Active Participation Bias

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Abstract

The human tendency to prefer activity over non-activity is a widely observed phenomenon, even in situations in which inactivity is payoff-maximizing. Such active participation bias, which leads to deviations from payoff-maximizing choices, could stem from different drivers in different situations, including social preferences, social image concerns, (false) beliefs, risk preferences, or simply errors in decision-making. Using a set of experiments, we show that a large majority of participants display an innate preference for activity, even when such confounding factors are ruled out. We also show that active participation bias potentially has huge negative consequences, especially in interaction with narrow framing which can lead individuals to even move further away from the optimal outcome.

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1 Introduction

The human tendency to prefer activity over non-activity is a widely observed phenomenon. While activity might be optimal in many situations, we also observe individuals become active in many different contexts, even if inactivity is payoff-maximizing. A CEO, for example, might invest in a project, which does not appear to be particularly promising, in the absence of alternative projects because she might believe that she is perceived as lazy, incompetent, or too risk averse by shareholders if she does not become active. Various motives could give rise to harmful activity in different settings, including, for example, social-image or self-image concerns, (false) beliefs, social preferences, risk preferences, or comprehension mistakes. However, it has neither been rigorously studied whether an intrinsic preference to become active even when the payoff-maximizing action is to stay passive exists, nor how prevalent such a preference is, which drives activity even in the absence of any other motive.

In this paper, therefore, we address three questions: Is becoming active the predominant choice in environments, in which the payoff maximizing strategy is staying passive? If so, does active participation bias prevail, even if social motives, risk preferences, and mistakes in comprehension are controlled for? And finally, how prevalent is an intrinsic preference to become active even when the payoff-maximizing action is to stay passive?

To answer these questions, we designed a set of experiments. In our experiments, participants play a sequential search game in groups of two players such that it is optimal for one player to stay passive. During the search phase, both players can separately draw offers by paying a fee. Each player knows the outcome of her draw but is not informed about the other group memberâs search behavior nor about his search outcome. At the end of the search phase, both group members are rewarded based on the highest draw of any of the two group members, whereas each player incurs only their own search costs. Both players are informed that group members draw numbers from different uniform distributions. In particular, one group member (high-type) draws from an interval that is shifted to the right along the number line compared to the interval that the other group member (low-type) draws from. In the unique equilibrium of the game, high-type players search until hitting a number that exceeds a reservation value, while low-types do not search at all. Nonetheless, low-types might become active and search for various potential reasons, including equity concerns, social image concerns, (false) beliefs about the search behavior of the high-type partner, curiosity or comprehension errors. In order to rule these factors out, we also conduct an experiment (computer treatment) in which human low-type players are matched with a computer that is programmed to search optimally as a high-type player.

The choices of participants in the setting of our controlled experiments reveal three main results. Firstly, active participation bias is prevalent as almost all low-type players (97 percent) search at least once. Notably, a large majority are aware of the optimal strategy for the low-type players, as participants answer when asked about the optimal behavior of the low-type players that they should not search. Moreover, 95% of the low-type player who answer this question correctly, searched nonetheless. This strongly suggests that participants intentionally chose to be active even if this is costly.

Secondly, active participation bias persists even when other factors are ruled out in the computer. This intrinsic preference for active participation is observed for a large majority (85 percent) of participants. 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 percentage points difference in the search activity while 85% remain unexplained by social motives. In addition, 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. In order to further rule out that wrong beliefs, distrust or experimenter demand effects drive these results, we designed a third treatment in which we offer low-type participants who are matched with a high-type computer bot a free outside option that guarantees a fixed amount higher than the expected payoff that could be achieved if the low-type would play his search subgame in isolation. In other words, even if the computer would not search at all or would not search optimally, the low type who accepts the free offer could not be better off by becoming active in the search game. Strikingly, 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.[1] Thus, the tendency to be active seems to be a distinct character trait.

Thirdly, when analyzing the behavior of these low-types who become active and engage in search, we observe another intriguing pattern. Search behavior of low-types is consistent with the optimal search strategy that would prevail if the search game was played in isolation, indicating that they become narrow-minded, thinking about the search game they started but apparently not considering the entire structure of the game anymore, akin to narrow framing.[2] This finding is important as narrow framing bias can exacerbate the harmful consequences of active participation bias. To illustrate, recall the example of the CEO who initiates the project although it would have been better not to invest in it. Narrow framing might prevent her from abandoning it, even if better investment options become available, leading her to keep investing more time and energy in the non-optimal project after it is initiated.

In order to test whether the interaction between active participation bias and narrow framing bias is systematic, we designed another set of experiments that follow the structure of our first set of experiments but alter the search game. In one experiment, we parameterized the search game for the low-type player such that the optimal stopping strategy in the isolated search game entails a higher reservation value, i.e. longer search, and therefore even further deviation from optimal non-activity. In another experiment, we altered the structure of the search games such that it would be optimal in the isolated search game of the low-type player to draw only once. We find strong evidence for low-type players to adhere to the optimal search strategy in the sub-game, which robustly corroborates that the harmful consequences of activity bias are

[1]This treatment can also be seen as 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 reject the offer.

[2]Barberis, Huang, and Thaler (2006) used the term narrow framing to describe that tendency to evaluate decisions in isolation without considering other related outcomes.

moderated by narrow framing.

Moreover, we conducted a follow-up survey to show that active participation bias is a consistent behavior in various contexts and is also relevant in real-life settings. In the survey, participants are asked about active participation behavior in different domains such as investment, political engagement, education, time management, and medical choices. The answers of a person to different questions are correlated with each other and they predict their active search behavior in the main experiment, indicating the external validity of the lab results.

Active participation bias is first 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. In a treatment condition with an alternative task available, 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. While Lei and coauthors coin the term *active participation bias* to explain the tendency to become active, they do not investigate the mechanism further. Since then, the active participation bias has been proposed as an explanation for several experimental results.[3] However, non of these studies rigorously scrutinized the various mechanism that might drive active participation. This is the first study that shows the prevalence of an innate preference to be active, apart from other biases and preferences, as a driver of active participation bias.

We believe that we can design work environments more efficiently on the grounds of the insights on active participation bias. For example, we can remind decision-makers of other related factors and suggest alternative strategies after they begin to engage in a task. Hence, vast and unnecessary costs can be avoided if managers and workers themselves are aware of this bias and act accordingly.

Similarly, we can design experiments more accurately by taking the pervasive tendency to be active into consideration. Otherwise, it would be impossible to distinguish a preference for a particular action from the general tendency to be active. For instance, one can reduce the noise and increase the precision of the experimental results by providing subjects with more

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

than one way of becoming active. Alternatively, we can frame alternative options such that they do not allude to passivity.

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

Many experimental settings resemble the situation of active participation bias such that participants have to wait passively if they do not take a particular action. For example, there is usually no alternative task available if a participant does not bid anything in an auction experiment. This design feature has a nontrivial effect on the behavior of individuals in various experiments in diverse contexts, from contests to auctions and many more. There is a common pattern such that whenever the equilibrium prediction is choosing zero bid, zero effort, or no action in general, a systematic deviation from the equilibrium is observed. Participants seem to deliberately avoid strategies that involve staying passive even if it is costly for them to do so.

Lei, Noussair, and Plott (2001) demonstrate non-optimal activity being chosen frequently in their double-sided asset market experiments. They always observe excess trading activity except for one treatment condition in which they provide an alternative task for participants. As a result, they conjecture that people engage in trading since there is no other activity available and they called this behavior, for the first time, *active participation bias*.

We observe active participation bias in numerous 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) increases participation drastically compared to a state-wide lottery. 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 eliminate some factors by simplifying the game further and observing their 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)) and 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 rooms, 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[4]. We use this demo task for two purposes. Firstly, 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[5]. 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.

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

[5]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 makes 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[6].

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 and 68 people were high-type players[7]. The average duration of the experiment was 45 minutes and the average payment was 16.4 Euros.

[6] 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).

[7] 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[8].

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.

Another important remark is that participants do not keep drawing offers indefinitely. Since each draw takes around 10 seconds, the total duration of search activity is approximately one minute for most of the participants. Hence, the waiting time for searchers (≈9 min.) is not very different from the waiting time of non-searchers (10 min.).

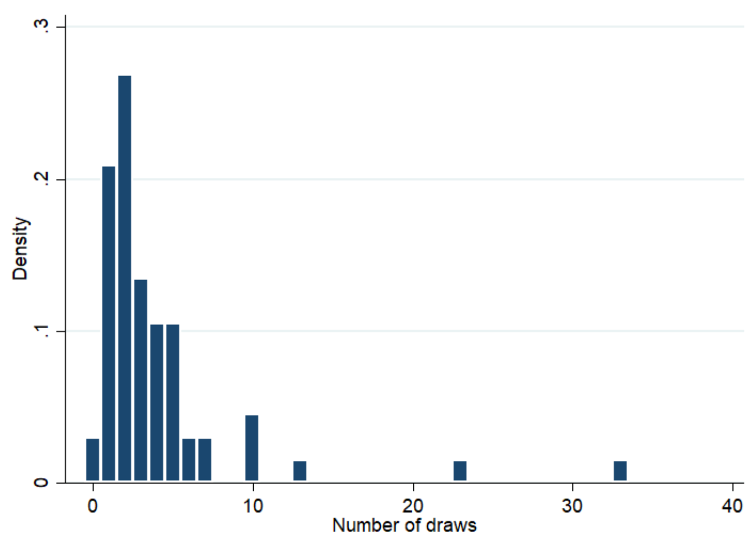

Figure 1: Histogram of number of draws by low-type players in the social treatment.

The second main result is that active participation bias cannot be explained by risk prefer-

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

ences, 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 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.

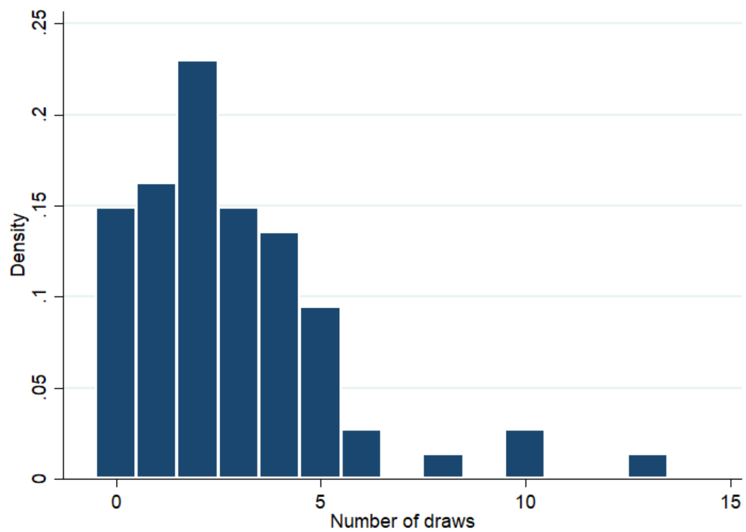

Figure 2: Histogram of number of draws by low-type players in the computer treatment.

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[9]. 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'

[9]There is no difference between the two treatments (see Table A3 in Appendix).

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[10], 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.

	(1)	(2)
	nosearch	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[11]. 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

[10]There is not a significant treatment difference in beliefs.

[11]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
computer 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.

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 if they play alone would be 54. Thus, we can easily conclude that 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[12]. The behavior of the remaining 72.7% is in line with a threshold strategy.

	(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.

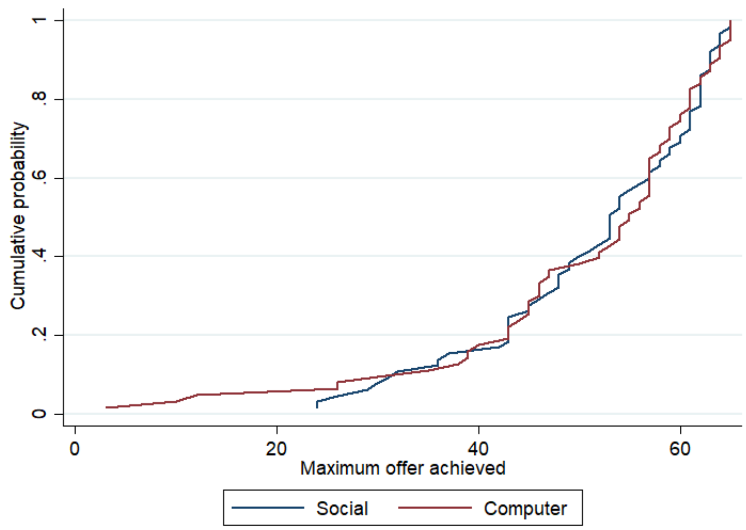

Figure 3: Cumulative distribution functions of achieved maximum offers in two treatments.

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[13]. On top of that, only 7% mentioned that they searched just for fun. These results provide additional evidence for focusing on the individual task and optimizing only that. Low-type players ignore the broad

[12]No significant treatment difference, see Table A8 in Appendix.

[13]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.

game and play as if they are alone.

Low-type players 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. 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. Then, they choose how to play the game. 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 and a follow-up survey to better understand this pattern. We explain the designs and the results of them in the next section.

6 Additional Treatments and the Follow-up Survey

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[14]. In this case, 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.

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.

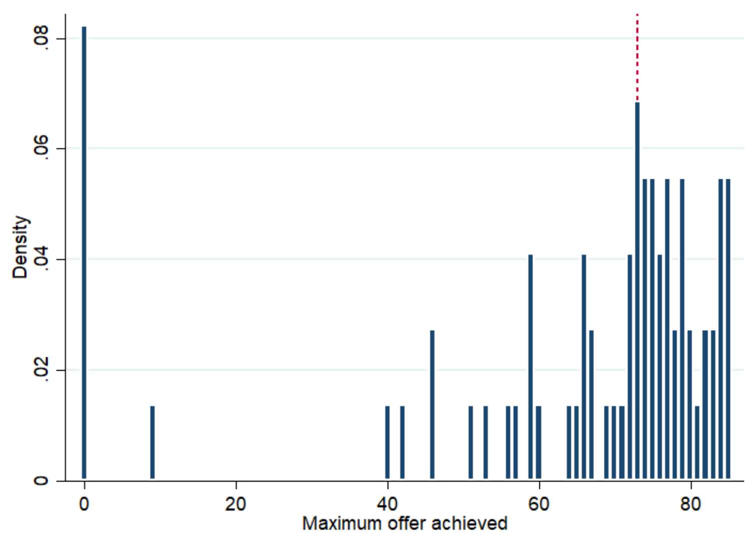

Figure 4: The histogram of maximum offers achieved in the high intensity treatment. The dashed red line represents the optimal threshold level of 73 in the alone search game.

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

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 individual 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 once they begin to play.

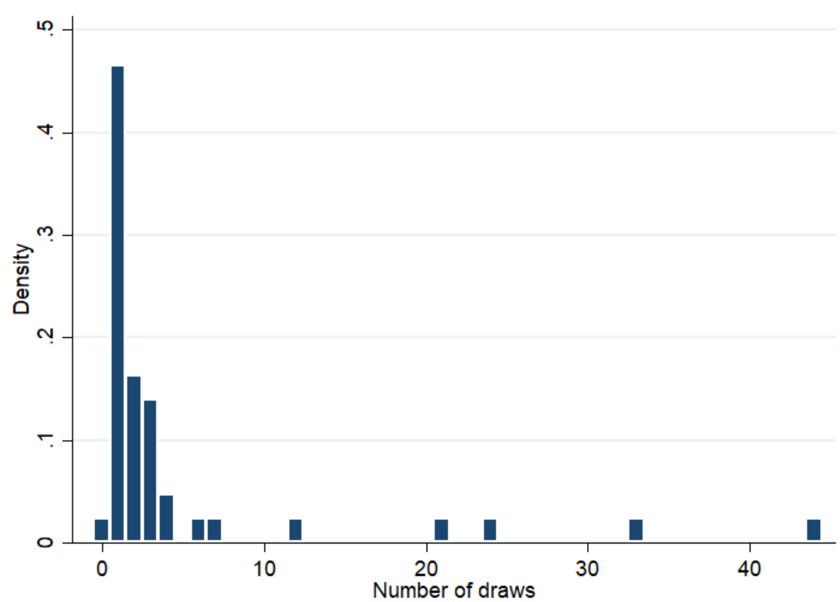

Figure 5: Histogram of the number of draws in the minmax treatment.

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.

On the other hand, this treatment can also be seen as a test of experimenter demand effect. It is plausible to think that subjects can think that researchers expect them to accept the offer if they present it. Hence, they might choose the outside option because they feel obliged to.

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. Even under the strongest conditions (i.e., the generous outside option and the potential experimenter demand effect), the active participation bias is still prevalent. A vast majority of low-types chose to search actively.

When we look at the characteristics of those who rejected the option, we see again that active participation bias is independent of other individual traits such as risk preferences or cognitive abilities. Additionally, we can also 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.

Moreover, 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[15]. Instead, they prefer to search actively even if they pay the search costs and attain a worse offer.

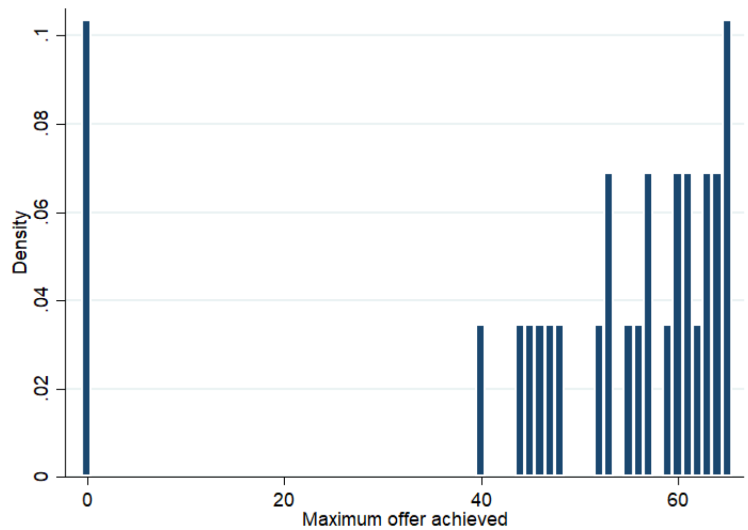

Figure 6: Histogram of maximum offers achieved in the outside option treatment

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.

6.4 Follow-up Survey

We employ a follow-up survey to inspect the relevance of active participation bias in real-life situations. In the survey, participants indicate how much certain behavior of active partic-

[15]62% of the players achieved a task outcome (max. offer - costs) of 55 or below.

ipation applies to them in various daily choices such as consumption, investment, and time management. The survey includes 7 questions related to active participation bias, 7 questions about narrow framing, 1 question on the importance of internal motivation, and 2 vignette questions. In the vignette, we depict a situation in which one person chooses whether to take costly action when there is no alternative task available and the expected gain from the action is negative. We also ask whether that person should keep engaging in that activity further.

The answer to vignette question about starting an activity is predicted by active participation bias index[16] and the question about engaging further in that activity is predicted by narrow framing index. Moreover, both active participation bias index and the related vignette question is correlated with whether a person starts searching in the main experiment.

These results show that active participation behavior is persistent across different domains which supports the external validity of or experiment. You can see Section A4 in Appendix for the exact questions and the detailed analysis.

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. On top of that, they focus on their task too much after they start such that they ignore the other options.

This insight can help us design our work environments in a much thoughtful way. Executives can be inclined to take ineffective actions if they are not presented with alternative options. Similarly, if an alternative side task is not provided to employees, 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, employees can allocate their time and energy more efficiently if the work environment encourages them to question their tasks frequently and

[16] The index is simply created as the sum of 7 relevant survey questions.

consider alternative options.

Likewise, the precision in experiments can be improved by considering active participation bias. 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. In fact, the results of this paper makes many previous studies questionable. We must reevaluate many existing findings to separate the effect of active participation bias.

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[17]. 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[18]. 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.

[17]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.

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

References

Abbink, Klaus et al. (2010). “Intergroup conflict and intra-group punishment in an experimental contest game”. In: *American Economic Review* 100(1), pp. 420–47.

Babcock, Bruce A, E Kwan Choi, and Eli Feinerman (1993). “Risk and probability premiums for CARA utility functions”. In: *Journal of Agricultural and Resource Economics*, pp. 17–24.

Bar-Eli, Michael et al. (2007). “Action bias among elite soccer goalkeepers: The case of penalty kicks”. In: *Journal of economic psychology* 28(5), pp. 606–621.

Barberis, Nicholas, Ming Huang, and Richard H Thaler (2006). “Individual preferences, monetary gambles, and stock market participation: A case for narrow framing”. In: *American economic review* 96(4), pp. 1069–1090.

Bilodeau, Marc, Jason Childs, and Stuart Mestelman (2004). “Volunteering a public service: an experimental investigation”. In: *Journal of Public Economics* 88(12), pp. 2839–2855.

Carpenter, Jeffrey, Allison Liati, and Brian Vickery (2010). “They come to play: Supply effects in an economic experiment”. In: *Rationality and society* 22(1), pp. 83–102.

Chen, Daniel L, Martin Schonger, and Chris Wickens (2016). “oTree - An open-source platform for laboratory, online, and field experiments”. In: *Journal of Behavioral and Experimental Finance* 9, pp. 88–97.

Dechenaux, Emmanuel, Dan Kovenock, and Roman M Sheremeta (2015). “A survey of experimental research on contests, all-pay auctions and tournaments”. In: *Experimental Economics* 18(4), pp. 609–669.

DellaVigna, Stefano et al. (2016). “Voting to tell others”. In: *The Review of Economic Studies* 84(1), pp. 143–181.

Evans, David J (2005). “The elasticity of marginal utility of consumption: estimates for 20 OECD countries”. In: *Fiscal studies* 26(2), pp. 197–224.

Forsythe, Robert et al. (1994). “Fairness in simple bargaining experiments”. In: *Games and Economic Behavior* 6(3), pp. 347–369.

Gerber, Alan S, Donald P Green, and Christopher W Larimer (2008). "Social pressure and voter turnout: Evidence from a large-scale field experiment". In: *American political Science review*, pp. 33–48.

Goerg, Sebastian J, Sebastian Kube, and Jonas Radbruch (2019). "The effectiveness of incentive schemes in the presence of implicit effort costs". In: *Management Science* 65(9), pp. 4063–4078.

Hey, John D (1982). "Search for rules for search". In: *Journal of Economic Behavior & Organization* 3(1), pp. 65–81.

Hörisch, Hannah and Oliver Kirchkamp (2010). "Less fighting than expected". In: *Public choice* 144(1-2), pp. 347–367.

Killingsworth, Matthew A and Daniel T Gilbert (2010). "A wandering mind is an unhappy mind". In: *Science* 330(6006), pp. 932–932.

Kuhn, Peter et al. (2011). "The effects of lottery prizes on winners and their neighbors: Evidence from the Dutch postcode lottery". In: *American Economic Review* 101(5), pp. 2226–47.

Lei, Vivian, Charles N Noussair, and Charles R Plott (2001). "Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality". In: *Econometrica* 69(4), pp. 831–859.

Li, Jiawei et al. (2021). "Running online experiments using web-conferencing software". In: *Journal of the Economic Science Association* 7(2), pp. 167–183.

Lugovskyy, Volodymyr, Daniela Puzzello, and Steven Tucker (2010). "An experimental investigation of overdissipation in the all pay auction". In: *European Economic Review* 54(8), pp. 974–997.

Ortmann, Regina, Matthias Pelster, and Sascha Tobias Wengerek (2020). "COVID-19 and investor behavior". In: *Finance research letters* 37, p. 101717.

Rogers, Todd, John Ternovski, and Erez Yoeli (2016). "Potential follow-up increases private contributions to public goods". In: *Proceedings of the national academy of sciences* 113(19), pp. 5218–5220.

Schotter, Andrew and Yale M Braunstein (1981). “Economic search: an experimental study”. In: *Economic inquiry* 19(1), pp. 1–25.

Sheremeta, Roman M (2010). “Experimental comparison of multi-stage and one-stage contests”. In: *Games and Economic Behavior* 68(2), pp. 731–747.

Sheremeta, Roman M (2011). “Perfect-substitutes, best-shot, and weakest-link contests between groups”. In: *Korean Economic Review* 27, pp. 5–32.

Wilson, Timothy D et al. (2014). “Just think: The challenges of the disengaged mind”. In: *Science* 345(6192), pp. 75–77.

Zeelenberg, Marcel and Rik Pieters (2004). “Consequences of regret aversion in real life: The case of the Dutch postcode lottery”. In: *Organizational Behavior and Human Decision Processes* 93(2), pp. 155–168.

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

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

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[19] $a < 0.02$ 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

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

alter the optimality of not searching for the low-types. Indeed, the constraint of 60 draws was never binding in our experiments.

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)
constant (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)	(2)	(3)
	bonus correct	bonus correct	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.

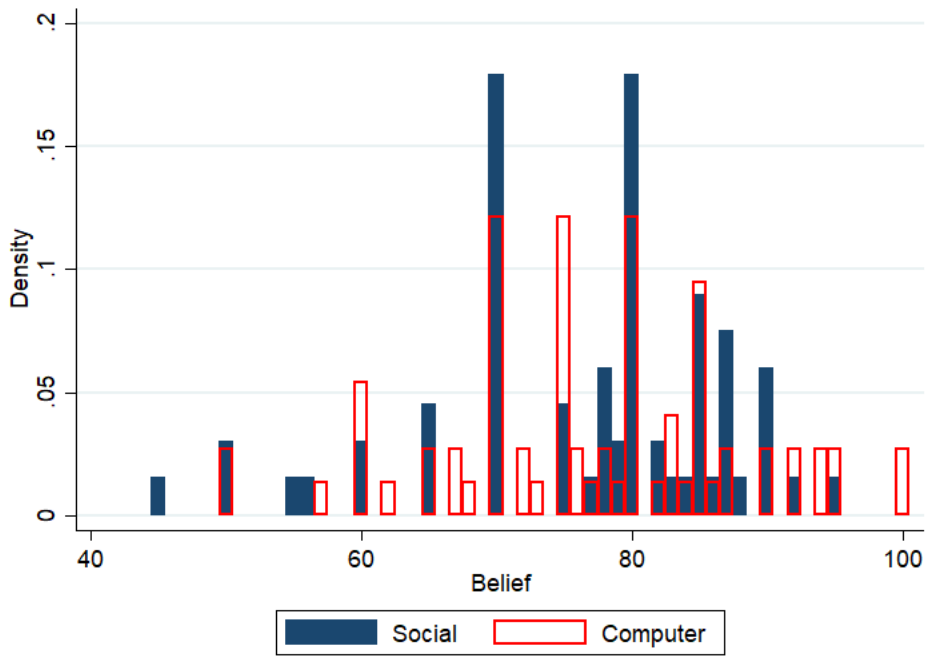

Figure A1: Histogram of the beliefs of low-types about the performance of their partners in social and computer treatments. A vast majority had beliefs above 55, particularly above 65.

	(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.

A4 Follow-up Survey

The English translation of the statements are listed below. Participants indicate how much each situation applies to them.

Active Participation Questions

1. When a new type of investment becomes popular and has made good returns recently, I want to invest in it too.
2. I think it is important to join public protests, even if the goals of the protests are not achieved.
3. I feel uncomfortable when I have nothing to do.
4. I'm more likely to read a book that's already a bestseller.
5. I try out the latest fashion trends.
6. Once I'm in Las Vegas, I also go to the casino and gamble.
7. I watch old movies again to kill time.

Narrow Framing Questions

1. I try to learn all the topics in a course, even if they won't be on the exam.
2. If I have a medical problem, I try to get as much information about it as possible.
3. Before I buy anything, I inform myself extensively about all alternatives.
4. When I start something, I want to finish it, even if it's less fun than I initially thought.
5. It bothers me not to continue watching a TV series for which more episodes are available.
6. I finish the fries in a restaurant, even if I'm full.
7. When I start a puzzle or crossword puzzle, I have to finish it, even if I get bored.

Internal Motivation Question: Internal motivation is more important to me than financial incentives.

We also ask two questions about the following scenario. The first question indicates active participation bias and the second question is on narrow framing.

> Charlie is moving to a new country where cricket is a popular sport. He has seen some cricket matches in his home country, but he did not like them at all. One evening Charlie is alone at home and has nothing to do. A cricket match starts on the television.

Question 1. Charlie should watch the match.

Question 2. He should try to better understand the playing styles of both teams so he can enjoy the game more.

	(1)		(2)	
	Charlie start		Charlie details	
Active Participation Bias Index	0.0658^{***}	(0.0179)	0.0399^{**}	(0.0178)
Narrow Framing Index	0.00822	(0.0177)	0.0310^{*}	(0.0177)
internal motivation	-0.0186	(0.0726)	0.0584	(0.0724)
constant	1.692^{***}	(0.398)	1.589^{***}	(0.397)
N	295		295	

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

Table A14: OLS regression of vignette questions on active participation bias index, narrow framing index, and internal motivation as a control variable. Starting to watch the match is associated with active participation whereas trying to learn the details of the game is associated with both indexes.

	(1)		(2)	
	zero search		zero search	
Charlie: start watching	-0.0399*	(0.0224)	-0.0465**	(0.0213)
Charlie: learn details	0.0532**	(0.0228)	0.0489**	(0.0218)
constant	0.0784	(0.0651)	0.0274	(0.0729)
N	190		190	
Treatment controls	No		Yes	

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

Table A15: OLS regression of the indicator for not searching on answers to the vignette question. People who report Charlie should start watching the game are more likely to show active participation in the experiment.

	zero search	
Computer Treatment	0.119*	(0.0664)
High Intensity Treatment	0.0427	(0.0623)
Minmax Treatment	-0.0291	(0.0716)
Option Treatment	0.329***	(0.0739)
Active Participation Bias Index	-0.00724	(0.00569)
Narrow Framing Index	0.00492	(0.00590)
internal motivation	0.0532**	(0.0229)
constant	-0.0669	(0.130)
N	190	

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

Table A16: OLS regression of the indicator for not searching on active participation and narrow framing indexes together with internal motivation and treatment controls. The effect of active participation index is not significant (possibly due to small sample size) but the coefficient is negative, indicating that a higher bias measure is associated with a higher probability of active search.