, the rich set of features of the search games enables us to modify them to adapt to our testing purposes. For instance, we can change the group and information structure or the search parameters in order to test the effect of different factors.

Lastly, we know that individuals are generally capable of understanding and optimally playing search games. Many studies such as Schotter and Braunstein (1981) and Hey (1982) showed decades ago that the search behavior of the participants is usually close to the optimal strategy. Hence, search games are a natural starting point to see the behavioral effects of some modifications to the game.

Timeline and Other Tasks: The timeline of the experiment is as follows.

1. Instructions and comprehension questions
2. Demo task
3. Main task: group search game
4. Questionnaire about the search game
5. The revelation of search outcomes in the group

6. Survey on demographics and preferences

7. Raven's matrices

8. Remote associates test

After reading the instructions and answering the comprehension questions, participants play a demo search game. The setup of the demo is exactly like the main task and each participant draws one offer[2]. We use this demo task for two purposes. First, players can get familiarized with the task. Secondly, and more importantly, we eliminate the curiosity motive with the demo draw. Hence, we can induce that players do not draw offers in the main task just to see the game flow.

We also implement an attention check mechanism to ensure that participants do not engage in other activities during the search phase. Participants are informed that a pop-up window appears on their screen at a certain time and they have to click a button in 5 seconds to confirm that they are paying attention[3]. If they fail to click the button, they lose all the earnings from the task and receive only the participation fee of 3 Euros.

After the search phase and before the revelation of group outcomes, we ask participants a few questions about the main task to better understand their strategy and decision rules. These are not incentivized. First, we ask them to describe the decision rule they followed in the task. Second, we ask them to state their beliefs about the highest offer of their partners.

Later, they fill out an extensive survey including demographic questions as well as subjective risk, patience, general trust, math ability, and other personality traits. Then, they solve 8 Raven's matrices with visual puzzles in 2 minutes. We use this measure as a proxy for cognitive ability or IQ. Finally, they solve a 10-question remote associates test in 3 minutes. This score is used as an indicator of creativity. We use a between-subject design such that participants are randomly placed in one of the two treatments described below.

[2]The offer they draw is the fixed to their expected offers (68 for high-types and 33 for low-types) to avoid any anchoring.

[3]The pop-up screen is set to appear just 5 seconds before the end of the search phase to avoid any impact on the search behavior afterward but the exact time is not declared to participants.

4.1 Social (Baseline) Treatment

In this treatment, participants play the search game as described above. In this setting, we can expect all the possible channels mentioned above to be effective. For instance, low-type players may try to get a high offer to signal to their partners that they are hard-working, capable, or fair. Alternatively, they may search to insure themselves against the case their partner might make a mistake and not search at all.

4.2 Computer Treatment

In this treatment, high-type players are replaced with a computer algorithm that plays an optimal strategy with a threshold of 90. Low-type players are informed that a computer bot undertakes the role of the high type and it plays the optimal strategy. However, the explicit strategy of the computer is not described[4].

In this setting, we would expect all of the social, fairness, and risk concerns to be irrelevant. Low-type players do not have any motive to signal something, reduce inequality, or insure themselves against possible mistakes. Hence, by comparing the behavior in this treatment to the baseline, we can clearly see the effect of all human factors combined.

5 Experimental Results

The experiment is conducted with the participants from the BonnEconLab subject pool. A total of 217 people participated and 80 of them were in the computer treatment. Out of 137 people in the social treatment, 69 people were low-type players (low-type) and 68 people were high-type players (high-type)[5]. The average duration of the experiment was 45 minutes and the average payment was 16.4 Euros.

[4]To make computer bot comparable to human players, we imposed the same time limit (10 min.) and draw time (10 sec.). Hence, computer can draw up to 60 offers and this is announced to participants. This constraint was never binding in our data (see Section A1 in Appendix).

[5]A few people had connection issues and left the experiment during the sessions. In those cases, their partners continued. Hence, the number of types does not match.

The first observation is that our attention manipulation is successful. Only 14 participants (8 in social, 6 in computer treatment) failed the attention check in the search phase. We can deduce that almost all of the participants have been waiting for the pop-up screen even when their search activity is finished. We discard participants who failed the attention check from the analysis since their behavior is not comparable to the behavior of other participants[6].

The first main result of the experiment is that active participation bias exists. In fact, it is almost universal. Nearly all players searched actively in the baseline treatment. Only 2 low-type players out of 67 (3%) have not drawn any offer in the social treatment. Although it is payoff maximizing to stay passive for low-type players, almost all of them chose to draw at least one offer. As Figure 1 shows, most of the low-type players drew more than one offer, and the average number of draws of searchers was 4.1.

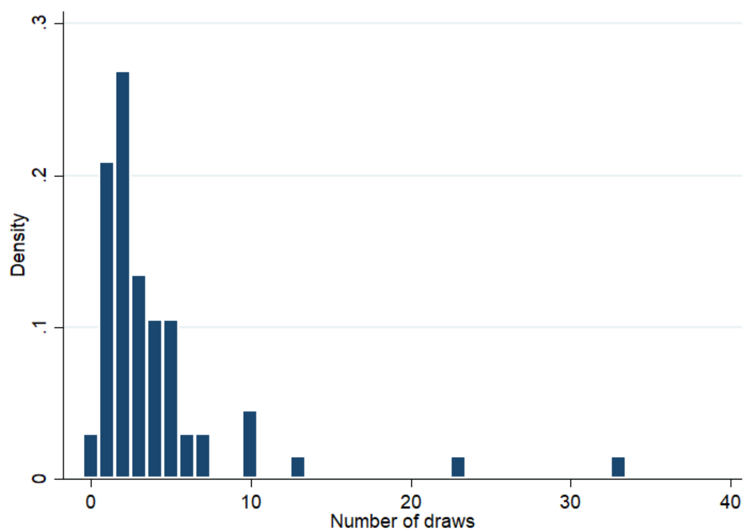

Figure 1: Histogram of number of draws by low-type players in the social treatment.

The second main result is that active participation bias cannot be explained by risk preferences, fairness or social motives. Only 14.86% of participants in the computer treatment have not drawn any offer. Despite the 11.86 percentage point increase from the 3% not searching in the social treatment, 85% of the low-type players still chose to search even when their partner is a computer algorithm that plays the optimal strategy. Thus, all of the human factors such as virtue signaling, altruism, or trust

[6]This selection criterion was also included in the preregistration.

can only account for a small fraction of active participation behavior. Similar to the social treatment, most of the participants drew more than one offer and the average number of draws was 3.3.

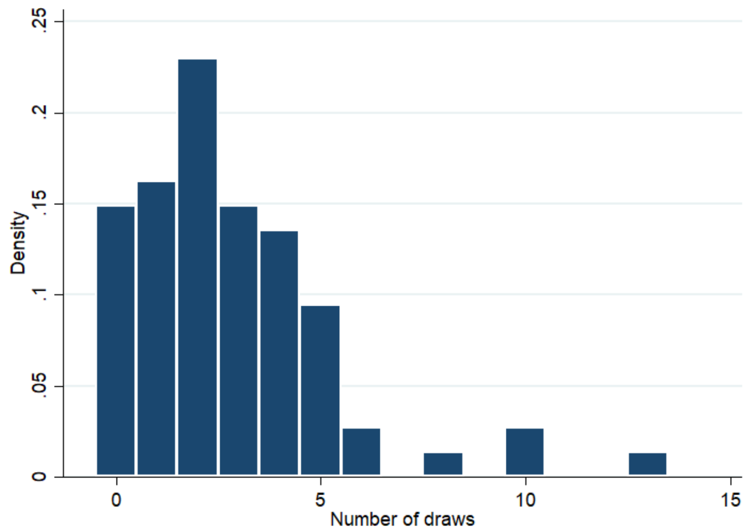

Figure 2: Histogram of number of draws by low-type players in the social treatment.

Moreover, active participation bias is not explained by a mistake caused by the inability to solve the problem correctly, as answers to the bonus question at the end of the main task reveal. The question asks participants about the optimal strategy for low-type players and 62.4% of the participants answered it correctly[7]. Nonetheless, 86.4% of the participants with the correct answer drew at least one offer even though they know the optimal strategy (see Table A4 in Appendix for details). Hence, we can deduce that the tendency to be active is not a simple error but a deliberate choice for a majority of participants.

We can also rule out that participation is driven by risk-taking behavior. We mentioned beliefs and risk preferences as potential mechanisms in Section 3. However, low-type players' beliefs about the high-types are too high to explain their search behavior. The average beliefs are 76.7 and 77.1 in the social and the computer treatments, respectively[8], which are much higher than the maximum possible offer for low-types. Moreover, as Table 1 shows, neither beliefs about the partner's performance nor risk preferences have a significant effect on starting to search.

[7]There is no difference between the two treatments (see Table A3 in Appendix).
[8]There is not a significant treatment difference in beliefs.

	(1) nosearch	(2) nosearch
computer treatment	0.119**	0.120**
	(0.0482)	(0.0478)
belief	-0.00113	
	(0.00226)	
risk aversion		0.0174
		(0.0105)
constant	0.116	-0.0572
	(0.177)	(0.0630)
N	141	141

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: OLS regressions of the indicator for not searching on belief and risk aversion measures.

Furthermore, the choice of active participation is independent of other skill and preference measures. As Table 2 shows, Raven's test score, remote associates test score, self-reported math ability, general trust in strangers, and patience have no significant effect on search behavior. In addition, the other demographic and personality variables are not correlated with active search, either[9]. Therefore, we can confirm that the active participation bias results from an intrinsic tendency to be active and is not a by-product of other preferences or mistakes.

The final result of the experiment is about the impact of the active participation bias. If people choose to be active but stop immediately after a brief activity, that would not have huge consequences. However, we see an opposite phenomenon. Low-type players try to have a good offer and keep searching until they reach a satisfactory level. In other words, they ignore the broader game and focus on their own task as if they are playing alone.

We can understand their search strategy by looking at a few indicators. Firstly, participants generally reject small offers and accept the high levels. We can investigate their strategy more precisely using a probabilistic regression to find the threshold level that fits the data best. As exhibited in Table 3, we estimate the threshold of 52.34 for the social treatment and 53.15 for the computer treatment. Note that the optimal threshold for low-type players when playing alone is 54. Thus, we can easily conclude that

[9]Only neuroticism (or emotional stability) seems to have a significant impact on search decisions but this effect vanishes in other treatments. See Appendix for a detailed analysis.

	(1) nosearch	(2) nosearch	(3) nosearch	(4) nosearch	(5) nosearch
comp.treatment	0.120**	0.118**	0.120**	0.117**	0.114**
	(0.0499)	(0.0482)	(0.0481)	(0.0484)	(0.0487)
Raven's score	-0.00171				
	(0.0186)				
rat score		0.00999			
		(0.0158)			
math ability			0.00763		
			(0.00860)		
trust				0.00436	
				(0.00918)	
patience					0.00859
					(0.0126)
constant	0.0371	0.0175	-0.0131	0.0106	-0.0324
	(0.0858)	(0.0401)	(0.0597)	(0.0534)	(0.0977)
N	141	141	141	141	141

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: OLS regressions of the indicator for not searching on the skill and preference measures.

those who become active follow a strategy similar to the optimal strategy of the search task in which they search alone. Furthermore, participants exhibit similar search behaviors in both treatments, as you can clearly see in Figure 3. The distributions of accepted offers are almost identical in the two treatments.

In addition, we can look at the recall behavior as an indication of a threshold strategy. Since a threshold strategy requires searching until a certain value, it never generates a stop after a low offer and a recall of a higher past offer. When we look at the 128 low-type players who drew at least one offer, only 27.3% of them recalled a past offer (no significant treatment difference, see Table A8 in Appendix). The behavior of the remaining 72.7% is in line with a threshold strategy.

Furthermore, the results from the question about the decision rule they followed in the search task also support the finding that they try to optimize their individual search task. Overall, 76% of the low-type players mentioned that they tried to maximize their own outcome and kept searching if the expected net return from a draw is positive[10]. On top of that, only 7% mentioned that they searched just

[10]Two research assistants digitized the verbal answers separately. We combined their data such that an answer mentions a certain decision rule if at least one of the two assistants indicates so.

	(1) social	(2) computer
threshold	52.34***	53.15***
	(0.14)	(0.14)
N	265	207

Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Probit regression to estimate the threshold levels used in two treatments.

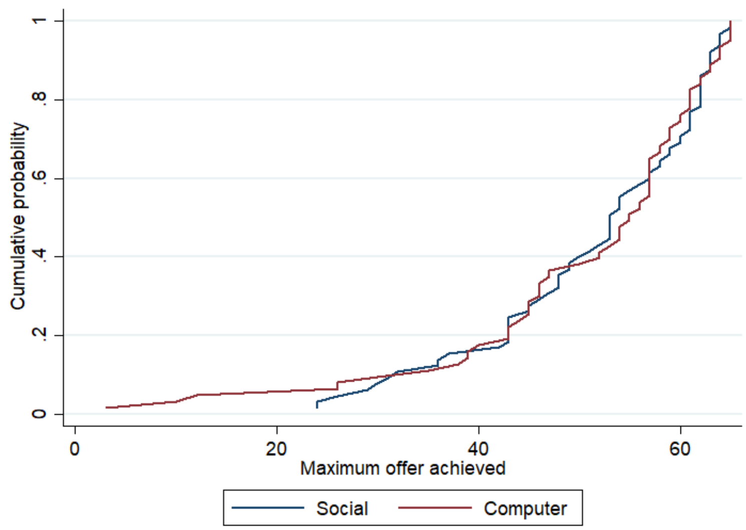

Figure 3: Cumulative distribution functions of achieved maximum offers in two treatments.

for fun. These results provide additional evidence for focusing on the individual task and optimizing only that. Low-type players ignore the broad game and play as if they are alone.

This behavior can be described as narrow framing such that individuals break the decision process into different parts and try to solve them separately. Agents first decide whether they start searching or not. In this first step, active participation bias can cause them to start playing the game to become active. Then, they choose how to play the game. In this second step, they tend to ignore the big picture and focus on their own tasks. Hence, they try to play their task as well as possible, despite the fact that each additional draw reduces their payoffs further since it is costly and their performance would be overridden by the high-type player. Therefore, that narrow framing exacerbates the impact of active participation bias since participants can keep searching and pay huge costs once they start playing a game.

We can consider the impact of active participation bias in two steps where the tendency to be active drives people into an activity and narrow framing causes them to focus on the confined task once they become active. Hence, active participation bias is problematic when it lures people into a situation in which they should not be. Also, its initial impact gets much worse if solving the problem in the new situation leads to an even stronger departure from the optimum in the overall game. We run three additional treatments to better understand this pattern. We explain the designs and results of the new treatments in the next section.

6 Additional Treatments

We designed three additional treatments to test the extent of active participation bias. Specifically, we provide additional evidence as a robustness check of the two-step activity decision. Particularly, we investigate whether people have an intrinsic preference to play the game themselves (i.e., the source of active participation bias) and whether they keep narrowly focusing on their task under different settings (i.e., narrow framing). All three new treatments are based on the computer treatment with small modifications.

6.1 High Intensity Treatment

In this treatment, we check if people keep searching more when their task is slightly changed. The treatment is exactly like the computer treatment except for the distribution of offers. The intervals for the draws are changed to $[0, 85]$ for low-type players and $[15, 100]$ for high-type players[11]. Now, the equilibrium remains similar to the computer treatment. In equilibrium, high-types search until 88, and low-types do not search. On the other hand, the optimal threshold for low-type players becomes 73 if they search as if they are alone. Therefore, by comparing the search behavior to the computer treatment (where the optimal threshold in the alone task was 54), we can test whether participants ignore their partner and try to play optimally alone in their own task.

[11] Remember that they were $[0, 65]$ and $[35, 100]$, respectively.

The data confirms again that individuals choose to be active since the vast 92% of the participants drew some offers. Furthermore, the results from the high intensity treatment clearly show that low-type players ignore their partners and search as if they play alone. As you can in Figure 4, most of the players stopped only after achieving a high enough offer. The estimated threshold using probabilistic regression is 73.52 (s.d.=0.13) which is extremely close to the threshold of 73 (depicted by a dashed red line in the graph), the optimal level in the alone search task.

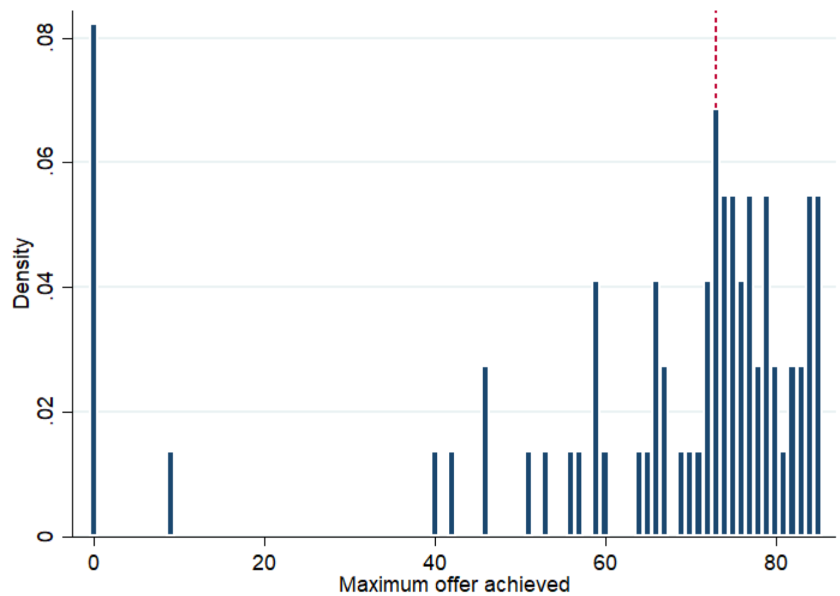

Figure 4: The histogram of maximum offers achieved in the high intensity treatment. The dashed red line represents the optimal threshold level of 73 in the alone search game.

6.2 Minmax Treatment

In this treatment, we test whether search duration reduces with a slight modification of the game. Particularly, the payoff structure is changed such that *the minimum* offer of each player determines their individual performance and *the maximum* of the individual performances determines the group performance (hence the name minmax). Therefore, the equilibrium becomes high-type players drawing once and low-type players not drawing. Since the expected draw of a high-type is 67.5 (the mean of $U[35, 100]$), it is not optimal for a low-type to draw (from $U[0, 65]$). However, low-type players would also draw once if they narrowly focus on their own tasks and try to maximize their performance. Thus, by looking at their search behavior we can understand the scope of the narrow framing.

The findings in this treatment also support the active participation bias and narrow framing. As depicted in Figure 5, only one participant stayed passive and almost half of the participants drew only one offer. Evidently, participants chose to be active and followed the optimal strategy of the alone search task.

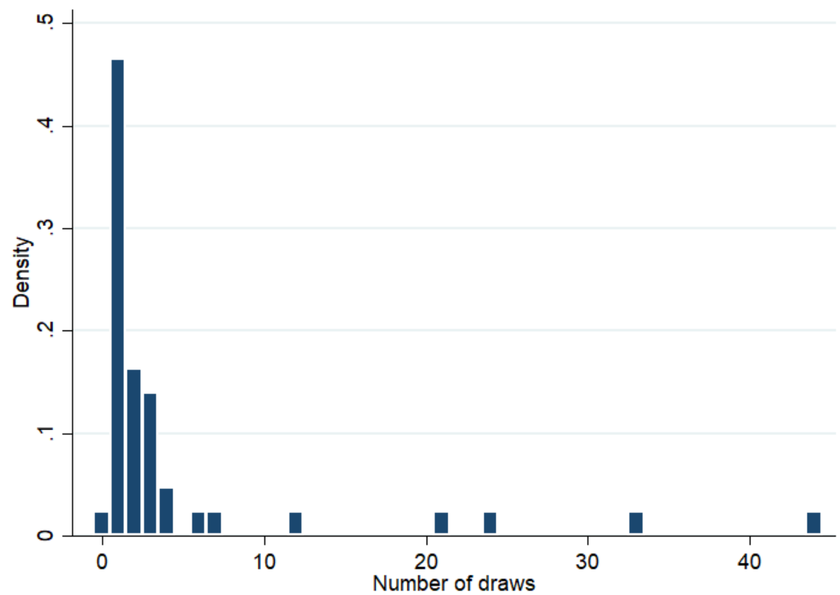

Figure 5: Histogram of the number of draws in the minmax treatment.

6.3 Option Treatment

In this treatment, participants are offered an outside option just before the search game begins. If they accept the outside option, their individual performance will be set as 55 with a total cost of 0. Then, they will wait for 10 minutes for the search phase to end. If they reject the outside option, they will play the search game as in the computer treatment.

Level 55 is chosen to exceed the expected value of playing the search game alone for the low-types. In other words, a low-type player cannot aim for an expected outcome above 55 by playing herself. Hence, we can deduce that they get an intrinsic utility from playing the game themselves if they reject the option and sacrifice some payoff. Thus, we can see the source of the active participation bias.

The result of the experiment supports our previous finding that people have an intrinsic preference to be active. Out of 39 participants, only 12 of them (31%) accepted the outside option and the remaining 27 participants (69%) rejected the option to search by themselves. When we look at the characteristics of those who accepted the option, we see that active participation bias is independent of other individual traits such as risk preferences or cognitive abilities.

Firstly, we can see that it is a deliberate choice and not only a mistake caused by some misunderstanding. Half of the participants who answered the bonus question correctly rejected the outside option (see Table A11 in Appendix for details). Hence, their choice reveals that they are willing to pay the search costs in order to be active.

Secondly, active participation bias is not a by-product of other preferences and skills. The regression results show that none of the ability and preference measures is correlated with the choice of accepting the outside option (see Appendix).

Lastly, we can look at the search behavior of the participants who rejected the outside option. The estimated threshold for searchers is 53.2 which is indistinguishable from the computer treatment or the optimal alone threshold. Furthermore, as shown in Figure 6, many people stopped searching with a maximum offer much below the outside option offer of 55. Thus, we can see that they do not reject the outside option to achieve an outcome higher than 55[12]. Instead, they prefer to search actively even if they pay the search costs and attain a worse offer.

As a consequence of the further evidence in additional treatments, we can confidently deduce that people have an intrinsic tendency to become active instead of staying passive even when it is costly. Moreover, they ignore the other parts of the problem and focus only on their own tasks once they become active.

[12] 62% of the players ended up with a task outcome (max. offer - costs) of 55 or below.

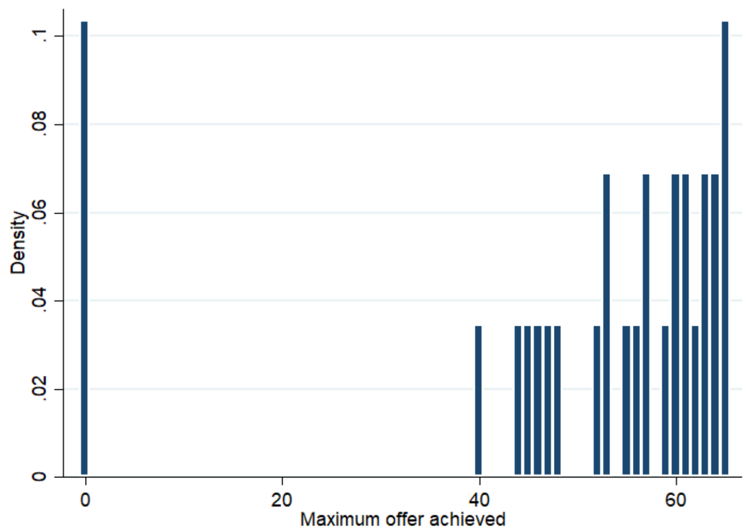

Figure 6: Histogram of maximum offers achieved in the outside option treatment

7 Conclusion

In this study, we show that active participation bias is a common phenomenon. People intrinsically prefer to be active and they are willing to pay considerable costs to avoid idleness. If there is only one activity available, people engage in it even when they know it is not optimal.

This insight can help us design our experiments in a much thoughtful way. When running an RCT, we must refrain from comparing an active behavior to the alternative of staying passive. Otherwise, it would not be possible to clearly distinguish the correct preference for that specific behavior from the general tendency to be active. Likewise, the efficiency in work environments can be improved by considering active participation bias. If an alternative side task is not provided to workers, they can involve in futile or even harmful tasks. This tendency to be active can lead to huge time and monetary costs when it is prolonged by narrow framing. Hence, workers can allocate their time and energy more effectively if the work environment encourages them to question their tasks and consider alternative options.

Furthermore, active participation bias can help us explain many puzzles in real life. For instance, it can be a reason behind the high levels of voter turnout. As a reflection of active participation bias, individuals may feel an urge to participate in a common activity even when the probability of being pivotal is minuscule[13]. Besides, active participation bias can be a motive behind the surge in stock exchange trading during COVID-19 lockdowns, both at the internal and the external margin[14]. Individuals might have been inclined towards financial trading as a way of participating in economic activities when most of the other sectors were on hold.

As the first study that examines active participation bias in detail, we mainly focus on why and how it operates. A natural next step in research would be finding some debiasing strategies. Since active participation motive was never shut down in our experimental settings, we believe that providing a promising debiasing rule will be challenging.

Finally, the root source of the intrinsic preference toward activity remains an open question. Due to the relative nature of ordinal preferences, we cannot determine using our data whether activity brings positive utility or idleness evokes negative feelings. Perhaps, neural imaging can suggest more evidence for the question but it is beyond the scope of this paper.

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[13]Both DellaVigna et al. (2016) and Rogers, Ternovski, and Yoeli (2016) reveal that social image concerns are weak and cannot explain voter turnout. On the other hand, Gerber, Green, and Larimer (2008) demonstrate that the probability to vote increases if people believe others vote, too.

[14]See Ortmann, Pelster, and Wengerek (2020) for a detailed description.

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A Appendix

A1 Theoretical Predictions

Reminder: In each group, there is a low-type (L) and a high-type (H) player. They search separately for offers and only the highest offer in the group is relevant for the payoff. At the end of the search period, each group member earns the highest offer in the group and pays individual search costs. The offers for the low-type are drawn from a uniform discrete random variable between 0 and 65 whereas the offers for the high-type are drawn from a uniform discrete random variable between 35 and 100. The cost of getting another offer is 1 for both players.

Equilibrium: First, we look at the individual search. Assume a player has the highest offer of x at some point in the search phase. The expected gain from drawing another offer becomes

$$V(x) = \sum_{x_i} Pr(x_i) \max\{x_i, x\} - x_i = \sum_{x_i > x} Pr(x_i)(x_i - x) \tag{1}$$

The agent keeps drawing offers whenever the continuation value $V(x)$ is bigger than the search cost of $c = 1$. Note that, $V(x)$ is decreasing in x since both summed values $(x_i - x)$ and the summation interval $(x_i > x)$ get smaller when x gets bigger. Thus, there must be a cutoff point R such that $V(x) > c$ for $x < R$ and $V(x) < c$ for $x > R$. Hence, the optimal strategy in a sequential search game is always a threshold strategy.

In our specifications, the continuation value for a high-type at an offer 89 is

$$V^H(89) = \sum_{x_i \in \{90,...,100\}} \frac{1}{66}(x_i - 89) = \frac{1}{66}(1 + 2 + ... + 11) = 1 \tag{2}$$

Since, it is equal to the search cost of $c = 1$, the high-type is indifferent between drawing another offer and stopping. For simplicity, we assume an agent stops if the net gain from continuation is equal to the cost. Thus, the optimal strategy for high-types becomes a threshold strategy of $R^H = 89$. This assumption does not change any of the results.

Similarly, the continuation value for a low-type at an offer of 54 is

$$V^L(54) = \sum_{x_i \in \{55,...,65\}} \frac{1}{66}(x_i - 54) = \frac{1}{66}(1 + 2 + ... + 11) = 1 \tag{3}$$

Therefore, the optimal strategy for a low-type in an individual search game is a threshold strategy of $R^L = 54$.

Now, we can look at the group level. The threshold strategy of $R^H = 89$ is a dominant strategy for the high-type because the low-type cannot reach an offer above 65 and the high-type is strictly better of by searching at any offer below 89. Therefore, in equilibrium, the high-type should follow the same strategy of $R^H = 89$ regardless of the low-type's strategy.

The best response of the low-type to high-type's strategy of $R^H = 89$ is not searching, i.e. a threshold of $R^L = 0$, since it is not possible for the low-type surpass the level 89. Any draw incurs a cost without any potential gain. Therefore, any strategy other than not searching is dominated for the low-type. Hence, the unique equilibrium of the game becomes $(R^H, R^L) = (89, 0)$. In equilibrium, the high-type searches until finding an offer of 89 or above and the low-type does not search.

The equilibrium described above assumes that agents maximize their expected earnings which is based on risk neutrality. Nonetheless, using different utility functions that entail risk aversion does not change the optimal strategies greatly. Table A1 shows optimal thresholds in individual search based on different utility functions and conventional risk aversion parameters used in the literature. Constant absolute risk aversion (CARA) utility has the following functional form with risk aversion parameter $a \geq 0$:

$$u(c) = \begin{cases} (1 - e^{-ac})/a, & a \neq 0 \\ c, & a = 0 \end{cases}$$

Constant relative risk aversion (CRRA) utility with a risk aversion parameter $\rho \geq 0$ has the following functional form:

$$u(c) = \begin{cases} \frac{c^{1-\rho}-1}{1-\rho}, & \rho \neq 1 \\ ln(c), & \rho = 1 \end{cases}$$

	CARA			CRRA		
	$a \leq 0.04$	$a = 0.05$	$a = 0.08$	$\rho \leq 4$	$\rho = 5$	$\rho = 8$
R_{high}	89	88	88	89	88	87
R_{low}	54	53	53	54	51	51

Table A1: Optimal threshold levels in individual search game for low and high types based on different utility functions and risk aversion parameters.

Note that, parameters $a = \rho = 0$ indicates risk neutrality. Almost all empirical findings estimate parameters[15] $a < 0.02$ and $\rho < 2$. As seen in Table A1, even extreme risk aversion parameters do not lead to dramatically different thresholds.

Remark: In the computer treatment, we imposed a time limit of 10 minutes and a draw time of 10 seconds onto the computer algorithm. Therefore, the maximum number of draws was 60 for the computer. The probability of not achieving the threshold of 90 in 60 draws is minuscule, such that

$$Pr\{\max x_i < 90 | n = 60\} = \left(\frac{55}{66}\right)^{60} < 2.10^{-5} \tag{4}$$

Moreover, the probability of high-type not receiving an offer above 65 is even much smaller:

$$Pr\{\max x_i < 65 | n = 60\} = \left(\frac{30}{66}\right)^{60} < 2.10^{-20} \tag{5}$$

Hence, it was almost impossible for low-types to have an offer higher than the maximum offer of the computer algorithm. Even the extreme risk aversion parameters mentioned above do not alter the optimality of not searching for the low-types. Indeed, the constraint of 60 draws was never binding in our experiments.

[15] See Babcock, Choi, and Feinerman (1993) and Evans (2005) as some examples.

A2 Main Treatments

	attention check successful
social, low-type	0.0606
	(0.0423)
computer, low-type	0.0146
	(0.0408)
constant (social, high-type)	0.910***
	(0.0301)
N	216

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Linear regression of attention check on treatment and type. There is no statistical difference between different groups players.

	bonus correct
computer treatment	0.0232
	(0.0822)
social treatment	0.612***
	(0.0596)
N	141

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: OLS regression of the indicator for answering the bonus question correctly on the treatment dummy.

	social		computer	
	correct	not	correct	not
searched	39	26	37	26
no search	2	0	10	1

Table A4: Distribution of the participants according to search activity, treatment, and the bonus question.

	(1) bonus correct	(2) bonus correct	(3) bonus correct
comp. treatment	-0.0234	0.0268	0.0255
	(0.0839)	(0.0816)	(0.0819)
IQ	0.0684**		
	(0.0312)		
math. ability		0.0258*	
		(0.0146)	
RAT score			-0.0392
			(0.0269)
constant	0.323**	0.467***	0.660***
	(0.144)	(0.101)	(0.0681)
N	141	141	141

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: The effect of cognitive ability on answering the bonus question correctly. The IQ score (measured by Raven's matrices) and self-reported math ability have a positive impact.

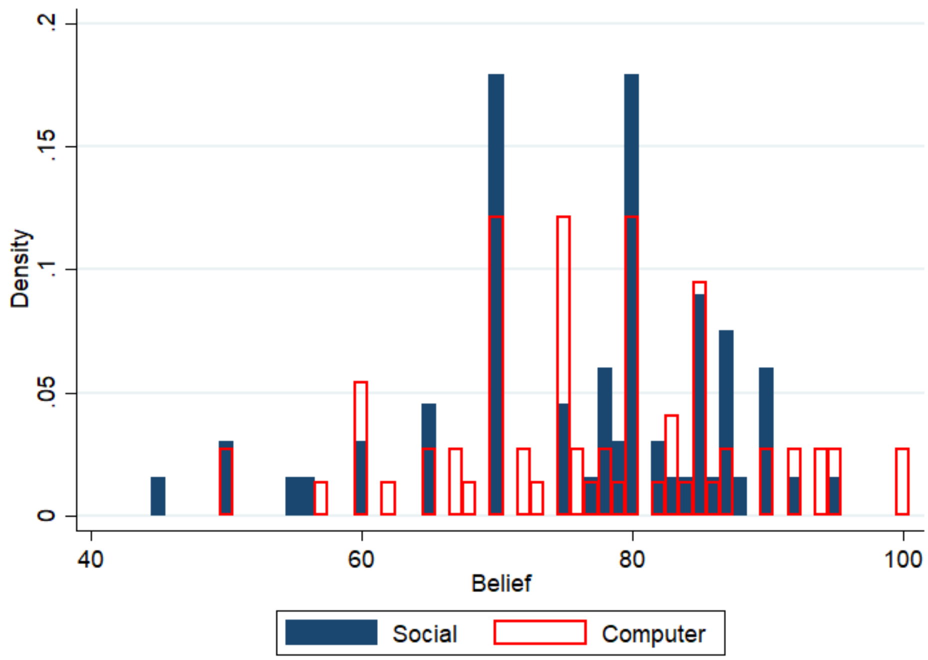

Figure A1: Histogram of the beliefs of low-types about the performance of their partners in social and computer treatments. A vast majority had beliefs above 55, particularly above 65.

	(1) nosearch	(2) nosearch	(3) nosearch	(4) nosearch	(5) nosearch	(6) nosearch	(7) nosearch
comp. treatment	0.124**	0.119**	0.119**	0.126**	0.119**	0.126**	0.119**
	(0.0485)	(0.0483)	(0.0483)	(0.0490)	(0.0483)	(0.0487)	(0.0482)
age	0.00545						
	(0.00575)						
income		-0.0116					
		(0.0397)					
education			0.00232				
			(0.0318)				
punish for me				0.00809			
				(0.00998)			
punish for others					-0.000125		
					(0.00975)		
altruism						-0.0105	
						(0.0109)	
self control							-0.00396
							(0.00785)
constant	-0.107	0.0396	0.0285	-0.000320	0.0305	0.104	0.0529
	(0.148)	(0.0483)	(0.0396)	(0.0510)	(0.0600)	(0.0841)	(0.0575)
N	141	141	141	141	141	141	141

Standard errors in parentheses. sym* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: OLS regression of the dummy for zero draws on demographics and personality measures. None of the factors have a significant impact on search behavior.

	(1) nosearch	(2) nosearch	(3) nosearch	(4) nosearch	(5) nosearch	(6) nosearch
treatment	0.118**	0.121**	0.114**	0.132***	0.116**	0.134***
	(0.0485)	(0.0483)	(0.0495)	(0.0478)	(0.0486)	(0.0503)
extraversion	0.00333					0.00663
	(0.0278)					(0.0315)
aggreeableness		-0.0169				-0.00610
		(0.0281)				(0.0287)
conscientiousness			-0.0103			0.0146
			(0.0235)			(0.0267)
neuroticism				-0.0526**		-0.0752***
				(0.0236)		(0.0288)
openness					0.0126	0.0417
					(0.0247)	(0.0283)
constant	0.0161	0.110	0.0762	0.271**	-0.0294	0.115
	(0.120)	(0.138)	(0.112)	(0.114)	(0.121)	(0.225)
N	141	141	141	141	141	141

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: OLS regression of the dummy for zero draws on big five personality traits. Only neuroticism has a significant impact but it disappears in other treatments.

	recall
computer treatment	0.0867
	(0.0790)
social treatment	0.231***
	(0.0555)
N	128

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: OLS regression of the indicator for recall behavior on the treatment dummy. There is no significant difference in recall frequencies.

A3 Additional Treatments

	Not drawing any offer	
computer treatment	0.164***	(0.0499)
high treatment	0.0784	(0.0495)
Raven score	-0.0106	(0.0142)
RAT score	0.0183	(0.0137)
math ebility	0.00184	(0.00739)
belief	-0.00146	(0.00195)
trust	-0.00296	(0.00783)
risk aversion	-0.0185**	(0.00935)
patience	0.0204*	(0.0108)
age	0.00110	(0.00596)
income	-0.0727**	(0.0366)
education	0.0610*	(0.0342)
punish for me	0.0127	(0.00864)
punish for others	-0.00560	(0.00927)
altruism	-0.0127	(0.00970)
control	0.00381	(0.00761)
extraversion	0.0149	(0.0281)
aggreeableness	0.00213	(0.0258)
conscientiousness	0.0361	(0.0223)
neuroticism	-0.0404	(0.0249)
openness	0.00899	(0.0241)
constant	0.0661	(0.292)
N	214	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: OLS regression of zero draws dummy on all the control variables in social, computer, and high intensity treatments. Only risk aversion, patience, income, and education have some effects.

	Drawing exactly one offer	
Raven score	-0.0822	(0.0609)
RAT score	0.121*	(0.0648)
math ability	-0.0257	(0.0465)
belief	0.000998	(0.00652)
trust	-0.0204	(0.0419)
risk aversion	0.0888*	(0.0497)
patience	0.0510	(0.0594)
age	0.0201	(0.0255)
income	-0.179	(0.168)
education	-0.105	(0.185)
punish for me	0.0171	(0.0409)
punish for others	0.0259	(0.0596)
altruism	-0.0427	(0.0420)
self control	0.0104	(0.0304)
extraversion	0.128	(0.123)
aggreeableness	-0.0356	(0.162)
conscientiousness	0.346**	(0.131)
neuroticism	-0.122	(0.165)
openness	0.0491	(0.0957)
constant	-1.697	(1.622)
N	42	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: OLS regression of the dummy for drawing only one offer on all the control variables in minmax treatment. Only RAT score, risk aversion, and conscientiousness have significant impacts.

	Bonus question	
Option	correct	wrong
accepted	11	1
rejected	11	16

Table A11: Distribution of participants by option choice and bonus question in option treatment.

	(1) accepted	(2) accepted	(3) accepted	(4) accepted	(5) accepted
Raven's score	-0.0177				
	(0.0456)				
rat score		-0.0506			
		(0.0476)			
math			-0.0198		
			(0.0226)		
risk aversion				0.0310	
				(0.0280)	
patience					-0.00162
					(0.0356)
constant	0.394*	0.383***	0.405***	0.156	0.322
	(0.229)	(0.0999)	(0.131)	(0.156)	(0.285)
N	42	42	42	42	42

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: OLS regression of accepting the option on skill and preference measures in option treatment. None of the variables has a significant effect.

	Accepting the option	
age	0.0270	(0.0224)
income	0.0102	(0.132)
education	-0.192	(0.142)
punish for me	0.0497	(0.0374)
punish for others	-0.0449	(0.0452)
altruism	0.0186	(0.0429)
self control	0.0187	(0.0250)
extraversion	-0.193	(0.127)
aggreeableness	0.0143	(0.0893)
conscientiousness	-0.0963	(0.0921)
neuroticism	-0.0140	(0.111)
openness	-0.00308	(0.106)
constant	0.707	(0.812)
N	39	

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: OLS regression of accepting the option on demographic and personality measures in option treatment. None of the variables has a significant effect.