Heads in the Sand: Theory and Experiment on Information Avoidance in Groups

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VERY PRELIMINARY AND INCOMPLETE

Abstract

Information avoidance is well-documented in individual decision-making. People may steer clear of useful information that could lead them to better outcomes, even when it's freely available. In many situations, including global warming, infectious diseases, or a company's success, individual outcomes are not independent but are correlated with those of others. This paper explores information avoidance in a group context, where individual decisions impact the whole group.

If more individuals remain ignorant, the outcome in the bad state of the world becomes worse for everyone. In this context, the risk of contagious ignorance looms large. If people are more likely to avoid information when their peers do, the group may end up trapped in an equilibrium where nobody acquires information, with potentially dire consequences. We design and run a novel experiment that studies information avoidance in groups. In the aggregate, we find that information avoidance increases when people think that avoidance is prevalent among their peers, in line with contagious ignorance. Data collected through the strategy method, however, reveals substantial heterogeneity at the individual level. About 20% of our subjects behave in accordance with contagious ignorance, while another 20% exhibit the opposite tendency: they become more likely to acquire information when others avoid it. Overall, the data suggest that contagious ignorance is a real phenomenon which can, however, be circumscribed by appropriate group design.

1 Introduction

Information avoidance—the tendency of individuals to actively steer clear of potentially useful information that is available at no cost— is well documented in individual decision-making (Oster et al., 2013; Ho et al., 2021; Falk and Zimmermann, 2024).[1] For instance, research has shown that people may choose not to learn whether they carry the gene for a potentially fatal disease, even though having this information would enable them to make better decisions and achieve better outcomes. In many situations, however, individual outcomes are not independent; rather, they are correlated with those of others. Examples include global warming, infectious diseases, or a company's success (or failure). Consider, for instance, a bank investing in assets that may either be of high quality or junk. Each employee understands that the bank's future depends not only on their own decisions but also on the choices of others—whether their peers stick to the current strategy (optimal if the assets are of high quality) or liquidate the assets (optimal if they are junk). Making the right decision, however, requires assessing the quality of the assets and potentially acknowledging that the bank may be on the brink of bankruptcy (and that all employees might be facing imminent unemployment). Importantly, if the assets turn out to be junk, the severity of the situation depends on the choices of others. If others continue as usual rather than taking action, the outcome will be much worse. Therefore, each employee's decision to bury their head in the sand or not impacts not only their own payoff but also everyone else's.

This paper studies information avoidance in a group setting characterized by externalities. People choose to remain ignorant or acquire information (and act on it) in an environment where, as in the example above, their decision impacts both their own payoff and the payoffs of others. When more individuals remain ignorant, the outcome in the bad state of the world becomes worse for everyone. In this context, several questions arise that set it apart from information acquisition in individual decision-making. First, are there interdependencies in information avoidance? In other words, do individuals base their decisions to acquire or avoid information on the choices of others in their group, and if so, how? Second, do social preferences influence information acquisition decisions, and in what direction?

These questions are crucial to understand information avoidance in the aggregate. In a seminal theoretical paper, Bénabou (2013) describes what he refers to as contagious ignorance— a situation in which individuals become more likely to avoid information if

[1] For a comprehensive review, see Golman et al. (2017)

others are doing the same. Intuitively, if everyone else chooses to bury their head in the sand, the severity of the bad state will be so overwhelming that individuals may prefer to stay unaware rather than confront such a potentially disastrous reality. History is filled with examples of collective information avoidance that appear consistent with the notion of contagious ignorance, from Easter Island to Lehman Brothers. However, the existing empirical literature lacks a systematic study of whether and how information avoidance self-reinforces in groups. This work aims to fill this gap.

Our investigation begins with a theoretical model inspired by Bénabou (2013), which studies the strategic interdependencies that may arise in group settings. As well as contagious ignorance, we show that in our setup there is also an alternative possibility. Depending on the nature of their utility function, individuals may exhibit strategic substitutability in information avoidance: when others bury their heads in the sand, these individuals become less inclined to shun information. These findings indicate that the dynamics of information avoidance in groups may vary considerably. Furthermore, the theory also shows that some individuals may not base their choices on the actions of others at all, and may instead always avoid or always acquire information, regardless of what others do.

To closely examine how information avoidance decisions are influenced by the choices of others in practice, we design and conduct a novel lab experiment.[2] In the experiment, participants are randomly divided in groups and are informed that there are two possible states of the world: *Screams* and *Quiet*. In the *Screams* state, everyone in the group will hear distressing screams through their headphones in the second part of the experiment. In the *Quiet* state, no noise will be heard. At the beginning of the experiment, we ask each participant to choose whether they want to discover the state immediately ("Now" option) or if they prefer to wait until the state is revealed ("Later" option). If the state is *Screams*, the volume of the screams will be reduced if more individuals choose Now. In other words, each participant understands that by selecting Now, they can lessen the intensity of the noise for both themselves and everyone else in their group, should the state turn out to be *Screams*. Our approach to examining how individuals respond to the decisions of others is twofold. First, we exogenously vary the subjects' expectations about the information avoidance of their peers by providing information about the incidence of information avoidance in a pilot experiment. In the Many treatment, subjects are informed that 80% of pilot participants avoided information, while in the Few treatment they are informed that

[2] The experiment was preregistered, AsPredicted #153871 and #175588.

the share is much smaller, only 20%. By comparing the rate of avoidance among participants in the Many and Few treatments, we can measure how a shift in expectations about others influences decision-making at the aggregate level. Second, we use the strategy method (Selten, 1967; Fischbacher et al., 2001) to examine how each participant reacts to varying levels of information avoidance within their group. This allows us to uncover potential heterogeneity in individual reaction patterns.

The data indicate that our treatment successfully influences the participants' beliefs about the likely incidence of information avoidance among their peers, in the expected direction. In turn, this affects the participants' choices. In the Many treatment, the share of participants who avoid information increases by approximately a third relative to the Few treatment (from 24% to 33%). This establishes that, at the aggregate level, the data are consistent with contagious ignorance. We show that, on average, the Many treatment worsens the anticipatory (dis-)utility participants believe they will experience if they find out that the state is Screams. We also find evidence that, in our group setting, social preferences matter for information avoidance. Ceteris paribus, more altruistic individuals are less likely to avoid information.

To shed light on mechanisms and to better understand determinants of the choice of avoiding information, we develop a novel elicitation of anticipatory utilities that subjects expect they will incur *conditional on each information set*—specifically, upon getting information and finding out good news about the state, upon getting information and finding out bad news, and upon getting no news at all. The elicitation allows us to decompose the net (anticipatory) incentives to avoid information, and to study through which components of such incentives the treatment operates. We find that in the *Many* condition —where subjects are exogenously led to believe that many others in their group will avoid information, and therefore that screams in the bad state will be more severe— subjects expect more anticipatory *dis*utility of finding out bad news relative to subjects in the Few condition, but there are no differences in the expectation of anticipatory utility upon finding good news nor upon getting no news across conditions. This pattern lends support to the groupthink mechanism, as distinct from other, more traditional mechanisms (such as conformity and herding).

Turning now to the individual-level data, we uncover significant heterogeneity in how participants respond to varying degrees of information avoidance in their group. Among those who are influenced by the choices of others (about 40% of the total), we find that half exhibit a pattern consistent with contagious ignorance (strategic complementarity), while the other half shows the opposite tendency (strategic substitutability). There is also a substantial share of participants making the same information avoidance choice independently of their teammates' decisions. The larger portion consists of those who choose to always acquire information (approximately 42%), while just under 9% of participants consistently choose to avoid information. This underscores the importance of group composition for information avoidance. Groups primarily composed of individuals who exhibit strategic complementarity in information acquisition are at risk of remaining trapped in a so-called Mutually Assured Ignorance (MAI) equilibrium (see 3), where no one acquires information. The presence of unconditional information avoiders can precipitate this outcome, pushing the group toward the MAI equilibrium. Similarly, the presence of unconditional information getters may drive the group toward a virtuous equilibrium where everybody acquires information (Mutually Assured Awareness equilibrium). In contrast, groups composed of individuals who exhibit strategic substitutability never reach a MAI equilibrium, but they are also unable to sustain an equilibrium characterized by universal information acquisition.

Our findings have implications for the design of organizations, in particular for screening of personnel and for organizational processes. In particular, organizations may want to assemble teams in such a way that limits the probability of a MAI equilibrium. Second, prosocial preferences are another important dimension, as these can naturally mitigate the avoidance of information, minimizing the scope of a groupthink equilibrium. A similar argument applies to general preferences for information, which could be measured, for example, with the Ho et al. (2021)'s scale (which, we find, is correlated with information avoidance in our experiment).

The remainder of the paper is organized as follows. In Section 2, we discuss related literature. In Section 3, we lay out our theoretical framework. In Section 4, we present the experimental design. In Section 5, we discuss the empirical findings. In Section 6, we capitalize on our data to calibrate how different group compositions may affect equilibrium outcomes. Finally, in Section 7, we conclude.

2 Related Literature

Our study relates mainly to two strands of literature: attitudes towards information and suboptimal decision-making in groups.

First, we contribute to the literature on attitudes towards information from both theoretical and empirical perspectives. On the theoretical side, standard economic theory recognizes that information is a valuable resource for decision-making and accordingly predicts that, if available at no cost, agents will acquire information about payoff-relevant states of the world to improve their subsequent decisions. However, a growing literature documents and acknowledges the possibility that economic agents may have intrinsic preferences for information beyond and above the instrumental, decision-making value of information. Starting from Kreps and Porteus (1978), the theoretical literature has generated a variety of models in which agents may prefer to remain uninformed, or delay the acquisition of information, despite information being available at no or low cost. Golman et al. (2017) provides a review of models of information avoidance, defined as the deliberate choice to avoid freely available information when the agent is aware of its existence. Bénabou (2013), the model closest to our work, extends the analysis of information avoidance decisions to group settings. It shows theoretically that when willful blindness to information makes other agents worse off, it can become contagious. This rises the possibility of multiple equilibria, including a pervasive one in which all agents remain ignorant. We contribute to this literature by empirically examining whether, as predicted by theory, information avoidance exhibits interdependences in groups. In addition, we theoretically examine how prosocial preferences affect incentives to avoid information in groups where remaining ignorant makes other agents worse off.

On the empirical side, several studies both in the lab and in the field documented that individuals often prefer to remain ignorant despite information being available at no or low cost and being useful for subsequent decision-making (e.g., Dana et al., 2007; Karlsson et al., 2009; Oster et al., 2013; Ganguly and Tasoff, 2017; Pagel, 2018; Ho et al., 2021; Meissner and Pfeiffer, 2022; Masatlioĝlu et al., 2023; Momsen and Ohndorf, 2023; Engelmann et al., 2024; Falk and Zimmermann, 2024). Across studies and contexts, rates of avoidance range from 5% (Ganguly & Tasoff, 2017) to more than 90% (Oster et al., 2013). The vast majority of empirical studies have focused on information avoidance in individual decision-making settings. We contribute by documenting that, in groups, a substantial proportion of individuals engage in information avoidance, even when it worsens the future outcomes for both themselves and other members of their group.

Our paper is most closely related to Falk and Zimmermann's (2024) work, which studies intrinsic preferences for information about a potentially adverse future event, in an individual setting. In their experiment, information acquisition generates no material returns: the decision-maker's future payoff is independent of whether information is acquired. We build on their experimental design to study information avoidance decisions in groups. In addition, we introduce a positive return of information acquisition. We show that, when remaining uninformed makes other people worse off, information avoidance decisions can be interdependent. In addition, we examine how prosocial preferences affect the decision to acquire information.

Second, our study also relates to the literature on non-Bayesian information processing, overconfidence, and suboptimal decision-making in groups. A recent literature suggests that decisions in groups can become correlated through the social transmission of biases. Suvorov et al. (2024) shows that members of a group share noisy feedback about their own ability to other group members in a selective and asymmetric way: group members are more likely to share positive feedback about their ability to perform in an investment task than negative feedback. This selective information sharing leads to groups becoming overconfident about the group's ability to perform in investment decisions, and this overconfidence leads to suboptimal investment decisions by low ability groups. A closely related study by Oprea and Yuksel (2022) shows that when individuals can socially exchange ego-relevant beliefs, their initial biases amplify because subjects respond to their counterparts' beliefs in an asymmetric way. We show that groups can also attain suboptimal outcomes by deliberately avoiding learning from freely available signals, when signals reveal the state perfectly and are not ego-relevant, and without communication among group members.

3 Theoretical Framework

We now describe our theoretical framework and key results. All proofs are in the Appendix. Consider the following setup, inspired by Bénabou (2013). There are three periods, date 0, 1 and 2 and two states of the world, B (bad), occurring with probability $p \in (0, 1)$ and G (good), occurring with probability $1 - p$. Material payoffs are received at date 2 and generate utility u_i. At date 1, agents evaluate lotteries over date-2 outcomes according to the expected utility function $U_i = E[u_i]$. At date 0, agents evaluate lotteries over date-1 utilities U_i according to the expected utility function $E[v_i(U)]$, where $v_i(.)$ is a strictly increasing function capturing i's preferences over expected utility lotteries in the spirit of Kreps-Porteus (1978). Denote with g the utility obtained at date 2 when the state of the world is good and with b^- when the state of the world is bad. b^- depends on whether an individual chooses to acquire or to avoid information about the state of the world at date 0. Intuitively, individuals who are aware that the state is bad can take corrective measures to reduce its negative consequences, whereas those who remain unaware cannot.[3] Thus, the utility at date 2 when the state is bad is equal to

$$b^- \equiv b - \lambda_{-i} - \Delta \text{ if } i \text{ avoids information}$$

and

$$b^- + \Delta = b - \lambda_{-i} > b^- \text{ if } i \text{ acquires information}$$

where $b < g$ is the payoff when the state of the world is bad and all group members acquire information (and undertake corrective measures as a result), $\lambda_{-i} \in [0, \frac{n-1}{n}]$ is the share of group members other than i who avoid information, n is the number of individuals in the group and $\Delta \equiv \frac{1}{n}$. In words, Δ captures the instrumental value of acquiring information. It reflects how much an agent can lessen the adverse effects of a bad state by obtaining information and taking appropriate corrective measures. Note that, when the state of the world is bad, utility is decreasing in λ_{-i}, the share of i's fellow group members who avoid information. By avoiding information, agents not only damage themselves but also exert a negative externality on others.

In what follows, we assume that

$$(1-p)(g-b) > \Delta. \tag{1}$$

This assumption is not necessary for our results but simplifies the exposition. In words, it ensures that the expected value of a lottery where i obtains b with probability p and g with probability $1-p$ exceeds the value of obtaining $b + \Delta$ for sure.[4]

An individual's date 0 *net* expected utility from avoiding information is

$$\phi_i \equiv v_i(pb^- + (1-p)g) - [pv_i(b^- + \Delta) + (1-p)v_i(g)] \tag{2}$$

where $v_i(pb^- + (1-p)g)$ is the date-0 expected utility from avoiding and $pv_i(b^- + \Delta) + (1-p)v_i(g)$ is the expected utility from acquiring information. If expression (2) is positive, individual i strictly prefers to avoid information at date 0, while if expression (2) is negative, individual i

[3]This is imposed exogenously for simplicity but could arise endogenously in a setup where taking corrective action is costly, so that under ignorance agents would choose not to exert any corrective measure.

[4]Formally, $pb + (1-p)g > b + \Delta$.

strictly prefers to acquire it.

We now explore how the nature of v_i determines an individual's information acquisition choices. The first two results consider v_i that is everywhere convex or everywhere concave.

Lemma 1 *If v_i is everywhere convex, individual i is an "Always Getter". At date 0, she acquires information independently of the information acquisition choices of other agents in her group.*

If v_i is convex, the utility boost obtained from discovering that the state is good outweighs the utility drop when the state is bad. Consequently, the agent always prefers to acquire information. Consider now the case where v_i is concave, as in Bénabou (2013).

Lemma 2 (Bénabou, 2013) *If v_i is everywhere concave, individual i (i) is an Always Getter (ii) is an "Always Avoider" or (iii) is affected by the choices of others in her group in the following way: there exists an interior threshold value λ_i^* such that i strictly prefers to avoid information if $\lambda_{-i} > \lambda_i^*$ and strictly prefers to acquire information if $\lambda_{-i} < \lambda_i^*$ (Strategic Complementarity).*

In the Appendix, we characterize the necessary and sufficient conditions for each of (i), (ii) or (iii) to apply. Always Getters and Always Avoiders make the same information acquisition choice independently of the choices of others in their group. Alternatively, the agent may condition her decision on the choices of others in her group, exhibiting strategic complementarity. The intuition for the result is as follows. Without the instrumental value of information, the agent would always prefer ignorance, since the utility loss from discovering the bad state outweighs the gain from finding out that the state is good (this follows directly from concavity). In the presence of instrumental value, as in our setup, the agent may opt to acquire information. However, as more agents choose to avoid information, the outcome in the bad state deteriorates, increasing the utility loss associated with discovering the bad state. As a result, meeting the conditions for information acquisition becomes increasingly challenging. This pattern may give rise to strategic complementarity in the agent's information acquisition strategy. The agent acquires information only if a sufficient share of her peers also do so; otherwise, she avoids information.

Consider now a reference dependent v_i. The agent's utility is largely insensitive to expected payoffs except around some reference level. Denoting i's reference expected utility as $\widehat{U_i}$, we have (i) $v_i''(U) < 0$ for $U > \widehat{U_i}$ and (ii) $v_i''(U) > 0$ for $U < \widehat{U_i}$.

Lemma 3 *If v_i is reference dependent, under some conditions the following applies: there exists an interior threshold value λ_i^{**} such that i strictly prefers to avoid information if $\lambda_{-i} < \lambda_i^{**}$ and strictly* *prefers to acquire information if $\lambda_{-i} > \lambda_i^{**}$ (Strategic Substitutability).*

In the Appendix, we provide sufficient conditions for strategic substitutability. To illustrate, assume that if the state is known to be bad utility is always below the reference level while it is above it in the good state. First, suppose that many agents in i's group avoid information. The final payoff in the bad state is so low that, at date 1, the expected utility under ignorance falls below the reference level. Relative to remaining ignorant, the utility loss from discovering the bad state is minimal (since both situations generate utility that is below the reference level), while the gain from discovering the good state is large. As a result, the agent prefers to acquire information. Now, suppose that many agents acquire information. The final payoff in the bad state is not too low and the expected utility under ignorance is above the reference level. In this case, under mild conditions, the agent prefers to avoid information, since the utility gain from discovering the good state is minimal relative to the utility loss from discovering the bad state.[5]

The following proposition summarizes our results.

Proposition 1 *Depending on the nature of v_i, i's propensity to avoid information may be (i) independent of, (ii) increasing (strategic complementarity) or (iii) decreasing (strategic substitutability) in the share of group members who avoid information.*

In what follows we will use the terminology "best response type" to indicate whether an individual is an Always Getter, an Always Avoider, or alternatively exhibits preferences featuring strategic complementarity (in short, is a "Complement") or substitutability (is a "Substitute").

Naturally, the nature of the information avoidance equilibria that may be reached varies depending on the agents' best response types. Bénabou (2013), for example, examines the risks that emerge when agents are Complements. In that case, groups may become trapped in a "Mutually Assured Ignorance" (MAI) equilibrium where no one seeks out information, and as a result, no corrective actions are taken to shield the group from adverse outcomes in the face of a bad state of the world — potentially with disastrous consequences.[6] By the same token, a "Mutually Assured Awareness" (MAA) equilibrium, where everyone acquires

[5]For example, suppose $b^-(\lambda_{-i} = 0) = -10$, $b^-(1) = -90$, $g = 50$, $p = 0.5$, $\widehat{U}_i = 0$, and $v_i(U) = U^{1/3}$ if $U > 0$ and $= -(-U)^{1/3}$ if $U < 0$. Then $\varphi^i(0) \approx 1.87$ and $\varphi^i(1) \approx -2.46$, so the agent exhibits strategic substitutability.

[6]Bénabou (2013) uses the acronym MAD (Mutually Assured Delusion) equilibrium. However, in the context of information avoidance MAI provides a more accurate description of the equilibrium. The same holds for the acronym MAA (Mutually Assured Awareness).

information, is also possible. The path taken depends critically on the agents' expectations about the actions of others in their group. Conversely, a group of Substitutes cannot fall into either a MUI or MAA equilibrium, as its agents are inherently inclined to resist such dynamics.[7]

The next step in our investigation is an experiment to explore how best-response types manifest in practice and how beliefs about others' choices influence information avoidance in groups.

3.1 Social Preferences and Information Avoidance in Groups

In this subsection, we extend the basic theoretical framework to allow for the possibility that agents have prosocial preferences.

Altruism First, we consider the possibility that individuals may have altruistic preferences. Specifically, given a date-2 material payoff u, common to all group members, an agent i derives a date-2 utility equal to $(1 + \alpha_i)\, u$, where $\alpha_i > 0$ is an altruism parameter.

Lemma 4 *Altruism has an ambiguous effect on information avoidance.*

Intuitively, since agent i cares about the payoff of other members of her group, the altruism parameter acts as an amplifier of the date-2 payoffs. On the one hand, more altruistic individuals have stronger incentives to acquire information since they internalize more the positive returns that this action will generate on the payoffs of other members. On the other hand, a higher altruism parameter spreads out the payoffs across states, increasing the variance of the expected utility lotteries associated with the decision to acquire information. Unless v_i is everywhere convex – in which case the agent always acquires information independently if the value of α_i – this higher variance may increase the agent's incentives to avoid information. In general, therefore, higher altruism produces countervailing forces whose net effect is ambiguous.

Reciprocity To be completed.

[7] Consider for instance a group composed of Substitutes with a 0.5 threshold. Then it is easy to show that, in the unique equilibrium, exactly half the group acquire information and half avoid it.

4 Experimental Design and Procedures

4.1 Experimental Design

We investigate whether, in groups, information avoidance is interdependent. We specifically ask: How do individuals respond, in terms of information avoidance, when they perceive that information avoidance is more prevalent within their group?

(3)((of To study interdependence in information avoidance, we design an experiment in which individuals in a group choose whether to acquire or avoid costless information. After being randomly assigned to groups, participants are told that, at the end of the experimental session, a state of the world (either good or bad) will be randomly drawn. In the bad state (or the "Screams" state), the group will experience a negative consumption event: listening to a series of unpleasant screams. Inthe good state (or the "Quiet" state), no such event happens.

Each member of the group can choose one of two options. If she chooses option "Now", she learns the state of the world immediately, while if she chooses option "Later" she defers learning the state of the world until it is revealed in the second part of the experiment.[8] The choice between "Now" and "Later" is the key decision of interest. In this paper, we refer to it as the **informational decision**.[9]

A distinctive feature of our experiment is that informational decisions generate a payoff externality: acquiring information creates a positive return *not only for oneself*, but also for other members of the group. If the state is *Screams*, the volume of the screams that all group members will hear is decreasing in the number of group members who choose Now. More precisely, each individual knows that by choosing Now, they will lower the volume of the potential screams by 2 points *for all* group members.[10] There are no monetary costs involved with either Now or Later.

A key distinction from previous studies on information avoidance in individual decision-making (e.g., Falk and Zimmermann, 2024) is that our study examines decision-making within a group context influenced by externalities—a context that has not been explored before. Accordingly, our analysis begins by examining whether information avoidance occurs at all in our group setting. This is a first, necessary condition to study interdependencies in

[8]Participants are aware that if they choose Later, they will be informed about the outcome just before the period in which screams are potentially played.

[9]In each group, decisions are simultaneous. Therefore, there is no social learning among members of the group.

[10]The contribution to the volume of screams is additively separable. Therefore, we examine whether informational decisions can exhibit interdependence even in the absence of in-built interdependencies in technology.

informational decisions.

To identify whether informational decisions are interdependent, we exogenously shock the participants' beliefs about the prevalence of information avoidance in their group. We do so through an information provision treatment. Before participants make their informational decisions, we inform them about the prevalence of information avoidance in a past pilot experiment. There are two between-group conditions: the "Many" and "Few" treatments. In Many (Few), we inform that 80% (20%) of subjects in a past pilot chose to avoid information. Participants are also reminded of the potential impact on scream volume if their group members exhibit similar information avoidance behaviors as those observed in the pilot study.[11] To check whether the treatment manipulation works as intended, after the information provision treatment we elicit the participants' beliefs about the share of information avoidance among their group mates.

We assess the interdependence of informational decisions by comparing the incidence of information avoidance between Many and Few.

To delve into potential heterogeneity in individual responses, we also use the strategy method (Selten, 1967) to examine how each participant responds to the choices of their group mates, in an incentive compatible way. To do so, we elicit the full schedule of each individual's best response to all the possible choices made by others in the group. We classify the best response schedules based on whether a participant chooses Later when the share of avoidance among other members is sufficiently large (Strategic Complement) or sufficiently small (Strategic Substitute). If the participant's choice is the same for all distributions of information avoidance in their group, we classify them as Always Getter (if they always choose to acquire information) or Always Avoider (if they always choose to avoid information). We refer to these classes of best responses as best response types.

Given the presence of payoff externalities in our environment, prosociality is a potentially relevant dimension of preferences. Intuitively, given that informational decisions affect others' payoffs, prosocial preferences may predict both unconditional and conditional informational decisions and moderate the treatment effect on information avoidance. To explore how social preferences and other preference traits affect informational choices, we also elicit measures of prosocial preferences by administering the Global Preferences Survey (GPS) (Falk et al., 2018), which measures altruism and reciprocity, as well as trust, risk

[11]Specifically, we inform each participant that, if their group mates behave like the participants of the pilot, the volume in the *Screams* state if (s)he avoids or acquires information would be 89 or 91 (in the Many treatment), 60 or 62 (in the Few treatment).

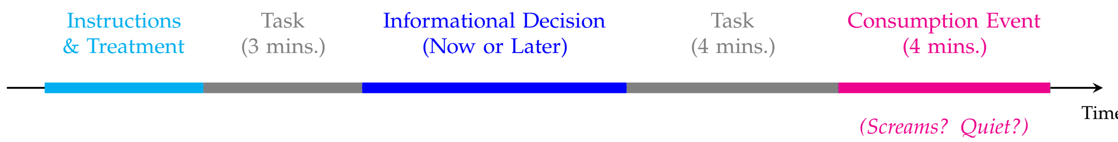


Figure 1: Timeline of experiment

attitudes and time preferences.

To shed light on mechanisms and determinants of informational decisions, we also introduce a novel elicitation of utilities over each possible combination of informational decision and lottery outcome (state of the world). Specifically, we ask participants: a) "How happy would you be thinking about the outcome ahead if you chose Now and then discovered that the lottery outcome is *Screams*?"; b) "How happy would you be thinking about the outcome ahead if you chose Now and then discovered that the lottery outcome is *Quiet*?"; and c) "How happy would you be thinking about the outcome ahead if you chose Later?" This granular elicitation enables us to study how the treatment changes the expected anticipatory utility of, e.g., acquiring information and learning good or bad news separately, which helps to distinguish among mechanisms. In addition, we elicit the participants' subjective belief of the probability that the state is *Screams*. We call this set of questions the Kreps-Porteus (KP) questions.

Following the design in Falk and Zimmermann (2024), we include an incentivized task for participants to complete in the first part of the experimental session, after the participants have taken the Now or Later decision and before the second part of the experiment where they may or may not experience the screams depending on the realization of the state. The experimental timeline is summarized in Figure 1.

4.2 Experimental Procedures

The experiment was conducted in the Centre for Decision Research and Experimental Economics (CeDEx) Lab at the University of Nottingham. Participants were recruited from the CeDEx subject pool. We recruited 493 participants across 18 experimental sessions. The average session lasted 1 hour.[12]

[12]The experiment was approved by the University of Nottingham's School of Economics Research Ethics Committee. At the start of the session, participants were informed about the nature of the experiment and provided written consent to participate.

At the start of each experimental session, participants were matched into groups, and each group was randomly assigned to a treatment condition.[13] Participants were then provided with detailed instructions on computer screens.[14] The instructions included a description of the state of the world lottery, the negative consumption event (screams), the timeline of the experiment, the informational decisions and its implications, and the task. In order to ensure understanding of the decision environment, we included control questions about the timing of learning the outcome and about the nature of returns and externalities from information acquisition/avoidance. During the instructions phase, we also implemented our information provision treatment.

A computerized lottery determined the outcome (either *Screams* or *Quiet*) for each group. If the outcome was *Screams*, in the second part of the experiment the members of the group would hear a series of unpleasant screams through headphones they were asked to wear during the whole session. We administered the scream sounds used in Beaurenaut et al. (2020).[15] To ensure the hearing safety of participants, the maximum possible volume level in the experiment, level 100, was calibrated at 80dB, in compliance with the UK hearing safety regulations. The calibration was done for each pair of headphone and computer station, ensuring that no subject would be exposed to unsafe levels of hearing. To enforce the take-up of the potential screams, we informed at the beginning of the session that the use of headphones was mandatory during the entire session and that attempts to break this rule would be a basis for expulsion from the session. To ensure compliance with this rule and that participants wore the headphones correctly, we placed two invigilators who monitored these conditions in each session. Participants were told they could leave the session at any time.[16]

The use of screams instead of electric shocks (employed in experimental studies on information avoidance in individual decision making) is based on three rationales. First, one of the motives that may lead to information avoidance are anticipatory emotions, such as anxiety about a future outcome, and studies show that the screams are able to sustain anxiety for longer periods than electric shocks (Beaurenaut et al., 2020). This feature is

[13]The random assignment of the treatment was blocked by week of year and time of session (morning and afternoon).

[14]The program was written in Lioness (Giamattei et al., 2020).

[15]While our participants did not listen to any sample screams before they made their informational decisions, they were informed that "[p]revious research has shown that people consider similar screams as *more aversive (disturbing) than* the sound of *nails sliding on a chalkboard*" Evidence backing this statement can be found in Kumar et al., 2009.

[16]Only one participant left, after about an hour of the session, reportedly due to the start of a lecture.

especially desirable for experiments with group decision-making, which typically take longer compared to individual decision-making. Second, the provision of human scream sounds is more scalable than electric shocks, since the only required equipment are computers and headphones, as opposed to devices specialized for the provision of shocks.[17] Non-scalability imposes a natural limit to group sizes, which, as discussed below, affect the likelihood of the emergence of complementarities in informational decisions (Bénabou, 2013). Third, screams allow a more granular manipulation and more intuitive understanding of variations in severity (i.e., volume levels as opposed to electric shock intensity); this granularity in severity is important as group sizes become larger and the marginal return of acquisition of information by any individual member becomes smaller. Fourth, the use of human screams alleviates ethical concerns compared to electric shocks.[18]

The experimental and model assumption is that screams are a bad. To assess whether this is the case, we elicit the participants' utility over two different levels of volume of screams. We ask: "Imagine that the Outcome is *Screams*, and that the volume of the screams will be level 100. How happy would you be thinking about the Outcome ahead?"; we ask a similar question for volume level 50. This allows us to identify subjects who, contrary to our assumption, derive higher utility from higher levels of volume of scream sounds.

For groups whose lottery outcome was *Screams*, the volume of the screams was determined by the informational decisions of its members. Specifically, the volume of the screams in group g was determined by the following function:

$$vol_g = 50 + (100 - 50)\left(\frac{1}{N_g}\sum_{i=1}^{N_g} Avoid_i\right), \tag{3}$$

where $vol_g \in [50, 100]$ is the volume of screams conditional on the lottery outcome being *Screams* for group g, N_g is the number of members in group g, and $Avoid_i = 1$ if subject i chooses Later and 0 otherwise. Information acquisition thus partially mitigates the volume of the screams.

[17]The lower implementation barrier also facilitates replicability.

[18]Recently, experimental literature in Economics has started using the prospect of money losses as a negative future event (Pagel, 2018, Engelmann et al., 2024). In particular, Engelmann et al. (2024) finds that money losses induce anticipatory anxiety and wishful thinking about the future event. The literature on intrinsic preferences for information has focused attention on future *consumption* events as distinct from *income* events, because knowing the latter introduces a planning advantage that motivates the acquisition of information about the future income event. To avoid introducing this extra planning advantage, in our experiment, we follow the latter tradition and focus on a consumption event. We argue that, theoretically, the relevant feature of the event is that the prospect of hearing human screams, much like the prospect of money losses, is perceived as a bad event by participants. In Section 5.2, we show evidence that, in our experimental sample, this is the case.

Each group was composed by an entire experimental session, with group sizes of approximately $N_g = 30$. This implies that the return to each participant's information acquisition (in terms of volume reduction) was $1/30 * 50 = 1.67$ volume points.[19]

Our main choice of interest is the informational decision, the decision between option Now and option Later, which is binary. To obtain a continuous measure of intensity of preferences, after participants select either Now or Later, we also ask them to rate the strength of preference for the selected option on a likert scale ranging from 0 ("I am indifferent") to 10 ("I have a very strong preference for the selected option"). From the measure, we construct a continuous version of the informational decision, ranging from -10 ("I have a very strong preference for option Now") to 10 ("I have a very strong preference for option Later"). We also ask participants to write down a reason for the selected option in an open text box.

To explore individual heterogeneity in how informational choices respond to others' choices, we elicit conditional choices between option Now and option Later for a range of possible shares of information avoiders among others in the group. We use the strategy method (Selten, 1967) to elicit the full schedule of each individual's best response to all the possible choices made by others in the group. More specifically, we ask participants to choose between Now and Later for a range of possible shares of information avoiders among others in the group: 0%, 20%, 40%, 60%, 80%, and 100%.

We make the strategy method elicitation incentive-compatible by assigning a strictly positive probability that these choices are implemented. Specifically, before the elicitation, we inform participants about the following procedure. After the group members make their (unconditional) informational decisions (between Now and Later), we randomly select $N_g - 1$ subjects and calculate the proportion of information avoiders *among these* $N_g - 1$ *subjects*, based on their unconditional decisions. For the remaining participant, we implement her selected best response to this share. Since, at the moment of elicitation of conditional choices, all participants have a strictly positive probability of their conditional choices being selected and implemented, they have an incentive to respond according to their preferences.

To measure general preferences for information, we administer the Information Preferences Scale, or IPS (Ho et al., 2021). This scale measures an individual's desire to obtain or avoid information that may be unpleasant but is instrumentally valuable, across several domains.[20] Measuring general preferences for information allows us to, first, assess the

[19]We described to participants the return to information acquisition as being equal to "around 2 out of 100 volume level points".

[20]The scale is constructed by averaging the answers to 18 questions that ask the subject's willingness to obtain

relationship between general preferences for information and the specific informational decisions in our experiment; second, to check that the randomization is balanced in this dimension, which is potentially important in determining informational decisions; and third, to control for general preferences for information in our analysis.

To measure social and economic preferences, we administer the Global Preferences Survey (GPS) (Falk et al., 2018). The GPS measures risk attitudes, time preferences, altruism, reciprocity, and trust. Each dimension of preferences is elicited through the responses to two questions. The preference measures elicited from the GPS questions have been experimentally validated and shown to be predictive of a wide range of economic behaviors in the lab. Following the procedure in Falk et al. (2018), we standardize the answers, transforming them into z-scores.[21] Higher z-scores indicate, respectively, higher risk seeking, patience, altruism, reciprocity, and trust. We also elicited demographics (e.g., age, gender), prior work experience, ratings about the perceived difficulty of instructions and quiz questions. Participants were given the opportunity to feedback on their experience in the experiment in open text boxes.

Following Falk and Zimmermann (2024), we include an incentivized task after the Now or Later decision and before the second part of the experiment. Participants are asked 90 general knowledge quiz questions, with earnings increasing in the number of correct answers. Each participant is paid according to his own performance. The performance in the quiz is the only source of monetary earnings in our experiment, apart from the show-up fee.

5 Results

In this section, we analyse our experimental data. We describe our sample in Section 5.1. We assess whether participants perceive the screams as a bad in Section 5.2, and whether information avoidance occurs in our sample in Section 5.3. By estimating the average treatment effect, we test whether information avoidance choices respond to expectations about the choices of group mates in Section 5.4. We characterize the heterogeneity in

information in hypothetical scenarios. The scenarios involve five domains: health, finance, social relations, ego-relevant characteristics, and occupation. For each question, the 4 possible answers are "Definitely don't want to know" (encoded as 1), "Probably don't want to know" (2), "Probably want to know" (3), and "Definitely want to know" (4). Therefore, higher IPS scores indicate greater general willingness to obtain information.

[21] For risk attitudes and time preference, one of the questions used by Falk et al. (2018) involve the staircase method. Since administering this could be time-consuming and cognitively burdening in the middle of our experiment, we did not include such questions.

individual reactions to different distributions of information avoidance choices in their group Section 5.5. Finally, we discuss the mechanisms through which the treatment affects informational decisions in Section 5.6.

5.1 The sample

The experimental sessions were run in two data collections ("waves"), in December 2023 and May-June 2024 respectively. Participants were recruited from the subject pool of the Centre for Decision Research and Experimental Economics (CeDEx), at the University of Nottingham. There were 465 participants in total, across 17 experimental sessions (each one becoming a "group").[22][23] On average, there were 27.35 ± 3.66 subjects per session. Participants earned on average £12.52 (± 2.00), including a £5 show-up fee.

Descriptive statistics of baseline characteristics are reported in Table 1. The average age of participants is 22.51 (± 3.71) years. The sample has a balanced representation of gender and fields of study. The average IPS score is 3.12 ± 0.41, indicating that individuals in our sample have on average a general preference to obtain information across domains. [24]

5.2 Are screams a bad?

Before presenting our findings, we first address a potential concern: contrary to the model and experimental assumption, it may be the case that subjects do not actually perceive the screams as a bad. We provide evidence that in our sample the assumption holds. First, recall that, in the KP questions, we asked subjects to rate their "(un)happiness" if, upon choosing the option Now, they found out that the state was *Screams* —and similarly for *Quiet*. By comparing the answers to these two questions, we obtain a measure of the utility of listening to the screams relative to not listening to these for each participant. If screams are perceived as a bad, we would expect lower ratings attached to finding out the *Screams* rather than the *Quiet* state. As expected, this is the case for the majority of the subjects: 81% of them report that discovering that the state is *Screams* is strictly worse than discovering

[22]Due to technical issues, data (including the main outcomes of interest) was not recorded for 22 subjects concentrated in a single session of 28 participants. The session is removed from the analysis. None of the results change with the inclusion of the 6 individuals for which data from this session is available.

[23]Only one subject left the session. After about an hour of the experimental session, she had to leave to join a lecture. Due to this, the number of observations in the analysis drops by one when involving variables elicited at later stages of the experiment.

[24]As a reminder, a score of 3 means "Probably want to know".

	N	Mean	SD	Median	Min	Max
Age	460	22.509	3.713	22.000	18.000	47.000
Female	465	0.583	0.494	1.000	0.000	1.000
Field: Medicine	465	0.213	0.410	0.000	0.000	1.000
Field: STEM	465	0.200	0.400	0.000	0.000	1.000
Field: Humanities	465	0.228	0.420	0.000	0.000	1.000
Field: Economics	465	0.108	0.310	0.000	0.000	1.000
Field: Business	465	0.211	0.408	0.000	0.000	1.000
Field: Others	465	0.056	0.230	0.000	0.000	1.000
Work Experience	460	0.154	0.362	0.000	0.000	1.000
IPS score	464	3.116	0.414	3.111	1.000	4.000
Patience	464	-0.017	1.016	0.118	-3.749	1.174
Risk seeking	464	-0.014	0.998	0.233	-2.754	1.600
Pos. Reciprocity	464	-0.003	0.804	0.027	-4.006	1.331
Neg. Reciprocity	464	0.018	0.833	0.106	-1.918	1.908
Altruism	464	0.004	0.835	0.076	-2.203	2.231
Trust	464	0.003	0.997	-0.155	-1.662	2.082

Table 1: Sample summary statistics

that the state is *Quiet*.[25] Second, we have also asked subjects how "(un)happy" they would be if screams were played at volume 50 —and similarly for volume 100. We compare the ratings for volume 50 and for volume 100. Again, the answers of a large majority of subjects imply lower utility attached to higher volumes: 82% of subjects report that screams played at volume 100 would be strictly worse than at volume 50.[26] Taken together, both pieces of evidence support the view that the vast majority of subjects perceive screams as a bad.

In addition, the fact that screams at higher volume are perceived as worse than screams at lower volume suggests that the instrumental value of information acquisition (which reduces the volume of screams) is non-trivial to participants.

In the main analysis, we refrain from excluding the subjects who have a weak preference for either screams ("scream lovers") or volume ("volume lovers"), or both.[27] Analyses excluding this subset of individuals are available in the Appendix Section B.1. Our main findings are robust to the exclusion of this subset of individuals.

[25]Among the remaining subjects, 6% are indifferent between discovering either state and 14% would prefer discovering the Screams state.

[26]Among the remaining subjects, 3% are indifferent between either levels of volume and 9% would prefer listening to the screams at volume 100. The distribution of types of preference screams and volume is shown in Figure B.1 and Figure B.2 in the Appendix.

[27]There are 111 subjects with such preferences. The distribution of preferences for screams and volume is reported in Section B.

5.3 Is there information avoidance in groups?

To assess whether information avoidance occurs in the aggregate, we focus on the informational decision —the binary choice between learning the state Now or Later. We encode this decision as $Avoid_{ig} = 1$ if individual i in group g chose Later and 0 if he chose Now. We also construct an alternative, continuous measure of the *strength of preference* for either Now or Later, the *information avoidance (IA) scale*.[28] Analyses of both variables yield very similar qualitative results. Therefore, we report the results about the binary informational decision, while referring the interested reader to the Appendix Section E for results about the information avoidance scale.

We find statistically significant evidence of information avoidance. The left panel of Figure 2 shows that the proportion of avoiders in our sample is 0.286. This is significantly different from zero at the 1% level. The right panel shows that the finding is robust across data collection waves.

This result relates to other findings in the literature. In an individual decision making context, Falk and Zimmermann (2024) find that 52% of subjects avoid information. The difference from our finding could be attributed to a series of factors. In addition to some differences in implementation, their setup implies that information provides no material benefit (i.e., it does not affect the severity of the future negative consumption event). This removes the instrumental motivation for information acquisition, making a higher degree of information avoidance more likely. Prosocial motives for information acquisition are accordingly also absent.

The decision to avoid information in our sample does not seem to be driven by indifference nor subject to trembling. Figure 3 shows the distribution of preference strength for avoiding information on a scale ranging from 0 ("I am indifferent") to 10 ("I have a very strong preference"), for the subsample of information avoiders. The average strength of preference is 6.6, far from indifference. Moreover, as shown by the cumulative distribution in panel (b), only 6% of information avoiders report being indifferent between Now and Later, and more than 80% report a preference strength of 5 or higher. This shows that for the majority

[28] We construct our measure of the strength of preference for information avoidance as follows. Recall that, after eliciting the informational choice, we asked participants how strong their preference for the selected option is (0="I am indifferent" to 10 = "I have a very strong preference"). For subject i, her IA scale is equal to her stated strength of preference if she chose to avoid information (Later choice), and equal to the negative of her stated strength of preference if she chose to obtain information (Now choice). Thus, the IA scale ranges from -10 (very strong preference for Now) through 0 (indifference between Now and Later) to 10 (very strong preference for Later), providing more variation than the binary informational decision.

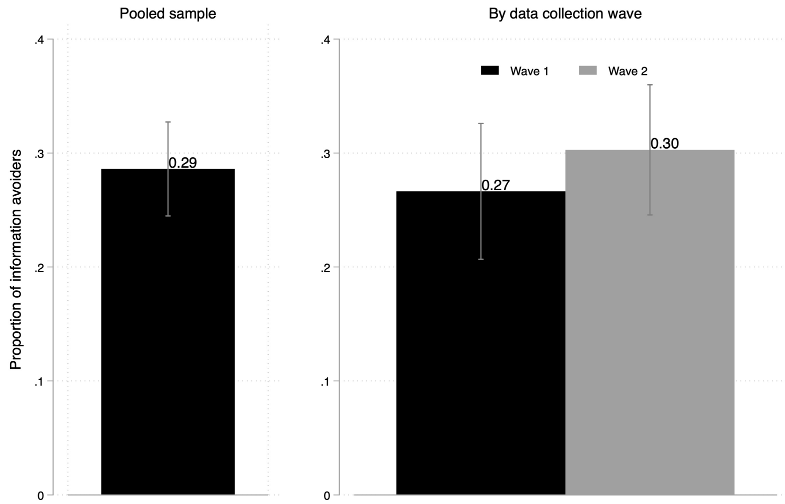
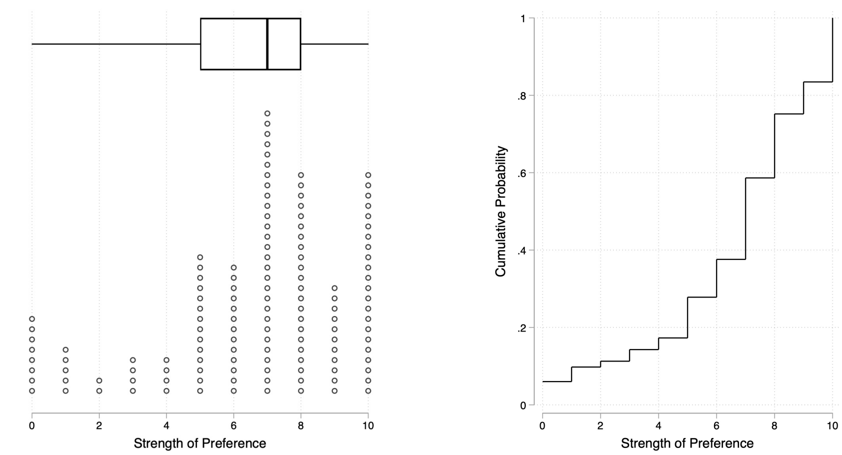


Figure 2: Share of information avoiders, by data collection wave

Notes: The bars show the proportion of subjects who chose to avoid information (option Later). The left panel shows the proportion in the whole sample, while the right panel shows the proportion by data collection wave. The whiskers show 95% confidence intervals.

of avoiders the informational decision is not driven by indifference, but is rather strongly preferred.

The decision to avoid information is predicted by individual characteristics. In the Appendix, Figure C.1, we report the results of a regression of information avoidance on individual characteristics: economic and social preferences, information preferences, demographics, and field of study. As expected, the IPS scale predicts the decision to avoid information in our experiment. In the economics and social preference domain, only altruism predicts information avoidance. As discussed in Lemma 4, the theoretical prediction on the effect of altruism on information avoidance is ambiguous. Our data shows that empirically, in our sample, altruism is significantly associated with a lower likelihood of avoiding information ($\hat{\beta} = -0.068$). The finding is consistent with the idea that prosocial individuals are more likely to acquire information to benefit others.



(a) Frequency of preference strength

(b) CDF

Figure 3: Distribution of strength of preference for avoiding information, among avoiders

Notes: The figure shows the distribution of the strength of preference for avoiding information among subjects who chose to avoid information. The strength of preference is elicited on a scale from 0 ("I am indifferent" between Now and Later) to 10 ("I have a very strong preference" for the selected option). Panel (a) shows the frequency of each strength of preference, with each dot representing a subject. At the top, the boxplot shows the median and the interquartile range of preference strength. Panel (b) shows the cumulative distribution of preference strength.

5.4 Are information avoidance decisions interdependent?

We now turn to the question of whether in groups information avoidance decisions are interdependent, starting from the results of the information provision treatments.

Treatment balance checks are reported in the Appendix Table C.1. All individual characteristics are balanced across conditions, with the exception of the representation of some fields of study.[29] We control for the field of study in the regressions. Importantly, the IPS scores are balanced across treatment groups, for both the overall scale and for each of the domain-specific sub-scales. Therefore, any difference in information avoidance across treatments is not attributable to baseline differences in general nor domain-specific preferences for information.

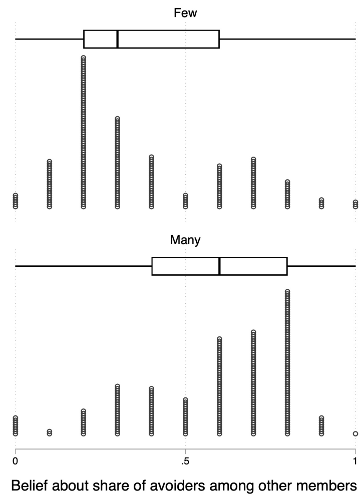
Our treatment manipulation is effective in shifting expectations about information decisions by other members of the group. Panel (a) in Figure 4 shows the distribution of beliefs by treatment. As intended, the treatment substantially shifts beliefs upwards. Panel (b) shows the average belief by treatment condition. The difference in beliefs about peers' informational decisions is large and significant: on average, subjects in Many believe that 0.219 higher proportion of their peers would avoid information, compared to those in the Few condition. This difference represents a 59.12% increase relative to the Few condition, and is significant at 1% level.

Table 2 reports a linear regression of the belief on the treatment dummy. On average, the expected share of avoiders among other group members is 21.9 percentage points higher in Many than in Few, representing a 59.1% increase. The difference is highly significant and robust to the inclusion of demographic controls, measures of economic and informational preferences, and strata fixed effects. Taken together, the results suggest that the treatment effectively manipulates beliefs about the share of avoiders among other members of the group.

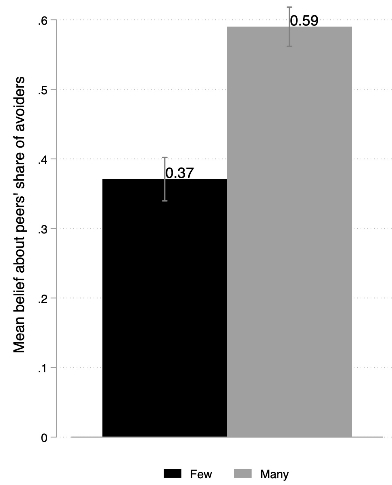
We now assess the hypothesis whether the proportion of subjects who choose to avoid information differs between Many and Few. Figure 5 shows the proportion of information avoiders across treatment conditions. Compared to Few, the share of information avoiders in Many is 0.084 higher ($p = 0.045$). This difference represents a 34.81% increase relative to the Few condition.

Table 3 reports the coefficients from a regression of the information avoidance dummy on the treatment and covariates, in a linear probability model. The uncontrolled treatment

[29] Compared to Few, there is a lower share of both Business and Economics students in Many.



(a) Belief distribution



(b) Average belief

Figure 4: Beliefs about share of avoiders among other members of group, by treatment condition

Notes: The figure shows the distribution of participants' beliefs about the share of information avoiders among other members of their group, by treatment condition. Panel (a) shows the frequency of each belief, with each dot representing a subject. The boxplot shows the median and the interquartile range of beliefs. Panel (b) shows the average belief by treatment condition. The error bars show 95% confidence intervals.

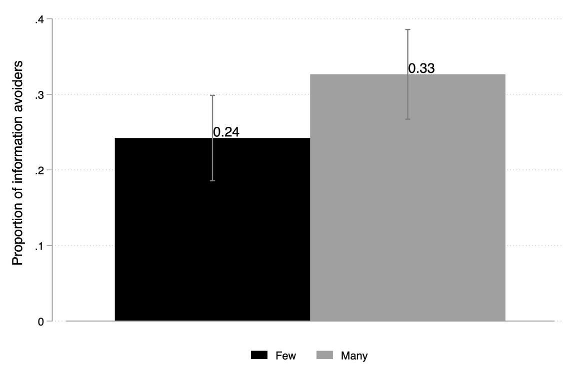


Figure 5: Treatment difference in proportion of avoiders

Notes: The figure shows the proportion of subjects who chose to avoid information (option Later), by treatment condition. The error bars represent 95% confidence intervals.

	Dep. Var: Belief about share of avoiders among others			
	(1)	(2)	(3)	(4)
Many	0.219***	0.215***	0.218***	0.221***
	(0.0215)	(0.0252)	(0.0254)	(0.0253)
Constant	0.371***	0.471***	0.394***	0.491***
	(0.0160)	(0.0720)	(0.137)	(0.162)
Strata FEs		✓	✓	✓
Demographics			✓	✓
Field FEs			✓	✓
Economic preferences				✓
Information Preferences Scale				✓
Observations	465	465	460	460

Standard errors in parentheses

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

Notes: The table shows the estimated coefficients of a regression of beliefs about the share of information avoiders among other members on the treatment dummy. The dependent variable is a continuous measure of beliefs, ranging from 0 ("no one will avoid information") to 1 ("everyone will avoid information"). The treatment dummy is equal to one if the subject was in the Many treatment and zero if in the Few treatment. Demographic controls include age and gender. Field of study fixed effects include dummies for fields of study. Economic preferences include risk-seeking, time preferences, altruism, reciprocity, and trust. The Information Preference Scale measures an individual's general preference for obtaining information. Strata fixed effects include dummies for week of year and time of day.

Table 2: Treatment effect on belief about share of avoiders among other members

effect (column 1) is 0.084, significant at 5%. This estimate is robust to the inclusion of individual characteristics and strata-fixed effects (0.099, significant at 5%). When all controls are included, the treatment effect increases to 0.123, becoming significant at 1%. In this specification, the treatment effect represents half of the baseline proportion of avoiders.

This estimate of the treatment effect is robust to a variety of alternative specifications. We find even stronger treatment effects when scream– and volume– lovers are excluded from the sample (Tables B.2 and B.3 in Section B.1). We also qualitatively similar results when the outcome variable is the continuous preference strength for information avoidance (Appendix Section E). Finally, the estimate is robust to the inclusion of different subsets of controls (Appendix Section D) selected by the post double selection procedure (Belloni et al., 2014).

Social preferences are predictive of the information decision and moderate the interdependence. In particular, reciprocity interacts with the treatment. Since avoiding information is a way of harming others and taking revenge, more reciprocal individuals are expected to be less inclined to avoid information in the *Few* condition (where the majority is expected to acquire information and hence do "good" by improving the outcome) than in the *Many* condition (where the majority is expected to avoid information and harm by worsening the outcome). In column 7, we include in the regression interactions of the treatment with social preferences and find that, indeed, more reciprocal subjects are less likely to avoid information in the *Few* condition, but are more likely to avoid information in the *Many* condition, although the interaction is significant at 10%.

In summary, our information provision experiment provides robust evidence that, relative to Few, in Many subjects both believe that a higher share of their group members are avoiding information, and are more likely to avoid information themselves. This supports the hypothesis that, on average, information avoidance exhibits strategic complementarity, in line with notion of contagious ignorance.

5.5 Heterogeneity in reactions to the choices of others

Beyond the average strategic complementarity, we uncover how individuals differ in the way they respond to the informational decisions of their group mates. To this end, we analyze the full schedule of each individual's best response to all the possible choices made by others in the group. As discussed in Section 4.1, to characterize heterogeneity, we categorize the best response schedules based on whether they are increasing in the share of avoiders in

	Dep. Var: Information Avoidance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Signal	0.0843**	0.0994**	0.112**	0.122**	0.114**	0.123**	0.123**
	(0.0418)	(0.0489)	(0.0489)	(0.0491)	(0.0486)	(0.0487)	(0.0489)
Age			0.00966	0.0123*	0.0116*	0.0144**	0.0144**
			(0.00626)	(0.00630)	(0.00634)	(0.00633)	(0.00640)
Female			−0.136***	−0.131***	−0.136***	−0.127***	−0.127***
			(0.0472)	(0.0484)	(0.0471)	(0.0484)	(0.0485)
Patience				−0.0132		−0.00943	−0.00631
				(0.0232)		(0.0228)	(0.0282)
Risk seeking				0.00138		0.00584	0.0296
				(0.0230)		(0.0228)	(0.0309)
Pos. Reciprocity				−0.0433		−0.0460	−0.0981**
				(0.0291)		(0.0288)	(0.0407)
Neg. Reciprocity				0.00748		0.0149	−0.00359
				(0.0258)		(0.0258)	(0.0356)
Altruism				−0.0643**		−0.0648**	−0.0547
				(0.0273)		(0.0274)	(0.0401)
Trust				0.0191		0.0186	−0.00203
				(0.0222)		(0.0223)	(0.0305)
IPS score					−0.125**	−0.131**	−0.119**
					(0.0506)	(0.0522)	(0.0537)
High Signal X Patience							−0.0145
							(0.0501)
High Signal X Risk seeking							−0.0391
							(0.0439)
High Signal X Pos. Reciprocity							0.104*
							(0.0600)
High Signal X Neg. Reciprocity							0.0311
							(0.0512)
High Signal X Altruism							−0.00207
							(0.0563)
High Signal X Trust							0.0406
							(0.0437)
Constant	0.242***	0.321**	−0.0192	−0.0751	0.326	0.290	0.282
	(0.0288)	(0.155)	(0.273)	(0.276)	(0.301)	(0.310)	(0.321)
Strata FEs		✓	✓	✓	✓	✓	✓
Field of study FEs			✓	✓	✓	✓	✓
Observations	465	465	460	460	460	460	460

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

Notes: The table shows the estimated coefficients regression of information avoidance on the treatment dummy in a linear probability model. The dependent variable is a binary indicator equal to one if the subject chose to avoid information and zero otherwise. The treatment dummy is equal to one if the subject was in the *ManyAvoided* condition and zero if in the *FewAvoided* condition. The regressions include strata fixed effects, demographic controls, field of study, and measures of economic and information preferences.

Table 3: Regression of information avoidance on treatment, social preferences, and information preferences

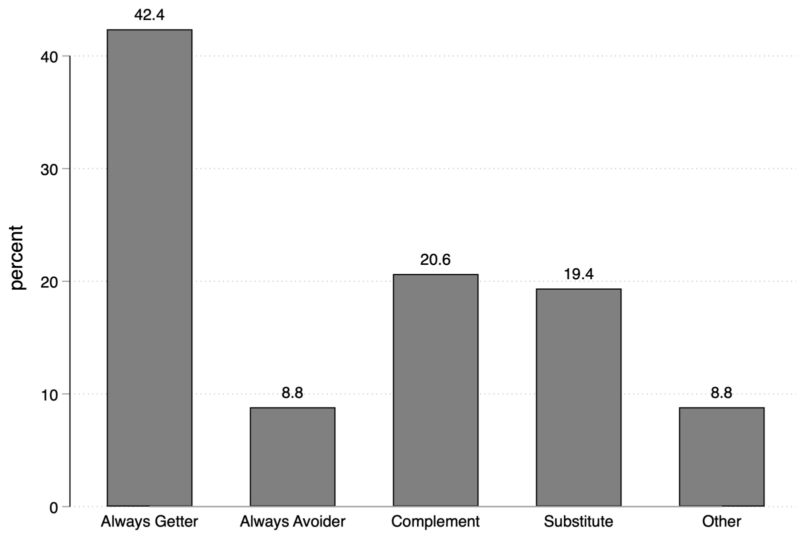


Figure 6: Distribution of best response types

their group (Strategic Complements), decreasing (Strategic Substitutes), or constant (either Always Getters or Always Avoiders). We refer to these categories as strategic types.

The data reveals substantial heterogeneity in the way individuals respond to the information avoidance decisions in their groups. Figure 6 shows the empirical distribution of individual types. The most prevalent type of response is the Always Getter (42.4 %), characterized by the acquisition of information independently of the share of avoiding peers. In the opposite extreme, the least common type of response is the Always Avoider (8.8%), which avoids learning the state independently of the share of avoiding peers.

In terms of types that exhibit dependence on others' behavior (around 40% of our sample), we identify two patterns. A share equal to 20.6 % are strategic complements, who avoid information only if a sufficiently high share of their group mates avoid information. The 99% confidence interval of the proportion is (0.171, 0.246), showing that it is statistically different from zero. A similar proportion are strategic substitutes (19.4%), who avoid information only if a sufficiently low share of their group mates avoid information. The remaining minority (8.8 %) are subjects who switch their informational decisions multiple times and hence whose best responses oscillate.

We now report our findings on heterogeneous treatment effects across types. In particular, we look at whether the treatment affects the distribution of types (extensive margin) and

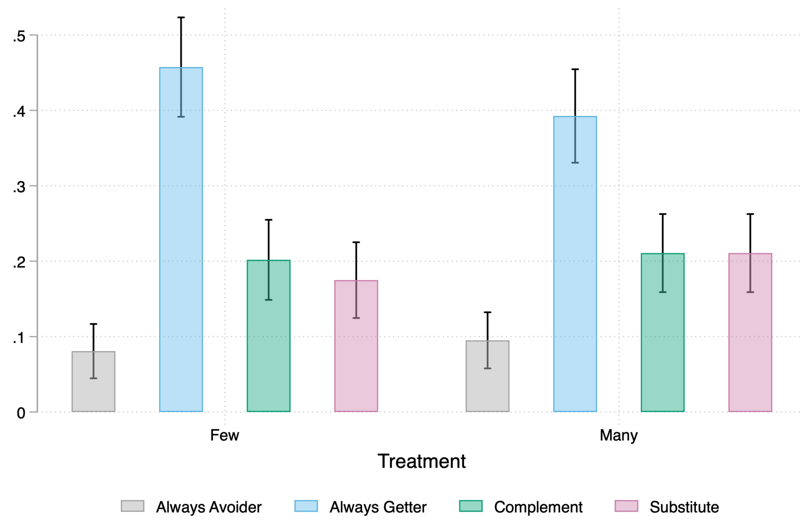


Figure 7: Distribution of best response types by treatment

Notes: The figure shows the relative frequency of best response types in each treatment condition. Bars represent the relative frequency of each type. The error bars represent 95% confidence intervals. The residual type composed by subjects who switch multiple times between Now and Later is omitted in the figure.

the probability of avoidance conditional on the type (intensive margin). On the extensive margin, we find that, reassuringly, the treatment has no effect on the distribution of types. Figure 7 shows the distribution of types split by treatment condition. Table 4 reports the estimated coefficients of a set of regressions where each type's dummy is regressed on the treatment. In these regressions, the treatment coefficient captures how the proportion of the type changes between Many and Few. We do not find any statistically significant difference. This distributional invariance across treatments is consistent with theory. The best reaction *schedules* themselves should not change unless a (perceived) feature or parameter of the environment changes, beyond the expected behavior of others. Since the treatment was designed to change only the expectation about others' behavior, but no other feature of the environment, there is no theoretical reason to expect a difference in the distribution of best responses across treatments.

We now turn to the intensive margin. Figure 8 shows the likelihood of avoidance for each best response type and treatment condition. Table 5 reports a linear regression of the information avoidance dummy on the treatment, for each best response type. The

	(1) A-Avoider	(2) A-Getter	(3) Complement	(4) Substitute
Many	0.0143	−0.0648	0.00895	0.0359
	(0.0263)	(0.0460)	(0.0377)	(0.0367)
Constant	0.0807***	0.457***	0.202***	0.175***
	(0.0183)	(0.0335)	(0.0270)	(0.0256)
Observations	465	465	465	465

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

Notes: The figure reports estimated coefficients of a linear regression of a dummy for each best response type on the treatment dummy. The dependent variable is a binary indicator equal to one if the subject's best response belongs to the type and zero otherwise. The treatment dummy is equal to one if the subject was in the Many condition and zero if she was in the Few condition.

Table 4: Treatment effect on distribution of types (Extensive margin)

coefficient associated with the treatment captures the difference in the proportion of avoiders between Many and Few, for each type. We find that the Many treatment increases the likelihood of information avoidance for participants with a strategic complements best response type. This is reasonable: the treatment strongly increases subjects' belief about others' avoidance, and this belief is the argument of the best response schedule, which is increasing for strategic complements. Therefore, strategic complements respond to the increase in beliefs by engaging in information avoidance. On the other hand, we do not find evidence that strategic substitutes significantly respond to the treatment. A possible explanation rests on the distribution of threshold levels of avoidance in their group at which strategic complements and strategic substitutes are willing to switch between acquiring and avoiding information. These distributions are shown in Figure 9 for strategic complements and strategic substitutes. As can be seen from the figure, for strategic complements the threshold at which they are willing to switch on average (0.52) is significantly higher than for strategic complements (0.40, p<0.001). The modal threshold of complements is between 0.4 and 0.6, i.e. around 0.5, making them particularly responsive to the change in beliefs induced by the treatment. In contrast, the modal threshold for strategic substitutes is between 0.2 and 0.4, making them less prone to react to the treatment. That's because, as shown in figure 4, as we move from Few to Many the participants' average estimate of the share of information avoidance in their group goes from 0.37 to 0.59 (beliefs do not statistically differ across best response types). Hence, we expect that the treatment will affect the behavior of

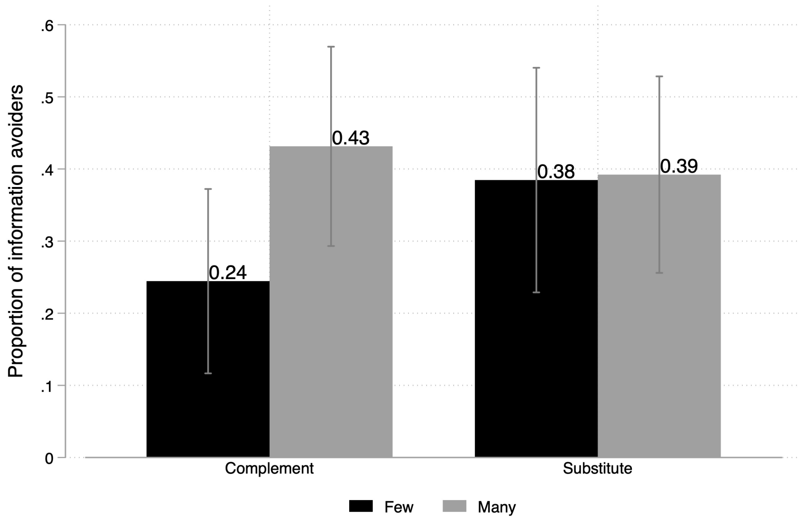


Figure 8: Heterogeneous treatment effects on information avoidance, by best response type

Notes: The figure shows the proportion of subjects who choose to avoid information by treatment and best response type. The bar represents the proportion of information avoiders. The error bars represent 95% confidence intervals.

those participants with a threshold lying between 0.4 to 0.6, approximately.[30] Finally, as expected, the treatment does not affect the prevalence of information avoiders for Always Getters and Always Avoiders, who, by definition, follow strategies that are irresponsive to the behavior of others.

The substantial heterogeneity we observe in best response types suggests that the composition of the group is an important determinant of equilibrium levels of information avoidance in groups.

5.6 Mechanisms

Section 5.4 showed that subjects who receive a signal that the prevalence of avoidance is High exhibit on average a higher share of avoidance, relative to subjects in the Low Signal condition. This section explores mechanisms underlying this treatment effect, i.e., what makes members of High signal groups more likely to avoid discovering the state than members of Low signal groups.

[30]This explanation is still exploratory and needs to be refined. We are currently working on it.

	Dep. var: Information Avoidance			
	(1)	(2)	(3)	(4)
	A − Avoiders	*A − Getters*	*Complements*	*Substitutes*
Many	0.0556	0.0141	0.187*	0.00754
	(0.0572)	(0.0332)	(0.0964)	(0.106)
Constant	0.944***	0.0490**	0.244***	0.385***
	(0.0572)	(0.0216)	(0.0655)	(0.0800)
Observations	41	197	96	90

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

Notes: The table shows the estimated coefficients of a linear regression of information avoidance on the treatment dummy, for each type of best response. The dependent variable is a binary indicator equal to one if the subject chose to avoid information and zero otherwise. The treatment dummy is equal to one if the subject was in the Many condition and zero if she was in the Few condition. Each column reports the estimated coefficients for each respective type.

Table 5: Treatment effect on information avoidance, by best response type (intensive margin)

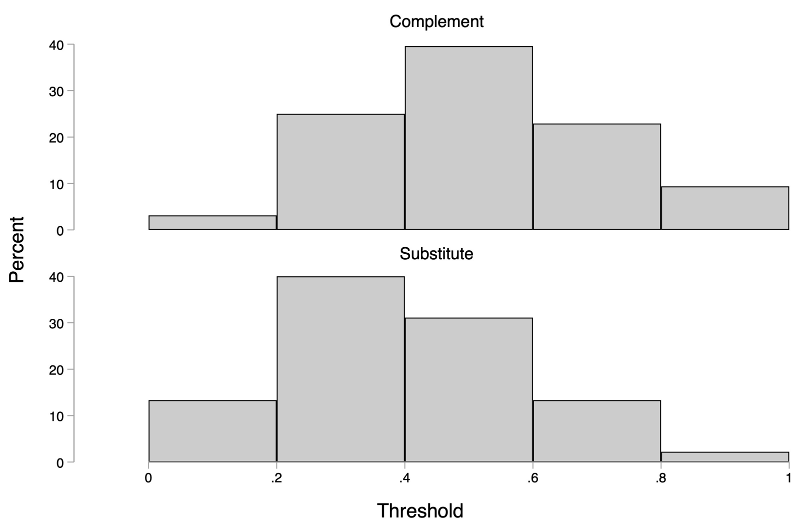


Figure 9: Distribution of switching thresholds by best response type

Notes: The figure shows the distribution of threholds at which subjects switch between avoiding and acquiring information in response to the share of avoiders among other group members, by best response type.

5.6.1 Anticipatory Utility and Information Decision

To shed light on mechanisms and determinants of information decisions, we use the KP questions to measure the expected anticipatory utility associated to information acquisition and avoidance. First, we show that our measures of anticipatory utility significantly predict the actual information decisions in our experiment, beyond the predicting capacity of the IPS. Next, we provide suggestive evidence that the treatment operates mainly through the utilities as captured by the KP measures. Finally, and importantly, we show that the treatment increases the net utility of avoiding information by lowering the expected anticipatory utility of finding out *bad* news, but has no effect on the expected anticipatory utility of finding out *good* nor *no* news, in line with Bénabou (2013)'s groupthink mechanism.

Inspired by the theory, our KP questions elicit subjects' estimation of their own anticipatory utility *conditional on each possible information set* —that is, upon finding out good news ($\hat{v}_i(g)$), bad news ($\hat{v}_i(b+\Delta)$), and no news ($\hat{v}_i(\hat{q}_i b + (1-\hat{q}_i)g)$)—. In addition, the KP questions elicit the subjective belief that the state is bad ($\hat{q}_i$). All the KP questions are elicited before subjects make their information decisions.[31]

Based on the answers to the KP questions, for each subject we estimate the expected anticipatory utility of acquiring information, by taking the expectation over states

$$U_{0,i}^{Get} \equiv \hat{q}_i \hat{v}_i(b+\Delta) + (1-\hat{q}_i)\hat{v}_i(g) \tag{4}$$

based on the reported subjective belief about the state, $\hat{q}_i$. On the other hand, the expected anticipatory utility of avoiding information is simply

$$U_{0,i}^{Avoid} \equiv \hat{v}_i(\hat{q}_i b + (1-\hat{q}_i)g) \tag{5}$$

Then the **net expected anticipatory utility of avoiding information** is defined as

$$\phi_i \equiv U_{0,i}^{Avoid} - U_{0,i}^{Get} \tag{6}$$

, implying the prediction that an individual i should avoid information when $\phi_i > 0$, acquire it if $\phi_i < 0$, and be indifferent if $\phi_i = 0$. We say that an individual i is "KP-concave" if $\phi_i > 0$, "KP-convex" if $\phi_i < 0$, and "KP-linear" if $\phi_i = 0$.

For the analysis, we consider a dummy variable denominated `KP-concave` that takes

[31] [DISCUSS WHY AND TRADE-OFFS]

	Dep. Var: Avoided Information							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
KP-concave	0.372***			0.379***			0.365***	
	(0.0460)			(0.0451)			(0.0465)	
KP net value of Later		0.0229***			0.0230***			0.0223***
		(0.00274)			(0.00274)			(0.00283)
IPS score			−0.129**	−0.148***	−0.136***			
			(0.0521)	(0.0485)	(0.0471)			
High Signal						0.122**	0.0807*	0.0607
						(0.0491)	(0.0454)	(0.0467)
Constant	−0.115	0.117	0.279	0.294	0.500*	−0.0751	−0.104	0.116
	(0.242)	(0.249)	(0.318)	(0.277)	(0.283)	(0.276)	(0.238)	(0.247)
Strata FEs	✓	✓	✓	✓	✓	✓	✓	✓
Demographics	✓	✓	✓	✓	✓	✓	✓	✓
Field of study FEs	✓	✓	✓	✓	✓	✓	✓	✓
Economic preferences	✓	✓	✓	✓	✓	✓	✓	✓
Observations	448	460	460	448	460	460	448	460
Adjusted R^2	0.211	0.186	0.071	0.227	0.199	0.071	0.215	0.187

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

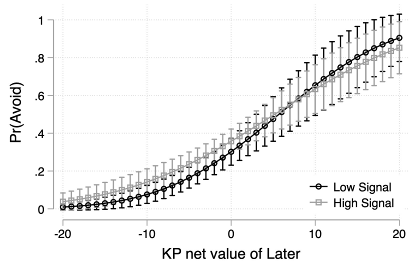
Notes: The table shows linear regression models of $Avoid_{ig}$ (a dummy that takes value 1 if the subject avoided information and 0 otherwise) on expected anticipatory utility (measured by the KP questions), the Information Preferences Scale (IPS) by Ho et al. (2021), and the treatment dummy. Regressions control for strata fixed effects, demographic characteristics and economic preferences. Robust standard errors.

Table 6: Association between measures of anticipatory utility and choice of avoiding information

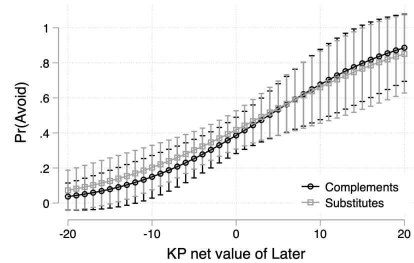
value 1 if the individual is KP-concave (161 subjects in our sample), 0 if the individual is KP-convex (292), and missing if the individual is KP-linear (12). Therefore, the prediction is that individuals should avoid if `KP-concave` = 1.

To assess how well our measures of anticipatory utility are associated with and predict actual information choices, we regress the dummy $Avoid_{ig}$ on our measures, controlling for strata fixed effects, demographic characteristics, field of study, and economic preferences. Results are reported in Table 6.

Columns (1) and (2) shows that both our continous and binary measures of anticipatory utility are strongly significantly and positively associated actual choices, explaining about 20% of the variation. Therefore, the higher net expected anticipatory utility of avoiding information, the higher the probability that the individual actually chooses to avoid information. The partial correlation between the `KP-concave` dummy and the information choice is 37.2%, significant at 1%. Columns (3) to (5) assess the performance of our measures when the IPS is also included as a predictor. In column (3), as expected, the IPS has a negative coefficient: individuals more willing to *know* potentially undesirable information in a variety of domains are *less* likely to avoid information in our experiment. Noticeably, when both the IPS and our measure of anticipatory utility are included as predictors, both



(a) By treatment group



(b) By best response type

Figure 10: Relationship between net anticipatory utility of avoiding information and actual information choice (Probit)

Notes: XXXXXXXXX

coefficients remain stable in sign, magnitude, and significance. This suggests that the IPS explains residual variation after controlling for anticipatory utilities [NEEDS REPHRASING]. Nonetheless, as evident from the adjusted R^2s, our anticipatory measures explain a higher portion of the variation in information avoidance (about 20% versus 7%), possibly because the KP questions elicit aspects that are specific to the decision environment.

Finally, we assess whether anticipatory utilities mediate the treatment effect in columns (6) to (8), by including the treatment dummy. Column 6 includes the treatment dummy but not the measures of anticipatory utility, reproducing the main result. When our measures of anticipatory utility are included in addition to the treatment dummy, the treatment effect reduces its size and its significance. This lends support to the view that anticipatory utility is a key mediating variable, and that the treatment operates mainly through it. This makes sense theoretically: the decision should depend only on the utility associated to it, so once we control for the utility, variations in the treatment dummy should become insignificant. To illustrate this point, in Figure 10 we report a probit model where the latent variable is ϕ_i, estimated separately for the treated (*Many Avoided*) and control (*Few Avoided*) conditions. The marginal probability of avoiding information increases with ϕ_i, and, notably, the relationship is statistically indistinguishable across treatment groups. We repeat the same exercise across best response types (complements and substitutes) and find the same pattern.

Results are similar when considering the continuous variables: the net utility of avoiding information, ϕ_i, and the strength of preference for avoiding information, $IA - scale_i$.

Taken together, the evidence suggests that the KP measures, designed to capture expected anticipatory utility, is strongly associated with and predictive of actual information decisions, and that the treatment operates (at least partially, if not mostly) through what the KP constructs measure.

5.6.2 Others' Behavior, Anticipatory Utility, and Groupthink

The complementarity of information choices can in principle be driven by a variety of mechanisms. We first consider the "groupthink" channel proposed by Benabou (2013): when a subject expects that others remain ignorant about the state, his own payoffs in the bad state become worse, which makes it more undesirable to find out the state. We provide evidence that supports this mechanism, using the KP constructs. We conceive the KP constructs (utilities) as mediators of the treatment. To assess the causal effect of the treatment on each of these mediators, we regress the KP constructs on the treatment.

Figure 11 shows the treatment effect on each of the KP constructs. Importantly, subjects in the High signal condition report a lower expected utility of discovering bad news than subjects in the Low signal condition. This is in line with theory, as the payoff in the bad state worsens as more group members avoid information. In contrast, there is no significant difference in the utility of discovering good news across treatment conditions. Again, this aligns with theoretical predictions, as the payoff in the good state is constant across treatment conditions. The treatment does not significantly change the reported utility of having no news either.

Unexpectedly, the treatment also increases the subjective belief that the state is bad. This effect is not predicted by the theory and, in principle, suggests that changes in beliefs about the state could be an additional mechanism or, alternatively, even interact with and amplify the groupthink mechanism. However, Falk and Zimmermann (2024) find that, in an individual decision-making setting, experimentally manipulating the probability of the bad state does not lead to changes in information avoidance.

Taken together, the effects on anticipatory utility and on subjective belief about the state combine to increase the implied *net* anticipatory utility of choosing Later (avoiding information), suggesting that one of the main sources of increased incentives to avoid information in the High signal condition arise from the deterioration of the utility of finding out bad news, in line with Benabou (2013).

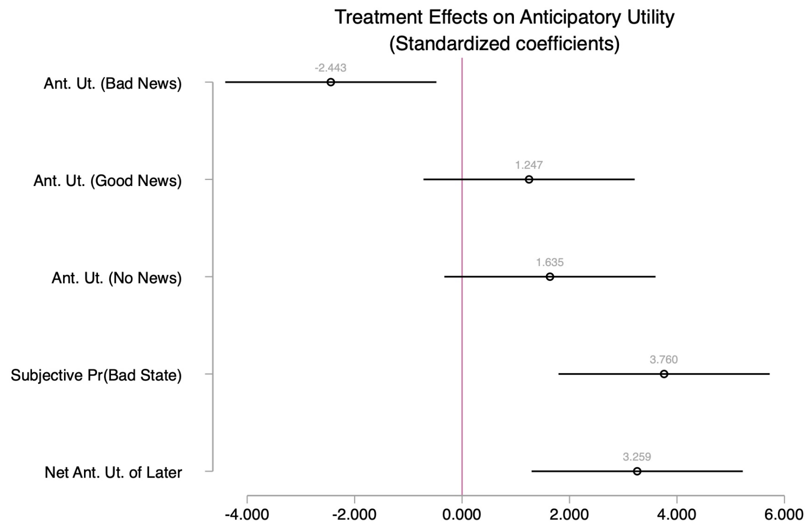


Figure 11: Treatment effect on KP measures (anticipatory utilities and belief about the state)

Notes: The figure shows the standardized treatment effect coefficient of separate regressions where the dependent variables are the expected anticipatory utilities upon finding out good, bad, and no news; the subjective belief about the state being bad; and the implied net expected anticipatory utility of avoiding information relative to obtaining it. Regressions control for demographic characteristics, strata fixed effects, economic preferences, and individual scores on the Information Preferences Scale.

5.6.3 Other Mechanisms

Next, we address potential competing mechanisms.

Conformity and herding A first order concern is the possibility that the positive correlation between beliefs about others' behavior and own behavior is driven by conformist preferences. We say that an individual is conformist if he derives *direct* utility from matching his actions to those of others. An alternative concern is information herding. Under this mechanism, subjects are unsure about which is the most convenient course of action (i.e., to avoid or acquire information) in our particular experimental setting; if they believe that the signal about others' behavior in the past is more informative about the most convenient decision than their own priors, they may rationally follow the crowd and match their actions to that of others. To assess these two empirically similar mechanisms, labeled jointly as "conformity" for brevity, we conduct four falsification tests. Specifically, if the observed treatment effect is purely driven by conformity, then we would expect four observable implications. First, since the treatment conditions are effective in varying the beliefs about others' information avoidance, the utility of acquiring information and discovering the good state should differ across conditions. We focus on the event of acquiring information *and discovering good news* because, unlike the event of discovering bad news, material payoffs g are constant across conditions, allowing a cleaner comparison. As Figure 11 shows, we don't find support for this implication of conformity. Second, under a pure conformity channel the belief about others' information avoidance should predict own avoidance *independently* of the subjective belief about the state. To test this, we regress $Avoid_{ig}$ on both beliefs and their interaction. We find that, contrary to the conformity channel, the interaction of both beliefs is highly significant, suggesting that the belief about others' behavior predicts own avoidance only if the subject believes that the probability of the bad state is high. Moreover, once the interaction is included, the coefficient on the belief about others' informational decisions becomes insignificant. This pattern lends support to the Benabou mechanism rather than to conformity. Third, conformity would operate through Strategic Complements only, and not through other types. Assuming that subjects derive utility from imitating behavior of people from *both* past and current sessions, we should observe a shift in the switching threshold of Strategic Complements caused by the treatment, given that the strategy method elicits choices conditional on the choices of group members in the current, but not past, session. We do not find evidence of different switching thresholds across conditions. Fourth, under a pure conformity channel the effect of the treatment should not interact with reciprocity. However, we find mild evidence of the interaction. Taken together, the four falsification tests do not provide statistically significant support for either the conformity or the information herding channel, while some reinforce the evidence for the groupthink mechanism.

Punishment A second potential competing mechanism is punishment. Under this mechanism, subjects in the High signal condition expect a worse payoff in the bad state as a result of others avoiding information, and respond to this mistreatment by reciprocating —i.e., by avoiding information, which is achieves punishment by worsening the outcomes of other members. Under this mechanism, we would expect that the treatment effect being stronger for more negatively reciprocal people. In other words, the interaction between the treatment and negative reciprocity should be significant and positive. We do not find evidence of this. In regressions including interactions with prosocial preferences, the interaction is insignificant.

Social Learning A third competing mechanism is social learning. Under this mechanism, subjects do not know the parameters of their preference over screams, and use the signal about behavior in the past to update their beliefs about their own preference parameters. As a result, this may generate differences in information avoidance across treatment conditions. Although we do not have a direct test for this channel, we expect this mechanism to be negligible. [NEEDS MORE EVIDENCE / DISCUSSION?]

Non-linear preferences over volume Finally a fourth competing mechanism relates to differences in the perceived benefit of a reduction of the 2 volume points across conditions. If subjects perceive that a 2 point reduction is less valuable in the High signal condition relative to the Low signal condition, they would have higher net incentives to avoid information. While this mechanism is possible in principle, casual experience suggests that an increase of 2 volume points in a computer generates only a subtly noticeable in perceived loudness. This suggests that the effect through this mechanism may be negligible, unless subjects exaggerate their expectations of changes in loudness both substantially and asymmetrically across conditions.

6 Group Composition and Equilibria

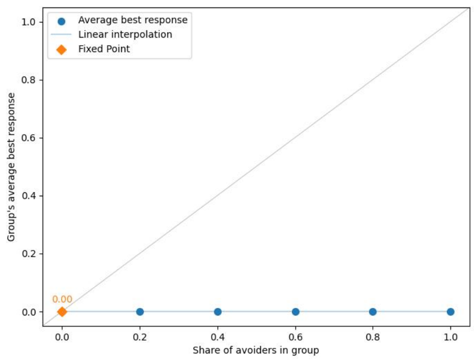
While the main treatment effect suggests that, on average, exogenously increasing beliefs about the prevalence of avoidance increases the likelihood of avoidance in a group, we have also documented heterogeneity in individuals' best responses to others' avoidance. This heterogeneity suggests that the composition of the group in terms of best responses types is an important determinant of the set of "informational equilibria", where an informational equilibrium is defined as an equilibrium proportion of avoiders in a group. In other words, a proportion of avoiders π^* is an informational equilibrium if a proportion π^* of group members best-responds to π^* by avoiding information and the remaining proportion best-responds by acquiring information. This section explores the relationship between group composition and the resulting set of informational equilibria.

To derive the informational equilibria of a group, we first construct the aggregate, group-level best response function from the individual best-response functions of its members, as follows. A group with N_g members is characterized by N_g individual best-response schedules, each defined as a function $f_i : \pi \to \{0, 1\}$, where 1 represents avoidance and 0 acquisition. To derive the group-level best response function F, we simply take the average of f_i across group members at each π. As a simple example, consider a group of size $N_g = 2$ composed by an Always Getter (with $f_i(\pi) = 0$ for all π) and an Always Avoider (with $f_j(\pi) = 1$ for all π). Then the group-level best response function is $F(\pi) = 0.5$ for all π, which indicates that, for any π, 50% of the group members would best-respond by avoiding information.

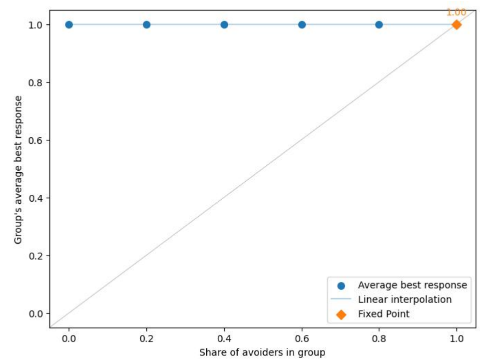
Because of implementation constraints, it is not possible to elicit f_i at *every* possible value of π: f_i can be practically elicited for only for a coarse set of values of π. This necessarily leads to a coarse representation of F. To recover the full shape of the group-level best response function F, we estimate the missing values by linear interpolation. This method has the advantages of simplicity and of providing good local approximations in the neighborhood of the observed values of F under a continuity assumption. It also ensures that F varies smoothly with π, avoiding estimating the location of thresholds leading to discountinuous jumps. Once the shape of F is estimated, we find the informational equilibria as the set of fixed points of F, i.e., the points where F crosses the identity line.

To gain intuition, Figure 12 shows the shape of F for "homogeneous" groups composed by a single type and the resulting informational equilibria. Blue dots represent the observed values of F and blue lines the values estimated by linear interpolation. The set of equilibria, indicated by the orange diamonds, is found at the intersection(s) of F and the identity line, represented by the gray line. Panels (a) and (b) show groups composed by the unconditional types. For the group composed only by Always Getters (Always Avoiders), F is constant and there is a unique informational equilibrium, with full information acquisition (avoidance). Panels (c) and (d) show groups composed by the conditional types. These groups are composed by the subset of, respectively, all Strategic Complements and Substitutes in our sample. The group composed by Strategic Substitutes (Complements) exhibits a negatively (positively) sloped F. The group of Strategic Substitutes exhibits a unique, interior equilibrium. Notably, the group of Strategic Complements exhibits multiple equilibria, including a fully informed and a fully uninformed equilibrium, in line with the theoretical result in Bénabou (2013).

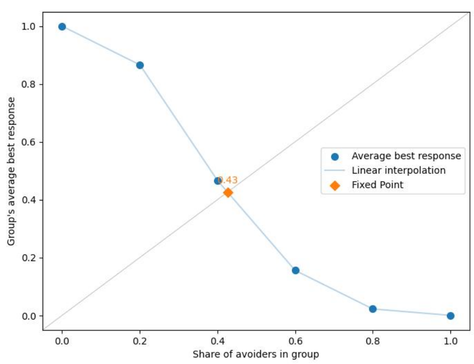
Next, we examine how the different types combine in the whole empirical sample. Figure 13 shows the estimated F for a group composed by our whole sample. Perhaps



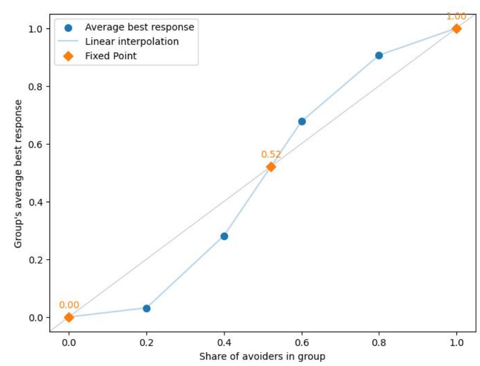
(a) Always Getters



(b) Always Avoiders



(c) Str. Substitutes



(d) Str. Complements

Figure 12: Informational Equilibria of Homogeneous Groups

Notes: Group-level best response schedules of "homogeneous" groups composed by a single type of best response. Each group is formed by subsetting the experimental sample on the type indicated by the caption. Blue dots represent values of the schedule at elicited values of π. Blue lines depict a linear interpolation. The gray, diagonal line indicates the identity line. Orange diamonds show the fixed points of the schedule, i.e., the informational equilibria.

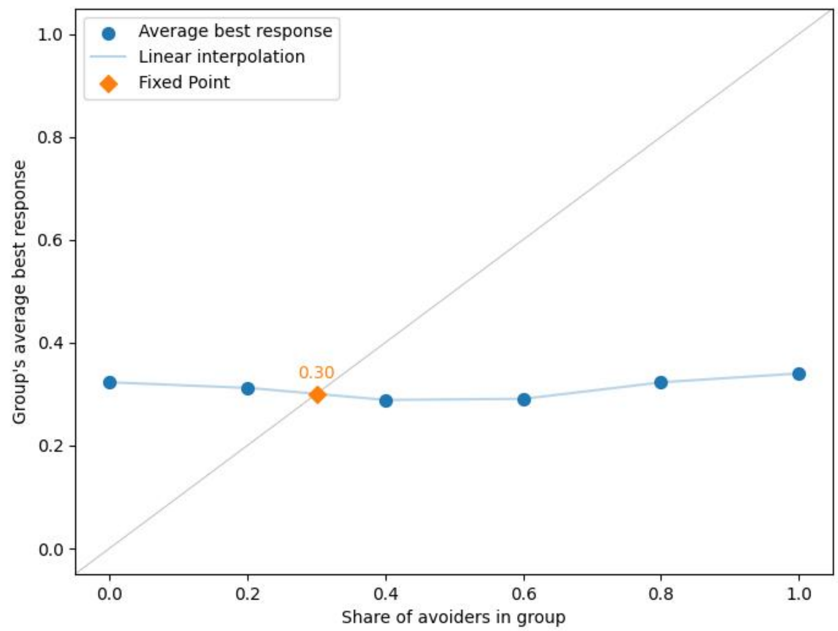


Figure 13: Informational Equilibria of Empirical Sample

Notes: Notes

unexpectedly, the aggregate F, while U-shaped, is almost constant. The flatness of F arises from two sources. First, around half of the individuals are either Always Getters or Always Avoiders, and hence contribute flat f_i's to the aggregation into F. Second, while there are around 40% of conditional types who could in principle break the flatness of F, these types are split equally into Complements and Substitutes, so that, roughly speaking, they average out each other. As a result, the group exhibits an almost horizontal F, with a unique interior equilibrium at $\pi^* = 0.30$.

The previous discussion, summarized in Figures 12 and 13, highlights how the group composition can determine very different sets of informational equilibria. This motivates a more detailed study of how variations in group composition impacts the set of informational equilibria. This could be useful, for example, if a principal of an organization wants to assemble a team of N_g members and is interested in some feature of the distribution of the set of informational equilibria, such as the median, the worst, or the best informational equilibrium in the set. She may also want to bound the probability of $\pi^* > \bar{\pi}$ for some critical level of interest $\bar{\pi}$ by optimally choosing her team composition. To study this, we employ simulations using bootstrap sampling to generate randomly drawn groups of a given composition to determine the distribution of equilibria corresponding to that particular group composition, and then track how the distribution of equilibria changes with changes in the group composition, and how fast.

The algorithm is described as follows. First, fix a group size N_g. Fix a sequence of group compositions $\tau \equiv \{\tau_t\}_{t=1,2,...,T}$, where each group composition τ_t is a vector $\tau_t \equiv (p_{AG}, p_{AA}, p_{SC}, p_{SS})_t$ whose elements are convex probabilities (respectively, for Always Getters, Always Avoiders, Complements, and Substitutes) that add up to 1. Start with $t = 1$. For $b = 1, ..., B$, draw a random group of size N_g through bootstrap sampling with replacement, with sampling probabilities of each type given by τ_t. This generates B simulated groups of size N_g with composition τ_t. For each group b, construct the group-level best response F_b (including the linear interpolation) and find the set of fixed points Π_b. Then, obtain the following statistics across bootstrap samples b: mean and 95% confidence interval of F_b at each π, and the relative frequency of each equilibrium level π^* across samples b. After this, let $t := t + 1$ and iterate for group composition τ_t until $t = T$.

To narrow down the space of group composition sequences, we focus on sequences starting with groups composed entirely by Complements (since these exhibit the highest multiplicity of equilibria and the highest uncertainty) and which gradually increase the proportion of another given type. Specifically, we restrict attention to two sequences: one starts from 100% Complements and increases the proportion of Always Getters by 10% in each step t, and the other starts from 100% complements and increases the proportion of Always Avoiders by 10% in each step t. Therefore, we study how the introduction of Getters or Avoiders can move a group with multiple equilibria towards a unique equilibrium.

For the simulations, we set $B = 500$ and $N_g = 13$[32]. In principle, it is also possible to study a large N_g, which would result in more precise estimates, but it would become more unlikely for a principal to control the composition of the group as N_g becomes very large. Hence, we focus on finite sample behavior.

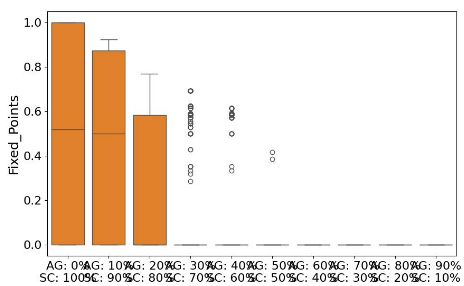
Figure 14 shows how the distribution of informational equilibria varies across the sequence of group compositions. The sequence of group compositions is spanned on the x-axis and the y-axis shows values of fixed points π^*. The upper panel provides a

[32]If N_g is a "round" number, such as 10, it is possible that, for some draws, continuous portions of F_b lie exactly on top of the identity line, introducing an infinite number of equilibrium points. This introduces technical details about how to count and adjust for these when calculating the relative frequency of equilibria, as well as apparent non-monotonicities in features of the distribution of equilibria as the group composition τ_t varies. To avoid these issues, we focus the discussion on cases constructed to prevent the emergence of infinite equilibria.

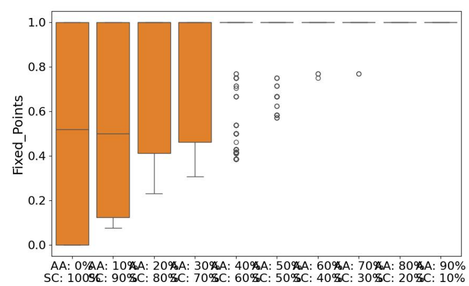
summary of the distribution of equilibria for each group composition, using boxplots. At the start of the sequence, groups composed by only Complements exhibit a wide range of equilibria, with a median at about 0.5. As t increases and Always Getters (Avoiders) are included, the distribution shifts downwards (upwards), towards information acquisition (avoidance). Notably, the median of the set of equilibria exhibits a strong non-linearity in group composition. As soon as 20% of Always Getters (Avoiders) are introduced, the median equilibrium moves sharply to full information acquisition (avoidance). Once the share of Getters (Avoiders) reaches 30%, the distribution of equilibria becomes compressed.

The lower panels of Figure 14 provides further detail on the distribution, by showing its quantiles. Of particular interest are the quantiles 0.0 and 1.0, which represent, respectively, the lower and upper bound of the support of the distribution of equilibria. These quantiles could be thought respectively as the "best" and the "worst" equilibrium in the set, if the principal is interested only in the level of information acquisition. Panels (c) and (d) show how the quantiles of the distribution vary with changes in group composition. Some patterns hold for both sequences of group compositions. First, adding Getters (Avoiders) preserves the quantile 0.0 (1.0) unaltered. This suggests there is a guarantee that, for example, when introducing Getters, the full information acquisiton equilibrium is preserved. Second, and more generally, quantiles typically respond (weakly) monotonically to the change in composition. Notably, the worst equilibrium in the set (quantile 1.0) improves monotonically as the proportion of Always Getters increases. Conversely, the best equilibrium in the set (quantile 0.0) worsens monotonically as the proportion of Always Avoiders increases. Third, there are non-linearities in the way quantiles respond to changes in the composition, suggesting that there are regions of the x-axis where the same amount of change in group composition leads to the largest gains in a feature of the distribution of interest. Fourth, the variance of the distribution shrinks with t.

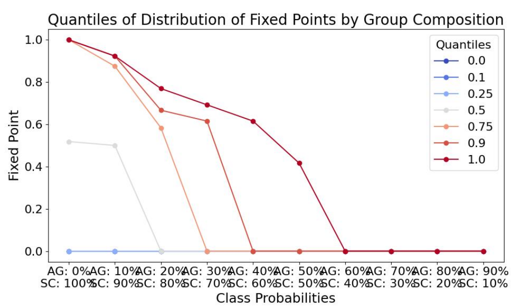
Finally, under the assumption that given a distribution of equilibria the equilibrium selection is at random, the quantiles provide a quick way to estimate the probability that an informational equilibrium in a group does not exceed a critical value $\bar{\pi}$. For example, if a principal is interested in assembling a group such that the probability of the equilibrium being below 0.6 is at most 75%, visual inspection of the 0.75 quantile in Panel (c) suggests that the group should contain at least 20% of Always Getters. More generally, under similar assumptions, our simulations could inform the decision of a principal who is interested in targeting any feature of the distribution of equilibria.



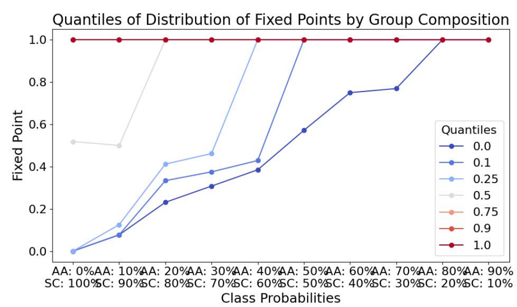
(a) Complements → A. Getters (Boxplots)



(b) Complements → A. Avoiders (Boxplots)



(c) Complements → A. Getters (Quantiles)



(d) Complements → A. Avoiders (Quantiles)

Figure 14: Group Composition and Distribution of Informational Equilibria

Notes: Notes

7 Conclusion

We live in an era of abundance of information in a variety of domains —politics, health, financial, environmental. However, sometimes individuals prefer to avoid readily available information, choosing, in effect, to remain in a state of willful ignorance. In this paper, we study whether this behavior is interdependent among individuals who are embedded in groups, in such a way that their information decisions end up impacting other members' outcomes. Our experimental evidence suggests that, on average, willful ignorance is contagious: individuals are more likely to avoid readily available information about the state when they expect others to do so, and hence, when they expect the outcome in the bad state to be more severe (and news revealing that the state is bad to be more undesirable). The interdependence is mediated by an increase in anticipatory disutility of finding out bad news, and it is moderated by social preferences, particularly, by reciprocity. However, we document substantial heterogeneity in individuals' reaction functions: while most individuals' reaction functions display independence from others' information decisions, about 40% the subjects display interdependence —they condition their information decisions on those of others. This heterogeneity of reaction functions suggests that the degree of aggregate contagiousness of willful ignorance may depend crucially on both the composition of the group in terms of reaction functions and the distribution of subjective expectations about others' behavior. Simulations show that changes in group composition can generate a wide variety of informational equilbria, ranging from full information acquisition to full willful ignorance in the group.

Our findings add nuance to the recommendations from the literature on information preferences, which typically focus on individual decision settings. Our results suggest that incentivizing a person to acquire information (which may be beneficial for the individual in isolation) may generate positive or negative informational externalities to other members, in the form of stronger or weaker incentives to acquire information. These "cognitive externalities" should be taken into account when designing policies that aim at increasing the aggregate take-up of information in groups when individuals' outcomes are interlinked.

Our results suggest some implications for organization design. Given that, usually, in organizations, information has instrumental value (i.e., subsequent decisions can be adjusted and improved if information about the state is acquired), a principal may be interested in incentivizing acquisition of information in her organization in order to minimize the emergence of a groupthink equilibrium where information avoidance is prevalent. Taking the group as given, a potential way to encourage information take-up is by correcting potential misperceptions about how others deal with information [EXPAND]. Another way is to design the group composition in terms of reaction functions when assembling teams. Our simulations show that the group composition has a strong impact in the distribution of equilibrium shares of informed members, and suggest the equilibrium responses are non-linear in the group composition, in such a way that there are regions in which the same amount of composition change delivers maximum results.

Our investigation has some limitations and motivates avenues for future research. First, because our experimental setup is based on the setup of Bénabou (2013) where there is a theoretical link between agents' decisions and the severity of the outcome, our design cannot disentangle whether (and how much of) the contagiousness arises from variations in the severity of the outcome ("severity effect") or from variations in the proportion of others who engage choose to remain ignorant ("herding effect"). Note that this limitation applies both to the average treatment effect and the individual reaction functions. We view our study as a first step in establishing the empirical existence of interdependence in information decisions. Further research is needed to disentangle the severity effect from the herding effect. Second, our study focuses on physical stimuli, which are important events in the lives of economic agents and have been experimentally proven to generate anticipatory anxiety. Future research could expand the set of stimuli to the monetary domain, using, for example, the prospect of money losses (Engelmann et al., 2024). Third, we consider a static decision-making settting, where all individuals choose their information decisions simultaneously. In many applications, such decisions occur sequentially. Studying sequential decisions, however, introduces experimental design challenges, such as reputation concerns and (possibly non-Bayesian) inference. Future studies could explore willful ignorance in groups in dynamic settings.

Our study highlights that understanding the ways in which individuals react to others' information decisions is crucial for designing environments that promote the acquisition of information, which, usually, allows improved subsequent decision-making in organizations.

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Appendices

A Proofs

Proof of Lemma 1

Consider v_i everywhere convex. Agent i prefers to avoid information if $\varphi_i > 0$, i.e.

$$v_i\left(pb^- + \left(1-p\right)g\right) > pv_i\left(b^- + \Delta\right) + \left(1-p\right)v_i\left(g\right)$$

Since $v_i\left(.\right)$ is strictly increasing, we have $v_i\left(b^- + \Delta\right) > v_i\left(b^-\right)$, hence we must have

$$v_i\left(pb^- + \left(1-p\right)g\right) > pv_i\left(b^-\right) + \left(1-p\right)v\left(g\right)$$

but this contradicts convexity. Therefore, the agent never avoids information, i.e., the agent is an Always Getter.

Proof of Lemma 2

Suppose v_i everywhere concave. First note that the net incentive to avoid information increases in the share of other group members who avoid information:

$$\begin{aligned}\frac{\partial \varphi_i}{\partial \lambda_{-i}} &= pv_i'\left(pb^- + \left(1-p\right)g\right)\frac{\partial b^-}{\partial \lambda_{-i}} - pv_i'\left(b^- + \Delta\right)\frac{\partial b^-}{\partial \lambda_{-i}} \\ &= \left[v_i'\left(pb^- + \left(1-p\right)g\right) - v_i'\left(b^- + \Delta\right)\right]p\frac{\partial b^-}{\partial \lambda_{-i}} \\ &> 0\end{aligned}$$

by concavity of v_i and assumption 1. It follows that:

- If $\varphi_i\left(\lambda_{-i} = 0\right) > 0$ then by monotonicity $\varphi_i\left(\lambda_{-i}\right) > 0$ for any λ_{-i}. Therefore, the agent is an Always Avoider if $\varphi_i\left(0\right) > 0$.
- If $\varphi_i\left(\lambda_{-i} = 1\right) < 0$ then by monotonicity $\varphi_i\left(\lambda_{-i}\right) < 0$ for any λ_{-i}. Therefore, the agent is an Always Getter if $\varphi_i\left(1\right) < 0$.
- If $\varphi_i\left(\lambda_{-i} = 0\right) < 0$ and $\varphi_i\left(\lambda_{-i} = 1\right) > 0$, then by continuity there exists an interior λ^*_{-i} such that the agent acquires information whenever $\lambda_{-i} < \lambda^*_{-i}$ and avoids it when $\lambda_{-i} > \lambda^*_{-i}$ (strategic complementarity).

Proof of Lemma 3

We assume throughout that $b^-(0) + \Delta < \widehat{U}_i$. Suppose that if everyone else avoids information, then at date 1 the expected utility under ignorance is so low that it falls below the reference level: $pb^-\left(1\right) + \left(1-p\right)g < \widehat{U}_i$. Then v_i is convex at $pb^-\left(1\right) + \left(1-p\right)g$. By convexity,

$$v_i\left(pb^-\left(1\right) + \left(1-p\right)g\right) < pv_i\left(b^-\left(1\right)\right) + \left(1-p\right)v_i\left(g\right)$$

so even without instrumental value of information Δ, avoiding information is dominated by acquiring it. Since v_i increasing, adding the instrumental value makes avoiding information even less desirable:

$$v_i\left(pb^-\left(1\right) + \left(1-p\right)g\right) < pv_i\left(b^-\left(1\right)\right) + \left(1-p\right)v_i\left(g\right) < pv_i\left(b^-\left(1\right) + \Delta\right) + \left(1-p\right)v_i\left(g\right)$$

Therefore, $\varphi^i(1) < 0$. When all other agents acquire information, agent i prefers to avoid. Suppose that if everyone else acquires information, then at date 1 the expected utility under ignorance goes above the reference level: $pb^-(0) + (1-p)g > \widehat{U}_i$. Then v_i is concave at $pb^-(0) + (1-p)g$. By concavity,

$$v_i\left(pb^-(0) + (1-p)g\right) > pv_i\left(b^-(0)\right) + (1-p)v_i(g)$$

For avoidance to be optimal, we need

$$v_i\left(pb^-(0) + (1-p)g\right) > pv_i\left(b^-(0) + \Delta\right) + (1-p)v_i(g)$$

Define the difference in expected utilities $d \equiv v_i(g) - v_i\left(pb^-(0) + (1-p)g\right)$. Then, the avoidance condition can be re-expressed as:

$$\begin{aligned} v_i(g) - d &> pv_i\left(b^-(0) + \Delta\right) + (1-p)v_i(g) \\ \text{i.e. } p\left[v_i(g) - v_i\left(b^-(0) + \Delta\right)\right] &> d \end{aligned}$$

When $d \to 0$, this always holds. Therefore, by continuity, there exists a value $d^* > 0$ such that for $d < d^*$ the agent avoids information. If $d < d^*$, the agent avoids information when all other agents in the group acquire it ($\varphi_i(\lambda_{-i} = 0) > 0$) and acquires information when all others avoid it ($\varphi_i(\lambda_{-i} = 1) < 0$). By continuity of $\varphi_i(\lambda_{-i})$, there exists an interior threshold λ^{**} such that agent i strictly prefers to avoid information if $\lambda_{-i} < \lambda_i^{**}$ and strictly prefers to acquire information if $\lambda_{-i} > \lambda_i^{**}$ (strategic substitutability).

Proof of Lemma 4

An altruistic agent with altruism parameter $\alpha_i > 0$ avoids information if

$$\varphi_i \equiv v_i\left((1+\alpha_i)\left(pb^- + (1-p)g\right)\right) - pv_i\left((1+\alpha_i)(b^- + \Delta)\right) - (1-p)v_i\left((1+\alpha_i)g\right) > 0$$

Increasing altruism increases her net incentive to avoid information iff $\partial\varphi_i/\partial\alpha_i > 0$:

$$\left(pb^- + (1-p)g\right)v_i'\left((1+\alpha_i)\left(pb^- + (1-p)g\right)\right) > p\left(b^- + \Delta\right)v_i'\left((1+\alpha_i)(b^- + \Delta)\right) + (1-p)gv_i'\left((1+\alpha_i)g\right)$$

which can be rearranged as

$$
\begin{aligned}
&pb^{-}\left[v_i'\left((1+\alpha_i)\left(pb^{-}+(1-p)\,g\right)\right)-v_i'\left((1+\alpha_i)\left(b^{-}+\Delta\right)\right)\right]\\
&+(1-p)\,g\left[v_i'\left((1+\alpha_i)\left(pb^{-}+(1-p)\,g\right)\right)-v_i'\left((1+\alpha_i)\,g\right)\right]\\
&\qquad > p\Delta v_i'\left((1+\alpha_i)\left(b^{-}+\Delta\right)\right)
\end{aligned}
$$

The RHS captures the fact that more altruistic agents have stronger instrumental motives to acquire information, since they internalize more the positive externalities of information acquisition on other members. Since $v' > 0$, the RHS is strictly positive. Thus a necessary condition for $\partial\varphi_i/\partial\alpha_i > 0$ is LHS > 0.

For v_i everywhere concave, the expression in the second square bracket is strictly positive, since $g > b^{-}$. The expression in the first square bracket is strictly negative, since $\alpha_i > 0$ and given the assumption on Δ. Therefore:

- If $b^{-} > 0$ then the sign of the LHS is ambiguous.
  - If $p = 0$, then $\partial\varphi_i/\partial\alpha_i > 0$, so more altruistic types have stronger incentives to avoid.
  - If $p = 1$, then $\partial\varphi_i/\partial\alpha_i < 0$, so more altruistic types have weaker incentives to avoid.
- If $b^{-} < 0$, then the LHS> 0.
  - If $p = 0$, then $\partial\varphi_i/\partial\alpha_i > 0$
  - If $p = 1$, then the sign of $\partial\varphi_i/\partial\alpha_i$ is ambiguous.

[Proof to be completed]

B Are Screams a Bad? Preferences for Screams and Volume

We identify Scream Haters (Lovers) as those subjects who report a higher (lower) utility of finding out that the state is Quiet than that it is Screams. We identify Volume Haters (Lovers) as those subjects who report a higher (lower) utility of hearing screams at volume 50 than at volume 100. Finally, for each individual, we obtain a measure of the strength of the hate for screams by taking the difference between the utility of finding out the Quiet state and the utility of finding out the Screams state. Similarly, we obtain a measure of the strength of the hate for volume by taking the difference between the utility of hearing screams at volume 50 and the utility of hearing screams at volume 100.

Figure B.1 shows the joint distribution of subjects' reported utilities of learning each state, identifying each type of scream preference. Figure B.2 shows the joint distribution of subjects' reported utilities of hearing screams at different volumes, identifying each type of volume preference. The distribution of the *strength* of hate for screams (volume) is shown in Figure B.3 (Figure B.4).

Figure B.1: Subject's reported utilities ("happiness") upon learning each state

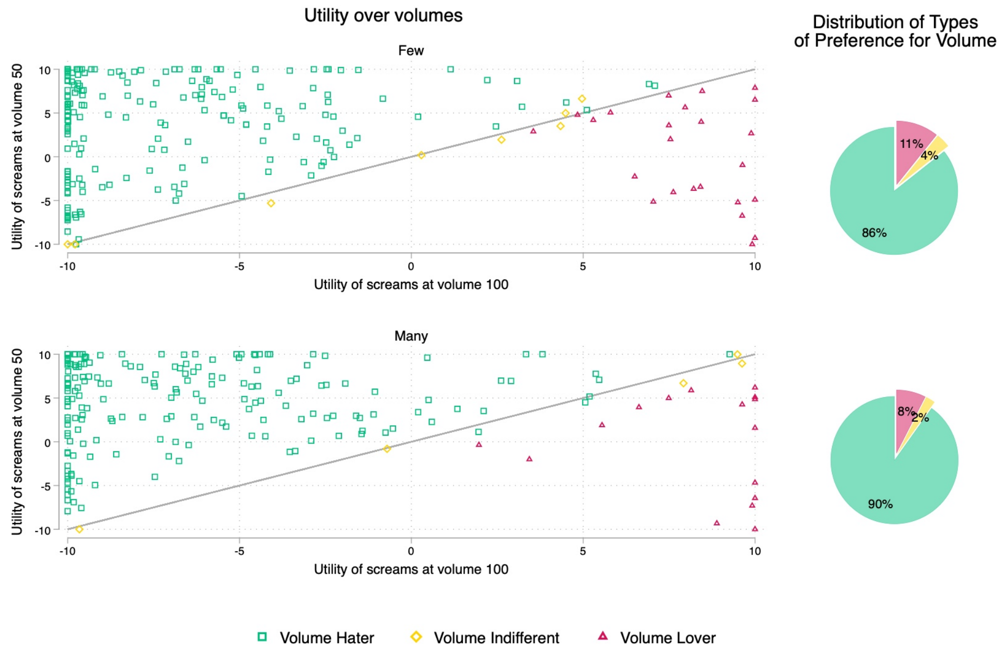


Figure B.2: Subject's reported utilities ("happiness") if he heard screams at different volumes

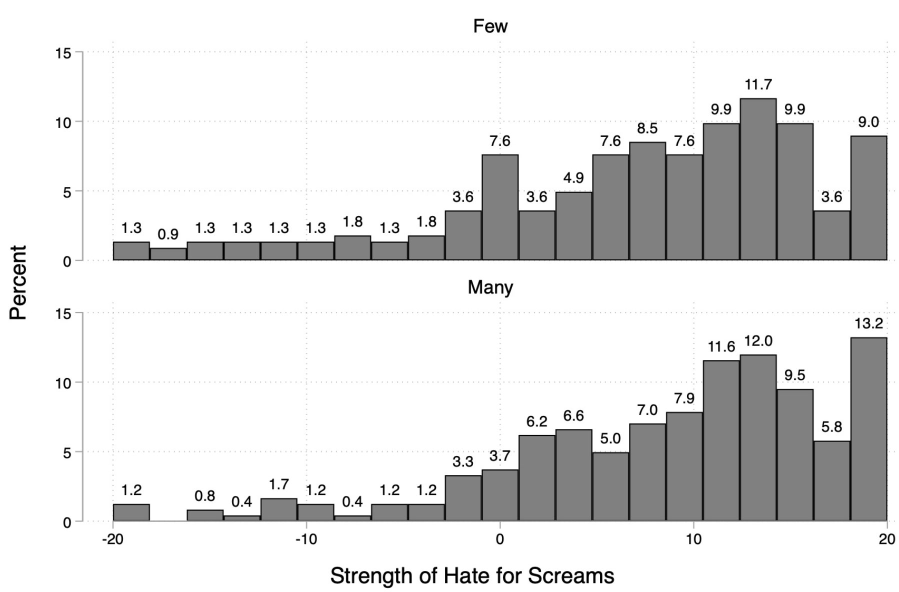


Figure B.3: Strength of Hate for Screams

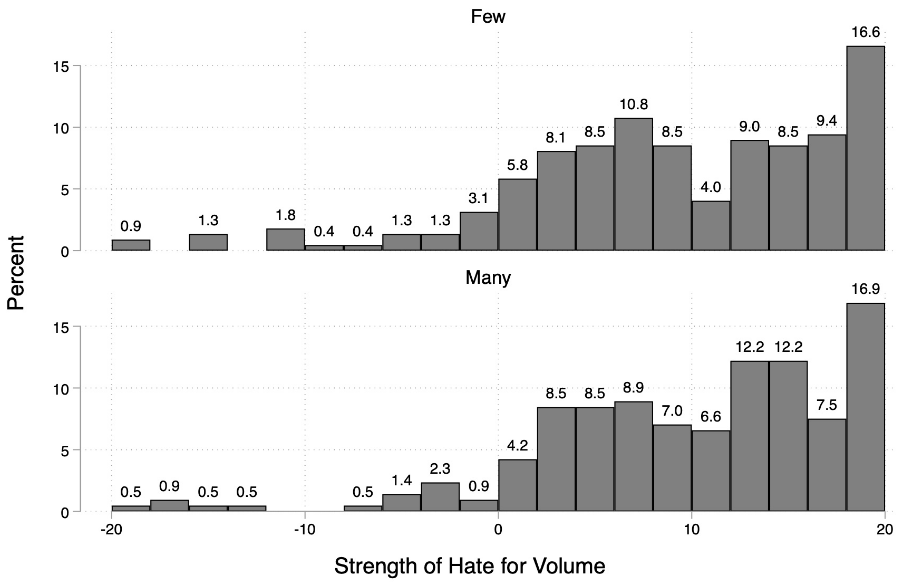


Figure B.4: Strength of Hate for Volume

The joint distribution of preference types over screams and volume is shown in Table B.1.

B.1 Robustness to Exclusion of Scream- and Volume-Lovers

The main regression results are robust to the exclusion of Scream- and Volume-Lovers. Figure B.5 shows the treatment effect on information avoidance by type of preference for scream (panel a) and for volume (panel b). The treatment effect is positive for scream- and volume-haters, but the direction of the effect is, if anything, the opposite for scream- and volume-lovers. This suggests that, by not excluding scream- and volume-lovers from our main regressions, the treatment effect is rather attenuated.

Table B.2 shows our main regression results if we exclude Scream-Lovers. Table B.3 shows our main regression results if we exclude Volume-Lovers. In both subsamples, the magnitude of the estimated treatment effect increases, compared to the full sample (reported in Table 3), for all the reported specifications. The treatment coefficient becomes significant at 1% for all specifications.

Scream Preference Type	Volume Preference Type				Total
	Volume Lover	**Volume Indiffer-ent**	**Volume Hater**		
Scream Lover	23	3	34	4	64
Scream Indifferent	1	5	19	1	26
Scream Hater	16	5	330	24	375
Total	40	13	383	29	465
Scream Lover	4.9%	0.6%	7.3%	0.9%	13.8%
Scream Indifferent	0.2%	1.1%	4.1%	0.2%	5.6%
Scream Hater	3.4%	1.1%	71.0%	5.2%	80.6%
Total	8.6%	2.8%	82.4%	6.2%	100.0%

Table B.1: Distribution of Scream- and Volume-Preference Types

C Supporting tables and figures

This section presents supporting tables and figures discussed but not shown in the body of the paper.

Figure C.1 shows the estimated coefficients of a regression of information avoidance on individual characteristics in a linear probability model. The individual characteristics include age, gender, field of study, and economic and general information preferences as measured by the IPS (Ho et al., 2021).

Table C.1 reports the treatment balance checks.

D Robustness of treatment effect

[To be completed.]

E Analyses of Information Avoidance Scale as Dependent Variable

[To be completed.]

	Dep. Var: Information Avoidance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Many	0.128*** (0.0448)	0.160*** (0.0515)	0.156*** (0.0510)	0.162*** (0.0524)	0.179*** (0.0519)	0.162*** (0.0518)	0.169*** (0.0518)
Age			0.0128* (0.00689)				0.0143* (0.00729)
Female			−0.150*** (0.0486)				−0.145*** (0.0524)
Patience					−0.0251 (0.0264)		−0.0129 (0.0253)
Risk seeking					0.0165 (0.0255)		−0.0134 (0.0265)
Pos. Reciprocity					−0.0329 (0.0325)		−0.0307 (0.0318)
Neg. Reciprocity					0.0303 (0.0285)		0.0331 (0.0283)
Altruism					−0.0378 (0.0310)		−0.0482 (0.0311)
Trust					0.0443* (0.0243)		0.0273 (0.0248)
IPS score						−0.113* (0.0577)	−0.124** (0.0586)
Constant	0.194*** (0.0305)	0.291* (0.172)	0.113 (0.224)	−0.0412 (0.240)	0.267 (0.172)	0.636** (0.247)	0.132 (0.339)
Strata FEs		✓	✓	✓	✓	✓	✓
Field of study FEs				✓			✓
Observations	375	375	371	375	374	374	371

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

Table B.2: Main regression, sample of scream haters only

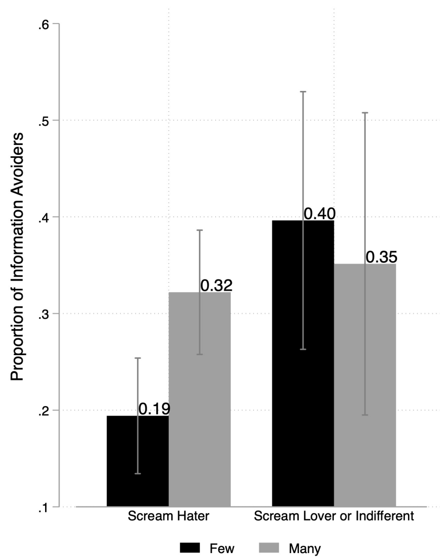
	Dep. Var: Information Avoidance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Many	0.134***	0.153***	0.156***	0.159***	0.159***	0.153***	0.165***
	(0.0440)	(0.0494)	(0.0485)	(0.0501)	(0.0501)	(0.0494)	(0.0497)
Age			0.0131**				0.0169***
			(0.00631)				(0.00645)
Female			−0.157***				−0.137***
			(0.0467)				(0.0516)
Patience					−0.00879		−0.00776
					(0.0266)		(0.0250)
Risk seeking					0.0192		−0.00630
					(0.0234)		(0.0250)
Pos. Reciprocity					−0.0241		−0.0240
					(0.0304)		(0.0302)
Neg. Reciprocity					0.0202		0.0219
					(0.0272)		(0.0274)
Altruism					−0.0491		−0.0615**
					(0.0298)		(0.0299)
Trust					0.0185		−0.00266
					(0.0235)		(0.0240)
IPS score						−0.107*	−0.133**
						(0.0566)	(0.0568)
Constant	0.183***	0.0700	−0.129	−0.136	0.0689	0.396**	−0.0785
	(0.0281)	(0.0481)	(0.149)	(0.162)	(0.0476)	(0.185)	(0.284)
Strata FEs		✓	✓	✓	✓	✓	✓
Field of study FEs				✓			✓
Observations	383	383	380	383	383	383	380

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

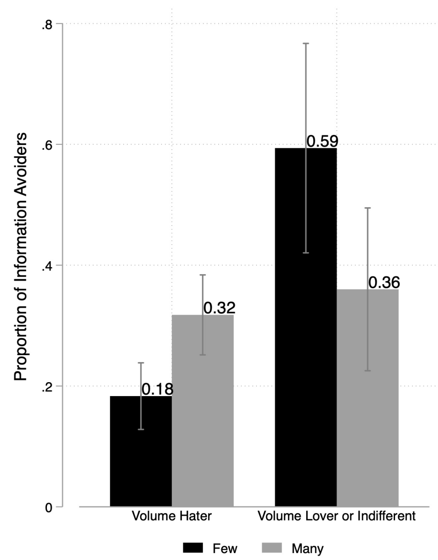
Table B.3: Main regression, sample of volume haters only

Variable	N	(1) Few Mean/(SE)	N	(2) Many Mean/(SE)	N	(2)-(1) Pairwise t-test Mean difference
Age	220	22.532	240	22.488	460	-0.044
		(0.268)		(0.223)		
Female	223	0.570	242	0.595	465	0.026
		(0.033)		(0.032)		
Medicine	223	0.193	242	0.231	465	0.039
		(0.026)		(0.027)		
STEM	223	0.184	242	0.215	465	0.031
		(0.026)		(0.026)		
Humanistic	223	0.193	242	0.260	465	0.068*
		(0.026)		(0.028)		
Economics	223	0.139	242	0.079	465	-0.061**
		(0.023)		(0.017)		
Business	223	0.247	242	0.178	465	-0.069*
		(0.029)		(0.025)		
Other fields	223	0.063	242	0.050	465	-0.013
		(0.016)		(0.014)		
IPS Score - All	223	3.104	241	3.127	464	0.022
		(0.028)		(0.026)		
IPS Score - All (excl. occ.)	223	3.033	241	3.061	464	0.029
		(0.031)		(0.027)		
IPS Score - Health	223	3.042	241	3.082	464	0.040
		(0.048)		(0.044)		
IPS Score - Finance	223	2.885	241	2.900	464	0.016
		(0.045)		(0.041)		
IPS Score - Personal	223	3.111	241	3.139	464	0.027
		(0.037)		(0.036)		
IPS Score - General	223	3.045	241	3.079	464	0.034
		(0.047)		(0.045)		
IPS Score - Occupational	223	3.291	241	3.296	464	0.006
		(0.032)		(0.032)		

Table C.1: Balance of pre-treatment characteristics



(a) By preference over screams



(b) By preference over volume

Figure B.5: Treatment effect on information avoidance by preference over screams and over volume

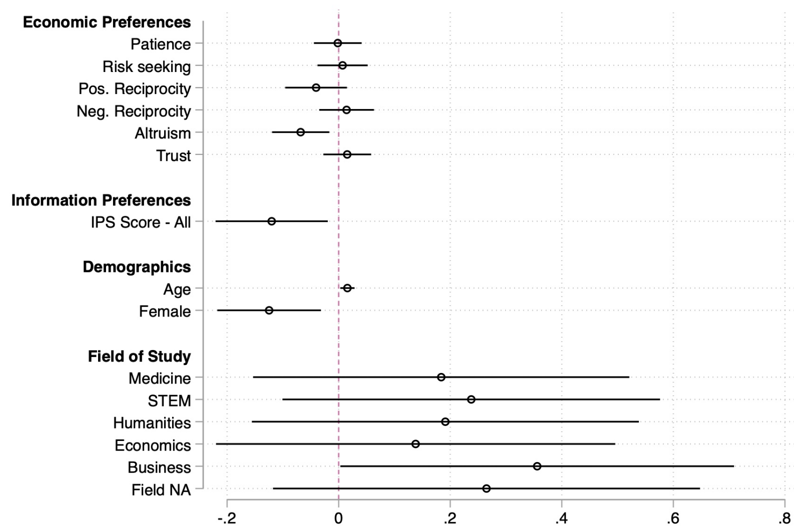


Figure C.1: Predictors of Information Avoidance

Notes: The figure shows the estimated coefficients of a regression of information avoidance on individual characteristics. The dependent variable is a binary indicator equal to one if the subject chose to avoid information and zero otherwise. The coefficients are estimated in a linear probability model. The error bars represent 95% confidence intervals. The regression includes all the characteristics shown in the figure. Economic preferences are measured by administering the relevant Global Preferences Survey questions (Falk et al., 2018). The information preferences are measured by the Information Preference Scale by Ho et al. (2021), with higher values indicating a higher propension to obtain information. The sample size is 465.