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This dissertation is the result of my own work and no other sources or means except the ones listed have been employed.

A mio padre.

Contents

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1 Introduction

A relatively recent strand of economic literature studies the design of information. Classical economic models analyze optimal decision-making (e.g., profit-maximizing firms choosing prices or quantities) taking a particular economic environment as given. Such an environment, and in particular the knowledge of its characteristics by decision-makers, is usually endogenous in the real world. The information that decision-makers process plays a role in determining their decisions. Therefore, it is fundamental to understand what is the content of the information available to decision-makers and why.

The analysis of information design must consider both the demand side and the supply side. The information suppliers are usually interested parties who design information to manipulate decision-makers' understanding of the economic environment. They may exploit their role to mislead decision-makers by recommending wrong decisions or hiding important characteristics of the environment. At the same time, decision-makers do not always process information that increases their understanding of the economic environment. Decision-makers could use information strategically to perceive the economic environment more pleasantly. Alternatively, they may not be willing to bear the cost of processing all information available.

The study of information design is particularly relevant in the current age of disinformation. Low-quality information (e.g., fake news, conspiracy theories) is spreading online, affecting how decision-makers understand the world, with disastrous effects on individual outcomes (e.g., health-related decisions) and collective outcomes (e.g., climate change denying). We lack a conclusive understanding of these phenomena, in particular of their causes and the best policies to handle them.

In this dissertation, I have employed both theoretical models and experimental/empirical analysis to make advances in the field of information design. My results inform policy-makers about relevant and novel issues relative to how information is generated and processed.

Chapter 1 Two stylized facts characterize the Internet: a great diversity of news sources and the proliferation of disinformation. I study a Bayesian Persuasion model that connects these observations. I consider news sources with opposite biases competing to persuade unbiased news consumers that have limited attention and heterogeneous beliefs. I find that media pluralism (i.e., the existence of multiple news sources) harms news consumers, reducing both their expected payoffs and the quality of information. The reason is the endogenous formation of echo chambers. According to the standard narrative, echo chambers arise because news consumers exhibit confirmation bias. I show that even unbiased and rational news consumers devote their limited attention to like-minded news sources in equilibrium. Confirmation bias thus arises endogenously because news sources have no incentive to provide valuable information. I show that the presence of many news sources and the widespread existence of misleading news are concurrent.

Chapter 2 In joint work with Linnéa Marie Rohde, we investigate whether strategic information acquisition harms the provision of a public good in an incentivized online experiment with a large and heterogeneous sample of the German population. The marginal returns of the public good are uncertain: it is either socially efficient to contribute or not. In the control treatment, individuals contribute to the public good given this uncertainty. In the information treatment, participants can choose between two information sources with opposite biases before contributing. One source is more likely to report low marginal returns, whereas the other is more likely to report high marginal returns. Most participants select the source biased towards low marginal returns, independent of their prior beliefs. As a result, the information treatment significantly reduces contributions and increases free-riding. When contributing is socially efficient, the information treatment reduces social welfare by up to 5.3%. We find that social preferences affect information acquisition: socially-oriented participants are more likely to acquire information and to select the source that is biased towards low marginal returns. We corroborate our findings by showing that participants' behaviour in our experiment is consistent with their attitudes towards actual public goods.

Chapter 3 In joint work with Yulia Evsyukova and Niccolò Lomys, we study a Bayesian persuasion model where agents have an asymmetric perception of the state space. Whereas Sender (he) perceives all payoff-relevant states of the world, Receiver (she) does not. Persuasion occurs in two stages. Sender first designs Receiver's optimal frame by expanding or refining her perception of payoff-relevant states. Then, given the chosen frame, Sender designs an optimal information structure. We characterize Sender's trade-off between keeping Receiver in the dark and expanding/refining her perception of the state space. The optimal frame depends on how Receiver reacts to the discovery of a new state or the refinement of her information partition. Sender benefits from growing awareness if it makes it easier to persuade Receiver. Whether Sender benefits from Receiver's under-reaction or her over-reaction to the discovery of a new state depends on Receiver's preferences. We show that our results are robust under various standard frameworks to model beliefs under growing awareness, for instance, reverse Bayesianism and partition dependence with sub-additive new beliefs. Our analysis may shed light on the management of public panic events such as those after the COVID-19 pandemic outbreak.

2 Can Media Pluralism Be Harmful to News Quality?

2.1 Introduction

A critical problem for modern democracies is that those who control the information flow can influence political and economic outcomes. Ideally, the presence of competing sources of information is beneficial. The more information an individual can receive, the more she knows about the issue, and the smaller is the influence of a particular source. For a long time, the Internet has been considered a very effective way to guarantee pluralism in information (Keen, 2015). But is competition among news sources on the Internet undoubtedly beneficial? Empirical evidence suggests a deterioration of the quality of the information at one's disposal. For instance, it is hard to find reliable online information about health conditions (Swire-Thompson and Lazer, 2019). More generally, conspiracy theories and "fake news" proliferate online.[1] I suggest a novel explanation for the deterioration of information quality online: the endogenous formation of echo chambers even when news consumers are unbiased.

The Cambridge dictionary defines an echo chamber as "a situation in which people only hear opinions that are similar to their own". Echo chambers are a prominent feature of the Internet. Online networks show high homophily: an individual learns from those who share her worldview (Del Vicario et al., 2016; Halberstam and Knight, 2016). The existence of echo chambers is a policy concern, as it endangers meaningful debate in a democracy. Within echo chambers, each individual never questions her beliefs. As a consequence, society divides into opposing factions. Moreover, the presence of echo chambers affects the quality of news. As I show, the media have no incentive to provide informative news in echo chambers.

The standard explanation for the existence of echo chambers is preference-based, namely that individuals are subject to confirmation bias. Nickerson (1998) defines confirmation bias as "seeking or interpreting of evidence in ways that are partial to existing beliefs, expectations, or a hypothesis in hand". I provide a complementary explanation: even if individuals seek the most informative news, echo chambers arise because of the interplay between limited attention of news consumers with heterogeneous beliefs and media bias of news sources.[2]

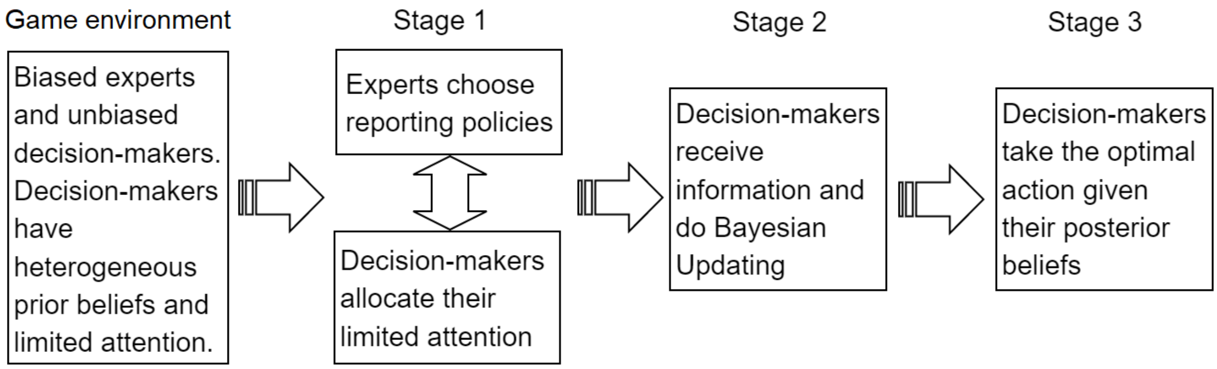
I study a Bayesian persuasion model with two states of the world and two actions (see Figure 1). There are two types of agents: experts and decision-makers. Each expert is biased: his preferred action is independent of the state of the world. In stage 1, each expert designs information about the state of the world to persuade decision-makers to take the expert's preferred action. Such information is public: all decision-makers that devote attention to the expert observe the same information. Each decision-maker is unbiased: she wants to match her action with the state. Decision-makers have partitioned into subgroups holding heterogeneous prior beliefs about the state of the world and have limited attention: each decision-maker can only devote attention to one expert. In stage 1, each decision-maker chooses which expert is worthy of attention and observes the information such an expert provides. Then, she updates her belief (stage 2) and takes the

[1] Fake news are of public concern since the 2016 US presidential election (Allcott and Gentzkow, 2017). Using the taxonomy proposed by Molina et al. (2021), my model captures partisan news, misreporting and persuasive advertising. All these lie in the "grey area" between objectively real and false news.

[2] Lee et al. (2017) show that perceived information overload is positively associated with selective exposure in online news consumption. Internet users fail to discriminate news based on quality (Qiu et al., 2017). My results are in line with recent advances in psychology showing that politically motivated reasoning does not drive selective exposure of online news consumers to confirmatory news (Pennycook and Rand, 2021).

optimal action given such belief (stage 3). I show that competition between experts is harmful to decision-makers when the latter strategically allocate their limited attention.

Figure 1: Stages of the game



As a benchmark, I consider a single expert and two subgroups of decision-makers with different beliefs that I label "sceptics" and "believers". Without information, believers choose the expert's preferred action, whereas sceptics do not. Hence, the expert designs information to change sceptics' behaviour. Such information is public - i.e., all decision-makers receive the same information. Thus, any attempt to change a sceptic's belief affects a believer's belief as well. Being exposed to information could induce believers to take the expert's undesired action. Therefore, the expert faces a trade-off between persuading sceptics and retaining believers. I show that there are two candidates for the optimal information design (or reporting policy).

The *hard-news policy* focuses on persuading sceptics. For this purpose, a message must be sufficiently credible - i.e., it can be misleading only to a limited extent. Therefore, this policy entails the cost of revealing the unfavourable state to all decision-makers with positive probability. If this state is revealed, believers take the expert's undesired action.

The *soft-news policy* focuses on retaining believers. The expert sends two messages of different credibility. One is credible enough to persuade sceptics. The other one is not, but at the same time, it does not induce believers to take the expert's undesired action. With this second message, the expert leverages believers' credulity. This policy ensures that believers will continue to choose the expert's preferred action.

I show that the hard-news policy is more informative than the soft-news policy according to the order defined by Blackwell (1953). Nevertheless, the expert prefers the soft-news policy if decision-makers have sufficiently polarized beliefs. In a context of severe polarization, it is very costly to persuade sceptics. To be credible, the expert has to reveal the unfavourable state with high probability. At the same time, it is particularly tempting to retain believers because it is easy to leverage their credulity. Both these arguments imply that the soft-news policy is more favourable for the expert. A second key parameter is the expert's belief. The higher is the expert's belief of his unfavourable state, the more he values his ability to mislead (at least) believers, making the soft-news policy more appealing.

Next, I show how media pluralism (i.e., the presence of multiple experts) makes decision-makers worse off. Two experts with different preferred actions compete to persuade two subgroups of decision-makers with heterogeneous beliefs. Because of limited attention, each decision-maker can only devote attention to one expert. Therefore, each expert behaves like a monopolist given his audience. In other words, for any expert, the allocation of attention by decision-makers determines the distribution of beliefs such an expert has to confront, and his reporting policy must be optimal given such a distribution.

Here, the novelty (compared to the benchmark) is the interaction between the optimal information design and the endogenous allocation of attention.

The allocation of attention depends on the policies of the experts. Each decision-maker allocates her attention to maximize her subjective probability of taking the correct action. This probability is at its minimum without information. An expert designs information to change decision-makers' behaviour. To be successful, the expert must provide sufficiently accurate information, and this makes decision-makers (weakly) better off. I define a decision-maker's information gain as the increase in her subjective probability of taking the correct action following information provision. Thus, each decision-maker allocates her attention to maximize her information gain.

It makes a difference for a decision-maker whether she is a *target* of an expert. An expert targets a subgroup of decision-makers if he tailors his policy to persuade them. For example, the sceptics are the targets when the expert uses his hard-news policy. An expert does not reveal more information than what is strictly necessary to change the behaviour of targets. Therefore, any target of a given expert receives zero information gain when devoting attention to him. Thus, each decision-maker aims to avoid being a target. At the same time, the optimal policy of each expert features (at least) one target, unless the expert faces only his believers. This tension determines which allocations of attention can support an equilibrium.

I label an equilibrium as "symmetric" if any two decision-makers of the same subgroup devote attention to the same expert. I show that the unique symmetric equilibrium of this game featuring two active experts is *echo chambers* with *babbling* (i.e., no information provision). In echo chambers, the audience of each expert is composed only of his believers. Therefore, the expert finds it optimal to leave their beliefs unchanged. Thus, babbling is the optimal policy for each expert. Given babbling by each expert, decision-makers have no incentive to deviate, as the information gain is zero in any case. In echo chambers, information quality is strictly lower than in monopoly for any decision-maker (whereas, in terms of information gains, targeted decision-makers are indifferent). This is because a monopolist uses either his hard-news policy or his soft-news policy. Both these policies produce some dispersion in posterior beliefs, hence have higher quality than babbling according to Blackwell (1953)'s criterion.

I extend the model to consider a general distribution of decision-makers' beliefs. I label an expert as "informative" if he uses either a hard-news policy or a soft-news policy. In any symmetric equilibrium, there is at most one informative expert. Indeed, if there are two informative experts, there is always (at least) one target who can get a positive information gain by changing her allocation of attention. Therefore, in any symmetric equilibrium, at least one expert is babbling. I label the audience of a babbling expert as an echo chamber. Limited attention makes media pluralism harmful to those decision-makers who cluster into an echo chamber by reducing the quality of the information they receive compared to a monopoly. In general, no decision-maker can benefit from media pluralism. For any equilibrium, there exists a monopoly outcome such that both information quality and information gain are (weakly) higher for any decision-maker.

My results show that the omnipresence of information - a characteristic of the Internet - can make all information useless. This negative result follows from the endogenous allocation of attention by decision-makers. As an extension, I study the problem of a platform that can allocate decision-makers' attention. The platform's goal is to maximize information quality. The platform can enable the coexistence of two informative experts. In particular, the platform can induce each expert to use his hard-news policy. In this way, such an altruistic platform can solve the problem of harmful competition, and media pluralism can enhance information quality.

2.1.1 Example

The widespread existence of misinformation about the COVID-19 vaccination provides a fitting example to illustrate my results. There are two possible states of the world: either a vaccine is safe or not (e.g., either it has long-run side effects or not). Each citizen wants to get vaccinated if and only if the vaccine is safe. Some citizens are sceptical about vaccinations being safe and are not willing to get vaccinated a priori (Paul et al., 2021). The government aims to reach herd immunity because the societal benefits of vaccination outweigh very rare private costs due to side effects. Therefore, a pro-government media wants to persuade citizens to get vaccinated.

In a monopoly, the supply of news by the pro-government media depends on its confidence about vaccinations' safety. If the pro-government media is very confident, it provides "hard evidence" (e.g., the evaluations by the European Medicines Agency based on clinical trials). The pro-government media attempts to persuade sceptics to get vaccinated because it expects persuasion to be very likely. If polarization is sufficiently high and the pro-government media is not confident enough, it also provides "soft evidence" (e.g., weaker statements such as "benefits are higher than risks"). In this way, the pro-government media is sure to retain those citizens who were already willing to get vaccinated.

In a competitive setting, a no-vax media opposes vaccinations to make profits with alternative treatments (Ghoneim et al., 2020). An equilibrium could be as follows: the pro-government media produces "hard evidence", whereas the no-vax media is babbling within its echo chamber.[3] Citizens who are sceptical about vaccinations understand that the pro-government media designs information to change their attitudes. Therefore, these citizens do not benefit from the information provided by the pro-government media and thus rationally allocate their limited attention to confirmatory news. This type of news does not allow sceptics to learn about the nature of vaccinations and create a negative externality on our society. Indeed, the pro-government media cannot persuade these citizens to get vaccinated. The existence of a large no-vax echo chamber can help to explain why herd immunity is difficult to reach (Diamond et al., 2021).

The rest of the paper is organized as follows. In Section 2.2, I review the literature. In Section 2.3, I present the theoretical model. In Section 2.4, I study optimal information design in a monopoly. In Section 2.5, I describe the effects of media pluralism. In Section 2.6, I examine some extensions. In Section 2.7, I discuss the applicability of my model to the real world. In Section 2.8, I conclude.

2.2 Related Literature

I contribute to the literature by exploring how the endogenous supply of (potentially misleading) information to decision-makers with heterogeneous beliefs interacts with limited attention. Therefore, my paper connects with the following streams in the literature.

Limited attention

> "In an information-rich world, the wealth of information [. . .] creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it." Simon (1971)

[3] Di Marco et al. (2021) find evidence of echo chambers about the COVID-19 pandemic. Jiang et al. (2021) show that segregation is stronger among far-right users.

The Internet has led to an information-rich economy as it allows news sources to reach more consumers at a lower per-consumer cost. The growth in consumers wealth and firms market power helped this process (Falkinger, 2008). Limited attention can explain many puzzling empirical patterns, for instance, asset-price dynamics (Peng and Xiong, 2006), the attraction effect (Masatlioglu et al., 2012), nominal rigidities (Matějka, 2016), persistently low inflation (Pfäuti, 2021), the superstar effect (Hefti and Lareida, 2021) and why minorities and extremists are very influential in the political process (Matějka and Tabellini, 2021).[4] In this paper, I offer new insights into the effects of limited attention. I show that limited attention can explain why rational and unbiased news consumers cluster into echo chambers and thus rationalizes the proliferation of low-quality information.

Limited attention influences price competition and advertising within and across industries (Anderson and de Palma, 2012; De Clippel et al., 2014; Hefti and Liu, 2020). My findings are complementary to Anderson and Peitz (2020), who show that increasing media diversity has the undesired effect of increasing advertising clutter and thus can make consumers worse off. Indeed, I show that media diversity can also harm news consumers by causing a reduction in information quality.

Bayesian persuasion A standard assumption in this literature - pioneered by Aumann and Maschler (1995) and Kamenica and Gentzkow (2011) - is the existence of a common prior belief. By contrast, I examine the problem of a sender (expert) who faces many receivers (decision-makers) endowed with heterogeneous beliefs.[5] In Guo and Shmaya (2019), a separating (soft-news) policy yields a higher payoff to the sender than a pooling (hard-news) policy if the receiver has sufficiently accurate private information. The distribution of private information is (strategically) equivalent to receivers holding heterogeneous beliefs. From this perspective, I show that more accurate private information can lead to less accurate public information. Indeed, if polarization is above a threshold, the sender provides information of lower quality. A similar effect arises in Gitmez and Molavi (2020). However, these authors focus on the ability of a sender to gather attention from receivers with heterogeneous beliefs.

Gentzkow and Kamenica (2017a,b) argue that competition among senders weakly increases information provision and benefits receivers. I show that this conclusion fails if receivers have heterogeneous beliefs and limited attention. My model incorporates endogenous allocation of attention between competing senders and endogenous persuasion.[6] In Knoepfle (2020), senders compete to gather the attention of a receiver. By contrast, senders are concerned about receivers' actions in my model. This difference leads to opposite results: endogenous echo chambers in my model, whereas full revelation is the final outcome in Knoepfle (2020).

Echo chambers The existence of echo chambers is a distinctive feature of the Internet. Indeed, there is evidence of echo chambers even in non-partisan contexts such as climate

[4] Gabaix (2019) and Mackowiak et al. (2021) survey the literature on behavioural and rational inattention, respectively.

[5] Alonso and Camara (2016) study the consequences of beliefs heterogeneity between one sender and one receiver. Beliefs are exogenous to the model, and it is beyond the purpose of this paper to study the origin of beliefs (Flynn et al., 2017). Bergemann and Morris (2019) and Kamenica (2019) survey the literature on information design.

[6] Che and Mierendorff (2019) and Leung (2020) study the problem of a receiver who has to allocate her limited attention between biased senders. In these papers, the information design is exogenous. Bloedel and Segal (2020), Gitmez and Molavi (2020), Lipnowski et al. (2020) and Wei (2021) study how limited attention by the receiver(s) affects optimal persuasion by a single sender.

change (Williams et al., 2015), vaccinations (Cossard et al., 2020) and the financial markets (Cookson et al., 2021). Echo chambers facilitate the proliferation of misinformation (Törnberg, 2018; Acemoglu et al., 2021). As a consequence, being part of an echo chamber affects individual behaviour. For instance, during the COVID-19 pandemic, Democrats and Republicans in the US show different attitudes towards social distancing (Allcott et al., 2020; Gollwitzer et al., 2020) and vaccinations (Fridman et al., 2021).

Jann and Schottmuller (2019) rationalize echo chambers in a many-to-many cheap talk model with biased decision-makers.[7] By contrast, even unbiased decision-makers may cluster into echo chambers in my model. Martinez and Tenev (2020) study a model where experts are unbiased. The experts are heterogeneous in terms of information precision. A decision-maker rationally infers that an expert has higher quality if he supplies information more in line with the decision-maker's belief. By contrast, experts are biased and precision is endogenous in my model. The strategic interaction between decision-makers and experts plays a crucial role in the formation of echo chambers.[8] Jann and Schottmuller (2019) and Martinez and Tenev (2020) argue that echo chambers can be helpful, either to enhance communication in a network or to separate high-quality and low-quality news. Instead, echo chambers have a negative effect in this paper. The reason is the endogenous supply of information by biased experts.

Detrimental competition in the market for news When biased media interact with rational and unbiased news consumers, the standard theoretical predication is that media competition increases news consumers' welfare (Gentzkow et al., 2015). I show that media competition harms news consumers when the latter have limited attention and heterogeneous beliefs. My contribution fits in an emerging literature about the downsides of competition in the market for news, which presents a number of complementary channels.[9] Information overload does not allow decision-makers to identify high-quality experts (Persson, 2018) and implies higher prices because consumers get lost in diversity (Hefti, 2018). Costly information acquisition or communication reduces each expert's effort in the presence of other experts: free-riding harms decision-makers (Kartik et al., 2017; Emons and Fluet, 2019). Competition increases informational specialization, which in turn increases social disagreement: in large enough societies, this reduces welfare (Perego and Yuksel, 2021). Competition also increases the pressure to publish without fact-checking because of the risk of being pre-empted (Andreottola and de Moragas Sánchez, 2020). Finally, because of the unbundling of journalism, online competition weakens the media's incentives to invest in news' quality, especially when news consumers' switching behaviour is particularly pronounced (Bisceglia, 2021).

2.3 Model

There are two states of the world and two actions. I denote with $\Omega := \{\omega_1, \omega_2\}$ the set of states and with $A := \{a_1, a_2\}$ the set of actions. Each agent l has a prior belief $\mu_l^0(\omega_1) \in (0, 1)$ that the state is ω_1. Clearly, $\mu_l^0(\omega_2) = 1 - \mu_l^0(\omega_1)$ is the agent l's prior belief that the state is ω_2. There are two types of agents: experts and decision-makers.

[7] Similarly, in Giovanniello (2021) echo chambers arise because biased voters have incentives to communicate useful information only to like-minded peers.

[8] Alternatively, echo chambers may arise because the cost of processing information is increasing in its precision (Nimark and Sundaresan, 2019) or when decision-makers look for disapproving evidence eventually supplied by like-minded experts (Hu et al., 2021). Levy and Razin (2019) survey the economics literature on echo chambers.

[9] A broader literature shows that competition can backfire in many different settings. See, for instance, Chen and Riordan (2008), Spinnewijn (2013), Janssen and Roy (2014) and Heidhues et al. (2021).

I denote with D the set of decision-makers and with J the set of experts. Decision-makers partition in homogenous subgroups: $D := \bigcup_{i \in I} D_i$ where I is the set of subgroups of decision-makers. Two decision-makers of the same subgroup share the same belief: $\mu_d^0(\omega_1) = \mu_{d'}^0(\omega_1) = \mu_i^0(\omega_1)$ for any $d, d' \in D_i$ and any $i \in I$.

Each decision-maker (she) takes an action $a \in A$, and her goal is to match the action with the state:

$$u(a, \omega_k) := \mathbb{1}\{a = a_k\} \tag{1}$$

Before taking an action, each decision-maker $d \in D$ pays attention to one expert $j_d \in J$ of her choice: she uses the information provided by the expert to update her belief. The allocation problem is analysed in greater detail in Section 2.5.

An expert (he) cannot implement an action on his own. Therefore, he designs information to manipulate decision-makers' behaviour. In particular, each expert $j \in J$ chooses a reporting policy $\pi_j : \Omega \to \Delta(S_j)$, that is, each expert commits to the probability $\pi_j(s|\omega)$ to send message s given state ω, for any message $s \in S_j$ and any state $\omega \in \Omega$.[10] Each expert j has a unique preferred action $a_j \in A$. For any state $\omega \in \Omega$, his payoff from a decision-maker who takes action $a \in A$ is:

$$u_j(a, \omega) = u_j(a) := \mathbb{1}\{a = a_j\} \tag{2}$$

In other words, each expert has state-independent preferences, and his payoff is 1 if and only if the action chosen by a decision-maker is the expert's preferred action.

The game has the following timing:

1. Each expert j chooses a policy π_j and, at the same time, each decision-maker d chooses which expert j_d to pay attention to.

2. Each decision-maker d observes the policy π_{j_d} of the expert she pays attention to, *and* the policy's realization $s \in S_{j_d}$ (that is, a message) chosen by Nature.

3. Given any posterior belief μ_d, each decision-maker d takes an optimal action. In case of indifference, I assume that decision-maker d chooses the preferred action of expert j_d.

The equilibrium notion is Perfect Bayesian Equilibrium. I consider the case that the preferred action of expert j_d is a_1.[11] By (1), the optimal action of decision-maker d with posterior belief μ_d is given by the following function:

$$\sigma(\mu_d) := \begin{cases} a_1 & \text{if } \mu_d(\omega_1) \geq \frac{1}{2} \\ a_2 & \text{otherwise} \end{cases}$$

Each decision-maker d forms the posterior belief μ_d using Bayesian updating:

$$\mu_d(\omega_1|s) := \frac{\pi_{j_d}(s|\omega_1)\mu_d^0(\omega_1)}{\pi_{j_d}(s|\omega_1)\mu_d^0(\omega_1) + \pi_{j_d}(s|\omega_2)\mu_d^0(\omega_2)}$$

Thus, for any decision-maker $d \in D_i$ to take action a_1, upon observing message s, the following condition must hold:

$$\mu_d(\omega_1|s) \geq \frac{1}{2} \iff \pi_{j_d}(s|\omega_1)\mu_i^0(\omega_1) \geq \pi_{j_d}(s|\omega_2)\mu_i^0(\omega_2)$$

In words, the expert must ensure that state ω_1 is more likely than state ω_2 for a decision-maker of subgroup i after receiving the message s. I label this condition *persuasion constraint*.

[10] I focus on straightforward policies without loss of generality (Kamenica and Gentzkow, 2011): the message set S_j contains two elements for any expert $j \in J$.

[11] The analysis is very similar when the preferred action of expert j_d is a_2.

Definition 1 (Persuasion constraints). *The persuasion constraint for a decision-maker of subgroup $i \in I$, who devotes attention to expert $j \in J$ and observes message $s \in S_j$, in order for her to take action a_1 is:*

$$\pi_j(s|\omega_2) \leq \frac{\mu_i^0(\omega_1)}{\mu_i^0(\omega_2)}\pi_j(s|\omega_1) := \phi_i \pi_j(s|\omega_1) \tag{3}$$

I denote with $H_j := \{d \in D | j_d = j\}$ the set of decision-makers who pay attention to expert j. For any $i \in I$, I define g_{ij} as the fraction of decision-makers in H_j who are of subgroup i. Mathematically,

$$g_{ij} := \begin{cases} 0 & \text{if } H_j = \varnothing \\ \frac{|\{d \in H_j | d \in D_i\}|}{|H_j|} & \text{otherwise} \end{cases} \tag{4}$$

These decision-makers have the same posterior belief. Therefore, the payoff of expert j from these decision-makers, upon observing message s, is:

$$v_{ij}(\pi_j, s) := g_{ij} u_j\Big(\sigma\Big(\mu_d(\omega_1|s)\Big)\Big)$$

The expert j maximizes the sum of expected utilities he derives from his audience H_j:

$$\max_{\pi_j} \sum_{i \in I} \sum_{s \in S_j} \sum_{\omega \in \Omega} \pi_j(s|\omega)\mu_j^0(\omega) v_{ij}(\pi_j, s) \tag{5}$$

The expert takes his audience H_j as given. Therefore, (5) is a best-response problem in a simultaneous-move game, where each decision-maker d chooses her allocation of attention j_d, and each expert j chooses his policy π_j.

This problem entails a trade-off for the expert. On the one hand, a message must be "credible" to induce a decision-maker to take the expert's preferred action. Formally, this message must satisfy the corresponding persuasion constraint. The former imposes an upper bound to the probability of observing such a message in the state associated with a different action. On the other hand, provided that a message is persuading, the expert would like to send this message as often as possible.

Lemma 1 (Persuasion constraint). *Consider any expert j and assume without loss of generality that $a_j = a_1$. In any best response π_j, either 1.) there exist a subgroup $i \in I$ of decision-makers and a message $s \in S_j$ such that $\pi_j(s|\omega_2) = \phi_i \pi_j(s|\omega_1)$ or 2.) the expert is babbling, that is, $\pi_j(s|\omega_1) = \pi_j(s|\omega_2)$ for any $s \in S_j$.*

By Lemma 1, I can restrict the set of policies that can be best responses: when there is scope for persuasion, then at least one persuasion constraint must hold with equality. In the following section, I use this insight to find candidates for the optimal policy.

2.4 Media Monism

As a benchmark, I study the problem of one expert - that is given by (5) - abstracting from the attention allocation problem of decision-makers (that I study in Section 2.5). I assume without loss of generality that the expert's preferred action is a_1, and I omit the index j for simplicity. By (3), a message s persuades a decision-maker of subgroup i to take action a_1 if and only if $\pi(s|\omega_2) \leq \phi_i \pi(s|\omega_1)$. The ratio of prior beliefs ϕ_i for each subgroup $i \in I$ will play a crucial role in the following analysis. From the perspective of the expert, there are two categories of decision-makers: believers and sceptics.

Definition 2 (Believers and sceptics). *Decision-makers of subgroup i are believers of state ω_1 relative to ω_2 if $\phi_i > 1$. Decision-makers of subgroup i are sceptics of state ω_1 relative to ω_2 if $\phi_i < 1$. I denote with $I_2 \subset I$ the set of subgroups of sceptics.*

Without information provision by the expert, believers choose the expert's preferred action, whereas sceptics do not. Therefore, sceptics require persuasion: the expert manipulates their beliefs through his policy π, to induce sceptics to take action a_1. However, the expert must account for the indirect effect that persuasion of sceptics has on the behaviour of believers, as all decision-makers receive the same information. Information provision could induce believers to take the expert's undesired action a_2. Therefore, the expert trades off between persuading sceptics and retaining believers.

In this section, I assume that there are two subgroups of decision-makers, that is, $I = \{1, 2\}$. I assume that subgroup 1 of decision-makers are believers i.e. $\phi_1 > 1$, whereas subgroup 2 are sceptics i.e. $\phi_2 < 1$.[12] Thus, the expert can use a message to persuade all decision-makers or only believers or nobody to take action a_1. In the optimal policy at least one persuasion constraint must hold with equality (Lemma 1). In particular, either only the persuasion constraint for sceptics holds with equality, or both persuasion constraints do so. Hence, I identify two candidates for the optimal policy: hard-news policy and soft-news policy.

Definition 3 (Hard-news policy). *The hard-news policy π_h consists of a persuading message s and a residual message s' such that*

$$\pi_h(s \mid \omega_1) = 1, \quad \pi_h(s' \mid \omega_1) = 0,$$

$$\pi_h(s \mid \omega_2) = \phi_2, \quad \pi_h(s' \mid \omega_2) = 1 - \phi_2$$

The hard-news policy implies the following posterior beliefs (Figure 2):

$$\begin{aligned} \mu_1(\omega_1 \mid s) = \frac{\phi_1}{\phi_1 + \phi_2} > \mu_2(\omega_1 \mid s) = \frac{1}{2} \\ \mu_1(\omega_1 \mid s') = \mu_2(\omega_1 \mid s') = 0 \end{aligned} \tag{6}$$

The hard-news policy persuades all decision-makers after seeing s and nobody after seeing s'. Thus, decision-makers choose the expert's preferred action in the state ω_1, and sometimes in the state ω_2. The expert provides sufficiently accurate information able to influence sceptics. However, this comes at a high cost to make the persuading message s credible. The credibility of s requires to send the residual message s' often enough when the state is ω_2. The message s' reveals the unfavourable state ω_2, inducing *all* decision-makers to choose the expert's undesired action.

Definition 4 (Soft-news policy). *The soft-news policy π_s consists of two messages s, s' such that*

$$\pi_s(s \mid \omega_1) = k, \quad \pi_s(s' \mid \omega_1) = 1 - k$$

$$\pi_s(s \mid \omega_2) = \phi_2 k, \quad \pi_s(s' \mid \omega_2) = \phi_1(1 - k)$$

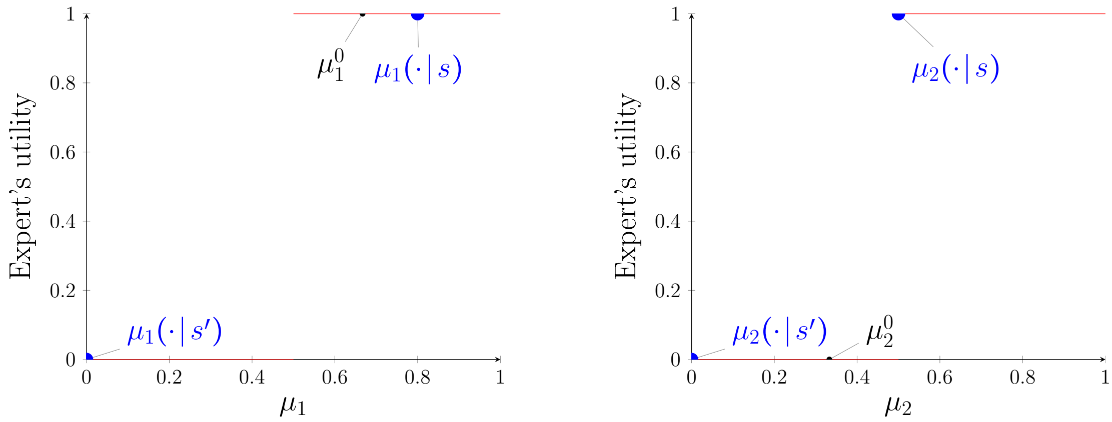
where $k := \frac{\phi_1 - 1}{\phi_1 - \phi_2}$ is strictly increasing in ϕ_1 and ϕ_2.

The soft-news policy implies the following posterior beliefs (Figure 3):

$$\begin{aligned} \mu_1(\omega_1 \mid s) = \frac{\phi_1}{\phi_1 + \phi_2} > \mu_2(\omega_1 \mid s) = \frac{1}{2} \\ \mu_1(\omega_1 \mid s') = \frac{1}{2} > \mu_2(\omega_1 \mid s') = \frac{\phi_2}{\phi_1 + \phi_2} \end{aligned} \tag{7}$$

[12] In Section 2.6.2 I consider the case of arbitrarily many subgroups of decision-makers.

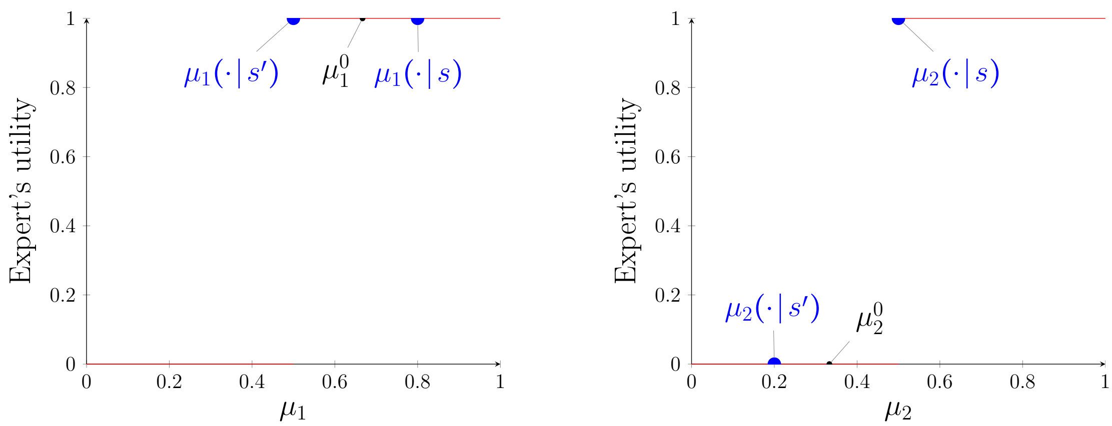
Figure 2: Posterior beliefs (in blue) with the hard-news policy.



(a) Believers (b) Sceptics

The soft-news policy persuades all decision-makers after seeing s and believers after seeing s'. Thus, believers choose the expert's preferred action *with probability one*, whereas sceptics choose it with a positive probability (but smaller than one) in either state. The expert alternates information of different accuracy. The message s' is not credible enough to persuade sceptics but ensures that believers keep choosing the expert's preferred action. The expert leverages the believers' credulity without completely giving up on the persuasion of sceptics. The value of k is the maximal extent of persuasion of sceptics, which is possible without affecting believers' behaviour.

Figure 3: Posterior beliefs (in blue) with the soft-news policy.



(a) Believers (b) Sceptics

Proposition 1 (Optimal persuasion). *Let $I = \{1,2\}$, $\phi_1 > 1$ and $\phi_2 < 1$. The unique optimal policy is either the hard-news policy or the soft-news policy. The hard-news policy is optimal if and only if*

$$\mu^0(\omega_1) \geq \frac{\phi_1 g_1 - \phi_2}{1 - \phi_2 + (\phi_1 - 1)g_1} \tag{8}$$

In words, the hard-news policy is optimal if 1.) decision-makers have sufficiently similar beliefs or 2.) the fraction of believers is sufficiently small or 3.) the expert's favourable state is sufficiently likely from his perspective.

By Proposition 1, three parameters influence optimal persuasion:

1. *Decision-makers' polarization, that is,* $\phi_1 - \phi_2$: The larger ϕ_1 is, the higher is the incentive to use the soft-news policy. Indeed, it is easier to leverage believers' credulity using the message s'. In other words, it is easier to prevent believers from taking the expert's undesired action. The smaller ϕ_2 is, the smaller is the incentive to use the hard-news policy. Indeed, it is more costly to persuade sceptics using the message s: the credibility of s requires revealing the unfavourable state with a higher probability. The difference $\phi_1 - \phi_2$ is a proxy for polarization, as the underlying beliefs become more extreme as such difference grows. Therefore, the higher polarization is, the higher the incentive to use the soft-news policy;

2. *Fraction of believers, that is,* g_1: The larger the subgroup of believers (the higher g_1), the higher is the incentive to retain believers (and the lower the incentive to persuade sceptics). This implies a higher incentive to use the soft-news policy;

3. *Expert's prior belief, that is,* $\mu^0(\cdot)$: The lower the expert's belief of his favourable state $\mu^0(\omega_1)$, the higher the cost of revealing the unfavourable state ω_2 to all decision-makers with the hard-news policy. In other words, the expert values his ability to mislead (at least) believers, especially when he is very unconfident about his favourable state being the true state of the world. It follows a higher incentive to use the soft-news policy.

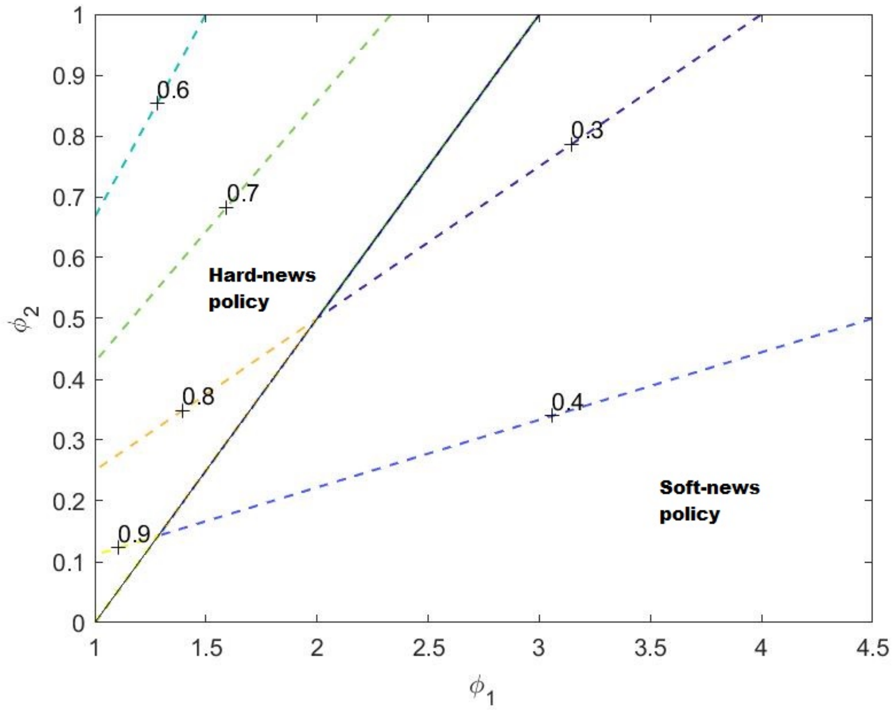
Proposition 1 relates to Kamenica and Gentzkow (2011) in the following way. Kamenica and Gentzkow (2011) assume a common prior belief and, if the decision-maker is a sceptic, the hard-news policy is optimal. Heterogeneous beliefs give rise to a new type of optimal policy - the soft-news policy - pointing out the importance of decision-makers' polarization for optimal persuasion. Moreover, Kamenica and Gentzkow (2011) argue that if a decision-maker chooses the expert's undesired action, then it must be the case that the state is one where such action is optimal. However, this holds only if the expert uses the hard-news policy. With the soft-news policy, sceptics may choose the expert's undesired action even if it is not optimal for them. Finally, persuasion is always optimal when decision-makers have heterogeneous beliefs. The expert uses either the hard-news policy or the soft-news policy. Babbling is never optimal.

Lemma 2 (Blackwell's criterion)**.** *The hard-news policy is more informative than the soft-news policy, according to the order over distributions of posterior beliefs defined by Blackwell (1953).*

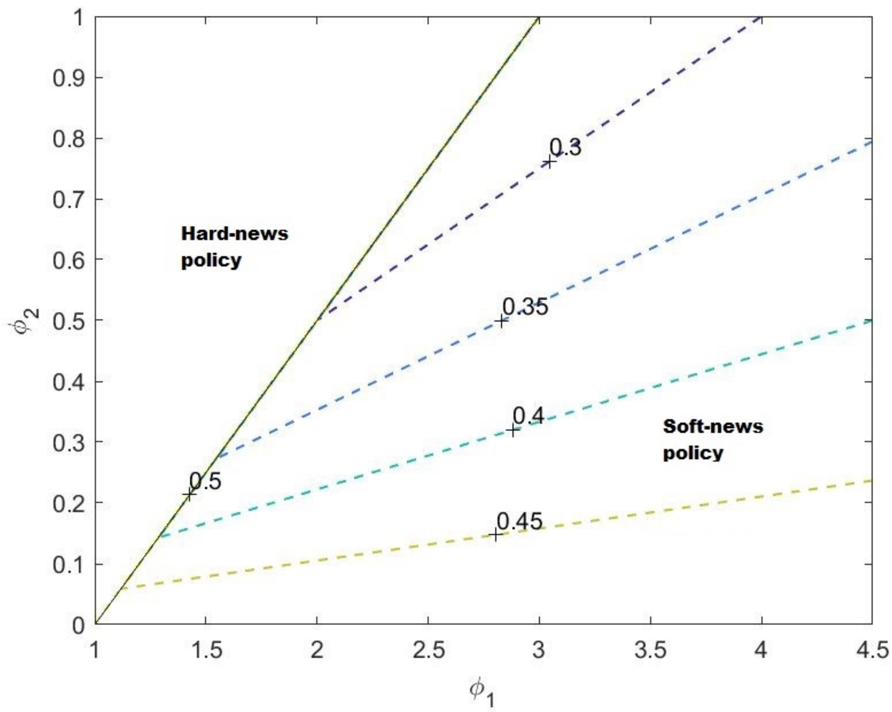
A policy π is more informative than π' according to Blackwell (1953) if the distribution of posterior beliefs induced by π constitutes a mean preserving spread of the distribution of posterior beliefs induced by π'. Following this definition, truth-telling is the most informative policy, as the posterior belief is either 0 or 1. Instead, babbling leaves beliefs unchanged, and thus it is the least informative policy. The hard-news policy is more informative than the soft-news policy, for all decision-makers. Indeed, it induces more dispersion in the posterior beliefs through the residual message, which reveals the unfavourable state for the expert.

As Figures 4a and 4b show, the effect of polarization on the informativeness of the monopolist's policy is non-monotonous. Polarization increases informativeness (i.e., the range of posterior beliefs). However, there is a discontinuity point, that is, when the expert shifts from the hard-news policy to the soft-news policy. Therefore, having some degree of heterogeneity in beliefs is beneficial, as it increases the quality of the information provided by the expert. However, if polarization becomes too high, the expert changes policy. Lemma 2 shows that the soft-news policy is less informative than the hard-news policy.

Figure 4: Relationship between polarization and informativeness



(a) Believers



(b) Sceptics

These figures depict the range of posterior beliefs for any couple of prior beliefs (ϕ_1, ϕ_2) when $\mu^0(\omega_1) = \frac{1}{2}$ and $g_1 = \frac{1}{2}$.

Example. I consider the example from the introduction. There are two states of the world: either a vaccine is safe or it has side effects. The pro-government media wants to persuade citizens that the vaccine is safe. There are two groups of citizens, 1 and 2, and $g_1 = g_2 = \frac{1}{2}$. Group 1 are believers whereas group 2 are sceptics, with prior beliefs $\mu_1^0(\text{Safe}) = 0.7$ and $\mu_2^0(\text{Safe}) = 0.2$ respectively. Therefore, $\phi_1 = \frac{7}{3}$ and $\phi_2 = \frac{1}{4}$. Each citizen decides whether to get vaccinated. Using Definition 3, the hard-news policy can be represented as follows:

ω	Safe	Side Effects	
s	*safe*		*side effects*
$\pi(s \mid \omega)$	1	0.25	0.75

The message *safe* persuades sceptics. To be credible, the pro-government media needs to commit to sending the message *side effects* often enough when the true state is "Side Effects".

Using Definition 4, the soft-news policy can be represented as follows:

ω	Safe		Side Effects	
s	*safe*			*anecdotal safe*
$\pi(s \mid \omega)$	0.64	0.36	0.16	0.84

The soft-news policy consists of two messages. The message *safe* (e.g., clinical trials) persuades sceptics but has a low chance to be misleading (that is, to induce decision-makers to choose the wrong action). The message *anecdotal safe* (e.g., vague comparisons of benefits and risks) has a higher chance to be misleading but persuades only believers.

The advantage of the soft-news policy is that believers get vaccinated with probability one. With *anecdotal safe* the pro-government media leverages believers' credulity. Meanwhile, it does not give up entirely from the persuasion of sceptics (message *safe*).

Given citizens' beliefs, whether the soft-news policy is better than the hard-news policy only depends on the pro-government media's belief. In particular, by (8) the pro-government media uses the hard-news policy only if its belief of the vaccine being safe is larger than $\frac{11}{17}$. When sufficiently uncertain about the existence of side effects and if citizens have sufficiently polarized beliefs, the pro-government media uses the soft-news policy.[13]

The natural question to ask is then: What happens if we allow competition by a no-vax media? The next section provides an answer.

2.5 Media Pluralism

In this section, I study how the existence of multiple experts affects the quality of information and the welfare of decision-makers. I restrict attention to competition between two experts with different preferred actions. Formally, $J = \{\alpha, \beta\}$ with $a_\alpha = a_1$ and $a_\beta = a_2$. Full revelation (i.e., truth-telling by both experts) is the equilibrium when decision-makers have unlimited attention (Gentzkow and Kamenica, 2017a,b; Ravindran and Cui, 2020). In the following, I introduce limited attention and show that full revelation is not an equilibrium. Competition is actually harmful to decision-makers as it deteriorates the quality of information.

Limited attention implies that each decision-maker can only devote attention to one expert. In other words, either $j_d = \alpha$ or $j_d = \beta$ for any decision-maker $d \in D$. The problem

[13] In Section 2.7, I discuss some possible caveats of this example.

for each expert j is identical to the one solved previously. However, the composition of his audience H_j is now endogenous. The distribution of prior beliefs each expert faces is the result of the optimal attention choices of decision-makers. The allocation of attention and the optimal policy are chosen simultaneously by each decision-maker and each expert, respectively.

The objective function of each decision-maker is her subjective probability of choosing the correct action (that is, her expected payoff). Suppose that a decision-maker $d \in D_i$ devotes attention to the expert $j \in J$. Mathematically, this probability can be expressed as follows:

$$\lambda_i(\pi_j) := \sum_{s \in S_j} \sum_{\omega_k \in \Omega} \pi_j(s \mid \omega_k) \mu_i^0(\omega_k) \mathbb{1}\left\{\sigma\big(\mu_d(\omega_1 \mid s)\big) = a_k\right\}$$

Lemma 3 (Decision-maker's payoff)**.** *The policy π_j is truth-telling if and only if $\lambda_i(\pi_j) = 1$. If π_j is babbling, then $\lambda_i(\pi_j) = \mu_i^0(\omega_m)$, where $m = \arg\max_{n \in \{1,2\}} \mu_i^0(\omega_n)$. It holds that $\lambda_i(\pi_j) \in [\mu_i^0(\omega_m), 1]$.*

Intuitively, the subjective probability of taking the correct action is maximal when an expert reveals the state of the world. Without information, a decision-maker of subgroup i chooses the action associated with her most plausible state given prior beliefs: $\mu_i^0(\omega_m)$ is the corresponding subjective probability of taking the correct action. Persuasion cannot decrease such a probability compared to the no information case. In particular, an expert can change a decision-maker's behaviour. However, this requires the expert to reveal some information and makes the decision-maker (weakly) better off. Therefore, $\Delta_{ij} := \lambda_i(\pi_j) - \mu_i^0(\omega_m) \geq 0$ is the subjective information gain from persuasion. I do not assume confirmation bias: babbling is the least desired policy by decision-makers. Even if the assessment of quality is subjective, each decision-maker prefers any informative policy (i.e., any policy with positive information gain) to babbling.

Definition 5 (Target)**.** *For any expert $j \in J$, a target is a subgroup $i \in I$ of decision-makers whose persuasion constraint holds with equality, given the policy of expert j. Let T_j be the set of targets for expert j.*

By Lemma 1, the set of targets is non-empty. A hard-news policy targets sceptics, whereas a soft-news policy targets sceptics and believers. A subgroup being a target means that the expert tailors his policy to persuade marginally decision-makers belonging to such subgroup and thus renders them exactly indifferent between the two actions.

Proposition 2 (Zero information gain for a target)**.** *For each expert $j \in J$ and each $i \in T_j$, it holds that $\Delta_{ij} = 0$.*

Proposition 2 states that when a subgroup is a target of an expert, such decision-makers receive zero information gain when devoting attention to this expert. Intuitively, an expert reveals only the information that is strictly necessary to persuade decision-makers of a targeted subgroup. Being a target is a sufficient condition for zero information gain from persuasion.[14]

Proposition 2 shapes decision-makers' incentives regarding the allocation of attention. The optimal allocation of attention for a decision-maker $d \in D_i$ is given by $j_d(\pi_\alpha, \pi_\beta)$, and $j_d(\cdot) = j$ requires that $j \in \arg\max_{j \in J} \Delta_{ij}$. In other words, each decision-maker devotes attention to the expert that grants her the highest information gain. Crucially, each decision-maker wants to avoid being a target, as in that case $\Delta_{ij} = 0$.

[14] However, it is not a necessary condition: decision-makers whose behaviour is not affected by beliefs updating have zero information gain as well.

Any equilibrium is thus characterized by a vector $(\pi_\alpha, \pi_\beta, j_1, \dots, j_{|D|})$. The set of decision-makers who pay attention to the expert j (his audience) is $H_j = \{d \in D \,|\, j_d(\cdot) = j\}$. Each policy must be a best response for the corresponding expert: for a given audience H_j, each expert j uses his optimal policy $\pi_j(H_j)$. At the same time, the allocation of attention must be consistent with decision-makers' incentives. In particular, for any expert $j \in J$ and any decision-maker $d \in H_j$, it must hold that $j_d(\pi_\alpha(H_\alpha), \pi_\beta(H_\beta)) = j$. I define two categories of equilibria:

Definition 6. *An equilibrium is "symmetric" if any two decision-makers of the same subgroup $i \in I$ pay attention to the same expert $j \in J$. Otherwise, the equilibrium is "asymmetric".*

Here, I continue to assume $I = \{1, 2\}$ with $\phi_1 > 1$ and $\phi_2 < 1$. Importantly, decision-makers of subgroup $i = 1$ ($i = 2$) are believers (sceptics) of ω_1 and sceptics (believers) of ω_2. There are three symmetric equilibrium candidates, namely:

1. *Monopoly.* All decision-makers devote attention to the same expert: $H_\alpha = D$ or $H_\beta = D$. The optimal policy follows Proposition 1. The non-active expert is indifferent between any policy;

2. *Echo chambers.* Each expert collects attention only by his believers: $H_\alpha = D_1$ and $H_\beta = D_2$. Therefore, for each expert the optimal policy is babbling;[15]

3. *Opposite-bias learning.* Each expert collects attention only by his sceptics: $H_\alpha = D_2$ and $H_\beta = D_1$. Therefore, for each expert the optimal policy is his hard-news policy.[16]

Proposition 3 (Equilibrium)**.** *Let $J = \{\alpha, \beta\}$ and $I = \{1, 2\}$, where decision-makers of subgroup 1 (2) are believers from the perspective of expert α (β). Echo chambers with babbling is the unique symmetric equilibrium such that both experts are active.*

In echo chambers, given babbling by both experts, decision-makers have no incentive to deviate, because each expert provides zero information gain. Therefore, echo chambers are an equilibrium.

An equilibrium with a monopolist requires that the non-active expert provides zero information gain. Otherwise, the targets of the monopolist would find it beneficial to deviate. However, the non-active expert is indifferent between any policy, thus he could provide a positive information gain. To support this equilibrium, the expert must break indifference in favour of babbling (or equivalent policies).

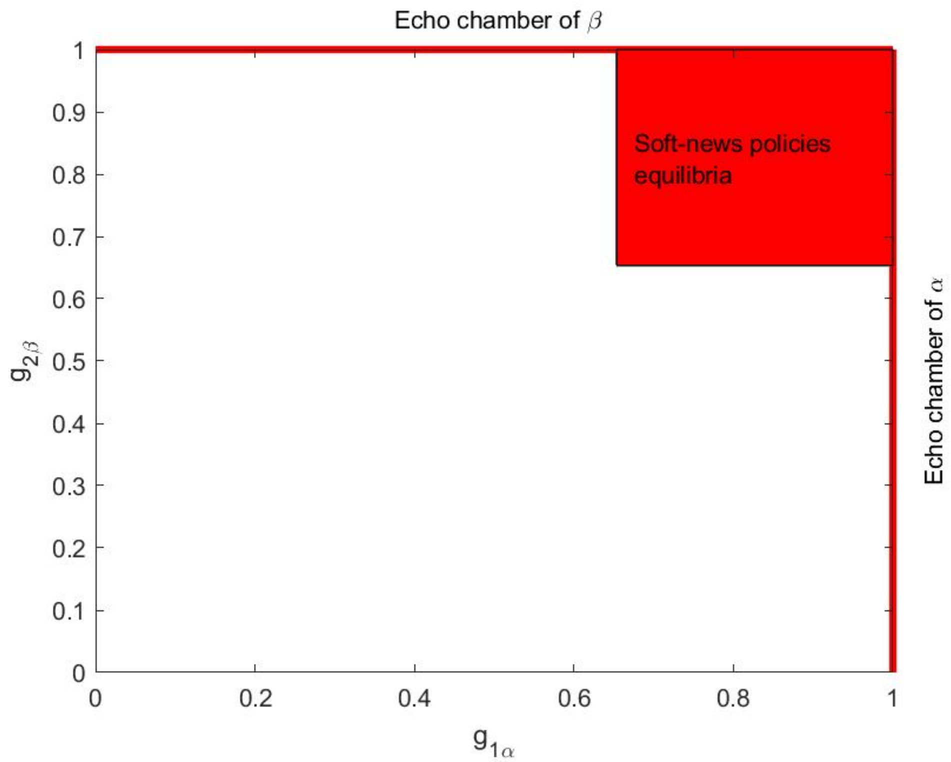
By Lemma 2, opposite-bias learning would be desirable as each expert would use his hard-news policy. However, opposite-bias learning cannot be an equilibrium because it is not coherent with each decision-maker's incentives. Each sceptic can get a strictly positive information gain by becoming a believer of her like-minded expert. Indeed, when a sceptic deviates and devotes attention to her like-minded expert, she is not a target given the like-minded expert's policy. In other words, the like-minded expert does not tailor information to manipulate his believers' behaviour. That is why sceptics benefits from the deviation.

The game has also asymmetric equilibria (see Figure 5). A necessary condition is that decision-makers of the same subgroup are indifferent about the allocation of attention.

[15]Each expert could use any policy that does not change believers' behaviour. I assume that each expert breaks indifference in favour of babbling. This assumption is without loss of generality because a policy is associated with positive information gain only if it changes decision-makers' behaviour. Babbling is the unique optimal policy when the expert pays a cost to generate information.

[16]The soft-news policy is useful to retain believers. Therefore, it cannot be optimal when only sceptics devote attention.

Figure 5: Set of equilibria



These are the allocations of attention that can support an equilibrium, when $\mu^0_\alpha(\omega_1) = \mu^0_\beta(\omega_2) = \frac{7}{10}$, $\phi_1 = 2$ and $\phi_2 = \frac{1}{2}$.

There exist asymmetric equilibria where one expert uses either his hard-news policy or his soft-news policy (i.e., informative expert), whereas the other expert is babbling (i.e., babbling expert). To support these equilibria, the babbling expert must collect attention only from his believers. If this is not the case, babbling is not optimal (Proposition 1). Thus, the informative expert collects attention from all his believers and some of his sceptics. If the informative expert uses his hard-news policy, his sceptics are targets (i.e. zero information gain, from Proposition 2) and thus indifferent about the allocation of attention, whereas his believers are strictly better off by devoting attention to him. If the informative expert uses his soft-news policy, all decision-makers are targets and thus indifferent about the allocation of attention. There also exist asymmetric equilibria where each expert uses his soft-news policy. All decision-makers are targets of each expert. Thus, each decision-maker gets zero information gain independently of the allocation of attention. Any allocation of attention that makes it optimal for each expert to use his soft-news policy constitutes an equilibrium.

Proposition 4 (Harmful competition)**.** *For any equilibrium, there exists a monopoly outcome such that information gain and information quality are (weakly) higher for any decision-maker.*

Proposition 4 implies that decision-makers are worse informed with competition. Media pluralism harms decision-makers when the latter have limited attention and can freely allocate it between experts. Each decision-maker attempts to achieve positive information gain from persuasion by avoiding devoting attention to an expert who targets her. However, this leads decision-makers to cluster into echo chambers. An echo chamber is harmful because the expert faces only his believers, and the best response is babbling. Thus, those decision-makers who cluster in an echo chamber receive information of lower quality than in a monopoly. Indeed, a monopolist uses either his hard-news policy or his soft-news policy: these policies produce some dispersion in posterior beliefs, whereas babbling leaves beliefs unchanged. Hence, babbling is less informative according to Blackwell (1953)'s order. Moreover, in terms of information gains, those decision-makers who are not targets of the monopolist are strictly worse off in echo chambers. The monopoly outcome also outperforms the asymmetric equilibria where each expert uses his soft-news policy. This follows Lemma 2 and all decision-makers being targets in these asymmetric equilibria.

Example. An asymmetric equilibrium could fit the COVID-19 vaccination example. The pro-government media collects attention from believers and sceptics and, thus, uses his hard-news policy. The no-vax media exploits his echo chamber and provides information that amounts to babbling. Therefore, decision-makers in the no-vax echo chamber are less informed than in a monopoly.

Citizens who are sceptical about vaccinations understand that the pro-government media tailors information to change their behaviour. Therefore, a sceptic has no advantage from devoting attention to the pro-government media and could decide to join the no-vax echo chamber.

The number of citizens that the pro-government media can persuade to get vaccinated depends on the equilibrium allocation of attention. Sceptics may cluster into the no-vax echo chamber and get confirmatory news. Their worldview cannot change and, thus, they are not willing to get vaccinated. An implication of this result is that herd immunity is unachievable if the no-vax echo chamber is too large.

2.6 Extensions

2.6.1 Platform

The negative effect of competition is related to the endogenous allocation of attention by decision-makers. In this section, I show that media pluralism can enhance information quality when the allocation of attention is exogenous for decision-makers. I assume that there exists a third agent (a platform) that chooses the allocation of attention to maximize aggregate informativeness (i.e., the average quality of news that decision-makers receive). In other words, the platform chooses g_{ij} for any subgroup $i \in I$ and any expert $j \in J$. Then, each expert j solves (5). Let $J = \{\alpha, \beta\}$, $a_\alpha = a_1$, $a_\beta = a_2$ and $I = \{1, 2\}$. I assume that decision-makers of subgroup 1 (2) are believers of state ω_1 (ω_2), that is, $\phi_1 > 1$ and $\phi_2 < 1$. By Lemma 2, the most informative policy (among those that are compatible with each expert's incentives) is the hard-news policy. By Proposition 1 (in particular equation (12) in the Appendix), each expert uses his hard-news policy if there are not too many believers in his audience:

$$g_{1\alpha} \leq \hat{g}_\alpha := \frac{\mu_\alpha^0(\omega_1) + \phi_2 \mu_\alpha^0(\omega_2)}{\mu_\alpha^0(\omega_1) + \phi_1 \mu_\alpha^0(\omega_2)} \tag{9}$$

$$g_{2\beta} \leq \hat{g}_\beta := \frac{\mu_\beta^0(\omega_2) + \frac{1}{\phi_1} \mu_\beta^0(\omega_1)}{\mu_\beta^0(\omega_2) + \frac{1}{\phi_2} \mu_\beta^0(\omega_1)} \tag{10}$$

I label $\hat{g}_\alpha$ and $\hat{g}_\beta$ as the *degrees of tolerance* of experts α and β, respectively. The degree of tolerance is the maximum fraction of believers an expert can have in his audience without finding it optimal to use his soft-news policy.

The previous conditions represent a constraint for the platform that chooses the allocation of attention to induce each expert to use his hard-news policy. There is no equivalent constraint when the allocation of attention is chosen by decision-makers, and this explains echo chambers. Indeed, given that each expert uses his hard-news policy, decision-makers have incentives to become believers. However, this makes the hard-news policy suboptimal for each expert and traps decision-makers into echo chambers.

A hard-news policy is *more informative* for a believer than for a sceptic. Therefore, the platform would like to allocate believers to like-minded experts ($g_{1\alpha}, g_{2\beta} \uparrow$). However, this is effective only if each expert uses his hard-news policy, and this requires the presence of enough sceptics ($g_{1\alpha}, g_{2\beta} \downarrow$). Some believers can be allocated to each expert without affecting his incentives to use his hard-news policy: (9)-(10) must hold. The following proposition summarizes the cases where the platform can find an allocation of attention (where both experts receive attention) that outperforms a monopoly in terms of aggregate informativeness.

Proposition 5 (Platform). *A platform with the objective to maximize aggregate informativeness prefers media pluralism if any of the following conditions holds:*

1. *Each expert uses his soft-news policy as monopolist;*
2. *Each expert can tolerate more than one believer for each sceptic, that is $\hat{g}_\alpha, \hat{g}_\beta > \frac{1}{2}$.*
3. *The expert α (β) uses his hard-news policy as monopolist but $\hat{g}_\alpha < \frac{1}{2}$ ($\hat{g}_\beta < \frac{1}{2}$), whereas the expert β (α) has degree of tolerance $\hat{g}_\beta > \frac{1}{2}$ ($\hat{g}_\alpha > \frac{1}{2}$) but he uses his soft-news policy as monopolist.*

If condition 1 holds, then by Lemma 2 any allocation of attention that gives to each expert incentives to use his hard-news policy (for instance, opposite-bias learning) is better than any monopoly. If condition 2 holds, the platform can exploit the fact that each expert is willing to use his hard-news policy *even if* there are more believers than sceptics in his audience. Therefore, the platform can increase the mass of believers receiving a hard-news policy, compared to any monopoly. If condition 3 holds, the platform can induce the expert with the highest degree of tolerance to use his hard-news policy by allocating some of his believers to the other expert. This is beneficial because overall there are more believers than in monopoly.

As a final remark, opposite-bias learning is never optimal for the platform. Indeed, each expert uses his hard-news policy, but each decision-maker is a sceptic. The platform can increase aggregate informativeness by allocating some but not too many believers to like-minded experts. Alternatively, the platform can increase the quality of information for each decision-maker with a monopolist using his hard-news policy. Therefore, even if opposite-bias learning is better than echo chambers (and any other equilibrium in Section 2.5), an heterogeneous audience is necessary to exploit fully media pluralism.

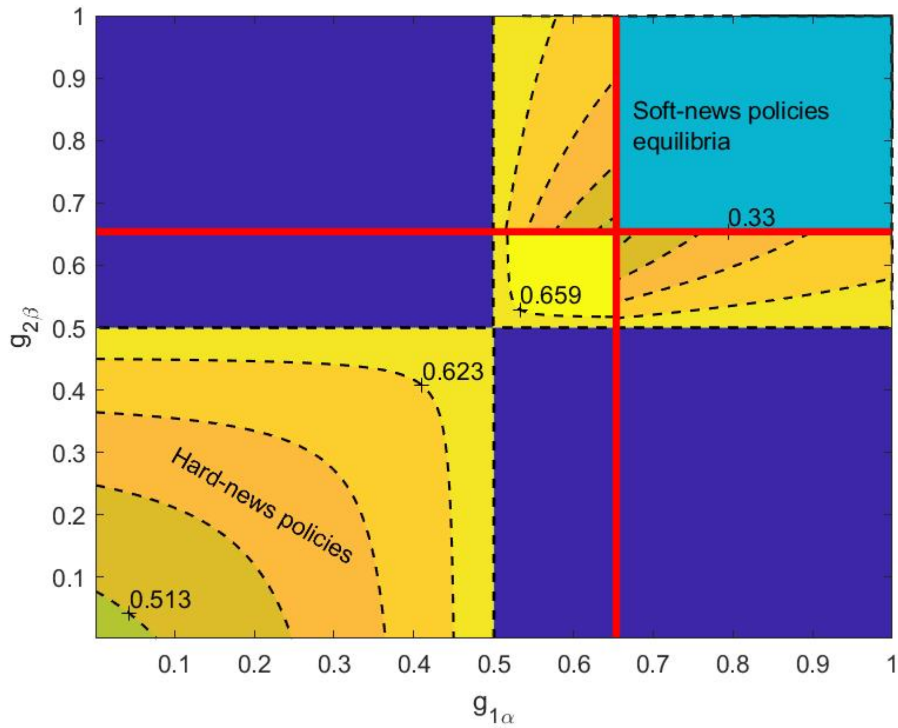
2.6.2 Many Decision-makers

In this section, I show that my results continue to hold with any arbitrary set I of subgroups of decision-makers. First of all, I consider finitely many subgroups, each one endowed with a different prior belief.

Proposition 6 (Optimal Persuasion). *Let $I = \{1, \ldots, R\}$ with $R > 2$, $\phi_1 < 1$ and $\phi_R > 1$. The unique optimal policy is either a hard-news policy or a soft-news policy. A hard-news (soft-news) policy is optimal if a subgroup of sceptics (believers) has the highest value of being persuaded marginally.*

Proposition 6 shows that optimal persuasion is robust to heterogeneity within believers and sceptics. The expert uses a hard-news policy if the subgroup with the highest value as a target is a subgroup of sceptics. Next, I use such insight to extend the analysis to a continuous distribution of decision-makers' beliefs.

Figure 6: Beneficial media pluralism with a platform



Aggregate informativeness (that is, the weighted sum of the ranges of posterior beliefs) when $\mu^0_\alpha(\omega_1) = \mu^0_\beta(\omega_2) = \frac{7}{10}$, $\phi_1 = 2$ and $\phi_2 = \frac{1}{2}$. In this example, assuming additionally that the two subgroups have equal size, the monopoly outcome is outperformed by a competitive setting where each expert uses his hard-news policy. The aggregate informativeness in monopoly amounts to $\frac{13}{20}$, whereas the platform can achieve aggregate informativeness equal to $\frac{87}{125}$. The platform allocates attention to expose as many believers as possible to hard-news policies, that is, $g_{1\alpha} = g_{2\beta} = 0.653$.

Proposition 7 (Optimal persuasion)**.** *Let $F(x)$ be a distribution with support $[0,\infty)$ and density $f(x) > 0$ $\forall x$. Let $\phi_i := \frac{\mu^0_i(\omega_1)}{\mu^0_i(\omega_2)} \sim F$. Then, the expert j with ratio of prior beliefs ϕ_j uses a hard-news policy if a unique solution $\phi \in [0,1]$ to the following equation exists*

$$h(\phi) = \frac{1}{\phi_j + \phi} \tag{11}$$

and condition (16) holds. Note that $h(x) := \frac{f(x)}{1-F(x)}$ is the hazard rate function.

It is possible to evaluate the quality of the information in real-world settings using condition (11). A researcher needs to know the distribution of decision-makers' beliefs and the expert's belief.[17] Then, condition (11) predicts whether the expert uses a hard-news policy or a soft-news policy.

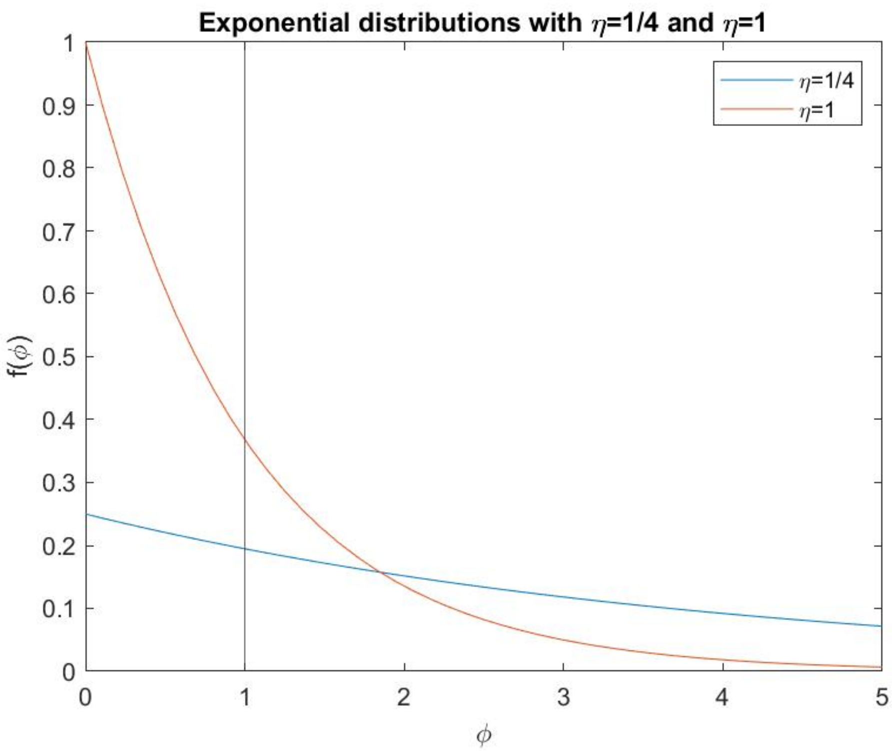
Gitmez and Molavi (2020) find a similar characterization of the optimal policy in a setting where the expert is trading-off between an extensive margin (how many decision-makers devote attention) and an intensive margin (how many decision-makers are persuaded). By contrast, in my setting devoting attention to one expert is costless, which means that all decision-makers devote attention.

As an example, I assume that F is the exponential distribution. In other words, $F(x;\eta) = 1 - e^{-\eta x}$ where η is a parameter. A special property of this distribution is a

[17] Similar knowledge could derive, for instance, from surveys.

constant hazard rate, that is, $h(x) = \eta$. Therefore, equation 11 implies $\phi = \frac{1}{\eta} - \phi_j$ and, by Proposition 7, the expert uses a hard-news policy if $\eta \geq \frac{1}{1+\phi_j}$. Fixing $\phi_j = 1$, Figure 7 depicts two examples of density functions that imply different optimal policies.

Figure 7: Constant hazard rate



The black line at $\phi = 1$ separates sceptics (at the left) from believers. When $\eta = 1$, the majority of decision-makers are sceptics and, thus, a hard-news policy is optimal. By contrast, a soft-news policy is optimal when $\eta = \frac{1}{4}$, because many decision-makers are believers.

Lemma 4 (Blackwell's criterion)**.** *A hard-news (soft-news) policy is more informative the more extreme are the prior beliefs of its target(s). The ranking of the policies in terms of informativeness is subgroup specific.*

More extreme targets (i.e., targets with beliefs closer to either 0 or 1) induce a more disperse distribution of posterior beliefs: the policy moves closer to truth-telling. Lemma 4 extends Lemma 2: some decision-makers may find a soft-news policy more informative than a hard-news policy if the former targets more extreme sceptics. See condition (17) in the Appendix.

Proposition 8 (Competition with limited attention)**.** *In any symmetric equilibrium, at least one expert is babbling.*

The key mechanism behind this result is the following: for any allocation of attention and corresponding optimal policies, there exists at least one target who can deviate and get a positive information gain, unless at least one expert is babbling.

The existence of more than two subgroups of decision-makers generates additional symmetric equilibria, which I label *partial echo chambers*. In these equilibria, an ordered subset of believers (those with the most extreme prior beliefs) join the echo chamber of the babbling expert. The other expert gets attention from the remaining decision-makers, including some of his sceptics. Thus, he uses either a hard-news policy or a soft-news policy or, in other words, he is an informative expert. Given babbling, nobody outside the echo chamber wants to join it. At the same time, any believer within the echo chamber would become the most sceptical decision-maker of the informative expert in case of a deviation: given the informative expert's policy, her behaviour would not change. Therefore, this deviation would yield zero information gain, and this supports the equilibrium.

Proposition 9 (Harmful competition)**.** *For any equilibrium, there exists a monopoly outcome such that information gain and information quality are (weakly) higher for any decision-maker.*

The negative effect of competition (Proposition 4) extends in a setting with any arbitrary distribution of decision-makers' beliefs. When comparing monopoly with partial echo chambers, a case distinction is necessary. If the informative expert as monopolist uses a hard-news policy, competition is harmful because information gains are (weakly) lower, and those decision-makers who cluster into the echo chamber receive babbling. When the informative expert uses different soft-news policies in monopoly and partial echo chambers, some decision-makers might be better off in partial echo chambers. In this case, competition is harmful to all decision-makers if the targets are strategic substitutes. In particular, decision-makers are worse off - in terms of both information gains and information quality - if both targets are less extreme in partial echo chambers than in monopoly. Intuitively, this sufficient condition should hold because the targeted sceptics are (by construction) less sceptical in partial echo chambers, and thus the expert might be tempted to retain less extreme believers.

2.6.3 Other Extensions

The results of this paper extend on many other dimensions, which I briefly describe in this section. The online Appendix includes a more detailed discussion. First, when attention is costly rather than limited, my results are robust for any positive cost. By contrast, full revelation is an equilibrium only when attention is costless (or, equivalently, unlimited). Second, I study what happens if decision-makers pay an entropy cost to process information. An entropy cost is a form of confirmation bias: any positive confirmation bias makes echo chambers the unique robust equilibrium. Third, if decision-makers can pay a cost to be second-movers, the results are robust if this cost is high enough (the higher polarization, the lower the threshold). By contrast, full revelation is the equilibrium only when the adjustment is costless. Fourth, if experts can only partial commit to their reporting policies, the results are robust, provided that experts have sufficient commitment power to persuade sceptics. Fifth, when decision-makers are subject to over-inference (i.e., they attribute more importance to the message rather than to their prior beliefs), the unique robust equilibrium is echo chambers. Sixth, the results are robust even if the experts are not exclusively biased, but they also care about gathering attention. Finally, the results are robust when considering a generic number of experts or continuous state space.

2.7 Applications

Throughout the paper, I have considered the COVID-19 vaccination as an example to illustrate my results. Such an example could have some caveats. Perhaps it is controversial to assume that the pro-government media has state-independent preferences. There is a trade-off between economic outcomes and the time needed to eradicate COVID-19, which means that herd immunity is a goal. However, the pro-government media is also concerned about safety. My model applies to a vaccine that has been approved for administration. Thus, it is safe overall. However, the pro-government media could avoid disclosing possible side effects. Moreover, many citizens are irrational and cannot be persuaded. Hence, my model applies to the subset of the population that is rational. I show that endogenous echo chambers can explain why many rational citizens are still sceptical about vaccinations and can be a threat to reaching herd immunity.

In this section, I argue that the applicability of my results goes beyond the previous example. My findings require five assumptions: on the one hand, experts are biased and have commitment power; on the other hand, decision-makers have heterogeneous beliefs and limited attention. Finally, I assume that decision-makers and experts make their choices simultaneously. Here, I briefly discuss what is the outcome if I relax any of these assumptions:

1. Under unlimited attention, experts are in direct competition to persuade decision-makers. As a consequence, full revelation is the unique equilibrium as discussed at the beginning of Section 2.5.

2. When decision-makers share the same prior belief, experts do not face a trade-off between persuading sceptics and retaining believers. As a consequence, each decision-maker has zero information gain independently of the allocation of attention.

3. Trivially, an unbiased expert is truth-telling and collects all attention.

4. When experts have no commitment power, decision-makers anticipate that babbling is optimal for each expert. Thus, decision-makers are indifferent about the allocation of attention.

5. When the allocation of attention is more flexible than the reporting policies of experts, the latter are implicitly attention-seekers. As a consequence, full revelation is the unique equilibrium (Knoepfle, 2020).

Therefore, each assumption is necessary for my results to hold. These assumptions allow me to build a model able to offer insights into the real world. By contrast, the outcome when relaxing any assumption is either full revelation or not conclusive (that is, any outcome is an equilibrium).

My assumptions are realistic in many contexts. First of all, there exist empirical evidence of the relative inflexibility of attention habits compared to the reporting policies of media. For instance, Eisensee and Strömberg (2007) show that politicians respond strategically to attention habits in the context of news coverage about natural disasters. Using data from Wikipedia, Ciampaglia et al. (2015) show that the demand for information (that is, the allocation of attention) precedes its supply. Anecdotally speaking, news consumers may know approximately how the media are biased but not the exact content of news before actually devoting attention (e.g., news consumers see an article's headline). Similarly, social media's users decide which media to follow and then are exposed to information. Second, the media may have commitment power, for instance, because of law or reputation concerns. Kamenica and Gentzkow (2011) discuss this assumption in detail. The media have incentives to build commitment power (Min, 2021). Fréchette et al. (2019) provide experimental evidence that news consumers react to commitment power as predicted by the Bayesian persuasion theory. Third, limited attention is a well-established fact. About two-thirds of Americans feel worn out by the excessive amount of news available to them (Pew Research Center, 2020). News consumers tend to interact with a very narrow set of news sources (Cinelli et al., 2020) and have an active role in determining this selective exposure (Bakshy et al., 2015). Fourth, heterogeneous beliefs are also very likely to exist in all situations where the objective probability for a claim to be true is ambiguous. For instance, politicians and bureaucrats may share the same goal but disagree about the best way to achieve it (Hirsch, 2016). Finally, whenever the true state of the world is disputed, there are likely competing interpretations of the current state of events. If this is true, the last requirement to apply my insights, namely competition between biased experts, is fulfilled. McCarthy and Dolfsma (2014) survey evidence that all media are biased, intentionally or unintentionally. In the following, I provide a non-exhaustive list of examples where my insights may be useful.

My model applies to the design of information about political issues. A politician wants to persuade voters to support a particular point of view. The optimal design of information trades off the desire of persuading sceptical voters and the goal of keeping loyalists. As a result, some information is provided. With competition and limited attention, some voters cluster into to echo chamber(s) and get no useful information.

A recent example is Trump's claim that the US Presidential election was fraudulent. The United States show increasing political polarization (Finkel et al., 2020). My model can explain why Republicans believe Biden won because of a "rigged" election, even though Trump has failed to provide any evidence about that (Rutenberg et al., 2020).

Climate change is another relevant example. A vast majority of scientists claim that climate change is real and warn that immediate intervention is necessary to avoid a sharp increase in mass disasters, whereas corporations (especially coal and oil producers) try to dispute such warnings. Endogenous echo chambers can explain the existence of climate change deniers. Similarly, believers of a long list of debunked conspiracy theories can survive within echo chambers. The common root is widespread scepticism about Science (Achenbach, 2015).

My model also applies to the advertising of differentiated products. A firm wants to persuade consumers to buy a product with uncertain value. Some consumers believe the product has a high value, whereas others believe it has low value. Each consumer buys if and only if she believes the product has high value. The firm designs the advertisement to maximize sales and then optimally provides some information about the product's value. With competition and limited attention, each consumer believes one product has a higher value than the other and may devote her attention only to the producer of this particular product. Echo chambers make it optimal for the firms to provide no information. My model can also rationalize asymmetric equilibria where one firm invest in informative advertising, whereas the other enjoys its market niche. If both firms design informative advertising, consumers rationally want to learn about their favoured products. But then providing informative advertising is not optimal for the firms. Cookson et al. (2021) provide evidence that investors' behaviour in the financial markets is in line with this application.

2.8 Conclusion

I show two main results about the quality of the information. First, it depends on agents' beliefs. When worldviews are sufficiently polarized, a monopolist provides lower quality information. Second, competition backfires when attention is limited: increasing the diversity of information sources reduces information quality even further. Echo chambers arise endogenously, and as a consequence, the incentives for the media to provide valuable information vanish.

My findings suggest that increasing media pluralism is likely to have a non-monotonous effect on information quality. In particular, the effect is positive when there are few media (or their ownership is concentrated) but negative as soon as there is information overload. Limited attention introduces an additional choice for news consumers: the subset of information to process. Policymakers should account for news consumers' incentives to cluster into echo chambers. I show that supporting media pluralism is a good idea only if news consumers are sufficiently attentive to process information from diverse sources.

The standard explanation for the existence of echo chambers is demand-driven: news consumers are biased, selfish or have some cognitive limitation. I show that there exists a complementary and supply-driven explanation. Because of information overload, even rational and unbiased news consumers end up devoting their limited attention to like-minded media. The latter, then, find it optimal to confirm news consumers' beliefs. Therefore, I provide a rational foundation for confirmation bias. Goette et al. (2020) provide experimental evidence that limited attention reinforces confirmation bias.

Whether the formation of echo chambers is mainly demand-driven or supply-driven is a fundamental question to address with future research. Understanding which is the main channel is necessary to design policy remedies. When the formation of echo chambers is supply-driven, as I suggest in this paper, one solution is to enhance attention, but it is unclear how to do this. An alternative is to manipulate the allocation of attention to improve information quality. In Section 2.6.1, I have shown how a platform that wants to maximize the informativeness of news should allocate attention. Such a platform can design each expert's audience to give him incentives to use his hard-news policy. In this way, media pluralism can enhance the average quality of information that news consumers receive. Platforms such as news aggregators may have the ability to shape how their users allocate attention. However, there is no guarantee that such platforms behave as a social planner would do.

A Proofs

Proof of Lemma 1

Proof. I assume there exists $i \in I$ such that $g_{ij} > 0$ and $\phi_i < 1$. Otherwise, persuasion is not necessary and babbling is the only optimal policy. I assume by contradiction that $\nexists\, s \in S_j$ such that $\pi_j(s|\omega_2) = \phi_i \pi_j(s|\omega_1)$ for some $i \in I$. Let $\{\phi_i\}$ be the ordered (in ascending order) set of constraints for each subgroup $i \in I$ such that $g_{ij} > 0$. If the n-th constraint holds for a message $s \in S_j$, then the m-th constraint holds too, for any $m > n$. Therefore, if n-th constraint holds there is more persuasion than if only the m-th constraint were holding, ceteris paribus. Thus, if the n-th constraint is slack, it is beneficial for the expert to increase the probability of the corresponding message, at the expense of the probability of a message which satisfy only the m-th constraint. There always exists a deviation for the expert unless at least one constraint holds with equality. $\square$

Proof of Proposition 1

Proof. The payoff for *Babbling* is $V_u := g_1$, whereas the payoff for the *Truth-telling policy* is $V_t := \mu^0(\omega_1)$. The *Hard-news policy* is as follows:

ω	ω_1	ω_2	
s	s	s	s'
$\pi_h(s\|\omega)$	1	ϕ_2	

$$\implies V_h := \mu^0(\omega_1) + \mu^0(\omega_2)\phi_2$$

The *Soft-news policy* is as follows:

ω	ω_1		ω_2	
s	s	s'	s	s'
$\pi_s(s\|\omega)$	k	$1-k$	$\phi_2 k$	$\phi_1(1-k)$

$$\implies V_s := kV_h + (1-k)\left[\mu^0(\omega_1) + \mu^0(\omega_2)\phi_1\right] g_1$$

where

$$1 - \phi_2 k = \phi_1(1-k) \iff k = \frac{\phi_1 - 1}{\phi_1 - \phi_2}$$

Any alternative policy with $\pi(s|\omega_1) < k$ is suboptimal, because the soft-news policy increases the probability of persuading sceptics without affecting the behaviour of believers.

Note that $V_h \geq V_t$. Hence, the expert does not use the truth-telling policy. Moreover, $V_s > V_u$ for any $g_1 \in (0,1)$. The hard-news policy is optimal if:

$$\begin{aligned} V_h \geq V_s &\iff \mu^0(\omega_1) + \mu^0(\omega_2)\phi_2 \geq \left(\mu^0(\omega_1) + \mu^0(\omega_2)\phi_1\right) g_1 \\ &\iff \mu^0(\omega_1)(1-g_1) \geq \mu^0(\omega_2)\left(\phi_1 g_1 - \phi_2\right) \qquad (12) \end{aligned}$$

Note that the RHS of (12) is increasing in ϕ_1 and decreasing in ϕ_2. The difference of these two values is a proxy for decision-makers' polarization in terms of prior beliefs. The RHS (LHS) of (12) is increasing (decreasing) in g_1, the share of believers among decision-makers. Finally, the RHS (LHS) of (12) is decreasing (increasing) in $\mu^0(\omega_1)$, the expert's belief of his favourable state. $\square$

Proof of Lemma 2

Proof. First of all, the distributions of posterior beliefs induced by these two policies have the same mean, which coincides with $\mu_i^0(\omega_1)$ for any $i \in I$, following Bayesian plausibility. It follows by (6)-(7) that π_h is characterized by more dispersion then π_s. Indeed, with the hard-news policy:

$$\mu_1(\omega_1 \,|\, s) - \mu_1(\omega_1 \,|\, s') = \frac{\phi_1}{\phi_1 + \phi_2}$$

$$\mu_2(\omega_1 \,|\, s) - \mu_2(\omega_1 \,|\, s') = \frac{1}{2}$$

whereas with the soft-news policy:

$$\mu_1(\omega_1 \,|\, s) - \mu_1(\omega_1 \,|\, s') = \frac{\phi_1}{\phi_1 + \phi_2} - \frac{1}{2}$$

$$\mu_2(\omega_1 \,|\, s) - \mu_2(\omega_1 \,|\, s') = \frac{1}{2} - \frac{\phi_2}{\phi_1 + \phi_2}$$

Therefore, π_h is more informative than π_s following Blackwell (1953). □

Proof of Lemma 3

Proof. Assume that π_j is truth-telling. Hence, $\pi_j(s \,|\, \omega_1) = \pi_j(s' \,|\, \omega_2) = 1$ and $\pi_j(s \,|\, \omega_2) = \pi_j(s' \,|\, \omega_1) = 0$. This implies that $\lambda_i(\pi_j) = 1$. Assume that π_j is not truth-telling, and without loss of generality $\pi_j(s \,|\, \omega_2) > 0$. Note that either $\sigma\big(\mu_i(\omega_1 \,|\, s)\big) = a_1$ or $\sigma\big(\mu_i(\omega_1 \,|\, s)\big) = a_2$. It follows that $\lambda_i(\pi_j) < 1$.

If π_j is babbling then, for any $s \in S_j$, $\sigma\big(\mu_i(\omega_1 \,|\, s)\big) = a_m$. It follows that $\lambda_i(\pi_j) = \mu_i^0(\omega_m)$. Assume that there exists $s \in S_j$ and $\omega_k \neq \omega_m$ such that $\pi_j(s \,|\, \omega_k) \neq \pi_j(s \,|\, \omega_m)$. By (3), $\sigma\big(\mu_i(\omega_1 \,|\, s)\big) = a_k$ if $\pi_j(s \,|\, \omega_k) \geq \frac{\mu_i^0(\omega_m)}{\mu_i^0(\omega_k)} \pi_j(s \,|\, \omega_m)$, and this implies that $\lambda_i(\pi_j) \geq \mu_i^0(\omega_m)$. □

Proof of Proposition 2

Proof. Assume without loss of generality $a_j = a_1$. If π_j is a hard-news policy then $T_j = \{i\}$ and $\phi_i < 1$. This implies $\lambda_i(\pi_j) = \mu_i^0(\omega_1) + \mu_i^0(\omega_2)\,[1 - \phi_i] = \mu_i^0(\omega_2)$. If π_j is a soft-news policy then $T_j = \{i, i'\}$ and without loss of generality $\phi_{i'} > 1 > \phi_i$. Therefore, $\lambda_i(\pi_j) = \mu_i^0(\omega_1)k + \mu_i^0(\omega_2)\,[1 - \phi_i k] = \mu_i^0(\omega_2)$ and $\lambda_{i'}(\pi_j) = \mu_{i'}^0(\omega_1)$. □

Proof of Proposition 3

Proof. Echo chambers: Given $H_\alpha = D_1$ and $H_\beta = D_2$, babbling is optimal for each expert. Therefore, by Lemma 3, $\Delta_{ij} = 0$ for any $i \in I$ and $j \in J$. Therefore, $j_1 = \alpha$ and $j_2 = \beta$ is optimal for decision-makers.

Monopoly: I assume without loss of generality $H_\alpha = D$ and $H_\beta = \varnothing$. The subgroup $i = 2$ must be a target. By Proposition 2, sceptics get zero information gain, that is $\Delta_{2\alpha} = 0$. Therefore, $j_2 = \alpha$ is optimal only if $\Delta_{2\beta} = 0$. Note that β is indifferent between any policy. This equilibrium breaks down if π_β is such that $\Delta_{2\beta} > 0$.

Opposite-bias learning: Given $H_\alpha = D_2$ and $H_\beta = D_1$, the hard-news policy is optimal for each expert. By Proposition 2, $\Delta_{1\beta} = \Delta_{2\alpha} = 0$. However, $\Delta_{1\alpha}, \Delta_{2\beta} > 0$. Therefore, $j_1 = \beta$ and $j_2 = \alpha$ cannot be optimal for decision-makers. □

Proof of Proposition 4

Proof. An asymmetric equilibrium where for each subgroup $i \in I$ two decision-makers of the same subgroup devote attention to different experts requires each expert to use his soft-news policy. Indeed, in this case all decision-makers are targets and get zero information gain independently of the allocation of attention: $\Delta_{i\alpha} = \Delta_{i\beta} = 0$ for any $i \in I$. These equilibria are equivalent to echo chambers in terms of information gains. Decision-makers are (weakly) better off in a monopoly: if the expert uses his hard-news policy, believers are better off; whereas if he uses his soft-news policy all decision-makers are indifferent. There cannot exist an asymmetric equilibrium such that one expert (say α) uses his hard-news policy whereas the other expert (say β) uses his soft-news policy. With the hard-news policy, believers (say subgroup 1) get a positive information gain, that is, $\Delta_{1\alpha} > \Delta_{1\beta} = 0$. Therefore, they are not indifferent about the allocation of attention. The alternative asymmetric equilibria is such that one expert (say α) uses his hard-news policy whereas the other expert (say β) is babbling. This requires the second expert to collect attention only from his believers, that is, $g_{2\beta} = 1$. Such asymmetric equilibria are equivalent to a monopoly with the hard-news policy in terms of information gains. For these equilibria to exist, there must be at least one expert such that as a monopolist he would use his hard-news policy. In this case, a sufficiently small mass of sceptics can devote attention to the other expert without changing the monopolist's optimal policy. If each expert as monopolist would use his soft-news policy, the mass of believers must be reduced to switch in favour of his hard-news policy. However, this is not compatible with the second expert babbling.

In any equilibrium with (at least) a babbling expert, those who devote attention to the latter receive information of the lowest quality. Indeed, babbling is the least informative outcome following Blackwell (1953): posterior beliefs are equal to prior beliefs. Instead, the hard-news policy and the soft-news policy produce both some dispersion in posterior beliefs. In any asymmetric equilibrium where each expert uses his soft-news policy, each decision-maker is equally informed. By (6)-(7),

$$\mu_1(\omega_1 \,|\, s) - \mu_1(\omega_1 \,|\, s') = \mu_2(\omega_1 \,|\, s) - \mu_2(\omega_1 \,|\, s') = \frac{\phi_1 - \phi_2}{2\left[\phi_1 + \phi_2\right]} < \frac{1}{2}$$

Therefore, in a monopoly each decision-maker is better (equally) informed if the expert uses his hard-news (soft-news) policy. □

Proof of Proposition 5

Proof. I denote with g the fraction of decision-makers belonging to the subgroup $i = 1$, that is, $g := \frac{|\{d \in D_1\}|}{|D|}$. Note that $g = g_{1j}$ when j is the monopolist. When there are two experts, that is $J = \{\alpha, \beta\}$, $g = g_\alpha + g_\beta$ where $g_j := \frac{|\{d \in H_j | d \in D_1\}|}{|D|}$. Similarly, $1 - g$ is the fraction of decision-makers belonging to the subgroup $i = 2$ and $1 - g = g'_\alpha + g'_\beta$ where $g'_j := \frac{|\{d \in H_j | d \in D_2\}|}{|D|}$. Note that $g_{1\alpha} = \frac{g_\alpha}{g_\alpha + g'_\alpha}$ and $g_{2\beta} = \frac{g'_\beta}{g_\beta + g'_\beta}$. I define news informativeness ψ_{ij} as the range of posterior beliefs for any subgroup of decision-makers $i \in I$ and any expert $j \in J$:

$$\psi_{i\alpha} = \begin{cases} \frac{\phi_i}{\phi_i + \phi_2} & \text{if (9) holds} \\ \frac{\phi_1 - \phi_2}{2(\phi_1 + \phi_2)} & \text{otherwise} \end{cases} \qquad \psi_{i\beta} = \begin{cases} \frac{\phi_1}{\phi_1 + \phi_i} & \text{if (10) holds} \\ \frac{\phi_1 - \phi_2}{2(\phi_1 + \phi_2)} & \text{otherwise} \end{cases}$$

Then, I define aggregate informativeness Ψ as the weighted sum of decision-makers' ranges of posterior beliefs:

$$\Psi := g_\alpha \psi_{1\alpha} + g'_\alpha \psi_{2\alpha} + g_\beta \psi_{1\beta} + g'_\beta \psi_{2\beta}$$

If the expert j is the monopolist, then aggregate informativeness is

$$\Psi_j^M := g\psi_{1j} + (1-g)\psi_{2j}$$

Here, I compare $\Psi_\alpha^M, \Psi_\beta^M$ with Ψ to determine whether a platform can make a competitive setting more informative than a monopoly. There are two cases to consider:

1. If each expert as monopolist uses his soft-news policy - that is, (9)-(10) do not hold given g - then a competitive setting is always better. By Lemma 2, opposite-bias learning is more informative than a monopoly with the soft-news policy. The platform can do even better than opposite-bias learning by allocating some believers to each expert, that is $g_\alpha, g'_\beta > 0$, making sure that (9)-(10) hold true.

2. When at least one expert as monopolist uses his hard-news policy, the result depends on the degrees of tolerance $\hat{g}_\alpha$ and $\hat{g}_\beta$. I assume without loss of generality that the expert α uses his hard-news policy as a monopolist. First of all, I show that a competitive setting must be better if $\hat{g}_\alpha, \hat{g}_\beta > \frac{1}{2}$. Note that, by assumption, $g < \hat{g}_\alpha$ and aggregate informativeness in monopoly is $\Psi_\alpha^M = g\left(\frac{\phi_1}{\phi_1+\phi_2}\right) + \frac{1-g}{2}$. Consider a fraction $\epsilon \in (0, 1-g)$ of sceptics of α (believers of β) and set $g'_\beta = \epsilon$. In a competitive setting, the expert β uses his hard-news policy if $g_{2\beta} = \frac{\epsilon}{\epsilon+g_\beta} \leq \hat{g}_\beta$. This is equivalent to $g_\beta \geq \left(\frac{1-\hat{g}_\beta}{\hat{g}_\beta}\right)\epsilon := \epsilon' < \epsilon$. Now, let $g_\alpha = g - \epsilon'$ and $g'_\alpha = 1 - g - \epsilon$ such that $g_{1\alpha} = \frac{g-\epsilon}{1-\epsilon-\epsilon'} \leq \hat{g}_\alpha$. Therefore, aggregate informativeness in a competitive setting is:

$$\Psi = (g-\epsilon')\left(\frac{\phi_1}{\phi_1+\phi_2}\right) + \frac{1-g-\epsilon}{2} + \epsilon\left(\frac{\phi_1}{\phi_1+\phi_2}\right) + \frac{\epsilon'}{2}$$

and the change in aggregate informativeness is positive:

$$\Delta\Psi := \Psi - \Psi_\alpha^M = \epsilon\left(\frac{\phi_1}{\phi_1+\phi_2}\right) + \frac{\epsilon'}{2} - \epsilon'\left(\frac{\phi_1}{\phi_1+\phi_2}\right) - \frac{\epsilon}{2} = (\epsilon-\epsilon')\left(\frac{\phi_1}{\phi_1+\phi_2} - \frac{1}{2}\right) > 0$$

If $\hat{g}_\alpha > \frac{1}{2}$ whereas $\hat{g}_\beta < \frac{1}{2}$, the steps are similar but the result is opposite. Indeed, $\epsilon' > \epsilon$ and therefore $\Delta\Psi < 0$. Hence, the monopoly (of expert α) is better. If $\hat{g}_\alpha < \frac{1}{2}$ whereas $\hat{g}_\beta > \frac{1}{2}$, there are two cases to consider. When each expert as monopolist uses his hard-news policy, it must be the case that $g < \frac{1}{2}$ and therefore $\Psi_\beta^M > \Psi_\alpha^M$. Then, the previous logic applies to the monopoly of expert β, which is the best outcome. Instead, when the expert β as monopolist uses the soft-news policy (that is, $1-g > \hat{g}_\beta$), the monopoly of β is not optimal. Here, I show that a particular competitive setting outperforms the monopoly of expert α. The idea is to induce the expert β to use his hard-news policy. Let $g_\beta = g$. Then, it must hold $g_{2\beta} = \frac{g'_\beta}{g'_\beta+g} \leq \hat{g}_\beta$. This is equivalent to $g'_\beta \leq \left(\frac{\hat{g}_\beta}{1-\hat{g}_\beta}\right)g > g$. Let $g'_\beta = \left(\frac{\hat{g}_\beta}{1-\hat{g}_\beta}\right)g$ and, by definition, $g'_\alpha = 1 - g - g'_\beta$. The aggregate informativeness in this competitive setting is:

$$\Psi = g'_\beta\left(\frac{\phi_1}{\phi_1+\phi_2}\right) + \frac{1-g'_\beta}{2}$$

and the change in aggregate informativeness is positive:

$$\Delta\Psi = (g'_\beta - g)\left(\frac{\phi_1}{\phi_1+\phi_2}\right) - \left(\frac{g'_\beta - g}{2}\right) = (g'_\beta - g)\left(\frac{\phi_1}{\phi_1+\phi_2} - \frac{1}{2}\right) > 0$$

Finally, consider the case where $\hat{g}_\alpha, \hat{g}_\beta < \frac{1}{2}$. Assume by contradiction that each expert as monopolist uses his hard-news policy and $g < \hat{g}_\alpha < \frac{1}{2}$. Therefore, it must be the case that $1 - g > \frac{1}{2} > \hat{g}_\beta$. But then the expert β uses his soft-news policy as monopolist, contradiction. Thus, the monopoly of expert α is better than the monopoly of expert β and of any competitive setting.

□

Proof of Proposition 6

Proof. Let $|I_2| = R_2 < R$. I order the subgroups of decision-makers from the most sceptical to the least:

$$\phi_1 < \cdots < \phi_{R_2} < 1 < \cdots < \phi_R$$

For any subgroup $r \in I$, I define the value for the expert of persuading marginally subgroup r as

$$E_r := \left[\mu^0(\omega_1) + \mu^0(\omega_2)\phi_r\right] \sum_{i=r}^{R} g_i \tag{13}$$

For any $r, r' \in I$, it is possible to define the following policies:

Definition 7 (Hard-news policy)**.** *A hard-news policy π_r, with target $T = \{r\}$ such that $r \leq R_2$, consists of a persuading message s and a residual message s' such that*

$$\pi_r(s\,|\,\omega_1) = 1 \quad \pi_r(s'\,|\,\omega_1) = 0$$

$$\pi_r(s\,|\,\omega_2) = \phi_r \quad \pi_r(s'\,|\,\omega_2) = 1 - \phi_r$$

The hard-news policy π_r implies the following posterior beliefs:

$$\mu_i(\omega_1\,|\,s) = \frac{\phi_i}{\phi_i + \phi_r}, \quad \mu_i(\omega_1\,|\,s') = 0 \quad \forall i \in I \tag{14}$$

Definition 8 (Soft-news policy)**.** *A soft-news policy $\pi_{\{r,r'\}}$, with targets $T = \{r, r'\}$ such that $r \leq R_2$ and $r' > R_2$, consists of two messages s, s' such that*

$$\pi_{\{r,r'\}}(s\,|\,\omega_1) = k \quad \pi_{\{r,r'\}}(s'\,|\,\omega_1) = 1 - k$$

$$\pi_{\{r,r'\}}(s\,|\,\omega_2) = \phi_r k \quad \pi_{\{r,r'\}}(s'\,|\,\omega_2) = \phi_{r'}(1 - k)$$

where

$$k := \frac{\phi_{r'} - 1}{\phi_{r'} - \phi_r}$$

is strictly increasing in $\phi_r \in [0, 1]$ and $\phi_{r'} \in [1, \infty]$.

The soft-news policy $\pi_{\{r,r'\}}$ implies the following posterior beliefs:

$$\mu_i(\omega_1\,|\,s) = \frac{\phi_i}{\phi_i + \phi_r}, \quad \mu_i(\omega_1\,|\,s') = \frac{\phi_i}{\phi_i + \phi_{r'}} \quad \forall i \in I \tag{15}$$

The payoff of a hard-news policy is

$$V_r := E_r$$

whereas the payoff of a soft-news policy is

$$V_{\{r,r'\}} := kE_r + (1 - k)E_{r'}$$

The payoff from the truth-telling policy is $V_t = \mu^0(\omega_1)$ and $V_1 > V_t$. The payoff from babbling is $V_u = G_1 := \sum_{i=R_2+1}^{R} g_i$. Note that $V_{\{r,R_2+1\}} > V_u$. Therefore, babbling is not optimal. I assume that there exist a unique $r^* = \arg\max_r E_r$. It follows that a monopolist uses optimally either a hard-news policy or a soft-news policy. This assumption rules out, for instance, any linear combination of hard-news policies targeting different subgroups of sceptics. If $r^* \leq R_2$, a hard-news policy with $T = \{r^*\}$ is optimal. Clearly $V_{r^*} > V_r$ for any $r \leq R_2$ and $r \neq r^*$. Moreover $V_{r^*} > V_{\{r,r'\}}$ as $E_{r^*} \geq E_r$ and $E_{r^*} > E_{r'}$ for any $r \leq R_2$ and any $r' > R_2$. If $r^* > R_2$, clearly $V_{\{r,r^*\}} > V_r$ for any $r \leq R_2$. Therefore, a soft-news policy is optimal. However, r^* is not necessarily the target: for any $r \leq R_2$, $V_{\{r,r^*\}} < V_{\{r,r'\}}$ if there exists a subgroup of believers $r' < r^*$ such that the difference $E_{r^*} - E_{r'}$ is sufficiently small. □

Proof of Proposition 7

Proof. The value of being persuaded marginally - a generalization of expression (13) - is:

$$E_\phi := \left[\mu^0(\omega_1) + \mu^0(\omega_2)\phi\right]\left[1 - F(\phi)\right]$$

As suggested by Proposition 6, the expert uses a hard-news policy or a soft-news policy depending on whether the solution to $\max_\phi E_\phi$ belongs to $[0,1]$ or to $[1,\infty)$, respectively. The F.O.C. is:

$$\mu^0(\omega_2)\left[1 - F(\phi)\right] - f(\phi)\left[\mu^0(\omega_1) + \mu^0(\omega_2)\phi\right] = 0$$

and implies condition (11), whereas the S.O.C. is:

$$-2\mu^0(\omega_2)f(\phi) - f'(\phi)\left[\mu^0(\omega_1) + \mu^0(\omega_2)\phi\right] < 0$$

which implies

$$\frac{f'(\phi)}{f(\phi)} > -\frac{2}{\phi_j + \phi} \tag{16}$$

Clearly, if the F.O.C. is always negative/positive (or the S.O.C. is violated) there exist a corner solution, namely the most valuable subgroup is $x = 0$ or $x = 1$. Following Proposition 6, $x = 0$ implies the truth-telling policy, which is a special case of a hard-news policy in this setting. Instead, $x = 1$ does not imply necessarily that such subgroup is a target. The actual targets of the soft-news policy depends on the shape of $F(\cdot)$. A sufficient condition for uniqueness is $f'(\phi) \geq 0$ for any $\phi \in [0,\infty)$. □

Proof of Lemma 4

Proof. Let us consider two hard-news policies π_r and $\pi_{r'}$, with targets $T = \{r\}$ and $T = \{r'\}$ respectively, such that $r < r'$. Then, π_r is more informative than $\pi_{r'}$ for any $i \in I$, according to the order from Blackwell (1953). This follows by (14) and $\phi_r < \phi_{r'}$.

Now, let us consider two soft-news policies $\pi_{\{r,r'\}}$ and $\pi_{\{r,r''\}}$, with targets $T = \{r, r'\}$ and $T = \{r, r''\}$ respectively, such that $r' > r''$. Then, $\pi_{\{r,r'\}}$ is more informative than $\pi_{\{r,r''\}}$ for any $i \in I$, according to the order from Blackwell (1953). This follows by (15) and $\phi_{r'} > \phi_{r''}$.

Finally, let us consider a hard-news policy with target $T = \{r\}$ and a soft-news policy with targets $T = \{r', r''\}$. If $r < r'$, Lemma 2 extends. If $r > r'$, there are two opposite effects: on the one hand, moving from a hard-news policy targeting r to another targeting r' increases informativeness; on the other hand, moving from a hard-news policy to a soft-news policy reduces informativeness. For each subgroup $i \in I$, with the hard-news policy, by (14):

$$\mu_i(\omega_1 \,|\, s) - \mu_i(\omega_1 \,|\, s') = \frac{\phi_i}{\phi_i + \phi_r}$$

whereas with the soft-news policy, by (15):

$$\mu_i(\omega_1 \,|\, s) - \mu_i(\omega_1 \,|\, s') = \frac{\phi_i}{\phi_i + \phi_{r'}} - \frac{\phi_i}{\phi_i + \phi_{r''}}$$

The hard-news policy is more informative if the following holds:

$$\frac{\phi_i + \phi_{r'}}{\phi_i + \phi_r} > \frac{\phi_{r''} - \phi_{r'}}{\phi_{r''} + \phi_i} \tag{17}$$

This condition may fail, especially if subgroup i are sceptics. □

Proof of Proposition 8

Proof. If at least one expert gathers attention exclusively from believers, then his best response is babbling. This supports the existence of an equilibrium in some cases. More details in the main text. Here, I focus on showing that this is a necessary condition. I assume that both experts gathers attention from some sceptics and some believers. By Proposition 6 each expert j uses either a hard-news policy with target r_j or a soft-news policy with targets $\{r_j, r_j'\}$. Consider a hard-news policy. It follows:

$$\lambda_i(\pi_j) = \begin{cases} \mu_i^0(\omega_2) & \text{if } i \le r_j \\ \mu_i^0(\omega_1) + \frac{\mu_i^0(\omega_2)}{\mu_{r_j}^0(\omega_2)}\left[\mu_{r_j}^0(\omega_2) - \mu_{r_j}^0(\omega_1)\right] > \mu_i^0(\omega_2) & \text{if } i \in (r_j, R_2] \\ \mu_i^0(\omega_1) + \frac{\mu_i^0(\omega_2)}{\mu_{r_j}^0(\omega_2)}\left[\mu_{r_j}^0(\omega_2) - \mu_{r_j}^0(\omega_1)\right] > \mu_i^0(\omega_1) & \text{if } i > R_2 \end{cases}$$

Therefore, $\Delta_{ij} > 0 \iff i > r_j$.

Consider a soft-news policy. It follows:

$$\lambda_i(\pi_j) = \begin{cases} \mu_i^0(\omega_2) & \text{if } i \le r_j \\ \mu_i^0(\omega_1)k + \frac{\mu_i^0(\omega_2)}{\mu_{r_j}^0(\omega_2)}\left[\mu_{r_j}^0(\omega_2) - \mu_{r_j}^0(\omega_1)k\right] > \mu_i^0(\omega_2) & \text{if } i \in (r_j, R_2] \\ \mu_i^0(\omega_1)k + \frac{\mu_i^0(\omega_2)}{\mu_{r_j'}^0(\omega_2)}\mu_{r_j'}^0(\omega_1)(1-k) > \mu_i^0(\omega_1) & \text{if } i \in (R_2, r_j') \\ \mu_i^0(\omega_1) & \text{if } i \ge r_j' \end{cases}$$

Therefore, $\Delta_{ij} > 0 \iff i \in (r_j, r_j')$.

There are three cases to analyse:

1. Each expert uses a hard-news policy. It follows that each expert targets a subgroup of sceptics, and they gets zero information gain. Such sceptics can deviate, become believers of the other expert, and get a positive information gain.

2. One expert uses a soft-news policy whereas the other uses a hard-news policy. The sceptics targeted by the soft-news policy can deviate, become believers of the other expert, and get a positive information gain.

3. Each experts uses a soft-news policy. Let $T_\alpha = \{r_\alpha, r_\alpha'\}$ and $T_\beta = \{r_\beta, r_\beta'\}$ be the set of targets for the experts α and β respectively. I assume without loss of generality that $r_\alpha < r_\beta' \le R_2 < r_\beta < r_\alpha'$. By Proposition 2, each target experiences zero information gain. Those targets who have intermediate prior beliefs (in this case, r_β' and r_β) have incentives to deviate, to get a positive information gain.

□

Proof of Proposition 9

Proof. To prove the result, I distinguish between symmetric and asymmetric equilibria.

Symmetric equilibria In the following, I compare the optimal policies of an informative expert in two scenario: monopoly and partial echo chambers. The difference is that in partial echo chambers some sceptics devote attention to the other expert, who is babbling. I denote with $\hat{r}$ the most sceptical subgroup of decision-makers who in partial echo chambers devote attention to the informative expert. There are two cases to consider:

1. The expert uses a hard-news policy in monopoly. Let r be the target under monopoly. If $\hat{r} \leq r$, by Proposition 6, the subgroup with the highest value of being marginal persuaded is still r. Therefore, the expert uses the corresponding hard-news policy. Decision-makers of any subgroup $i < \hat{r}$ are indifferent about the allocation of attention, that is, get zero information gain in any case. However, because they devote attention to the babbling expert, they get lower quality information. If $\hat{r} > r$, then the subgroup of sceptics that is targeted must change, and the new target is $r' > r$. The new policy could be either a hard-news policy or a soft-news policy. In both cases, all decision-makers have a (weakly) lower information gain and, by Lemma 4, receive information of lower quality.

2. The expert uses a soft-news policy in monopoly with targets $T = \{r, r'\}$. For any $\hat{r} \leq R_2$, a subgroup of believers has the highest value of being marginal persuaded. Therefore, by Proposition 6, the expert uses a soft-news policy in partial echo chambers. If $\hat{r} \leq r$, the expert's payoffs do not change, thus the expert uses the same soft-news policy. Decision-makers of any subgroup $i < \hat{r}$ are indifferent about the allocation of attention, but they get lower quality information. If $\hat{r} > r$, the new targets are $\hat{T} = \{i, i'\}$, where $i > r$. Now, if $i' \leq r'$ all decision-makers have a (weakly) lower information gain and, by Lemma 4, receive information of lower quality.

In the following, I find a sufficient condition for $i' \leq r'$. The optimal policy in monopoly is the soft-news policy with the highest payoff. Therefore, it is the solution of the following maximization problem:

$$\max_{\phi_r, \phi_{r'}} k \left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_r\right]\left[1 - F(\phi_r)\right] + (1-k)\left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_{r'}\right]\left[1 - F(\phi_{r'})\right]$$

subject to $k = \frac{\phi_{r'}-1}{\phi_{r'}-\phi_r}$, $\phi_r \in [0,1]$ and $\phi_{r'} \in [1,\infty)$. The F.O.C. are:

$$\Psi^F_{\phi_r} := \frac{\partial k}{\partial \phi_r}\Big\{\left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_r\right]\left[1 - F(\phi_r)\right] - \left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_{r'}\right]\left[1 - F(\phi_{r'})\right]\Big\} +$$

$$+ k\mu_j^0(\omega_2)\left[1 - F(\phi_r)\right] - kf(\phi_r)\left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_r\right] = 0$$

$$\Psi^F_{\phi_{r'}} := \frac{\partial k}{\partial \phi_{r'}}\Big\{\left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_r\right]\left[1 - F(\phi_r)\right] - \left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_{r'}\right]\left[1 - F(\phi_{r'})\right]\Big\} +$$

$$+ (1-k)\mu_j^0(\omega_2)\left[1 - F(\phi_{r'})\right] - (1-k)f(\phi_{r'})\left[\mu_j^0(\omega_1) + \mu_j^0(\omega_2)\phi_{r'}\right] = 0$$

In partial echo chambers, the distribution of beliefs changes. In particular, I denote with $G(\cdot)$ the new distribution that the informative expert faces. By (4), it follows

$$g(\phi_i) = \begin{cases} 0 & \text{if } i < \hat{r} \\ \frac{f(\phi_i)}{1-F(\phi_{\hat{r}})} & \text{if } i \geq \hat{r} \end{cases} \implies 1 - G(\phi_i) = \begin{cases} 1 & \text{if } i < \hat{r} \\ \frac{1-F(\phi_i)}{1-F(\phi_{\hat{r}})} & \text{if } i \geq \hat{r} \end{cases}$$

Therefore, $\Psi^F_{\phi_r} = \Psi^G_{\phi_r}$ and $\Psi^F_{\phi_{r'}} = \Psi^G_{\phi_{r'}}$ for any $i \geq \hat{r}$, which is the subset of possible targets of the informative expert. Because it must hold that the new targets as sceptics are a subgroup $i > r$, then $i' \leq r'$ if the targets are strategic substitutes, that is if $\frac{\partial \Psi_{\phi_{r'}}}{\partial \phi_r} \leq 0$.

There exist other symmetric equilibria where disjoint subsets of sceptics devote attention to the babbling expert. These equilibria do not differ significantly from partial echo chambers and, under the previous conditions, are worse for decision-makers than some monopoly outcome. In particular, there cannot exists an equilibrium where i devotes attention to the babbling expert and $i \geq r$, where r is the target of the informative expert.

Asymmetric equilibria Any symmetric equilibria described before is such that decision-makers devoting attention to the babbling expert are indifferent about the allocation of attention. Therefore, there exists asymmetric equilibria where decision-makers belonging to the corresponding subgroups behave differently in terms of allocation of attention. However, these equilibria do not differ significantly from the symmetric equilibria, and the result that competition is harmful holds true under the previous conditions.

Finally, there could exists asymmetric equilibria where both experts use soft-news policies with the same targets. If targets were different, some targeted decision-makers would find optimal to deviate (for the same logic of the proof of Proposition 8). I denote with $F_\alpha(\cdot)$ and $F_\beta(\cdot)$ the distributions of beliefs that the two experts α and β face, respectively. If these distributions are atomless, then the two experts target the same subgroups only if they face the same distribution, that is $F_\alpha(\cdot) = F_\beta(\cdot) = F(\cdot)$, and have the same prior beliefs, almost surely. Therefore, $F(\cdot)$ must coincide with the distribution that a monopolist face. It follows that the monopolist must have the same targets. Hence, these equilibria are equivalent to a monopoly. □

B Other Extensions

B.1 Costly Attention

The results in my paper are derived under the assumption that each decision-maker can devote attention to just one expert. Now, I endogenize this decision by allowing each decision-maker to devote attention to a second expert at a cost $c \geq 0$.

Proposition 10. *Full revelation is an equilibrium if and only if* $c = 0$.

Assume that π_α and π_β are truth-telling policies. It follows that $\lambda_i(\pi_\alpha) = \lambda_i(\pi_\beta) = \lambda_i(\pi_J) = 1$ for any $i \in I$. Therefore, it is sufficient to devote attention to one expert to maximize the subjective probability of taking the correct action. If $c = 0$, decision-makers can pay attention to both experts without any cost. This is equivalent to unlimited attention, and full revelation is indeed the equilibrium in such a setting. If $c > 0$, each decision-maker strictly prefers to devote attention to just one expert, as she gains no additional information from the second one. However, it is not optimal for the experts to reveal the true state when decision-makers pay attention to only one expert.

The equilibria of the game are robust for any $c \geq 0$. Given any equilibrium, it follows by Proposition 8 that there is no incentive to devote attention to a second expert. Multi-homing is not optimal because at least one expert is babbling. For instance, consider partial echo chambers with β babbling. For any $i \in H_\alpha$, it holds $\lambda_i(\pi_\alpha) = \lambda_i(\pi_J)$ because π_β does not affects posterior beliefs, hence optimal actions. For any $i \in H_\beta$ it must be the case that both experts are providing zero information gains, and $\lambda_i(\pi_\alpha) = \lambda_i(\pi_\beta) = \lambda_i(\pi_J) = \mu_i^0(\omega_m)$. Therefore, decision-makers are not willing to pay $c \geq 0$ to devote attention to a second expert.

B.2 Costly Information

In the paper, I assume that the information is costless to produce for experts and to process for decision-makers. Here, I study the effects of relaxing this assumption. In particular, I assume that either experts or decision-makers have to pay an entropy cost (Gentzkow and Kamenica, 2014; Matysková and Montes, 2021). For any policy π_j by expert j and any decision-maker d, its cost is proportional to the expected reduction in uncertainty:

$$c(\pi_j) := \chi[H(\mu_d^0) - \sum_{s \in S_j} \pi_j(s) H(\mu_d(\cdot|s))]$$

where $H(\mu) := -[\mu(\omega_1)\ln(\mu(\omega_1)) + (1 - \mu(\omega_1))\ln(1 - \mu(\omega_1))]$ is the entropy and $\chi > 0$ is a parameter. The cost of babbling is zero by definition. Following Bayesian plausibility and strict concavity of $H(\cdot)$,

$$H(\mu_d^0) = H\left(\sum_{s \in S_j} \pi_j(s)\mu_d(\cdot|s)\right) > \sum_{s \in S_j} \pi_j(s) H(\mu_d(\cdot|s))$$

Therefore, it holds that $c(\pi_j) > 0$ for any policy π_j different from babbling.

When decision-makers bear this cost, a decision-maker is not indifferent between being a target of an expert and receiving babbling: she prefers the second option. As a consequence, all the equilibria with one informative expert and one babbling expert, for instance partial echo chambers, are not robust to this extension. The unique symmetric equilibrium is echo chambers. Remarkably, an entropy cost by news consumers can be interpreted as a form of confirmation bias. In particular, news consumers bear a cognitive cost every time they change their beliefs. I show that even a very small confirmation bias makes echo chambers the unique robust equilibrium.

When experts bear this cost, the optimal policies change as shown by Gentzkow and Kamenica (2014). In particular, it is costly to induce extreme posterior beliefs. However, the objective of an expert is to persuade decision-makers i.e., to make them just indifferent. Extreme posterior beliefs are an indirect effect, see for instance the hard-news policy. It turns out that a posterior belief $\mu = \frac{1}{2}$ is the cheapest for an expert, that is $\arg\max_{\mu} H(\mu) = \frac{1}{2}$. Therefore, experts keep targeting decision-makers, unless information is so costly that babbling is the best option. Proposition 2 continue to hold and the incentives of decision-makers about the allocation of attention are not affected. The game has the same equilibria but costly information reduces the overall quality of information. Nevertheless, the negative effect of competition on quality continues to exist.

B.3 Multi-Homing

In Section B.1, I show that decision-makers have no incentive to devote attention to a second expert in equilibrium. Here, I assume that some decision-makers are exogenously multi-homing and study the impact on the equilibria of the game.

The first result is that full revelation cannot be achieved unless all decision makers have unlimited attention. Given truth-telling by the rival, multi-homing decision-makers cannot be persuaded. Therefore, the expert can focus on single-homing decision-makers and persuade them. This incentive exists independently on the share of single-homing decision-makers. Indeed, there is no cost on the multi-homing side from using a policy different from truth-telling.

Differently, targeting multi-homing decision-makers is costly for an expert because it lowers the probability to persuade single-homing decision-makers by ϵ arbitrarily small but positive. Therefore, when the set of multi-homing decision-makers has zero measure, there is no incentive to deviate (by Lebesgue's theorem). In this case, the equilibria of the game are robust.

When there is a positive mass of multi-homing decision-makers and experts find it optimal to target them, this creates the same undercutting incentives that exist with competition under unlimited attention. Therefore, a policy involving persuasion of multi-homing decision-makers cannot be part of an equilibrium. Theorem 5b in Dasgupta and Maskin (1986) can be used to establish the existence of mixed-strategy equilibria. However, the characterization and the interpretation of mixed-strategies is a hard task. It is not possible to establish a priori whether the consequent equilibrium of the game is better or worse than a monopoly in terms of information quality.

B.4 Alternative Timing

In the main text, I assume that optimal persuasion and the allocation of attention are simultaneous. Now, I examine the possibility that the two are sequential.

If the allocation of attention is chosen *before* persuasion takes place, my results extend. Remarkably, a monopoly is a much more credible equilibrium in this case. The allocation of attention cannot react to optimal persuasion by a monopolist. Therefore, it does not matter what is the policy of the non-active expert in the second stage of the game.

If the allocation of attention is chosen *after* persuasion takes place, babbling by both experts (with any allocation of attention) is not an equilibrium. Suppose, by contradiction, the opposite. Believers take each expert's preferred action, but any expert can deviate and persuade also his sceptics with positive probability (for instance, with his soft-news policy). To do so, it is sufficient to provide a strictly positive information gain, which requires to avoid targeting sceptics.

At the same time, truth-telling is the equilibrium policy. If any expert deviates, he does not collect attention. Therefore, he is not able to persuade, and indifference follows. This result is in line with Knoepfle (2020). Experts are implicitly attention-seekers: persuasion is effective only if an expert gets attention in the second stage. Optimal persuasion involves targeting of some decision-makers. However, by Proposition 2 a target gets zero information gain from persuasion. Therefore, she is unlikely to devote attention in the second stage of the game.

The latter setting is in line with the literature on media bias, where consumers buy news knowing the media's reputation or slant (Gentzkow et al., 2015). In turn, the latter is influenced by the incentive to steal consumers from the rival, and this is likely to generate beneficial competition. My approach is different because I assume that persuasion is rather flexible compared to the attention habits. Experts behave strategically taking as given the allocation of attention, and this is a source of persuasion power.

B.5 Second-movers

In this section, I maintain the timing as in the paper. However, decision-makers have the faculty of adjusting their allocation of attention at a cost $\zeta \geq 0$ after the reporting policies have been settled.

Proposition 11. *Full revelation is the equilibrium if and only if* $\zeta = 0$.

Full revelation requires all decision-makers to be second-movers. Assume by contradiction that there is one decision-maker who does not adjust her attention habit to experts' reporting policies. Then, the expert who receives her attention has an incentive to persuade her. Indeed, given truth-telling by the rival, the expert can deviate from truth-telling: he loses the attention of the second-movers, but this does not affect his payoff. At the same time, given full revelation, a decision-maker is not willing to pay a positive cost to be a second-mover. Indeed, she is already achieving the highest payoff, independently of whom she pays attention. Therefore, full revelation is the equilibrium only if $\zeta = 0$ and all decision-makers are second-movers.

The equilibria that I have identified in the paper are robust if ζ is large enough. I take the perspective of expert α without loss of generality. Expert α can attract second-movers of subgroup i only if $\zeta \leq \lambda_i(\pi_\alpha) - \lambda_i(\pi_\beta)$. As an illustration, I consider the echo chambers equilibrium. In this case, expert α can attract his sceptics $i = 2$ as second-movers if $\lambda_2(\pi_\alpha) \geq \mu_2^0(\omega_2) + \zeta$. Therefore, a sufficient condition for the robustness of echo chambers is $\zeta > \mu_2^0(\omega_1)$. Remarkably, the higher polarization (the more extreme believers' prior belief), the lower the threshold of ζ for echo chambers to be robust. If $\zeta \leq \mu_2^0(\omega_1)$ and $\mu_\alpha^0(\omega_1) \geq g_1$, then truth-telling is a beneficial deviation for expert α. Indeed, expert α prefers to attract his sceptics and reveal the truth to all decision-makers instead of exploiting his echo chamber. If this is not the case, expert α must persuade sceptics (to some extent) to find it optimal to deviate from echo chambers. However, this lowers sceptics' payoff and hence the threshold for ζ that makes echo chambers robust. Finally, when ζ is positive but small enough, there exist mixed-strategy equilibria, as in Section B.3.

B.6 Partial Commitment

In the paper, I assume that the experts can fully commit to their reporting policies. Trivially, in a cheap talk model the unique possible outcome is babbling by experts, and therefore the model has no predictive power. Here, I study the intermediate cases between cheap talk and Bayesian persuasion, in the spirit of Min (2021). In particular, I assume that with probability $\delta \in (0,1)$ the expert can deviate from his reporting policy. Therefore, each decision-maker expects that:

- with probability $1-\delta$, the message she receives is originated from the expert's optimal policy π;
- with probability δ, the message amounts to babbling.

This changes the way each decision-maker updates beliefs, and therefore changes the persuasion constraints. I assume that the expert wants to persuade to take action a_1. The persuasion constraint for subgroup i is:

$$\pi(s\,|\,\omega_2) \leq \phi_i \pi(s\,|\,\omega_1) + \left(\frac{\delta}{1-\delta}\right)(\phi_i - 1) \tag{18}$$

Clearly, when $\delta = 0$ the persuasion constraint (18) becomes (3). One first result of partial commitment is that it may make impossible to persuade sceptics. An expert can design a hard-news policy targeting a subgroup i of sceptics only if $\phi_i \geq \delta$.

The second effect of partial commitment is that a targeted sceptic has a positive information gain. In order to see this, I generalize the definitions of hard-news and soft-news policies:

Definition 9 (Hard-news policy)**.** *A hard-news policy π_r, with target $T = \{r\}$ such that $r \leq R_2$ and $\phi_r \geq \delta$, consists of a persuading message s and a residual message s' such that*

$$\pi_r(s\,|\,\omega_1) = 1 \quad \pi_r(s'\,|\,\omega_1) = 0$$

$$\pi_r(s\,|\,\omega_2) = \frac{\phi_r - \delta}{1-\delta} \quad \pi_r(s'\,|\,\omega_2) = 1 - \frac{\phi_r - \delta}{1-\delta}$$

The corresponding subjective probability of taking the correct action is:

$$\lambda_i(\pi_r) = \begin{cases} \mu_i^0(\omega_2) & \text{if } i < r \\ (1-\delta)\mu_i^0(\omega_1) + \frac{\mu_i^0(\omega_2)}{\mu_r^0(\omega_2)}\left[\mu_r^0(\omega_2) - \mu_r^0(\omega_1)\right] + \delta\mu_i^0(\omega_2) & \text{if } i \in [r, R_2] \\ \mu_i^0(\omega_1) + \frac{\mu_i^0(\omega_2)}{\mu_r^0(\omega_2)}\left[\mu_r^0(\omega_2) - \mu_r^0(\omega_1)\right] & \text{if } i > R_2 \end{cases}$$

Therefore, $\Delta_i > 0 \iff i \geq r$.

Definition 10 (Soft-news policy)**.** *A soft-news policy $\pi_{\{r,r'\}}$, with targets $T = \{r, r'\}$ such that $r \leq R_2$, $\phi_r \geq \delta$ and $r' > R_2$, consists of two messages s, s' such that*

$$\pi_{\{r,r'\}}(s\,|\,\omega_1) = k \quad \pi_{\{r,r'\}}(s'\,|\,\omega_1) = 1-k$$

$$\pi_{\{r,r'\}}(s\,|\,\omega_2) = \phi_r k + \left(\frac{\delta}{1-\delta}\right)(\phi_r - 1) \quad \pi_{\{r,r'\}}(s'\,|\,\omega_2) = \phi_{r'}(1-k) + \left(\frac{\delta}{1-\delta}\right)(\phi_{r'} - 1)$$

where

$$k := \frac{\phi_{r'} - c}{\phi_{r'} - \phi_r} \quad \textit{and} \quad c := \frac{1 - \delta(\phi_r + \phi_{r'} - 1)}{1-\delta}$$

The corresponding subjective probability of taking the correct action is:

$$\lambda_i(\pi_{\{r,r'\}}) = \begin{cases} \mu_i^0(\omega_2) & \text{if } i < r \\ (1-\delta)\mu_i^0(\omega_1)k + \frac{\mu_i^0(\omega_2)}{\mu_r^0(\omega_2)}\left[\mu_r^0(\omega_2) - \mu_r^0(\omega_1)(k(1-\delta)+\delta)\right] + \delta\mu_i^0(\omega_2) & \text{if } i \in [r, R_2] \\ (1-\delta)\mu_i^0(\omega_1)k + \mu_i^0(\omega_2)\left[\phi_{r'}((1-k)(1-\delta)+\delta) - \delta\right] + \delta\mu_i^0(\omega_1) & \text{if } i \in (R_2, r') \\ \mu_i^0(\omega_1) & \text{if } i \geq r' \end{cases}$$

Therefore, $\Delta_i > 0 \iff i \in [r, r')$.

As a consequence, all the equilibria which rely on targeted sceptics being indifferent about the allocation of attention (i.e., the asymmetric equilibria) do not exist with partial commitment. Instead, the symmetric equilibria (echo chambers and partial echo chambers) are robust to this extension.

Even if targeted sceptics have a positive information gain, the most moderate among targeted sceptics still have incentives to become believers of the other expert. For instance, when both experts α and β use hard-news policies with targets $T_\alpha = \{r_\alpha\}$ and $T_\beta = \{r_\beta\}$ such that $\phi_{r_\alpha} < 1 < \phi_{r_\beta}$, decision-makers of subgroup r_α (r_β) have incentives to deviate if $\phi_{r_\alpha} > \frac{1}{\phi_{r_\beta}} \left(\phi_{r_\alpha} < \frac{1}{\phi_{r_\beta}}\right)$. A similar reasoning applies for any combination of experts' policies, and therefore Proposition 8 extends.

B.7 Non-Bayesian Persuasion

Decision-makers with limited attention are probably unwilling to use a complex updating rule such as Bayesian updating. Drawing from the insights in de Clippel and Zhang (2020), I study my model under the following generalized version of the persuasion constraint for subgroup i:

$$\pi(s|\omega_2) \leq \phi_i^\rho \pi(s|\omega_1) \tag{19}$$

where $\rho \geq 0$ is a parameter. Clearly, when $\rho = 1$ the persuasion constraint (19) becomes (3). When $\rho \in (0,1)$, decision-makers are subject to base-rate neglect or over-inference. Instead, when $\rho > 1$, decision-makers overweight priors or are subject to under-inference. Let $\hat{\phi}_i = \phi_i^\rho$. Given a distribution of beliefs' ratio ϕ_i, $\rho \in (0,1)$ makes the distribution of $\hat{\phi}_i$ more moderate, whereas $\rho > 1$ makes it more extreme. In particular, if $\rho \in (0,1)$ then $\hat{\phi}_i > \phi_i$ for any $i \leq R_2$ and $\hat{\phi}_i < \phi_i$ for any $i > R_2$, whereas if $\rho > 1$ then $\hat{\phi}_i < \phi_i$ for any $i \leq R_2$ and $\hat{\phi}_i > \phi_i$ for any $i > R_2$. This is important because $\hat{\phi}_i$ is relevant for the expert's information design, whereas decision-makers keep evaluating information based on their original priors. It follows that:

$$\lambda_i(\pi_r) = \begin{cases} \mu_i^0(\omega_2) & \text{if } i < r \\ \mu_i^0(\omega_2)(\phi_i + 1 - \hat{\phi}_r) & \text{if } i > r \end{cases}$$

$$\lambda_i(\pi_{\{r,r'\}}) = \begin{cases} \mu_i^0(\omega_2) & \text{if } i < r \\ \mu_i^0(\omega_2)(\phi_i k + 1 - \hat{\phi}_r k) & \text{if } i \in [r, r') \\ \mu_i^0(\omega_1) & \text{if } i \geq r' \end{cases}$$

Therefore, $\Delta_r < 0$ if $\phi_r < \hat{\phi}_r$, that is if $\rho \in (0,1)$. Targeted sceptics have a negative information gain when are subject to base-rate neglect or over-inference. In this scenario, the unique equilibrium of the game is echo chambers.

When $\rho > 1$, the targeted sceptics have a positive information gain. However, as in Section B.6, the most moderate among targeted sceptics still have incentives to become believers of the other expert. In particular, either $\lambda_{r_\alpha}(\pi_\beta) > \lambda_{r_\alpha}(\pi_\alpha) \iff (\phi_{r_\alpha}\phi_{r_\beta})^\rho > \phi_{r_\alpha}$ or $\lambda_{r_\beta}(\pi_\alpha) > \lambda_{r_\beta}(\pi_\beta) \iff (\phi_{r_\alpha}\phi_{r_\beta})^\rho < \phi_{r_\beta}$ hold. Therefore, Proposition 8 extends.

B.8 Profit-maximizing experts

In the paper, I assume that experts are biased. Each expert has a preferred action and achieves positive utility only if a decision-maker takes such an action. Here, I modify experts' preferences by introducing a second component that captures each expert's desire to gather attention. In particular, expert j payoff from a decision-maker who takes action $a \in A$ and devotes attention to expert $j_d \in J$ is:

$$u_j(a, j_d) := \mathbb{1}\{a = a_j\} + \gamma \mathbb{1}\{j_d = j\}$$

See (2) for a comparison. The models are equivalent when $\gamma = 0$. Each expert is better off the larger is his audience, but this does not affect the equilibria of the game. Indeed, when experts decide their reporting policies, they take as given their respective audiences. In other words, a change in π_j can influence the action a taken by a decision-maker d but does not affect her allocation of attention j_d. In particular, an expert does not expand his audience by making his reporting policy more informative. Therefore, his reporting policy is oriented uniquely by the persuasion motive, as in the baseline model.

B.9 Competition with Homogenous Experts

With unlimited attention, having two experts with the same preferences does not affect information provision compared to a monopoly.

Proposition 12 (Homogeneous experts)**.** *Consider $J = \{\alpha, \beta\}$ and assume $a_\alpha = a_\beta$ and $\mu^0_\alpha(\omega_1) = \mu^0_\beta(\omega_1)$. In the equilibrium one expert (say α) behaves as a monopolist whereas the other one (say β) is babbling.*

Given babbling by β, α uses the optimal policy as monopolist (Proposition 1). The two experts have the same preferences and the same belief. Therefore, the policy of α is optimal also for β. There is no incentive to change the posterior beliefs by providing further information. Hence, babbling is optimal for β.

The entry of (potentially many) experts with the same preferences and belief as the incumbent is not affecting information provision. The intuition is that the entrant cannot refine the optimal policy of the incumbent.[18]

With limited attention, two experts using the same policy can be active. Indeed, each decision-maker is indifferent about her allocation of attention, as each expert provides her the same information gain.[19] This allows to extend the prediction of my model beyond a duopoly. The existence of additional experts has the effect of splitting attention, but it does not affect the equilibria of the game qualitatively.

With costly attention, a decision-maker could rationally pay attention to multiple experts providing her a positive information gain. However, multi-homing triggers a strategic response by the experts (Proposition 12). In this setting, the unique equilibrium is a monopoly.

B.10 Micro-Targeting

In the paper, persuasion is public. By contrast here, I assume that decision-makers are micro-targeted: each expert uses a specific policy for each subgroup of decision-makers. Let π^i_j be the policy of expert $j \in J$ which targets subgroup $i \in I$. In a monopoly, π^i_j is babbling if subgroup i are believers, whereas it is the hard-news policy if subgroup i are sceptics. This follows from Kamenica and Gentzkow (2011). With competition and single-homing, $\lambda_i(\pi^i_j) = \mu^0_i(\omega_m)$ for any $i \in I$ and any $j \in J$. In words, there cannot be a positive information gain from persuasion, for any decision-maker. This follows

[18] Experts with heterogeneous beliefs can have different optimal policies (in monopoly). However, there is no incentive to undercut the rival because the preferred actions coincide.

[19] If the experts use different policies, then decision-makers have incentive to devote attention to the most informative one.

from Lemma 3 and Proposition 2. Therefore, decision-makers are indifferent about the allocation of attention.

An expert benefits from the possibility to target many different decision-makers. By contrast, the effect of micro-targeting on decision-makers is ambiguous: believers are always worse off, but the sceptics might benefit. For instance, assume that public persuasion is given by a soft-news policy. With micro-targeting, each subgroup of sceptics is tailored with a specific hard-news policy, and she could be better informed by Lemma 4.

Here, the equivalence between public and private persuasion (Kolotilin et al., 2017) fails because the expert knows the prior beliefs of each decision-maker.

B.11 Many States

In this section, I examine how my model can be extended allowing for more than two states of the world.

A first approach is to consider a continuous state space i.e. $\Omega := [0,1]$ while keeping the action binary i.e. $A := \{a_0, a_1\}$. Here, I adopt a setting similar to Guo and Shmaya (2019). Each agent $l \in I \cup J$ has distinct prior beliefs with full support: $\mu_l^0(\cdot) \in \Delta_+(\Omega)$, where $\mu_l^0(\omega)$ is agent l's belief that the state is ω. Following Bayesian updating, posterior beliefs are:

$$\mu_i(\omega \mid s) := \frac{\pi_{j_i}(s \mid \omega)\mu_i^0(\omega)}{\int_0^1 \pi_j(s \mid \omega')\mu_i^0(\omega')d\omega'}$$

I assume that each decision-maker follows a threshold rule: she wants to take action a_1 if and only if the state ω is above a threshold $\bar{\omega}$. It follows that the optimal action for each decision-maker of subgroup i becomes:

$$\sigma(\mu_i) = \begin{cases} a_1 & \text{if } \int_{\bar{\omega}}^1 \mu_i(\omega)d\omega \geq \frac{1}{2} \\ a_2 & \text{otherwise} \end{cases}$$

Upon receiving message s, the implied persuasion constraint is

$$\int_{\bar{\omega}}^1 \pi_j(s \mid \omega)\mu_i^0(\omega)d\omega \geq \int_0^{\bar{\omega}} \pi_j(s \mid \omega)\mu_i^0(\omega)d\omega$$

In such a setting, I keep the restriction of two subgroups of decision-makers, believers ($i = 1$) and sceptics ($i = 2$). A believer is such that $\int_{\bar{\omega}}^1 \mu_1^0(\omega)d\omega > \frac{1}{2}$, whereas a sceptic is such that $\int_{\bar{\omega}}^1 \mu_2^0(\omega)d\omega < \frac{1}{2}$. As in the baseline model, the optimal policy focuses either on persuading sceptics or on retaining believers. However, the structure of the optimal policy changes.

If the focus is to persuade sceptics (hard-news policy), then a candidate optimal policy must satisfy the following constraint:

$$\int_{\bar{\omega}}^1 \mu_2^0(\omega)d\omega = \int_0^{\bar{\omega}} \pi(s \mid \omega)\mu_2^0(\omega)d\omega \tag{20}$$

I denote with Π_H the subset of policies such that (20) holds. Note that in the baseline model Π_H is singleton, whereas here the expert has degrees of freedom on the distribution of probability for each state $\omega \in [0, \bar{\omega}]$. By (5), the incentive of the expert is to pool states with high $\mu_j^0(\omega)$, while fully revealing others.

If the focus is to retain believers (soft-news policy), then a candidate optimal policy must satisfy the following constraints:

$$\int_{\bar{\omega}}^1 \pi(s \mid \omega)\mu_2^0(\omega)d\omega = \int_0^{\bar{\omega}} \pi(s \mid \omega)\mu_2^0(\omega)d\omega \tag{21}$$

$$\int_{\bar{\omega}}^1 \pi(s' \mid \omega)\mu_1^0(\omega)d\omega = \int_0^{\bar{\omega}} \pi(s' \mid \omega)\mu_1^0(\omega)d\omega \tag{22}$$

I denote with Π_S the subset of policies such that (21)-(22) hold, and note that in the baseline model Π_S is singleton. In this case, the goal of the expert is to maximize the probability of persuading sceptics subject to the constraint that believers chooses the preferred action with probability one. The incentives of the expert are difficult to disentangle, as these depend on $\mu_j^0(\omega)$, $\mu_1^0(\omega)$ and $\mu_2^0(\omega)$.

However, even if the structure of the optimal policy changes, my results are not affected. In particular, Proposition 2 generalizes to this setting. Note that

$$\int_0^{\bar{\omega}} \mu_2^0(\omega)d\omega = \int_0^{\bar{\omega}} \pi(s|\omega)\mu_2^0(\omega)d\omega + \int_0^{\bar{\omega}} \pi(s'|\omega)\mu_2^0(\omega)d\omega$$

which implies

$$\int_0^{\bar{\omega}} \pi(s'|\omega)\mu_2^0(\omega)d\omega = \int_0^{\bar{\omega}} \mu_2^0(\omega)d\omega - \int_0^{\bar{\omega}} \pi(s|\omega)\mu_2^0(\omega)d\omega$$

It follows that sceptics get zero information gain. By (21),

$$\lambda_2(\pi) = \int_{\bar{\omega}}^1 \pi(s|\omega)\mu_2^0(\omega)d\omega + \int_0^{\bar{\omega}} \pi(s'|\omega)\mu_2^0(\omega)d\omega = \int_0^{\bar{\omega}} \mu_2^0(\omega)d\omega$$

Hence, $\Delta_2 = 0$. Proposition 2 characterizes the incentives of decision-makers about the allocation of attention. Therefore, the effect of competition with limited attention is unchanged.

The analysis of optimal persuasion becomes generally intractable when the cardinality of Ω is equal to the cardinality of A.[20] I define $\phi_i(\omega,\omega') := \frac{\mu_i^0(\omega)}{\mu_i^0(\omega')}$ for any $\omega,\omega' \in \Omega$. A message s persuades decision-makers of subgroup i that the state is ω if $\pi(s|\omega') \leq \phi_i(\omega,\omega')\pi(s|\omega)$ for any $\omega' \in \Omega$. Decision-makers of subgroup i are true believers (sceptics) of state ω if $\phi_i(\omega,\omega') \geq 1$ (< 1) for any $\omega' \in \Omega$. A hard-news policy can target true sceptics. A soft-news policy can solve the trade-off between persuading true sceptics and retaining true believers. Therefore, if an expert faces only true sceptics and true believers, the result of Proposition 6 extends. However, different policies could be optimal if there exist decision-makers who believe that some states are a priori more plausible than ω, whereas others are not.

Example I consider the COVID-19 vaccination example, and I assume that there exists a third state of the world: safe but with caution (simply caution now on). Therefore $\Omega = \{\omega_1,\omega_2,\omega_3\} = \{\text{caution, safe, side effects}\}$. I assume that the monopolistic expert (say a politician) is biased towards caution. For instance, the politician might want to vaccinate only the elderly.

There are two subgroups of decision-makers as before: believers and sceptics, respectively, about the vaccine being safe. I assume $\phi_1(\omega_1,\omega_3) > 1 > \phi_1(\omega_1,\omega_2)$ and $\phi_2(\omega_1,\omega_2) > 1 > \phi_2(\omega_1,\omega_3)$. A soft-news policy is not useful because there are not true believers. Let π_h be a hard-news policy:

$$\pi_h(s|\omega_1) = 1 \quad \pi_h(s'|\omega_1) = 0$$

$$\pi_h(s|\omega_2) = \phi_1(\omega_1,\omega_2) \quad \pi_h(s'|\omega_2) = 1 - \phi_1(\omega_1,\omega_2)$$
$$\pi_h(s|\omega_3) = \phi_2(\omega_1,\omega_3) \quad \pi_h(s'|\omega_3) = 1 - \phi_2(\omega_1,\omega_3)$$

[20] A full characterization of prior beliefs requires $|\Omega|!$ subgroups of decision-makers. Unlike Section 2.6.2, there is no useful ordering of the subgroups of decision-makers.

Let us consider as alternative π_s:

$$\pi_s(s|\omega_1) = k \quad \pi_s(s'|\omega_1) = 1-k$$

$$\pi_s(s|\omega_2) = \phi_1(\omega_1,\omega_2)k \quad \pi_s(s'|\omega_2) \le \phi_2(\omega_1,\omega_2)(1-k)$$
$$\pi_s(s|\omega_3) = \phi_2(\omega_1,\omega_3)(1-k) \quad \pi_s(s'|\omega_3) \le \phi_1(\omega_1,\omega_3)k$$

The favourable state of the politician is caution, that is a compromise between opposite decision-makers' beliefs. If decision-makers have sufficiently polarized beliefs (and the politician is sufficiently uncertain about the true state), then it is optimal to use π_s. The intuition is similar to Proposition 1. With π_s, the politician randomizes between messages that either support one extreme state or the other. In other words, to persuade citizens that the best option is to take caution, a politician alternates positive and negative news about vaccinations. These news are not designed to move one group from one extreme to the other, but just from one extreme to a compromise. The alternative is to provide "hard evidence" that vaccinations are safe given precautions. This is extremely costly with high polarization, as both extreme views have to be contrasted at the same time. Note that π_s is not a soft-news policy, but it works similarly: the goal is to leverage believers' credulity.

The intractability of optimal persuasion does not allow to study the whole game. However, intuitively my results should not be affected by the existence of many states of the world and corresponding actions. For instance, let us consider Proposition 3. True believers clustering into echo chambers is an equilibrium. Indeed, no information is provided and hence the decision-makers do not have incentives to deviate. Decision-makers are better informed with a monopoly, because the existence of heterogeneous beliefs makes optimal for the expert to use some informative policy, where informativeness is defined following Blackwell (1953). Moreover, Proposition 8 continues to hold. Targeted sceptics have zero information gain also in this setting. Therefore, they want to deviate unless there is at most one informative expert.

B.12 Biased Decision-makers

In the paper, decision-makers are unbiased in their utilities. All the results are driven exclusively by heterogeneous prior beliefs. Now, I show that the same results can be obtained in a setting where decision-makers share a common prior belief $\mu^0(\omega_1)$, but each subgroup of decision-makers i is endowed with a vector of biases $b_i := \{b_i^\omega\}_{\omega\in\Omega}$. The utility of a decision-maker of subgroup i is $u_i(a,\omega_k) := \mathbb{1}\{a = a_k\}b_i^\omega$. See (1) for a comparison. The corresponding optimal action is as follows:

$$\sigma(\mu, b_i) = \begin{cases} a_1 & \text{if } \mu(\omega_1) \ge \frac{b_i^{\omega_2}}{b_i^{\omega_1}+b_i^{\omega_2}} \\ a_2 & \text{otherwise} \end{cases}$$

Upon observing message s, action a_1 is chosen if and only if:

$$\mu(\omega_1\,|\,s) \ge \frac{b_i^{\omega_2}}{b_i^{\omega_1}+b_i^{\omega_2}} \iff \pi_j(s\,|\,\omega_2) \le \frac{\mu^0(\omega_1)}{\mu^0(\omega_2)}\frac{b_i^{\omega_1}}{b_i^{\omega_2}}\pi_j(s\,|\,\omega_1) \tag{23}$$

A model with unbiased decision-makers and heterogeneous beliefs is equivalent to a model with biased decision-makers and a common belief only if, for any $i \in I$ and any $\omega \in \Omega$, $b_i^\omega = \frac{\mu_i^0(\omega)}{\mu^0(\omega)}$. This follows immediately from the comparison of conditions (3) and (23). Note that $b_i^\omega > 1$ if and only if $\mu_i^0(\omega) > \mu^0(\omega)$. Hence, a larger bias is equivalent to a decision-maker having a higher prior belief that the state ω is the true state. Remarkably, this multiplicative bias is different from the common definition of bias. In the literature, the utility of biased decision-makers depends on the action, but not on the state. By contrast here, each decision-maker has a strict preference to take the correct action given the state. The bias is limited to each decision-maker valuing some states more than others ex ante.

Hu et al. (2021) consider a model where decision-makers have different default actions. Given a common belief, each decision-maker would take her default action. Decision-makers of subgroup i are characterized by a specific threshold $c_i \in [0, 1]$ for the posterior belief which makes them indifferent:

$$\sigma(\mu, c_i) = \begin{cases} a_1 & \text{if } \mu(\omega_1) \geq c_i \\ a_2 & \text{otherwise} \end{cases}$$

Thus, the models are equivalent if $c_i = \frac{b_i^{\omega_2}}{b_i^{\omega_1} + b_i^{\omega_2}}$.

3 Selective Exposure Reduces Voluntary Contributions: Experimental Evidence from the German Internet Panel

joint with Linnéa Marie Rohde

3.1 Introduction

In today's information-rich world, with many different sources of information available, individuals are unable to pay attention to all information. Therefore, each individual has to constantly select which sources are worthy of attention. Moreover, misleading or false information spreads easily on the Internet and especially on social media (Lazer et al., 2018). The fact that individuals selectively expose themselves to information that is not necessarily true, but confirms their own beliefs or aligns with their preferences, leads to the formation of echo chambers, which has been well established in the empirical literature (Del Vicario et al., 2016).

The consequences of selective exposure, however, depend on how the information obtained affects actions. On the one hand, if the information an individual receives affects only her own, private actions and individual outcomes, her selective exposure can only affect her well-being. On the other hand, if the individual engages in *collective* action, then the information she obtains and the way she reacts to this information will affect the collective outcome of all individuals involved as well as overall welfare. An important area of collective action where information might play a crucial role is the provision of public goods. Often the exact returns of the public good are uncertain in advance, which can lead to under-provision of the public good (Levati et al., 2009). At first glance, providing more information about the returns of the public good could mitigate the problem of under-provision. If however different information sources have opposing claims about the returns of the public good, and individuals strategically select the source which supports their selfish interests, they can use the information to justify lower contributions. Then, information provision backfires and, contrary to expectations, further reduces the provision of the public good.

Environmental protection and COVID-19 containment are two salient examples of public goods with uncertain returns, where information acquisition plays a crucial role. First, climate change denial is a well documented phenomenon (Björnberg et al., 2017). On the one side, science denial campaigns by politicians like Donald Trump have a negative impact on climate change awareness, whereas on the other side environmental activism of groups like Fridays for Future have a positive impact (Baiardi and Morana, 2020). Second, social distancing, tests, and vaccinations can be interpreted as contributions to the public good of COVID-19 containment. However, the returns to these containment measures were initially uncertain since it was not yet clear how the pandemic would evolve. Misleading and false information about the virus and the containment measures spread quickly - causing the World Health Organization to declare an "infodemic" in February 2020 (World Health Organization, 2020; Cinelli et al., 2020).

In this paper, we answer the following research question: What is the effect of strategic information acquisition on the level and efficiency of voluntary contributions to a public good, and on social welfare? To this end, we investigate how participants acquire information when facing unreliable, biased information sources. Specifically, we analyze how social preferences affect strategic information acquisition.

In our experiment, we implement a one-shot Voluntary Contribution Mechanism where the marginal returns of the public good are uncertain. There are two states of the world: If the marginal returns are high, it is socially efficient to contribute to the public good, whereas if they are low, it is socially inefficient. We employ two main treatments. In the *no info* treatment, there is no further information available such that participants make their contribution decision based on their prior beliefs. In the *info* treatment, participants have the opportunity to acquire one unit of costless information about the returns of the public good from two unreliable sources with opposing biases. The high-biased source is biased towards claiming that the returns of the public good are high, whereas the low-biased source is biased towards claiming that the returns of the public good are low. In particular, in a non-preferred state, a source will not necessarily reveal the truth, but might instead claim the preferred state. Within each treatment, we experimentally vary the prior beliefs about the state of the world.

When participants behave rationally and do not exhibit any social preferences, the equilibrium contribution to the public good in this game is zero – independent of beliefs. Then, information acquisition does not change the optimal level of contribution, such that an individual is indifferent towards all information as long as it is costless. However, if social preferences play a role, information might matter. On the one hand, an individual purely interested in maximizing efficiency aims to match her action to the state of the world and hence aims to find out the true state. To this end, the direction of optimal information acquisition should depend on prior beliefs (Che and Mierendorff, 2019). Our experimental design allows us to test how prior beliefs affect information acquisition. On the other hand, it has been established - especially in the literature on Dictator games - that participants strategically avoid information that compels them to be more generous (Dana et al., 2007), or strategically seek information that justifies less generous behavior (Spiekermann and Weiss, 2016). To gain insight into whether participants are selfish or socially oriented, we elicit the motives behind the contribution decision in a post-experimental question. Thus, we can investigate how social preferences affect information acquisition.

We conduct our experiment on the German Internet Panel (GIP), which is a long-term online study based on a random probability sample of the general population in Germany. The GIP reaches more than 4,000 participants and regularly asks them about a multitude of political topics as well as socio-demographic variables. Embedding our experiment in the GIP allows us to complement the results from our experiment with available GIP data so that we can investigate whether the social preferences revealed in our experiment are indicative of actual public good contributions. We use the two examples of public goods with uncertain returns introduced in the beginning, and analyze whether the information acquisition and contribution behavior in the experiment are correlated with the willingness to contribute to environmental protection and COVID-19 containment.

The results from our experiment yield several insights. Most participants in the *info* treatment choose to acquire information, but a sizeable share of 13% does not acquire any information. Among the participants who acquire information, a majority of 65% selects the low-biased source, with no significant differences between prior beliefs. The selective choice of this source causes the beliefs of most participants to decline. As a result, the *info* treatment significantly reduces average contributions compared to the *no info* treatment. The share of participants who free-ride increases significantly in the *info* treatment, whereas the share of participants who contribute their entire endowment decreases. In terms of efficiency, the treatment effect is positive only for those groups where the public good has low marginal returns, i.e. where it is indeed socially efficient to contribute zero. In that case, the increase in efficiency implies an increase in social welfare by up to 12.4%. However for those groups where the public good has high marginal returns, i.e. where it is socially efficient to contribute, the effect of the *info* treatment on the efficiency of contributions is negative. In that case, the reduction in efficiency implies a reduction in social welfare by up to 5.3%.

Furthermore, we find that those participants who indicate that they are interested in maximizing the payoff of their entire group are more likely to acquire information than participants with other motives. Among the participants who acquire information, those who indicate that they are interested in maximizing their own payoff are more likely to acquire information from the high-biased source than those interested in maximizing the payoff of their entire group. This result is consistent with the findings from the literature on self-image concerns and self-serving biases (in particular Spiekermann and Weiss, 2016; Grossman and van der Weele, 2016). If a relatively selfish individual still feels compelled to contribute as long as there is a positive probability that the returns of the public good are high, acquiring information from the high-biased source is attractive: If the source claims high marginal returns, the obligation to contribute is unchanged, but if the source reveals low marginal returns with certainty, it allows the individual to contribute less.[21]

We find robust evidence that the level of contributions in our experiment is correlated with the willingness to voluntarily contribute to environmental protection and COVID-19 containment. Moreover, we find that those who acquire information that is biased towards high marginal returns display a lower willingness to contribute to environmental protection than those who acquire information that is biased towards low marginal returns. This is coherent with our finding that more selfish participants acquire information that is biased towards high marginal returns.

Finally, we rationalize the results from our experiment in a theoretical model: An individual has an incentive to choose the low-biased source if she has social preferences (or, equivalently, has a preference for efficiency) and self-image concerns. In particular, each individual has a reference point for contributions she aims to match, which can be interpreted as the social obligation to contribute. We show that, if the social obligation to contribute increases when an individual becomes certain that the marginal returns of the public good are high, she acquires information from the low-biased source. Indeed, this source communicates that the marginal returns are high only if this is true. For a similar reason, an individual acquires information from the high-biased source if the social obligation to contribute decreases when the individual becomes certain that the marginal returns of the public good are low. This model connects two of our findings: the majority of participants have social preferences, but contributions are lower in the information treatment. The majority of participants in our experiment would like to find out that the public good has high marginal returns (i.e., it is efficient to provide it). However, to this end, they have to acquire information from the low-biased source, which in expectation reduces posterior beliefs. Overall, this reduces the amount of contributions and harms efficiency.

The remainder of the paper is structured as follows. In section 3.2 we relate our contribution to the existing literature. In section 3.3 we describe the experimental design and the implementation of the experiment as a survey in the GIP and give more details on the additional data we exploit from the GIP. In section 3.4 we present our results. In section 3.5 we study a theoretical model to rationalize our experimental results. In section 3.6 we conclude.

[21]Note that this behavior can be interpreted in the sense of a confirmation bias: The individual is actively seeking information that confirms that her preferred contribution level is socially desirable. Thus, a selfish individual seeks information that reveals that marginal returns are low with certainty, while a socially oriented individual seeks information that reveals that marginal returns are high with certainty.

3.2 Literature Review

Public Goods With Uncertainty There exists a growing literature on environmental uncertainty in public good games. In contrast to strategic uncertainty, which arises endogenously because of imperfect information about the other participants' behavior, environmental uncertainty arises for instance if the marginal returns of the public good are uncertain (Levati et al., 2009; Levati and Morone, 2013; Björk et al., 2016). Their findings can be summarized as follows: Consider a standard linear public good game with risky marginal returns, where the expected marginal per capita return (MPCR) equals the MPCR in the control group game with certain marginal returns. If the risky MPCR is calibrated such that full contributions are socially efficient even for the lowest possible realization of the MPCR, the average unconditional contributions are largely unaffected (Levati and Morone, 2013; Björk et al., 2016). If however the risky returns are calibrated such that full contributions are not socially efficient for at least one of the possible realizations of the MPCR, the average unconditional contributions are significantly lower than in the game with certain marginal returns and there occurs significantly more full free-riding (Levati et al., 2009). The same pattern can be found if the stochastic returns are heterogeneous among the participants (Théroude and Zylbersztejn, 2020; Colasante et al., 2020), or if the participants observe different signals about the true value of the risky MPCR (Butera and List, 2017). Fischbacher et al. (2014) find that, in a game with heterogeneous returns, uncertainty about the own MPCR significantly lowers average *conditional* contributions.

A different approach considers a public good with a known MPCR which is provided only with a certain probability $p < 1$, independent of the aggregate contributions. In this case, full contributions are not socially efficient with probability $1 - p$. In this setting, average contributions are significantly lower compared to a game with a certain provision of the public good (Dickinson, 1998; Gangadharan and Nemes, 2009). In particular, Gangadharan and Nemes (2009) find that allowing the participants to make a costly investment to reduce the uncertainty enhances cooperation.

We contribute to this literature by allowing for different priors about the risky MPCR and by adding the possibility to acquire (unreliable) information about the MPCR.

Strategic Information Acquisition The idea that participants exploit a "moral wiggle room" by remaining ignorant about the consequences of their actions to justify selfish behavior was first established by Dana et al. (2007) in a dictator game. Strategic information avoidance and strategic information acquisition have been studied extensively in the dictator game context, providing different explanations for such behavior. If individuals are concerned about their self-image as an altruistic person, they face a trade-off between taking a costly pro-social action and being revealed as selfish. Therefore they reveal a perfectly informative signal only when they are sufficiently altruistic (Grossman and van der Weele, 2016). When facing a noisy signal, selfish individuals strategically seek information that validates the innocuousness of their selfishness (Chen and Heese, 2019). If individuals are duty-oriented but perceive moral responsibility as a burden, information that reveals that the socially optimal action is higher than expected is harmful and will be avoided (Nyborg, 2011). If participants feel compelled to perform an action implied by a norm, but use their participative beliefs to interpret these normative obligations, they can strategically acquire information to manipulate their beliefs to reduce the participative normative pressure (Spiekermann and Weiss, 2016).

Only a few papers study strategic information avoidance and strategic information acquisition in a public good setting. Aksoy and Krasteva (2020) conduct a public good game in which participants facing uncertain returns are *exogenously* uninformed about the true MPCR. They find that participants react differently to the information depending on their general level of generosity and depending on whether they receive "good news" or "bad news", i.e. whether the true MPCR is above or below the expected MPCR. Momsen and Ohndorf (2019, 2020) study endogenous information acquisition in a framed experiment with repeated carbon-offset purchasing decisions, where the externalities are uncertain. When the signal about the externalities is perfectly informative, participants strategically avoid this information only when it is costly, but not when it is costless. This result is consistent with the explanation that individuals use information costs as a situational excuse to avoid information that would prohibit them from selfish behavior. Moreover, participants avoid information more frequently if the externality is negative and affects other participants rather than the purchase of carbon offsets (Momsen and Ohndorf, 2020). In the same framing, Momsen and Ohndorf (2019) introduce stochastic, potentially unreliable information revelation. They also introduce two information sources to allow for selective exposure, where participants are allowed to acquire one signal from each source. In this case, they find evidence for information avoidance but not for selective exposure. Our experiment differs in several dimensions from Momsen and Ohndorf (2019). First, we study an unframed setting that allows us to investigate how underlying social preferences affect information acquisition and contribution behavior without an associated context. Second, in their setting, rational individuals have a preference to acquire all available information, while in our setting, rational (selfish) individuals are indifferent towards information acquisition. Therefore, information avoidance arises as a consequence of cognitive dissonance in their setting, but is a rational action in our setting. Third, while we employ a similar information revelation process, we allow participants to acquire only one signal. Thus, we can observe preferences for different types of information. Fourth, we test whether selective exposure depends on prior beliefs.

3.3 Experimental Design

We study a Voluntary Contribution Mechanism (VCM) in which the marginal per-capita return (MPCR) is stochastic. Participants interact in groups of $n = 4$. They receive an endowment e of which they can invest some amount $0 \leq g_i \leq e$ in Project A, which is the public account. The remaining amount $e - g_i$ is automatically invested in Project B, the private account. The VCM is played only for one round, i.e. participants make exactly one contribution decision. Let ω denote the MPCR of the public good, which is the same for all group members. Then the payoff of individual i is given by

$$\pi_i = e - g_i + \omega \sum_{j=1}^{4} g_j \tag{24}$$

such that, if $\omega \in (\frac{1}{4}, 1)$, it is socially efficient to contribute the entire endowment to the public good, but individually rational to contribute nothing. With a prior probability of μ, the MPCR is high, ω_h, and with a prior probability of $1 - \mu$, the MPCR is low, ω_l. We use a value of $\omega_h = 0.5$ for the high MPCR and a value of $\omega_l = 0.1$ for the low MPCR. Thus, the high MPCR ω_h creates a social dilemma situation, because it is socially efficient to contribute but not individually rational, while for the low MPCR ω_l, it is socially efficient not to contribute to the public good and there is no social dilemma situation. Therefore, selfish and social interests are aligned if the MPCR is low, but they diverge if the MPCR is high. To study the effect of priors, we consider three different prior probabilities $\mu \in \{0.25, 0.5, 0.75\}$. For a risk-neutral individual who makes her contribution decision according to the expected MPCR, full contributions are socially efficient when $\mu = 0.5$ or

$\mu = 0.75$, but not when $\mu = 0.25$.

We have two main treatments: *no info* and *info*. In the *no info* treatment, which is our control group, participants do not have the opportunity to acquire further information about the payoff of the group project. They are informed about the prior probability of the high MPCR and then immediately make their contribution decision. In the *info* treatment, participants have the opportunity to reveal one unit of – potentially unreliable – information about the MPCR before making their contribution decision: They face two information sources with opposing bias, S_H and S_L, which send one of the two possible signals *high* or *low*. For this information revelation process, we follow Che and Mierendorff (2019). The *H-biased source*, S_H, is biased towards sending the signal that the MPCR is high: If the true MCPR is ω_h, the S_H source always sends the signal $\sigma_H = high$. If however the true MPCR is ω_l, the S_H source sends the signal $\sigma_H = low$ only with probability λ. With probability $1 - \lambda$, it also sends the signal $\sigma_H = high$. Analogously, the *L-biased source*, S_L, is biased towards sending the signal that the MPCR is low: If the true MCPR is ω_l, the S_L source always sends the signal $\sigma_L = low$. If however the true MPCR is ω_h, the S_L source sends the signal $\sigma_L = high$ only with probability λ. With probability $1 - \lambda$, it also sends the signal $\sigma_L = low$. The probability $\lambda \in (0, 1)$ is the probability that a source reveals a non-preferred state and can be interpreted as the probability of receiving breakthrough-news (Che and Mierendorff, 2019). In our experiment, we use a value of $\lambda = 0.5$. Participants can acquire exactly one unit of information from one of the two sources, or decide not to acquire any further information about the MPCR. In the experiment, the information is costless.

If the participant acquires a signal from the S_H source and receives the signal $\sigma_H = low$ (i.e. breakthrough news), she updates her belief to $\mu'_H = Pr(\omega = \omega_h | \sigma_H = low) = 0$. If she receives the signal $\sigma_H = high$, she updates her belief to

$$\mu'_H = Pr(\omega = \omega_h | \sigma_H = high) = \frac{\mu}{\mu + (1 - \mu)(1 - \lambda)}$$

with $\mu'_H > \mu$ for all $\mu \in (0, 1)$. Using $\lambda = 0.5$, the posterior belief simplifies to $\mu'_H = \frac{2\mu}{1+\mu}$.

Analogously, when she acquires a signal from the S_L source and receives the signal $\sigma_L = high$ (i.e. breakthrough news), she updates her belief to $\mu'_L = Pr(\omega = \omega_h | \sigma_L = high) = 1$. If she receives the signal $\sigma_L = low$, she updates her belief to

$$\mu'_L = Pr(\omega = \omega_h | \sigma_L = low) = \frac{\mu(1 - \lambda)}{\mu(1 - \lambda) + (1 - \mu)}$$

with $\mu'_L < \mu$ for all $\mu \in (0, 1)$. Using $\lambda = 0.5$, the posterior belief simplifies to $\mu'_L = \frac{\mu}{2-\mu}$.

After having acquired information, the participants in the *info* treatment make their contribution decision based on their posterior belief.

3.3.1 The German Internet Panel

The German Internet Panel (GIP) is a long-term online study based on a random probability sample of the general population in Germany aged 16 to 75.[22] The GIP is an infrastructure project of the Collaborative Research Center (SFB) 884 "Political Economy of Reforms" at the University of Mannheim. It started in 2012, and refresher samples were recruited in 2014 and 2018, resulting in a current participant pool of over 6,000 potential participants. The participants are invited to take part in a survey on the first day

[22] For details on the GIP methodology, see Blom et al. (2015, 2016, 2017); Herzing and Blom (2019) and Cornesse et al. (2020).

of every other month, and the surveys remain open for the whole month. The questionnaires take 20-25 minutes and cover socio-demographic information as well as a multitude of topics including political attitudes. To incentivize participation, the participants receive 4 euros for each completed questionnaire plus a yearly bonus of 10 euros if they completed all surveys in that year, or 5 euros if they completed all but one survey of the year. The GIP data are publicly available in the GIP data archive at the GESIS-Leibniz Institute for the Social Sciences.

Our experiment was fielded in March 2021 in wave 52 of the GIP. From the same wave, we exploit a question which asked the participants how difficult they found the entire questionnaire, including our experiment. To address the question of how the experimental results relate to actual public good contributions, we use data on socio-demographics and attitudes towards environmental protection from several other waves of the GIP.[23] For the attitudes towards COVID-19 containment, we additionally exploit a sub-study of the GIP, the Mannheim Corona Study (MCS). For 16 weeks, from March 20 to July 10, 2020, around 3,600 participants of the GIP were interviewed about the impacts of the COVID-19 pandemic.[24] The study contains e.g. socio-economic aspects of the pandemic, frequency of social interactions, as well as attitudes towards containment measures. The MCS data are publicly available in the GIP data archive at the GESIS-Leibniz Institute for the Social Sciences as well.

3.3.2 Implementation of the Experiment

We implemented the experiment using five survey questions. In the GIP, participants are not used to incentivized economic experiments like ours. Therefore, we deliberately refrained from using standard elements of public good experiments, such as elicitation of conditional contributions or repetition of the VCM over several rounds. Instead, we simplified the game to a one-shot decision that can be captured in a single survey question. Moreover, we adapted the instructions to be understandable for members of the general population,[25] who might be less able than students in the laboratory to deal with numbers and in particular with probabilities. Therefore, we presented all probabilities in terms of frequencies.[26] To reduce cognitive costs and avoid any non-Bayesian updating, we provided the correct Bayesian posterior beliefs to those participants who acquired information.

For the random allocation into treatments, we proceeded as follows: 25% of the participants were randomly selected to be in the *no info* treatment, and 75% of the participants were randomly selected to be in the *info* treatment.[27] Within each of these two treatments, one-third of the participants was randomly allocated to each prior $\mu \in \{0.25, 0.5, 0.75\}$. Within the groups for each prior belief, we randomly allocated the high MPCR to a share of the participants corresponding to μ, and the low MPCR to a share of $1 - \mu$. For the information revelation, we proceeded as follows: 50% of the participants were randomly

[23] A detailed overview of the additional data used, including how variables were constructed, and a list of all questions used, can be found in appendix F.

[24] For details on the MCS methodology, see Blom et al. (2020a).

[25] We also used abstract framing, neutral language and avoided possibly loaded words like "public good" or "bias", to be able to study the participants' underlying preferences without an associated context. A common problem in an online survey is that the participants might not be willing to read lengthy or complicated instructions so that we made an effort to reduce the instructions to a minimum.

[26] Note that since the participants are randomly split into groups of pre-determined size to allocate them into the treatments, the representation in terms of frequencies is mathematically correct and does not constitute deception.

[27] We chose to have a larger number of participants in the *info* treatment to have a sufficiently large number of observations for each posterior belief.

allocated to the signal *high* and 50% were randomly allocated to signal the *low*. This variable then decided which signal the chosen source would reveal in the cases where the revelation of the true MCPR is possible, i.e. if the MPCR allocated to the participant is high and she acquires the signal σ_L, or if the MPCR allocated to the participant is low and she acquires the signal σ_H.

To incentivize the experiment, we paid out the payoffs from the game to 50 randomly selected groups of 4 participants each, i.e. to 200 participants in total. With an endowment of 10 euros (around 12 USD at the time the survey was fielded), it was possible to earn up to 25 euros depending on the MPCR and on the other group members' decisions. Compared to the payment of 4 euros for a completed questionnaire, or the German minimum hourly wage of 9.50 euros in 2021, both the endowment and the potential payoff of the experiment were quite sizable. On average, the participants who were randomly selected for payment earned 12.62 euros. The lowest payment was 1.70 euros, while the highest payment was 24.50 euro.

Our questionnaire contained the following parts:[28] First, the participants were informed about the payment procedure. Second, we explained the VCM. We told the participants that they would receive 10 euros on a virtual account and that they could decide how much of this amount to invest in a group project and how much to keep on their virtual account. To reduce the level of abstraction, we called the group project a "gold" project if the MPCR was $\omega_h = 0.5$, and a "silver" project if the MPCR was $\omega_l = 0.1$. We also provided an example of how to calculate the return from the group project in each case. Those in the *info* treatment were informed that they would later have the opportunity to potentially find out the true type of the group project.

Then, those in the *no info* treatment directly proceeded to the contribution stage, while those in the *info* treatment were informed about the information revelation process. To again reduce the level of abstraction and increase plausibility, we presented them with four envelopes, as inspired by the design by Spiekermann and Weiss (2016). Two of the envelopes were gold, corresponding to the H-biased source, and two envelopes were silver, corresponding to the L-biased source. We told the participants that exactly one of them contained the correct information about the true type of the project, and carefully explained the interpretation of the envelopes. We also informed the participants that they would receive an exact explanation of how certain they can be about the type of their project if they choose to acquire information. Then, the participants answered a comprehension question about the interpretation of the content of the envelopes and afterwards, they made their information acquisition decision. They could choose between opening one of the four envelopes or indicating that they do not want to open any envelope. Depending on what they chose, we asked them for their minimum willingness to pay for the envelope they chose, or for their minimum willingness to accept to open an envelope if they chose not to. As the other parts of the experiment were already complex, we decided not to incentivize this question, but to ask it hypothetically.

Then, at the contribution stage, those in the *info* treatment received the information about the content of the envelope and the correct Bayesian posterior.[29] All participants were then asked to decide which amount between 0 and 10 euros they wanted to invest in the group project.

After the contribution decision, we elicited potential contribution types in a multiple-choice question by asking about the motives for the contribution decision. For the answer

[28] An overview of the experimental stages, screenshots of the instructions and questions in German, as well as the English translations, can be found in Appendix G.

[29] Once the participants reached the contribution stage, it was not possible to go back to the information stage, making it impossible to open more than one envelope.

options, we follow the literature which finds that most participants in public good games are either free-riders, unconditional cooperators, or conditional cooperators (Fischbacher et al., 2001; Fischbacher and Gächter, 2010): Participants could indicate that they wanted to maximize their own payoff, maximize the payoff of the entire group, or that they wanted to contribute neither more nor less than other group members. We also included the option to indicate that they had other reasons.

3.4 Results

In total, 4,374 participants took part in GIP wave 52. Of those participants, 100 broke off the survey and several others decided not to take part in our experiment or completed only part of it. We dropped all participants who skipped the question on information acquisition or the question on the public good contribution, resulting in an overall sample size of 4,187 participants. In this sample, the average age is around 52 years, 48% of the participants are female, and 34% have an academic education, i.e. a Bachelor's degree or higher.

We now present the results of our experiment in terms of descriptive statistics. Then, we perform a regression analysis that shows how the contribution types elicited in our questionnaire affect information acquisition decisions, and how strategic information acquisition, in turn, affects voluntary contributions. Finally, we corroborate the findings from our experiment by investigating whether the information acquisition and contribution decisions in the experiment correlate with the willingness to voluntarily contribute to two real-world public goods: environmental protection, and the containment of the COVID-19 pandemic.

3.4.1 Descriptive Results

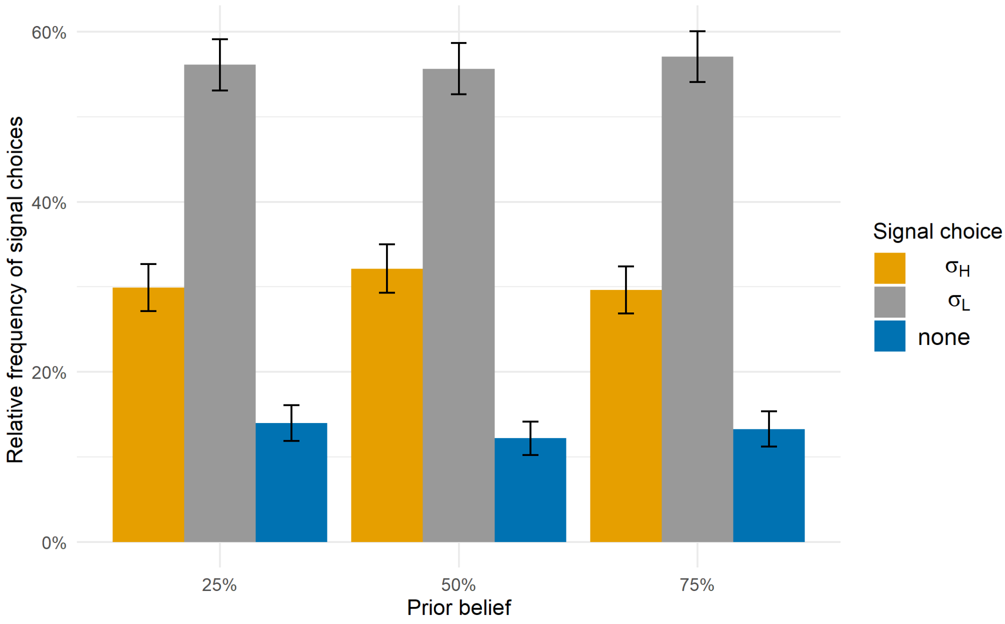
Selective Exposure Most participants in the *info* treatment (87%) choose to acquire a signal from either of the two sources, while only a small share (13%) chooses not to acquire any information. Among those participants who do acquire information, a majority of 65% chooses signal σ_L. A binomial test rejects the Null Hypothesis that participants are equally likely to choose σ_H and σ_L ($p < 0.0001$).[30] The finding that σ_L is the most frequent information acquisition choice is in line with the results of Spiekermann and Weiss (2016), whose experiment exploits the same information revelation process as ours. Between the three different prior beliefs, the signal choices do not differ significantly (figure 8).

Among the participants who acquired signal σ_H, the average willingness to pay for this signal is 4.12 euros, which is significantly higher than the average willingness to pay for signal σ_L of 3.51 euros among the participants who acquired this signal (Wilcoxon rank sum test, $p < 0.0001$). Among the participants who did not acquire information, the average willingness to accept to acquire signal σ_H is 3.83 euros, which however is not significantly different from the average willingness to accept to acquire signal σ_L of 3.32 euros (Wilcoxon rank sum test, $p = 0.11$). For both signal σ_H and signal σ_L, the willingness to pay is significantly different from the willingness to accept (Wilcoxon rank sum test, $p = 0.0048$ and $p = 0.0021$, respectively). These questions however were not incentivized, and therefore capture only hypothetical willingness to pay and willingness to accept.

To analyze how the information acquisition choices affect the voluntary contributions compared to those in the *no info* treatment, it is important to consider how the signal choice affects posterior beliefs. The selective choice of signal σ_L causes the beliefs of most

[30] All statistical tests reported are two-sided.

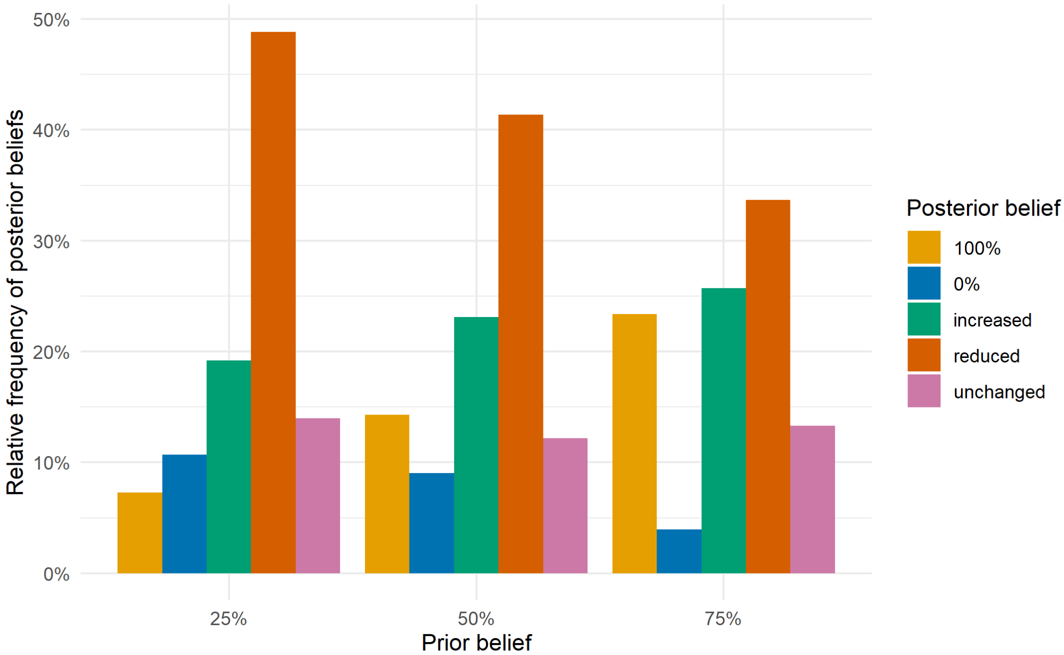
Figure 8: Information acquisition choices for the different prior beliefs



Error bars represent 95% confidence intervals.

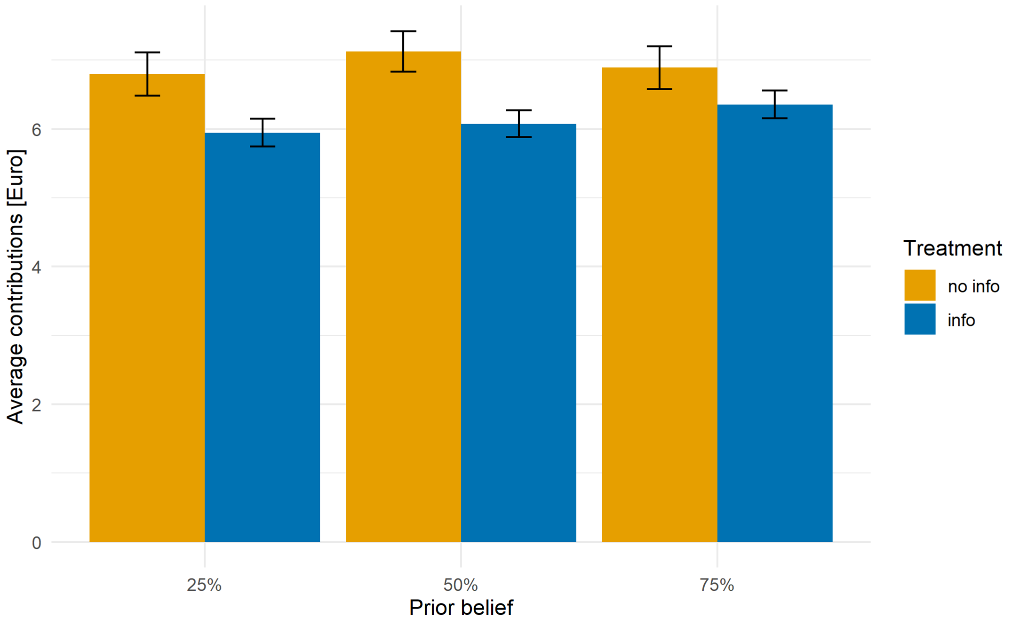
(41%) of the participants in the *info* treatment to decline. Only 8% of the participants reveal that the true MPCR of the public good is low with certainty, while 15% reveal that the true MPCR is high with certainty. Figure 9 shows the changes in the posterior beliefs by prior.

Figure 9: Changes in the posterior beliefs in the *info* treatment for each prior belief.



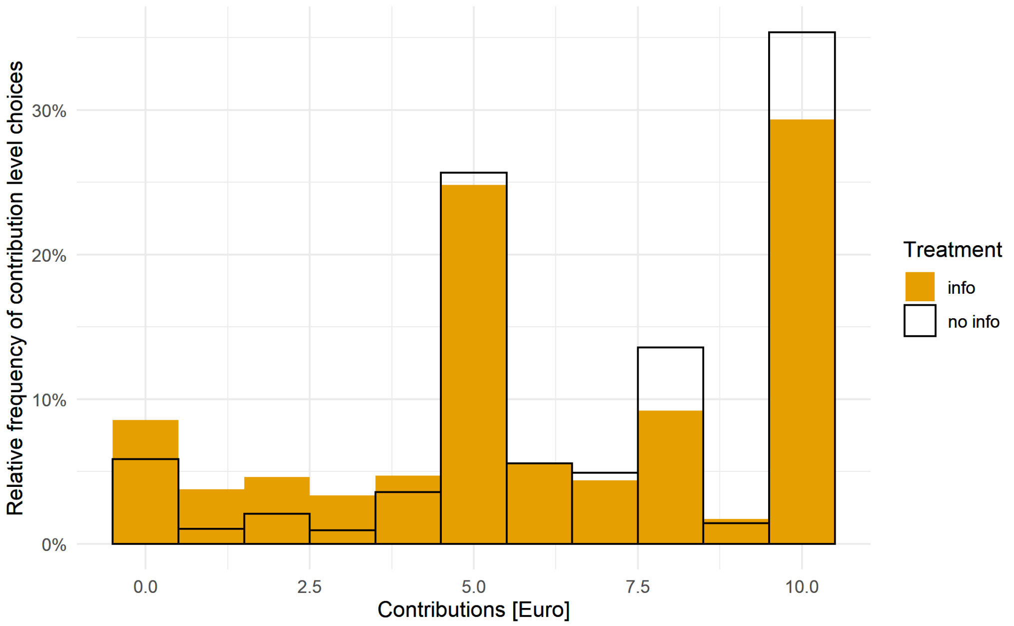
An increase in the belief comes from the choice of signal σ_H and results in posterior beliefs $\mu'_H \in \{0.4, 0.67, 0.86\}$. A reduction in the belief comes from the choice of signal σ_L and results in posterior beliefs $\mu'_L \in \{0.14, 0.33, 0.6\}$. "Unchanged" means that the participants did not acquire information, such that their posterior belief is equal to their prior belief.

Figure 10: Average contributions to the public good in the two treatments, for each prior belief.



Error bars represent 95% confidence intervals.

Figure 11: Distribution of contributions to the public good in the two treatments.



Voluntary Contributions At the contribution stage, we are interested in how the information treatment affects three main features of the distribution of the voluntary contributions to the public good: average contributions, the share of free-riders who contribute zero, and the share of participants who contribute their entire endowment.

In the *no info* treatment, participants contribute on average 6.94 euros to the public good. The *info* treatment significantly reduces the average contributions to 6.13 euros (Wilcoxon rank sum test, $p < 0.0001$), which corresponds to a reduction by 8.1% of the endowment. Average contributions do not differ significantly between prior beliefs (figure 10).

Figure 11 displays the distribution of voluntary contributions to the public good in the two treatments. In both treatments, the most frequently chosen contribution levels are at 10 euros, which is the whole endowment, and at 5 euros, which is half of the endowment. Comparing the distribution of contributions in the *no info* to the *info* treatment, we observe a shift of the distribution to the left, resulting in lower contribution levels being chosen more frequently. In particular, only 6% of the participants contribute zero in the *no info* treatment, while this share increases to 9% in the *info* treatment, which is a significant difference (two-proportions z-test, $p = 0.0066$). At the same time, the share of participants who contribute their entire endowment of 10 euros significantly decreases from 35% in the *no info* treatment to 29% in the *info* treatment (two-proportions z-test, $p = 0.0003$).

Comparing our results for the voluntary contributions to results from the literature on public good experiments, we find that our sample from the general population seems to be more generous than the typical sample of students in the laboratory.[31] Although we introduce uncertainty about the MPCR of the public good as well as the possibility that contributing zero is socially desirable, we observe only a comparably small share of participants who do not contribute.

Concerning the motives behind their contribution decision, the large majority of participants indicated exactly one motive only:[32] 12% want to maximize their own payoff, 45% want to maximize the payoff of the entire group, 21% want to contribute neither more nor less than other group members, and 13% had "other reasons".[33] Among the 8% who indicated more than one of the three main motives, the combination of maximizing the own payoff and maximizing the group payoff is the most frequent one.

Because most participants exclusively chose one of the three main motives – maximizing their own payoff, maximizing the group payoff, or contributing neither more nor less than other group members – we will focus on these three groups in the further analysis.[34] Figure 12 shows how the contribution decisions differ by contribution motive. In line with the theoretical predictions, those who indicate that they are interested in maximizing the group payoff contribute the largest amount on average (figure 12). They are also least likely to contribute zero (figure 12b) and most likely to contribute the entire endowment (figure 12c).

Efficiency and Welfare Finally, we are interested in how the information treatment affects the level of efficiency of contributions – which in turn affects social welfare. Recall that, if the true MPCR is high, i.e. $\omega_h = 0.5$, it is socially efficient to contribute the entire endowment to the public good. If the true MPCR however islow, i.e. $\omega_l = 0.1$, it is socially efficient to contribute nothing. Therefore, define the level of efficiency of a contribution

[31] Fischbacher et al. (2001) for example find that participants on average contribute about 33% of their endowment, while our participants contribute more than 60%. Moreover, they observe that about 30% of all participants are free-riders who contribute zero independent of others' contributions.

[32] When we designed the question which elicits potential contribution types by asking for the motives behind the contribution decision, we were interested in whether participants might have conflicting interests, in particular between the selfish interests and the social interests when the MPCR of the public good is high. Therefore, we used a multiple-choice instead of a single choice question.

[33] We included an open answer field for those who had "other reasons", to allow them to explain their contribution decision. Many participants indicate risk-averse behavior (not investing because of the uncertainty about the returns) or risk-seeking behavior (investing the entire endowment to gamble) or a tendency to evenly split the money between the private and public account, which might explain the high share of investments of 5 euros. Some participants also mention that they contribute for altruistic reasons. However, for the majority, the open answers indicated confusion and lack of comprehension. Therefore, we will not focus on the category of "other reasons" in the further analysis.

[34] In the following analysis, we interpret the motive "contributing neither more nor less than other group members" as reciprocity concerns, in the sense of conditional cooperation.

Figure 12: Contribution decisions by the three contribution motives.

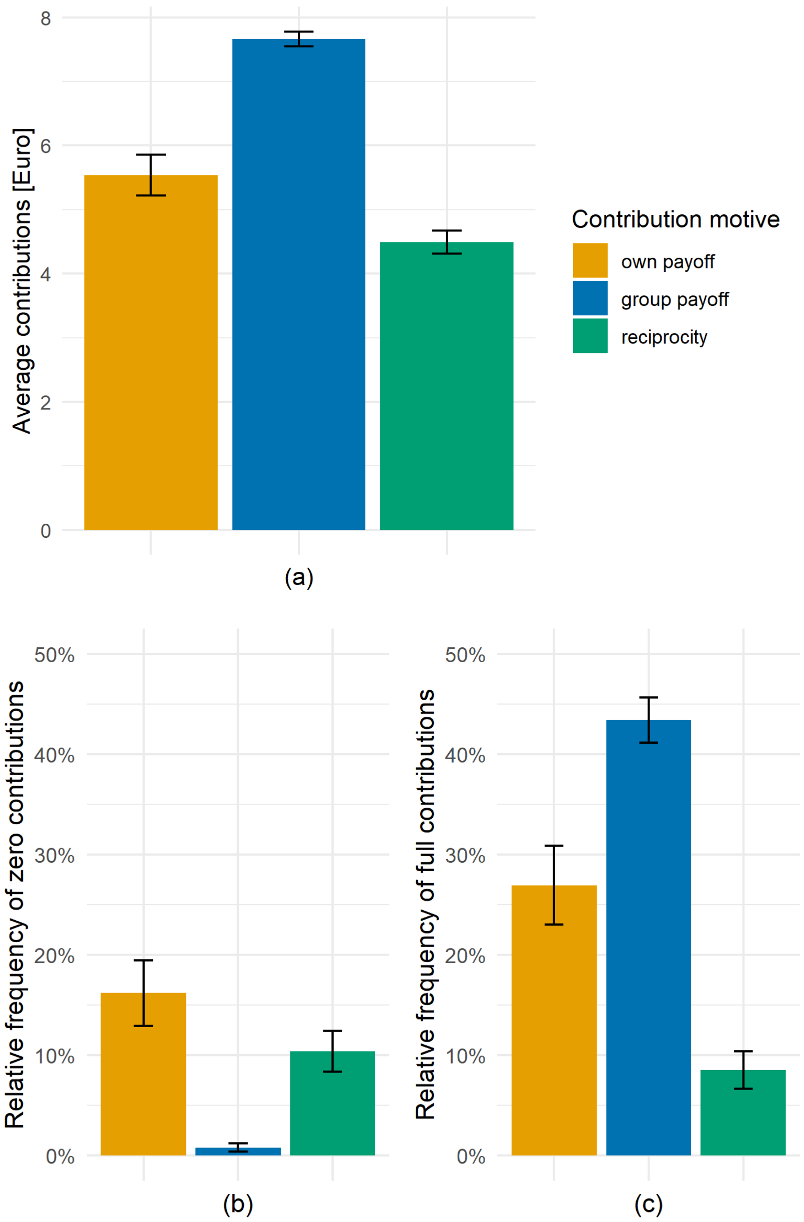


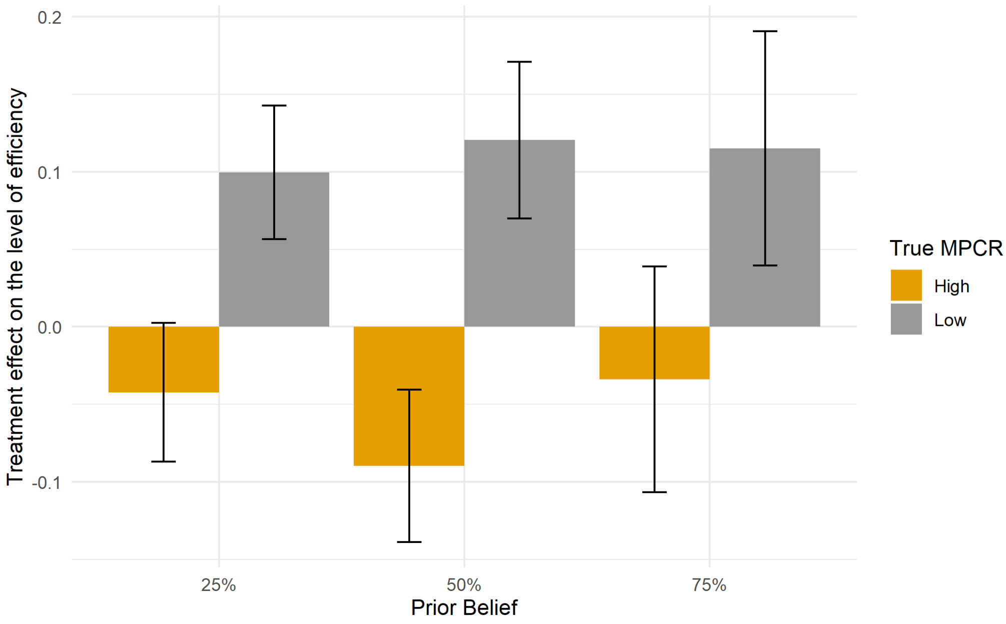
Figure (a) displays average contributions, (b) displays the relative frequency of zero contributions, (c) displays the relative frequency of full contributions of the whole endowment. "Own payoff" means that the participants indicated that they are only interested in maximizing their own payoff. "Group payoff" means that the participants indicated that they are only interested in maximizing the payoff of their entire group. "Reciprocity" means that the participants indicated that they are only interested in contributing neither more nor less than other group members. Error bars represent 95% confidence intervals.

as

$$E(g_i,\omega) = \begin{cases} 1 - \frac{g_i}{10} & \text{if} \quad \omega = \omega_l \\ \frac{g_i}{10} & \text{if} \quad \omega = \omega_h \end{cases}$$

where $E \in [0,1]$. We find that while the average level of efficiency is 0.51 in the *no info* treatment, it is 0.54 in the *info* treatment, where the difference is significantly different from zero (Wilcoxon rank sum test, $p = 0.0157$). This finding is surprising because we have seen that the information treatment reduces contributions. However, a reduction in contributions can only increase efficiency if the MPCR is low. Otherwise, it harms efficiency. Figure 13 shows that the treatment effect on efficiency is indeed only positive

Figure 13: Effect of information on efficiency.



The treatment effect on the average level of efficiency is the difference between the average level of efficiency in the *info* treatment and the average level of efficiency in the *no info* treatment. If the true MPCR is high, it is socially efficient to contribute the entire endowment to the public good. If the true MPCR is low, it is socially efficient to contribute nothing. Error bars represent 95% confidence intervals.

for those participants whose true MPCR is low. For those participants whose true MPCR is high, the treatment effect for prior beliefs of $\mu = 0.25$ and $\mu = 0.75$ is not significantly different from zero, but it is significant and negative for a prior belief of $\mu = 0.5$.

The effect of the information treatment on the level of efficiency of contributions has an immediate effect on social welfare. To calculate payoffs, we randomly partition the participants that share the same state of the world – i.e. the same true MPCR, the same prior, and the same treatment – into groups of four.[35] We then calculated the individual payoffs (equation 24) and social welfare, which is given by the sum of the payoffs of the four group members. To compare social welfare between treatments, we consider average social welfare across groups. We find that for those groups whose true MPCR is low, the increase in efficiency implies an increase in average social welfare ranging from 10% ($\mu = 0.25$) to 12.4% ($\mu = 0.5$). For those groups whose true MPCR is high, the reduction in efficiency implies a reduction in average social welfare ranging from 2% ($\mu = 0.75$) to 5.3% ($\mu = 0.5$).

3.4.2 Regression Analysis

We are interested in two main questions about the interplay of selective exposure and voluntary contributions in our experiment. First, how do contribution types affect information acquisition decisions? And second, how does strategic information acquisition affect voluntary contributions in the *info* treatment compared to the *no info* treatment? We address these using regression analysis.

[35]If the number of participants within a state of the world was not divisible by four, at most one group had less than four members. For this group, it was of course impossible to calculate payoffs.

Table 1: Probit model for the decision to acquire information.

	Dependent variable:			
	acquired information			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.018	−0.012	−0.011	−0.012
	(0.015)	(0.014)	(0.014)	(0.014)
prior = 0.75	−0.011	−0.012	−0.007	−0.008
	(0.015)	(0.014)	(0.014)	(0.014)
own payoff		−0.033*	−0.029*	−0.028
		(0.017)	(0.017)	(0.017)
reciprocity		−0.131***	−0.095***	−0.094***
		(0.017)	(0.015)	(0.016)
Constant	-	-	-	-
Further motives	No	Yes	Yes	Yes
Comprehension	No	No	Yes	Yes
Difficulty	No	No	No	Yes
Observations	3,127	3,111	3,111	3,100
Log Likelihood	−1,216.005	−1,122.230	−1,023.089	−1,018.124
Note:		*p<0.1; **p<0.05; ***p<0.01		

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those in the *info* treatment. The dependent variable *acquired information* is a binary indicator variable which takes the value 1 if the participant chose to acquire either of the two signals, and the value 0 if the participant did not acquire any signal. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Own payoff*, *reciprocity* and *further motives* belong to the same categorical variable which captures the motives behind the contribution decision, with *group payoff* as the omitted reference category. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

Selective Exposure The information acquisition decision consists of two separate decisions: First, each participant has to decide whether she wants to acquire a signal or not. Second, only if she decides to acquire information, she has to choose between σ_H and σ_L. Therefore, we estimate two probit regressions that model these two decisions separately.[36]

Table 1 presents the probit estimates of the marginal effects of priors and contribution motives on the decision whether to acquire information or not. Table 2 presents the effects on the decision whether to signal σ_H or signal σ_L among those who acquired information.

The tables highlight two main results. First, compared to those who indicated that they are interested in maximizing the payoff of their entire group, those who are care about reciprocity are less likely to acquire information. Second, again compared to those who indicated that they are interested in maximizing the payoff of their entire group, those who are care about their own payoff are more likely to acquire signal σ_H. Both effects remain significant at the 1% level when controlling for the comprehension of the

[36] An alternative approach is to model the overall decision problem between the three options of acquiring no signal, acquiring σ_H, or acquiring σ_L using multinomial logit regression. The results of the multinomial logit regression are similar to the findings of the two separate probit regressions in terms of direction and significance of the coefficients (appendix table 15).

Table 2: Probit model for the decision to acquire signal σ_H among those who acquire information.

	Dependent variable:			
	acquired σ_H			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.018	−0.016	−0.018	−0.019
	(0.023)	(0.023)	(0.022)	(0.022)
prior = 0.75	−0.024	−0.023	−0.028	−0.030
	(0.022)	(0.022)	(0.022)	(0.022)
own payoff		0.084***	0.087***	0.092***
		(0.030)	(0.029)	(0.029)
reciprocity		0.045*	0.027	0.032
		(0.025)	(0.025)	(0.025)
Constant				
Further motives	No	Yes	Yes	Yes
Comprehension	No	No	Yes	Yes
Difficulty	No	No	No	Yes
Observations	2,716	2,707	2,707	2,697
Log Likelihood	−1,761.147	−1,747.780	−1,699.499	−1,685.868
Note:		*p<0.1; **p<0.05; ***p<0.01		

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those who acquired information. The dependent variable is a binary indicator variable which takes the value 1 if the participant acquired signal σ_H, and the value 0 if the participant acquired signal σ_L. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Own payoff*, *reciprocity* and *further motives* belong to the same categorical variable which captures the motives behind the contribution decision, with *group payoff* as the omitted reference category. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

experiment. Priors however affect neither information acquisition decision in a statistically significant manner.

We conduct several robustness checks to ensure that the effects are not driven by potential comprehension problems. First, we re-run the regressions on the subsample of those participants who indicated that they did not find the questionnaire difficult. Second, we use the response times contained in the "paradata" of the survey, which capture the time a participant spent on each question page including the instructions. We drop the top 10% and the bottom 10% with respect to the time spent on the instructions for the public good game. Third, we use the subsample of those who answered the comprehension question about the information revelation process correctly. All tables for these robustness checks can be found in appendix D. The two main findings are robust to these modifications.

Voluntary Contributions To analyze how strategic information acquisition affects voluntary contributions in the *info* treatment compared to the *no info* treatment, we performed several regressions with the signal choices as well as the revealed information as explanatory variables.

As we have seen in figure 11, the distribution of contributions displays two pileups at the endpoints, i.e. at $g_i = 0$ and $g_i = 10$, with a roughly continuous distribution in between. Therefore, we are interested in three main features of the distribution of contributions: the probability of contributing zero, the probability of contributing the entire endowment, and the average level of contributions for those who contribute $0 < g_i < 10$. We use a three-part model to model these three features of the distribution separately. This model provides the highest possible flexibility by allowing separate mechanisms to determine the three decisions of interest.[37]

Table 3 summarizes the three-part model.[38] We first use a probit regression to model the decision to contribute zero (columns 1 – 3). Then we use a truncated normal model for the contribution level on the subsample of participants who contribute $0 < g_i < 10$, with zero and full contributions truncated. The truncated model takes into account that there are no observations with $g_i \leq 0$ or $g_i \geq 10$ in the subsample. We then use another probit regression to model the decision to contribute the entire endowment.

[37] Alternative models potentially suitable for our type of data include the two-limit Tobit model (appendix table 18) which takes into account the pileups at the endpoints but does not allow for separate mechanisms to determine the different decisions. Another alternative is the two-part hurdle model (appendix tables 16 and 17) which models only the participation decision separately from the amount decision, but it does not consider the decision to contribute the entire endowment. Our main results are robust to using these alternative models. Comparing the values of the log-Likelihood function reveals that the three-part model reported in this section provides the best model fit. Details about the model selection process can be found in the appendix section C.3.

[38] The full regression tables, including the coefficients for the contribution motives and difficulty, are in the appendix section C.1.

Table 3: Three-Part Model for Contributions.

	Dependent variable:								
	zero contribution			contributions			full contribution		
	probit			*Tobit*			*probit*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
info	0.026***			−0.648***			−0.061***		
	(0.009)			(0.083)			(0.017)		
prior = 0.25	0.029***	0.019**	0.018**	0.030	0.098	0.150*	−0.012	−0.0001	0.010
	(0.010)	(0.009)	(0.009)	(0.094)	(0.089)	(0.089)	(0.017)	(0.017)	(0.017)
prior = 0.75	0.018*	0.013	0.016*	0.145	0.168*	0.120	0.031*	0.033**	0.021
	(0.010)	(0.009)	(0.009)	(0.094)	(0.088)	(0.088)	(0.018)	(0.017)	(0.017)
acquired signal σ_H		−0.001			−0.476***			−0.011	
		(0.010)			(0.102)			(0.020)	
acquired signal σ_L		−0.003			−0.619***			−0.048***	
		(0.009)			(0.088)			(0.017)	
no signal acquired		0.164***	0.165***		−0.969***	−0.975***		−0.021	−0.025
		(0.019)	(0.019)		(0.160)	(0.160)		(0.028)	(0.028)
posterior = 1			−0.009			−0.018			0.073***
			(0.013)			(0.142)			(0.025)
posterior = 0			0.042**			−0.832***			−0.038
			(0.018)			(0.183)			(0.032)
posterior increased			−0.019*			−0.354***			−0.003
			(0.010)			(0.109)			(0.022)
posterior reduced			−0.001			−0.771***			−0.097***
			(0.010)			(0.092)			(0.018)
Constant	–	–	–	5.729***	6.236***	6.232***	–	–	–
				(0.087)	(0.121)	(0.121)			
Motives	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Difficulty	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	4,187	4,153	4,153	2,567	2,544	2,544	4,187	4,153	4,153
Log Likelihood	−1,141.922	−861.967	−855.206	−5,364.466	−5,155.317	−5,136.760	−2,577.495	−2,305.045	−2,278.855
Note:									*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. Columns 1 – 3 and 7 – 9 report marginal effects. *Zero contribution* is a binary indicator variable which takes the value 1 if the participant did not contribute, and 0 otherwise. *Contributions* is the level of contributions (in euros) for the subset of participants who contributed an amount g_i with $0 < g_i < 10$. *Full contribution* is a binary indicator variable which takes the value 1 if the participant contributed the entire endowment, and 0 otherwise. The probit models in columns 1 – 3 and 7 – 9 are estimated on the entire sample. The truncated normal model in columns 4 – 6 is estimated on the subsample of those who contributed $0 < g_i < 10$. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Signal choice* and *posterior* are categorical variables with "no info treatment" as the omitted reference category. The control variable *motives* captures the difference contribution motives, and *difficulty* captures the perceived difficulty of the entire questionnaire. The varying number of observations is caused by participants who did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

For each part, we report three different specifications of the explanatory variables. First, we are interested in the overall effect of the *info* treatment on the three decisions, compared to the *no info* treatment (columns 1, 4, and 7). Second, to gain insight into the mechanisms behind this treatment effect, we include the signal choices (columns 2, 5, and 8), and the changes in the posterior beliefs (columns 3, 6, and 9).[39] Because the contribution motives affect both the signal choice and the contribution decisions, we include them as a control variables. We additionally control for the perceived difficulty of the questionnaire.

The three-part model highlights several results. Most importantly, the probability of contributing zero is higher in the *info* treatment than in the *no info* treatment, while both the amount contributed among those with $0 < g_i < 10$ and the probability to contribute the entire endowment are smaller in the *info* treatment than in the *no info* treatment. The increase in zero contributions in the *info* treatment is mainly driven by those who did not acquire information, whereas the decrease in full contributions is mainly driven by those who acquire signal σ_L. Among those who contribute $0 < g_i < 10$, both those who acquire any signal and those who do not acquire a signal reduce their contributions compared to those in the *no info* treatment. The changes in posterior beliefs mainly affect the contribution decisions in the expected direction. In particular, obtaining a posterior belief of $\mu'_L = 1$ (i.e. revealing that the true MPCR of the public good is high) significantly increases the probability of contributing the entire endowment compared to the *no info* treatment. Obtaining a posterior belief of $\mu'_H = 0$ (i.e. revealing that the true MPCR of the public good is low) significantly increases the probability of contributing zero, and significantly reduces the amount contributed among those with $0 < g_i < 10$, compared to the *no info* treatment. Only the negative effect of an increased posterior $\mu < \mu'_H < 1$ on the level of contributions is unexpected. This effect is most likely caused by the selection at the information stage – because those who acquire signal σ_H are generally less willing to contribute than those in the *no info* treatment.[40]

We also estimate the three-part model again on the two subsamples of those who acquired signal σ_H and those who acquired signal σ_L separately, using priors and changes in posterior beliefs as explanatory variables (appendix table 14). Then, in each subsample, the information revelation is exogenous and random by construction. The results show that the participants react in the expected direction when they reveal the true state of the world.

[39] To test whether the effects of information on the contribution decisions differs by prior belief, we also estimated models for all three parts in which we included interactions between prior beliefs and signal choices, or prior beliefs and posterior beliefs (appendix tables 8 – 13). Our main results are robust to including these interaction effects. In each case, a Likelihood-Ratio test fails to reject the null hypothesis that the more complex model including the interaction effects fits the data as well as the nested model without the interactions. Therefore, we conclude that adding the interaction terms does not improve the model so that we focus on the simpler model here.

[40] Another potential explanation might be confusion among the participants concerning the information received. Our robustness checks address this potential problem. First, we re-run the regression analysis using the subsample of participants who did not find the questionnaire difficult (appendix table 33). Second, we make use of the response times contained in the dataset, which capture how much time a respondent spent on each question page, for a regression where we drop from the sample the bottom 10% and top 10% with respect to the time spent on the instructions for the public good game (appendix table 36). In both cases, the sign and significance of the coefficients remain the same. Therefore, we believe that it is unlikely that our results are driven by confusion or lack of understanding.

3.4.3 Additional Results

The results from our experiment suggest that both the information acquisition decision and the contribution decision are affected by social preferences. More selfish participants are less likely to acquire information, and if they do, they are more likely to acquire signal σ_H. They are also less likely to contribute, and if they do, they contribute less than more socially oriented participants. We so far draw these conclusions based on the *stated* preferences elicited in our final question about the contribution motives, which was specific to the setting of our experiment. If the behavior in our experiment was driven by underlying social preferences, we should observe similar behavior in real-world public good contexts as well. To explore this line of thought, we come back to the two salient examples of public goods with uncertain marginal returns introduced at the beginning: environmental protection and the containment of the COVID-19 pandemic.

Willingness to Voluntarily Contribute to Environmental Protection To investigate the relationship between information acquisition and contribution decisions in our experiment and the willingness to voluntarily contribute to environmental protection, we exploit three questions that capture the individual, voluntary, and costly contributions in the most narrow sense. These questions ask whether the participants (i) support a carbon tax, (ii) changed their lifestyle in the past six months to protect the climate, and (iii) pursued sustainable activities such as volunteering for an environmental project or buying regional organic products in the past six months.[41] We conduct a Principal Component Analysis (PCA) to condense the answers to these three questions into the first standardized principal component, which we then take as a dependent variable (following Kerschbamer and Müller, 2020).[42] Higher values of the dependent variable are associated with a higher willingness to contribute to environmental protection. Table 4 presents the results of the OLS regression, both for the entire sample and for the subsample of those in the *info* treatment.[43]

The regression yields two main results. First, the level of contributions to the public good in the experiment is positively correlated with the willingness to contribute to environmental protection. The effect is robust to including including controls for socio-demographic variables and comprehension of the experiment. Thus, the contribution behavior observed in the experiment appears to be indicative of actual contributions to a public good, which suggests that our results concerning contribution behavior might be externally valid.

Second, those who acquired signal σ_L are significantly more likely to contribute to environmental protection than those in the *no info* treatment. Among the participants in the *info* treatment, those who acquired signal σ_H are significantly less likely to contribute to environmental protection than those who acquired signal σ_L.

To test that our results do not rely on the selection of the variables, we run two robustness checks, where we include several other questions (appendix tables 29 and 30). Our results remain robust to using these alternative variable specifications.

Willingness to Voluntarily Contribute to COVID-19 Containment To investigate the relationship between information acquisition and contribution decisions in our experiment and the willingness to contribute voluntarily to COVID-19 containment, we

[41] See appendix F for a detailed description of why these questions were selected and how the variables were constructed, as well as for an overview of all questions used.

[42] We additionally report the regression results for every single variable in appendix tables 22 – 24.

[43] The full table including the coefficients for all control variables is appendix table 20.

Table 4: OLS regression for the willingness to voluntarily contribute to environmental protection, measured by three variables.

	Dependent variable:				
	willingness to contribute to environmental protection				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	-0.135^{**}	-0.097	-0.263^{***}	-0.198^{***}	-0.178^{***}
	(0.066)	(0.070)	(0.061)	(0.065)	(0.066)
acquired signal σ_L	0.132^{**}	0.107^{*}			
	(0.059)	(0.062)			
no signal acquired	0.014	0.089	-0.136	-0.037	0.004
	(0.101)	(0.107)	(0.097)	(0.104)	(0.106)
contributions	0.029^{***}	0.029^{***}	0.020^{**}	0.020^{**}	0.018^{*}
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
Constant	-0.211^{***}	-0.691^{***}	-0.023	-0.609^{***}	-0.592^{***}
	(0.072)	(0.145)	(0.070)	(0.169)	(0.169)
Difficulty	No	Yes	No	Yes	Yes
Comprehension	No	No	No	No	Yes
Controls	No	Yes	No	Yes	Yes
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,892	2,450	2,154	1,820	1,820
R^2	0.011	0.064	0.011	0.069	0.070
Adjusted R^2	0.010	0.060	0.009	0.064	0.065
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the first principle component of three variables capturing the willingness to contribute to environmental protection: (i) support of a carbon tax, (ii) lifestyle changes the past six months to protect the climate, and (iii) pursuing sustainable activities in the past six months. Higher levels of the dependent variable represent higher willingness to contribute to environmental protection. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the info treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 euros. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly. The other control variables include gender, age, income, and education.

exploit four questions about the usage of the corona warning app. The questions ask whether the participants are (i) willing to enter test results in the app, (ii) intend to comply with the app's request to get tested or (iii) to quarantine, and (iv) whether the app was installed.[44] We again conduct a PCA to condense the answers to these four questions into the first standardized principal component, which we then take as a dependent variable.[45] Higher values of the dependent variable are associated with a higher willingness to contribute to COVID-19 containment.

Table 5 presents the results of the OLS regression.[46] The two main insights are in line with the results for environmental protection. First, the regression results show that the level of contributions in the experiment is positively correlated with the willingness to contribute to COVID-19 containment, and the effect remains significant at least at the 10% level when including controls.

Second, those who acquired signal σ_L are significantly more likely to contribute to COVID-19 containment than those in the *no info* treatment, although the effect is not robust to including controls. Among the participants in the *info* treatment, those who acquired signal σ_H and those who did not acquire information are less likely to contribute to COVID-19 containment than those who acquired signal σ_L, but the coefficients are not significant.

Thus, while the effects go in the same direction as in the regression for environmental protection, they are less significant in this regression. This could follow from the fact that the two public goods are very different, and that the willingness and ability to contribute to the public good are affected by more external factors in the case of COVID-19 than in the case of the environment. For instance, adopting a more sustainable lifestyle is a personal and free decision that is arguably unaffected by other circumstances. Compliance with the corona warning app's request to go into home quarantine however might be affected by the individual's circumstances, e.g. whether they can work from home.

All in all, these findings suggest that our results concerning the contribution behavior in the experiment can be extended to contributions to actual public goods. Moreover, they corroborate our result that underlying social preferences affect strategic information acquisition: It appears that more selfish individuals with a lower willingness to contribute to an actual public good are indeed selecting the H-biased source, while more socially oriented individuals with a higher willingness to contribute are selecting the L-biased source.

[44] See appendix F for a detailed description of why these questions were selected and how the variables were constructed, as well as for an overview of all questions used.

[45] We additionally report the regression results for every single variable in appendix tables 25 – 28.

[46] The full table including the coefficients for all control variables is appendix table 21.

Table 5: OLS regression for the willingness to voluntarily contribute to COVID-19 containment, measured by four variables.

	Dependent variable:				
	willingness to contribute to COVID-19 containment				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	0.149	0.080	−0.058	−0.061	−0.051
	(0.107)	(0.115)	(0.093)	(0.100)	(0.101)
acquired signal σ_L	0.205**	0.133			
	(0.092)	(0.097)			
no signal acquired	0.117	−0.030	−0.078	−0.165	−0.145
	(0.144)	(0.152)	(0.132)	(0.142)	(0.147)
contributions	0.038***	0.021*	0.043***	0.025*	0.024*
	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)
Constant	−0.374***	−1.928***	−0.201**	−1.803***	−1.794***
	(0.111)	(0.224)	(0.100)	(0.254)	(0.255)
Difficulty	No	Yes	No	Yes	Yes
Comprehension	No	No	No	No	Yes
Controls	No	Yes	No	Yes	Yes
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,377	2,080	1,779	1,550	1,550
R^2	0.006	0.051	0.007	0.049	0.049
Adjusted R^2	0.005	0.046	0.005	0.043	0.043
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the first principle component of four variables capturing the willingness to voluntarily contribute to COVID-19 containment via usage of the corona warning app: (i) willingness to enter test results in the app, (ii) compliance with the app's request to get tested or (iii) to quarantine, and (iv) having installed the app. Higher levels of the dependent variable represent higher willingness to contribute to COVID-19 containment. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 euros. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly. The other control variables include gender, age, income, and education.

3.5 A Theoretical Model

In this section, we offer a potential theoretical explanation for the behavior observed in the experiment. In particular, we look for a model that can rationalize the fact that a majority of participants choose to open a silver envelope in our experiment. From our regression analysis we find that this tendency cannot be explained by participants holding different priors, which is the prediction of Che and Mierendorff (2019), for instance. In this model individuals gain utility directly from their own monetary payoff, and – depending on the strength of their efficiency concerns – also from the payoff of the other group members. Moreover, they may have self-image concerns: Each individual has a reference point for the optimal contribution, which is a level of contribution she believes the society expects from her. This conjecture is not new in the literature (see e.g. Grossman and van der Weele, 2016; Nyborg, 2011). Depending on the strength of her self-image concerns, the individual loses utility when her contribution does not match the reference point.

In the *info* treatment, participants first decide whether to acquire information and what type of information. Then having information at their disposal, they decide how much to contribute. Similarly, our model has two stages: information acquisition and contribution. In the following, we study it using a backward induction logic.

3.5.1 Contribution Stage

Consider the Voluntary Contribution Mechanism described in section 3.3. Suppose that the MPCR is ω and let $\hat{g}$ denote a given expected contribution by any other participant. Then the utility of an individual who contributes an amount g to the public good is:

$$U(g,\hat{g},\omega) = u(g,\hat{g},\omega) + \alpha\ v(g,\hat{g},\omega) + \frac{\gamma}{2}\ l(g,g^*)$$

where u is the utility from monetary payoff, v is the utility from others' expected welfare given all others' expected contribution $\hat{g}$ and the individual's own contribution g, and l is a loss function representing self-image concerns. In particular, the utility is decreasing in the difference between the contribution of individual and what the society expect her to contribute g^*. The parameters α, γ describe the individual's type: α is the relative importance of social welfare compared to individual welfare, whereas γ is the relative importance of self-image. Let n be the total number of participants in a group. We will assume the following functional forms:

$$\begin{aligned} u(g,\hat{g},\omega) &= e - (1-\omega)g + (n-1)\omega\hat{g} \\ v(g,\hat{g},\omega) &= (n-1)[e + [(n-1)\omega - 1]\hat{g} + \omega g] \\ l(g,g^*) &= -[g - g^*(\mu)]^2 \end{aligned}$$

We abstract from strategic considerations and therefore treat $\hat{g}$ as exogenous. The reference point $g^*(\mu)$ differs across individuals and is a function of beliefs μ. In particular, there are two types of individuals, L and H, and for each individual there are two possible reference points, $\bar{g}$ and $\underline{g}$, such that $0 \le \underline{g} < \bar{g} \le e$, and

$$g_L^*(\mu) = \begin{cases} \bar{g} & \text{if } \mu = 1 \\ \underline{g} & \text{otherwise} \end{cases} \qquad g_H^*(\mu) = \begin{cases} \underline{g} & \text{if } \mu = 0 \\ \bar{g} & \text{otherwise} \end{cases}$$

In words, each participant of type L feels socially obliged to contribute a higher amount $\bar{g}$ only if she is completely certain that it is socially efficient to contribute to the public good. In any other case, she will contribute $\underline{g}$. Instead, each participant of type H feels always contributes the high amount $\bar{g}$ unless she is completely certain that it is not socially efficient to contribute to the public good.

For a given belief μ, the expected utility of an individual is given by

$$\begin{aligned}\mathbb{E}[U(g,\hat{g},\mu)] &= \mu U(g,\hat{g},\omega_h) + (1-\mu)U(g,\hat{g},\omega_l)\\ &= e - [1-(\omega_l+\mu(\omega_h-\omega_l))]\, g + (n-1)\,(\omega_l+\mu(\omega_h-\omega_l))\,\hat{g}\\ &+ \alpha(n-1)\,\{e - [1-(n-1)\,(\omega_l+\mu(\omega_h-\omega_l))]\,\hat{g} + (\omega_l+\mu(\omega_h-\omega_l))\,g\}\\ &- \frac{\gamma}{2}\,[g-g^*(\mu)]^2\end{aligned}$$

The derivative of the expected utility with respect to the contribution g_i is:

$$\frac{\partial\mathbb{E}[U(g,\hat{g},\mu)]}{\partial g} = -[1-(\omega_l+\mu(\omega_h-\omega_l))] + \alpha(n-1)\,(\omega_l+\mu(\omega_h-\omega_l)) - \gamma\,[g-g^*(\mu)] \tag{25}$$

The optimal contribution is a function of beliefs μ:

$$g(\mu) = \min\left\{\max\left\{g^*(\mu) + \frac{1}{\gamma}\,[(1+\alpha(n-1))\,(\omega_l+\mu(\omega_h-\omega_l)) - 1]\,, 0\right\}, 10\right\} \tag{26}$$

3.5.2 Information Acquisition Stage

Consider an individual with a current belief μ. If this individual does not acquire any further information, her belief μ implies her optimal contribution $g(\mu)$ which yields an expected utility $\mathbb{E}[U(\mu)] \equiv \mathbb{E}[U(g(\mu),\hat{g},\mu)]$. Let μ'_H denote the updated belief after using the H-biased source and μ'_L the updated belief after using the L-biased source. If the individual uses the H-biased source, and receives the signal $\sigma_H = low$ (i.e. breakthrough news), she updates her belief to $\mu'_H = Pr(\omega=\omega_h|\sigma_H = low) = 0$. If she receives the signal $\sigma_H = high$, she updates her belief to

$$\mu'_H = Pr(\omega=\omega_h|\sigma_H = high) = \frac{2\mu}{1+\mu}$$

with $\mu'_H > \mu$ for all $\mu \in (0,1)$. Therefore, the expected utility from acquiring one unit of information from the H-biased source is

$$\mathbb{E}_{\sigma_H}[U(\mu'_H)] \equiv \left(\frac{1+\mu}{2}\right)\,\mathbb{E}[U(g(\mu'_H),\hat{g},\mu'_H)] + \left(\frac{1-\mu}{2}\right)\,U(g(0),\hat{g},0).$$

Analogously, when she uses the L-biased source and receives the signal $\sigma_L = high$ (i.e. breakthrough news), she updates her belief to $\mu'_L = Pr(\omega=\omega_h|\sigma_L = high) = 1$. If she receives the signal $\sigma_L = low$, she updates her belief to

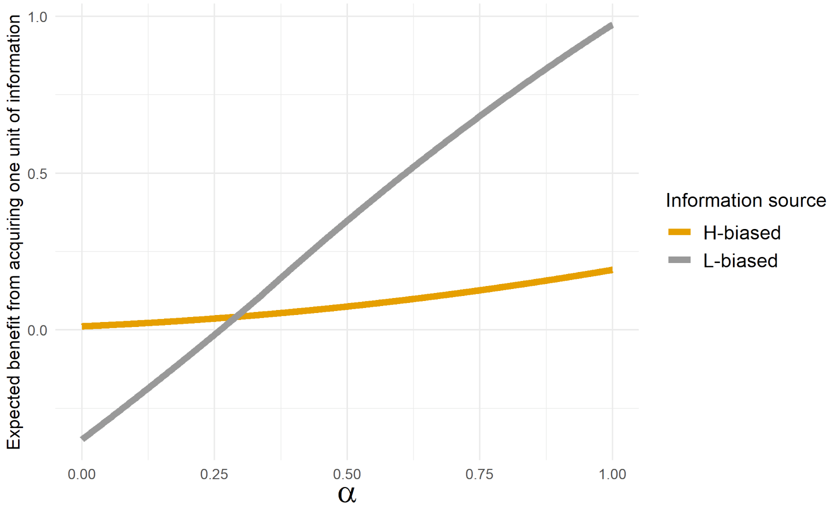
$$\mu'_L = Pr(\omega=\omega_h|\sigma_L = low) = \frac{\mu}{2-\mu}$$

with $\mu'_L < \mu$ for all $\mu \in (0,1)$. Therefore, the expected utility from acquiring one unit of information from the L-biased is

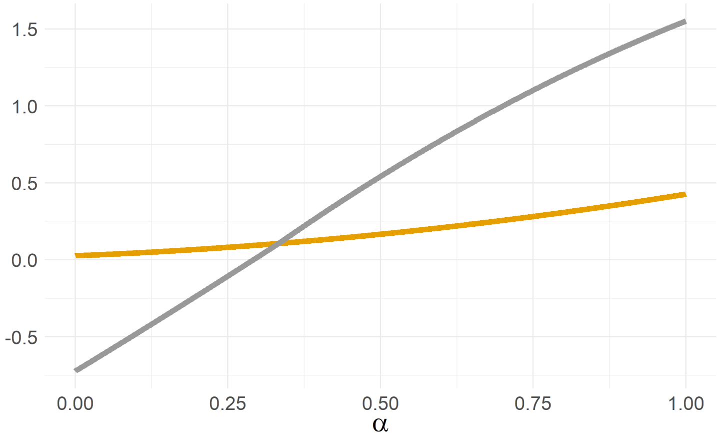
$$\mathbb{E}_{\sigma_L}[U(\mu'_L)] \equiv \left(1-\frac{\mu}{2}\right)\,\mathbb{E}[U((g(\mu'_L),\hat{g},\mu'_L)] + \frac{\mu}{2}\,U(g(1),\hat{g},1).$$

Then, compared to not acquiring further information, the expected gain from acquiring one unit of information from the H-biased source is given by $\phi_H \equiv \mathbb{E}_{\sigma_H}[U(\mu'_H)] - U(\mu)$ and the expected gain from acquiring one unit of information from the L-biased source

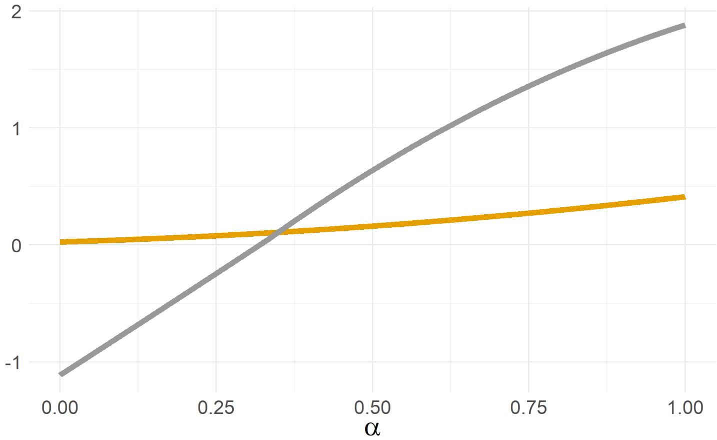
Figure 14: Net expected benefit from acquiring one unit of information from either source for type L.



(a) $\mu = 0.25$



(b) $\mu = 0.5$



(c) $\mu = 0.75$

We assume $\gamma = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$.

is given by $\phi_L \equiv \mathbb{E}_{\sigma_L}[U(\mu'_L)] - U(\mu)$. The comparison of these two expression allows to determine which information source an individual wants to acquire a signal from.

A selfish individual (i.e. with $\alpha = \gamma = 0$) contributes zero independent of her belief μ. Therefore, updating the belief is meaningless for her such that she is indifferent towards all costless information. As soon as information acquisition entails at least marginal costs $\varepsilon > 0$, she prefers to remain uninformed. Hence even a small attention cost is sufficient to rationalize information avoidance.

When $\alpha > 0$ but $\gamma = 0$, an individual cares at least to some extent of the payoff of the other participants, but does not have any self-image concerns. In that case, the optimal contribution is a step function: it is either zero or the entire endowment. Whether an individual desires to contribute the entire endowment depends on her belief about the MPCR. Therefore, there is scope for belief updating. Whether it is optimal to devote attention to the L-biased source or to the H-biased source however depends on the prior belief μ as well. Thus, such a model would predict information acquisition choices that vary with the prior belief, as in Che and Mierendorff (2019) – but this is in contrast with the findings from our experiment.

Once self-image concerns play a role as well, i.e. when $\alpha > 0$ and $\gamma > 0$, we can rationalize our finding that information acquisition choices are independent of prior beliefs, as well as the finding that choices are affected by social preferences. Figures 14 and 15 display the net expected gains in expected utility from acquiring one unit of information from each source for increasing values of the social preferences α for the L-Type and the H-type, respectively, assuming that the individuals have self-image concerns of intermediate strength.[47]

The figures illustrate two insights: On the one hand, an individual of type L will acquire information from the L-biased source if her social preferences α are sufficiently large. Figure 14 shows that for the L-type, the expected gains from information from either source are increasing in her social preference α, making information acquisition more valuable. For low levels of social preferences, the H-biased source is preferred, but it yields only very low expected gains. Thus, for sufficiently high information costs, such an individual might prefer not to acquire information. There exists a threshold of the level of social preferences such that when the social preferences are sufficiently strong to exceed this threshold, the L-type prefers the L-biased source. On the other hand, an individual of type H will always acquire information from the H-biased source: Figure 15 shows that for the H-type, the expected gains from the H-biased source always exceed the expected gains from the L-biased source.

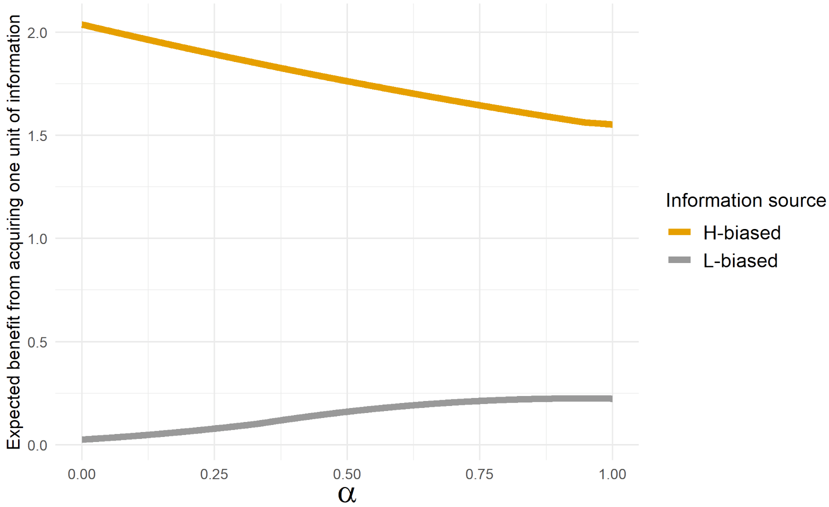
3.6 Conclusion

In this paper, we investigate whether strategic information acquisition can harm the provision of a public good. We find that the majority of participants acquires information that is biased towards low marginal returns, causing posterior beliefs to decline. Thus, average contributions decline and free-riding increases compared to the *no info* treatment. Moreover, we find that social preferences affect the information acquisition decision, such that more selfish participants are less likely to acquire information, and if they do so, they are more likely to acquire information that is biased towards high marginal returns than those who have more social preferences. They do so because this source might reveal that the marginal returns are low with certainty, thus allowing them to reduce their contributions.

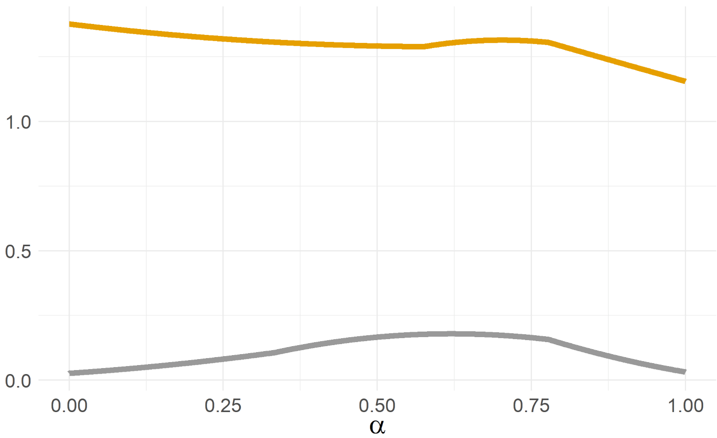
The fact that participants avoid information that compels them to behave more generously, while they strategically seek information that justifies selfish behavior has already

[47] The effects of varying the self-image concerns γ on the net gain in expected utility from acquiring one unit of information is displayed in appendix figure 16 for the L-type and in appendix figure 17 for the H-type.

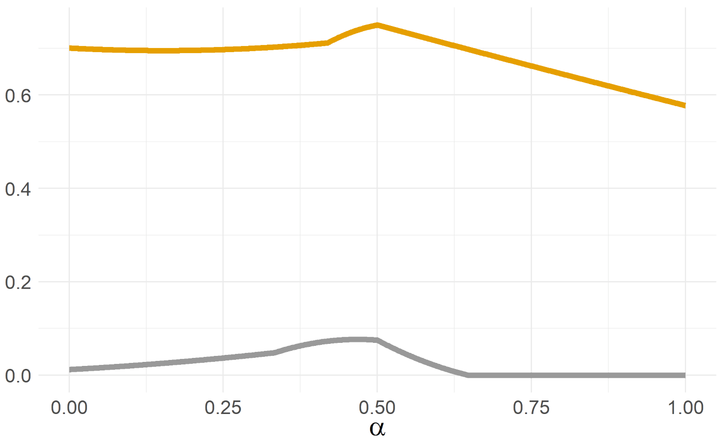
Figure 15: Net expected benefit from acquiring one unit of information from either source for type H.



(a) $\mu = 0.25$



(b) $\mu = 0.5$



(c) $\mu = 0.75$

We assume $\gamma = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$.

been documented in the literature about Dictator games. Observing the same behavior in a public good game has more far-reaching consequences. Social welfare in the Dictator Game is always equal to the endowment and therefore unaffected by the participants' actions. Instead, social welfare in the public good game depends directly on participants' actions. Therefore, we find that selective exposure leading to more selfish behavior has a detrimental effect on social welfare when contributions are required for efficiency.

Embedding our experiment in the GIP allows us to relate the preferences revealed in our incentivized experiment to self-reported field behavior. Thus, we contribute to the question of the external validity of experimental results (see e.g. Kerschbamer and Müller, 2020) and provide insights that are valuable beyond the abstract setting of our unframed experiment. In particular, we find robust evidence that the public good contributions in the experiment are correlated with the willingness to contribute to two actual public goods: environmental protection and COVID-19 containment. We also find that those who select different information sources in our experiment also differ in their willingness to contribute to environmental protection, which suggests that underlying social preferences indeed affect the information acquisition behavior.

All in all, our results show that more information is not always better. Compared to the case where no further information is available, strategic information acquisition can harm efficiency and social welfare. Therefore, a policymaker concerned with the provision of a public good that requires citizens' investments, such as the improvement of environmental quality or the containment of a virus, should take the information environment into account. Media diversity can be exploited by citizens to lower their contributions to a public good without suffering a loss in terms of their self-image. This leaves an open question for future research: How can desirable collective outcomes, such as the provision of a public good, be reached despite strategic information acquisition? Moreover, it might be the case that a policymaker is more informed about the actual state of the world than the citizens – e.g. because she is directly in contact with scientists – and that she might want to persuade citizens of her belief. How can she credibly convey her information, when other information sources might make different, unreliable claims? This question is especially relevant during times of low trust in governments and general skepticism towards science.

Acknowledgments

This article uses data from waves 38, 41, 44, 48, 49, and 52 of the German Internet Panel (DOIs: 10.4232/1.13391, 10.4232/1.13464, 10.4232/1.13614, 10.4232/1.13681, 10.4232/1.13682, 10.4232/1.13794), (Blom et al., 2019, 2020b,c, 2021b,c,d). A study description can be found in Blom et al. (2015). Moreover, this article uses data of the Mannheim Corona Study (MCS), (DOI: 10.4232/1.13700), (Blom et al., 2021a). A description of the MCS can be found in Blom et al. (2020a). The MCS is part of the German Internet Panel, which is part of the Collaborative Research Center 884 (SFB 884) funded by the German Research Foundation (DFG) – Project Number 139943784 – SFB 884. Additional funding for the MCS was provided by the German Federal Ministry for Labor and Social Affairs (BAMS).

C Additional Regression Tables

First, we provide the full regression tables that correspond to the shortened versions in section 3.4.2. Tables 6 and 7 report the marginal effects of the probit regressions for the information stage. Tables 8, 10 and 12 report the coefficients for the three-part model where the signal choice is the main explanatory variable, including a specification with interaction effects. Tables 9, 11 and 13 report the coefficients for the three-part model where the posterior belief is the main explanatory variable, including a specification with interaction effects. Table 14 shows the three-part model estimated separately on the subsets of those who acquired signal σ_H and those who acquired signal σ_L.

Then we present alternative model specifications. Table 15 reports the results of a multinomial logistic regression for the information acquisition decision. Table 16 and table 17 form a two-part hurdle model for the contribution decision. The probit regression in table 16 models the participation decision, i.e. the decision whether to contribute zero or a positive amount. The censored regression in table 17 models the amount decision among those who decide to contribute, i.e. those with $0 < g_i < 10$. Table 18 presents a two-limit Tobit model for the contribution decision, which is a censored regression on the complete sample that takes into account that contributions cannot be below 0 or above 10.

In section C.3, we explain how we selected the model for the contribution decision among the three possible models.

Finally we provide the additional regression tables for section 3.4.3. Tables 20 and 21 are the full tables corresponding to the shortened versions in section 3.4.3. Tables 22 – 28 present the regression results for the single variables employed in our main specifications separately. Tables 29 and 30 present the regression results for alternative specifications, in which further variables that capture willingness to contribute to environmental protection are added.

C.1 Regression Tables: Experimental Results

Table 6: Probit model for the decision to acquire information.

	Dependent variable:			
	acquired information			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.018	−0.012	−0.011	−0.012
	(0.015)	(0.014)	(0.014)	(0.014)
prior = 0.75	−0.011	−0.012	−0.007	−0.008
	(0.015)	(0.014)	(0.014)	(0.014)
own payoff		−0.033*	−0.029*	−0.028
		(0.017)	(0.017)	(0.017)
reciprocity		−0.131***	−0.095***	−0.094***
		(0.017)	(0.015)	(0.016)
own payoff and group payoff		0.070***	0.070***	0.070***
		(0.010)	(0.015)	(0.015)
own payoff and reciprocity		0.009	0.027	0.025
		(0.070)	(0.060)	(0.062)
group payoff and reciprocity		−0.129**	−0.134**	−0.134**
		(0.063)	(0.061)	(0.062)
own payoff, reciprocity, and group payoff		0.076***	0.084***	0.084***
		(0.007)	(0.008)	(0.008)
other motives		−0.165***	−0.141***	−0.141***
		(0.022)	(0.019)	(0.019)
no comprehension			−0.158***	−0.156***
			(0.011)	(0.011)
difficulty = 2				−0.001
				(0.018)
difficulty = 3				−0.001
				(0.017)
difficulty = 4				−0.038
				(0.024)
Constant	−	−	−	−
Observations	3,127	3,111	3,111	3,100
Log Likelihood	−1,216.005	−1,122.230	−1,023.089	−1,018.124
Note:			*p<0.1; **p<0.05; ***p<0.01	

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those in the *info* treatment. The dependent variable *acquired information* is a binary indicator variable which takes the value 1 if the participant chose to acquire either of the two signals, and the value 0 if the participant did not acquire any signal. *Prior* is a categorical variable with 0.5 as the reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

Table 7: Probit model for the decision to acquire signal σ_H among those who acquire information.

	Dependent variable:			
	acquired signal σ_H			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.018	−0.016	−0.018	−0.019
	(0.023)	(0.023)	(0.022)	(0.022)
prior = 0.75	−0.024	−0.023	−0.028	−0.030
	(0.022)	(0.022)	(0.022)	(0.022)
own payoff		0.084***	0.087***	0.092***
		(0.030)	(0.029)	(0.029)
reciprocity		0.045*	0.027	0.032
		(0.025)	(0.025)	(0.025)
own payoff and group payoff		0.015	0.046	0.044
		(0.041)	(0.041)	(0.040)
own payoff and reciprocity		−0.051	−0.070	−0.068
		(0.132)	(0.119)	(0.119)
group payoff and reciprocity		0.033	0.052	0.056
		(0.085)	(0.090)	(0.090)
own payoff, reciprocity, and group payoff		−0.114	−0.085	−0.071
		(0.105)	(0.111)	(0.111)
other motives		−0.038	−0.036	−0.036
		(0.028)	(0.028)	(0.028)
no comprehension			0.184***	0.189***
			(0.018)	(0.018)
difficulty = 2				−0.006
				(0.028)
difficulty = 3				−0.067**
				(0.028)
difficulty = 4				−0.078**
				(0.037)
Constant	−	−	−	−
Observations	2,716	2,707	2,707	2,697
Log Likelihood	−1,761.147	−1,747.780	−1,699.499	−1,685.868
Note:				*p<0.1; **p<0.05; ***p<0.01

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those in the *info* treatment. The dependent variable *acquired information* is a binary indicator variable which takes the value 1 if the participant chose to acquire either of the two signals, and the value 0 if the participant did not acquire any signal. *Prior* is a categorical variable with 0.5 as the reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

Table 8: Probit Model for the decision to contribute zero. Signal choice as main explanatory variable. With interactions.

	Dependent variable:			
	zero contribution			
	probit			
	(1)	(2)	(3)	(4)
info	0.196***			
	(0.070)			
prior = 0.25	0.200***	0.199***	0.170**	0.168
	(0.071)	(0.074)	(0.083)	(0.175)
prior = 0.75	0.130*	0.120	0.120	0.167
	(0.072)	(0.075)	(0.084)	(0.178)
acquired signal σ_H		−0.024	−0.011	0.034
		(0.091)	(0.104)	(0.183)
acquired signal σ_L		−0.074	−0.031	−0.061
		(0.080)	(0.093)	(0.172)
no signal acquired		1.047***	0.971***	1.037***
		(0.090)	(0.102)	(0.189)
own payoff			1.455***	1.462***
			(0.124)	(0.124)
reciprocity			1.038***	1.042***
			(0.117)	(0.118)
own payoff and group payoff			0.455**	0.457**
			(0.230)	(0.231)
own payoff and reciprocity			−2.956***	−2.997***
			(0.708)	(0.816)
group payoff and reciprocity			0.029	0.043
			(0.442)	(0.447)
all reasons			−2.647***	−2.645***
			(0.114)	(0.115)
other reasons			1.550***	1.550***
			(0.116)	(0.116)
difficulty = 2			−0.139	−0.142
			(0.098)	(0.098)
difficulty = 3			−0.076	−0.073
			(0.099)	(0.099)
difficulty = 4			−0.133	−0.133
			(0.135)	(0.137)
prior = 0.25 * acquired signal σ_H				0.057
				(0.248)
prior = 0.75 * acquired signal σ_H				−0.226
				(0.261)
prior = 0.25 * acquired signal σ_L				0.070
				(0.224)
prior = 0.75 * acquired signal σ_L				0.008
				(0.233)
prior = 0.25 * no signal acquired				−0.146
				(0.253)
prior = 0.75 * no signal acquired				−0.034
				(0.248)
Constant	−1.682***	−1.678***	−2.546***	−2.564***
	(0.076)	(0.077)	(0.134)	(0.170)
Observations	4,187	4,187	4,153	4,153
Log Likelihood	−1,141.922	−1,041.278	−861.967	−860.379
Note:			*p<0.1; **p<0.05; ***p<0.01	

Robust standard errors in parentheses. *Zero contribution* is a binary indicator variable which takes the value 1 if the participant did not contribute, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Signal choice* is a categorical variable with "no info treatment" as the omitted reference category.

Table 9: Probit Model for the decision to contribute zero. Posterior beliefs as main explanatory variable. With interactions.

	Dependent variable:			
	zero contribution			
	probit			
	(1)	(2)	(3)	(4)
info	0.196***			
	(0.070)			
prior = 0.25	0.200***	0.188**	0.168**	0.169
	(0.071)	(0.075)	(0.083)	(0.175)
prior = 0.75	0.130*	0.157**	0.147*	0.167
	(0.072)	(0.076)	(0.084)	(0.178)
posterior = 1		−0.254**	−0.097	−0.277
		(0.128)	(0.149)	(0.308)
posterior = 0		0.366***	0.343**	0.484**
		(0.124)	(0.136)	(0.220)
posterior increased		−0.242**	−0.224*	−0.363
		(0.109)	(0.127)	(0.246)
posterior reduced		−0.020	−0.015	−0.016
		(0.084)	(0.097)	(0.179)
no signal acquired		1.047***	0.970***	1.036***
		(0.090)	(0.102)	(0.189)
own payoff			1.446***	1.462***
			(0.126)	(0.126)
reciprocity			1.032***	1.038***
			(0.120)	(0.120)
own payoff and group payoff			0.476**	0.478**
			(0.232)	(0.234)
own payoff and reciprocity			−2.980***	−3.004***
			(0.455)	(0.795)
group payoff and reciprocity			0.029	0.044
			(0.446)	(0.451)
all reasons			−2.621***	−2.633***
			(0.119)	(0.120)
other reasons			1.540***	1.548***
			(0.117)	(0.118)
difficulty = 2			−0.131	−0.129
			(0.098)	(0.098)
difficulty = 3			−0.066	−0.057
			(0.099)	(0.099)
difficulty = 4			−0.125	−0.120
			(0.136)	(0.138)
prior = 0.25 * posterior = 1				0.289
				(0.424)
prior = 0.75 * posterior = 1				0.209
				(0.375)
prior = 0.25 * posterior = 0				−0.342
				(0.309)
prior = 0.75 * posterior = 0				0.004
				(0.371)
prior = 0.25 * posterior increased				0.417
				(0.317)
prior = 0.75 * posterior increased				−0.068
				(0.327)
prior = 0.25 * posterior reduced				0.020
				(0.231)
prior = 0.75 * posterior reduced				−0.034
				(0.250)
prior = 0.25 * no signal acquired				−0.148
				(0.253)
prior = 0.75 * no signal acquired				−0.034
				(0.248)
Constant	−1.682***	−1.687***	−2.555***	−2.573***
	(0.076)	(0.077)	(0.135)	(0.171)
Observations	4,187	4,187	4,153	4,153
Log Likelihood	−1,141.922	−1,030.113	−855.206	−851.004
Note:				*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. *Zero contribution* is a binary indicator variable which takes the value 1 if the participant did not contribute, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Posterior* is a categorical variable with "no info treatment" as the omitted reference category.

Table 10: Probit Model for the decision to contribute the entire endowment. Signal choice as main explanatory variable. With interactions.

	Dependent variable:			
	full contribution			
	probit			
	(1)	(2)	(3)	(4)
info	−0.169***			
	(0.046)			
prior = 0.25	−0.034	−0.030	−0.0002	−0.077
	(0.050)	(0.050)	(0.053)	(0.102)
prior = 0.75	0.088*	0.091*	0.105**	−0.026
	(0.050)	(0.050)	(0.052)	(0.102)
acquired signal σ_H		−0.083	−0.034	−0.065
		(0.058)	(0.062)	(0.105)
acquired signal σ_L		−0.174***	−0.153***	−0.313***
		(0.051)	(0.054)	(0.094)
no signal acquired		−0.368***	−0.066	−0.042
		(0.079)	(0.087)	(0.151)
own payoff			−0.443***	−0.441***
			(0.067)	(0.068)
reciprocity			−1.187***	−1.185***
			(0.069)	(0.069)
own payoff and group payoff			0.247***	0.248***
			(0.092)	(0.092)
own payoff and reciprocity			−4.867***	−4.862***
			(0.091)	(0.085)
group payoff and reciprocity			−0.572***	−0.569***
			(0.183)	(0.185)
all reasons			−0.058	−0.058
			(0.274)	(0.273)
other reasons			−0.608***	−0.608***
			(0.065)	(0.065)
difficulty = 2			−0.237***	−0.238***
			(0.058)	(0.058)
difficulty = 3			−0.379***	−0.378***
			(0.061)	(0.061)
difficulty = 4			−0.284***	−0.278***
			(0.093)	(0.093)
prior = 0.25 * acquired signal σ_H				0.025
				(0.151)
prior = 0.75 * acquired signal σ_H				0.065
				(0.151)
prior = 0.25 * acquired signal σ_L				0.174
				(0.131)
prior = 0.75 * acquired signal σ_L				0.301**
				(0.130)
prior = 0.25 * no signal acquired				0.016
				(0.212)
prior = 0.75 * no signal acquired				−0.084
				(0.210)
Constant	−0.393***	−0.395***	0.112*	0.180**
	(0.049)	(0.049)	(0.066)	(0.083)
Observations	4,187	4,187	4,153	4,153
Log Likelihood	−2,577.495	−2,571.111	−2,305.045	−2,301.016
Note:				*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. *Full contribution* is a binary indicator variable which takes the value 1 if the participant contributed the entire endowment, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Posterior* is a categorical variable with "no info treatment" as the omitted reference category.

Table 11: Probit Model for the decision to contribute the entire endowment. Posterior beliefs as main explanatory variable. With interactions.

	Dependent variable:			
	full contribution			
	probit			
	(1)	(2)	(3)	(4)
info	−0.169***			
	(0.046)			
prior = 0.25	−0.034	0.009	0.032	−0.077
	(0.050)	(0.051)	(0.054)	(0.101)
prior = 0.75	0.088*	0.043	0.067	−0.027
	(0.050)	(0.050)	(0.053)	(0.102)
posterior = 1		0.288***	0.216***	−0.001
		(0.071)	(0.074)	(0.131)
posterior = 0		−0.192**	−0.118	−0.135
		(0.094)	(0.102)	(0.168)
posterior increased		−0.047	−0.009	−0.041
		(0.063)	(0.067)	(0.114)
posterior reduced		−0.367***	−0.316***	−0.450***
		(0.055)	(0.059)	(0.103)
no signal acquired		−0.368***	−0.077	−0.052
		(0.079)	(0.087)	(0.150)
own payoff			−0.427***	−0.428***
			(0.068)	(0.068)
reciprocity			−1.162***	−1.160***
			(0.070)	(0.070)
own payoff and group payoff			0.221**	0.223**
			(0.092)	(0.093)
own payoff and reciprocity			−4.842***	−4.851***
			(0.097)	(0.098)
group payoff and reciprocity			−0.541***	−0.537***
			(0.184)	(0.186)
all reasons			−0.070	−0.088
			(0.267)	(0.270)
other reasons			−0.590***	−0.591***
			(0.065)	(0.065)
difficulty = 2			−0.243***	−0.245***
			(0.058)	(0.059)
difficulty = 3			−0.373***	−0.373***
			(0.061)	(0.061)
difficulty = 4			−0.267***	−0.264***
			(0.094)	(0.094)
prior = 0.25 * posterior = 1				0.403*
				(0.208)
prior = 0.75 * posterior = 1				0.293*
				(0.170)
prior = 0.25 * posterior = 0				0.047
				(0.228)
prior = 0.75 * posterior = 0				−0.038
				(0.294)
prior = 0.25 * posterior increased				0.026
				(0.168)
prior = 0.75 * posterior increased				0.065
				(0.159)
prior = 0.25 * posterior reduced				0.211
				(0.140)
prior = 0.75 * posterior reduced				0.191
				(0.146)
prior = 0.25 * no signal acquired				0.015
				(0.211)
prior = 0.75 * no signal acquired				−0.084
				(0.209)
Constant	−0.393***	−0.392***	0.109	0.176**
	(0.049)	(0.049)	(0.066)	(0.083)
Observations	4,187	4,187	4,153	4,153
Log Likelihood	−2,577.495	−2,527.262	−2,278.855	−2,275.053
Note:				*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. *Full contribution* is a binary indicator variable which takes the value 1 if the participant contributed the entire endowment, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Posterior* is a categorical variable with "no info treatment" as the omitted reference category.

Table 12: Truncated normal model on the sample with 0<gi<10. Signal choice as main explanatory variable. With interactions.

	Dependent variable:			
	contributions			
	Tobit			
	(1)	(2)	(3)	(4)
info	−0.648***			
	(0.083)			
prior = 0.25	0.030	0.038	0.098	−0.007
	(0.094)	(0.094)	(0.089)	(0.158)
prior = 0.75	0.145	0.149	0.168*	0.027
	(0.094)	(0.093)	(0.088)	(0.158)
acquired signal σ_H		−0.477***	−0.476***	−0.497***
		(0.108)	(0.102)	(0.166)
acquired signal σ_L		−0.645***	−0.619***	−0.744***
		(0.091)	(0.088)	(0.145)
no signal acquired		−1.191***	−0.969***	−1.292***
		(0.165)	(0.160)	(0.282)
own payoff			−0.927***	−0.934***
			(0.136)	(0.136)
reciprocity			−1.451***	−1.459***
			(0.086)	(0.086)
own payoff and group payoff			0.273	0.269
			(0.180)	(0.180)
own payoff and reciprocity			−1.762***	−1.738***
			(0.540)	(0.547)
group payoff and reciprocity			−0.293	−0.286
			(0.269)	(0.267)
all reasons			−1.030***	−1.028***
			(0.304)	(0.297)
other reasons			−1.005***	−1.012***
			(0.116)	(0.116)
difficulty = 2			0.201*	0.214*
			(0.114)	(0.114)
difficulty = 3			0.029	0.042
			(0.116)	(0.116)
difficulty = 4			0.014	0.045
			(0.161)	(0.161)
prior = 0.25 * acquired signal σ_H				−0.009
				(0.249)
prior = 0.75 * acquired signal σ_H				0.062
				(0.241)
prior = 0.25 * acquired signal σ_L				0.120
				(0.209)
prior = 0.75 * acquired signal σ_L				0.256
				(0.208)
prior = 0.25 * no signal acquired				0.706*
				(0.385)
prior = 0.75 * no signal acquired				0.197
				(0.387)
Constant	5.729***	5.725***	6.236***	6.310***
	(0.087)	(0.087)	(0.121)	(0.143)
Observations	2,567	2,567	2,544	2,544
Log Likelihood	−5,364.466	−5,354.735	−5,155.317	−5,152.238
Note:			*p<0.1; **p<0.05; ***p<0.01	

Robust standard errors in parentheses. The sample is the subsample of those who contributed $0 < g_i < 10$. The dependent variable is the contribution level. *Signal choice* is a categorical variable with "no info treatment" as the omitted reference category .

Table 13: Truncated normal model on the sample with 0<gi<10. Posterior beliefs as main explanatory variable. With interactions.

	Dependent variable:			
	contributions			
	Tobit			
	(1)	(2)	(3)	(4)
info	−0.648***			
	(0.083)			
prior = 0.25	0.030	0.106	0.150*	−0.009
	(0.094)	(0.093)	(0.089)	(0.158)
prior = 0.75	0.145	0.089	0.120	0.028
	(0.094)	(0.093)	(0.088)	(0.158)
posterior = 1		0.131	−0.018	−0.156
		(0.148)	(0.142)	(0.230)
posterior = 0		−0.884***	−0.832***	−0.825***
		(0.185)	(0.183)	(0.274)
posterior increased		−0.342***	−0.354***	−0.379**
		(0.117)	(0.109)	(0.179)
posterior reduced		−0.842***	−0.771***	−0.899***
		(0.095)	(0.092)	(0.151)
no signal acquired		−1.193***	−0.975***	−1.291***
		(0.165)	(0.160)	(0.282)
own payoff			−0.894***	−0.902***
			(0.135)	(0.134)
reciprocity			−1.413***	−1.422***
			(0.087)	(0.087)
own payoff and group payoff			0.266	0.255
			(0.176)	(0.176)
own payoff and reciprocity			−1.678***	−1.674***
			(0.558)	(0.560)
group payoff and reciprocity			−0.250	−0.250
			(0.263)	(0.264)
all reasons			−0.989***	−1.023***
			(0.296)	(0.296)
other reasons			−0.958***	−0.963***
			(0.116)	(0.115)
difficulty = 2			0.172	0.180
			(0.113)	(0.113)
difficulty = 3			0.008	0.009
			(0.115)	(0.114)
difficulty = 4			−0.004	0.019
			(0.159)	(0.159)
prior = 0.25 * posterior = 1				0.676
				(0.413)
prior = 0.75 * posterior = 1				0.047
				(0.310)
prior = 0.25 * posterior = 0				0.228
				(0.394)
prior = 0.75 * posterior = 0				−0.674
				(0.519)
prior = 0.25 * posterior increased				−0.070
				(0.274)
prior = 0.75 * posterior increased				0.103
				(0.252)
prior = 0.25 * posterior reduced				0.173
				(0.215)
prior = 0.75 * posterior reduced				0.238
				(0.222)
prior = 0.25 * no signal acquired				0.698*
				(0.385)
prior = 0.75 * no signal acquired				0.194
				(0.387)
Constant	5.729***	5.722***	6.232***	6.316***
	(0.087)	(0.087)	(0.121)	(0.142)
Observations	2,567	2,567	2,544	2,544
Log Likelihood	−5,364.466	−5,327.867	−5,136.760	−5,130.249
Note:				*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The sample is the subsample of those who contributed $0 < g_i < 10$. The dependent variable is the contribution level. *Posterior* is a categorical variable with "no info treatment" as the omitted reference category .

Table 14: Separate three-Part Models for those who acquired signal σ_H or signal σ_L.

	acquired signal σ_H			acquired signal σ_L		
	zero_contribution	contributions	full_contribution	zero_contribution	contributions	full_contribution
	probit	*Tobit*	*probit*	*probit*	*Tobit*	*probit*
	(1)	(2)	(3)	(4)	(5)	(6)
prior = 0.25	0.022	0.031	−0.008	0.019*	0.200	0.054**
	(0.017)	(0.193)	(0.036)	(0.012)	(0.137)	(0.025)
prior = 0.75	0.004	−0.014	0.007	0.016	0.201	0.057**
	(0.017)	(0.182)	(0.036)	(0.012)	(0.135)	(0.025)
posterior = 0	0.056***	−0.512***	−0.034			
	(0.019)	(0.195)	(0.035)			
posterior = 1				−0.010	0.753***	0.160***
				(0.012)	(0.145)	(0.025)
Constant	–	6.168***	–	–	5.215***	–
		(0.230)			(0.192)	
Motives	Yes	Yes	Yes	Yes	Yes	Yes
Difficulty	Yes	Yes	Yes	Yes	Yes	Yes
Observations	950	590	950	1,747	1,145	1,747
Log Likelihood	−158.828	−1,204.320	−550.716	−289.839	−2,341.271	−892.781

Note: *p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. Columns 1 – 3 present the three part model for the subset of those participants who acquired signal σ_H. Columns 4 – 6 present the three part model for the subset of those participants who acquired signal σ_L. Columns 1, 3, 4 and 6 report marginal effects. *Zero contribution* is a binary indicator variable which takes the value 1 if the participant did not contribute, and 0 otherwise. *Contributions* is the level of contributions (in euros) for the subset of participants who contributed an amount g_i with $0 < g_i < 10$. *Full contribution* is a binary indicator variable which takes the value 1 if the participant contributed the entire endowment, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Posterior* is a categorical variable with "increased posterior" as the omitted reference category when signal σ_H was acquired (columns 1-3), and "reduced posterior" omitted when signal σ_L was acquired (columns 4 – 6). The control variable *motives* captures the difference contribution motives, and *difficulty* captures the perceived difficulty of the entire questionnaire. The varying number of observations is caused by participants who did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

C.2 Alternative Models

In this section, we present the regression's results for different model specifications.

Table 15: Alternative model: Multinomial logit model for the information acquisition decision.

	Dependent variable:							
	signal σ_H	none	signal σ_H	none	signal σ_H	none	signal σ_H	none
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
prior = 0.25	−0.080	0.127	−0.081	0.101	−0.085	0.076	−0.094	0.078
	(0.098)	(0.135)	(0.099)	(0.139)	(0.100)	(0.147)	(0.101)	(0.147)
prior = 0.75	−0.106	0.061	−0.103	0.095	−0.128	0.026	−0.134	0.029
	(0.098)	(0.136)	(0.099)	(0.141)	(0.100)	(0.148)	(0.101)	(0.148)
own payoff			0.357***	0.537***	0.369***	0.563***	0.389***	0.559***
			(0.124)	(0.197)	(0.126)	(0.206)	(0.126)	(0.206)
reciprocity			0.199*	1.230***	0.106	1.025***	0.133	1.026***
			(0.108)	(0.145)	(0.111)	(0.153)	(0.111)	(0.153)
own payoff and group payoff			0.067	−2.528**	0.220	−2.117**	0.203	−2.127**
			(0.178)	(1.010)	(0.181)	(1.014)	(0.182)	(1.014)
own payoff and reciprocity			−0.244	−0.218	−0.351	−0.475	−0.328	−0.431
			(0.595)	(1.054)	(0.604)	(1.080)	(0.605)	(1.080)
group payoff and reciprocity			0.147	1.194***	0.211	1.352***	0.226	1.354***
			(0.355)	(0.409)	(0.359)	(0.438)	(0.360)	(0.438)
own payoff, reciprocity, and group payoff			−0.574	−11.547	−0.440	−10.937	−0.372	−11.102
			(0.570)	(243.138)	(0.576)	(213.374)	(0.576)	(214.963)
other motives			−0.176	1.296***	−0.217	1.241***	−0.200	1.236***
			(0.133)	(0.156)	(0.136)	(0.165)	(0.136)	(0.165)
no comprehension					0.836***	1.976***	0.855***	1.965***
					(0.085)	(0.130)	(0.086)	(0.131)
difficulty = 2							−0.032	−0.010
							(0.124)	(0.192)
difficulty = 3							−0.306**	−0.136
							(0.124)	(0.188)
difficulty = 4							−0.341**	0.171
							(0.173)	(0.230)
Constant	−0.549***	−1.519***	−0.615***	−2.152***	−0.902***	−3.094***	−0.755***	−3.052***
	(0.069)	(0.098)	(0.081)	(0.133)	(0.088)	(0.162)	(0.128)	(0.217)
Observations	3,127	3,127	3,111	3,111	3,100	3,100	3,100	3,100
AIC	5,966.304	5,966.304	5,779.635	5,779.635	5,461.605	5,461.605	5,457.775	5,457.775
Note:								*p<0.1; **p<0.05; ***p<0.01

The model is estimated on the subsample of those in the *info treatment*. The dependent variable is the information acquisition decision, with "signal σ_L" as the omitted reference category. *Prior* is a categorical variable with 0.5 as the omitted reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. AIC is the Akaike Information Criterion.

Table 16: Probit model for the decision to contribute zero.

	Dependent variable:				
	zero contribution				
	probit				
	(1)	(2)	(3)	(4)	(5)
info	0.026***				
	(0.009)				
prior = 0.25	0.029***	0.026***	0.019**	0.024**	0.018**
	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)
prior = 0.75	0.018*	0.015	0.013	0.020**	0.016*
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
acquired signal σ_H		−0.003	−0.001		
		(0.010)	(0.010)		
acquired signal σ_L		−0.008	−0.003		
		(0.009)	(0.009)		
no signal acquired		0.242***	0.164***	0.242***	0.165***
		(0.024)	(0.019)	(0.024)	(0.019)
posterior = 1				−0.024**	−0.009
				(0.011)	(0.013)
posterior = 0				0.056**	0.042**
				(0.022)	(0.018)
posterior increased				−0.023**	−0.019*
				(0.010)	(0.010)
posterior reduced				−0.002	−0.001
				(0.010)	(0.010)
own payoff			0.156***		0.154***
			(0.017)		(0.017)
reciprocity			0.077***		0.076***
			(0.009)		(0.009)
own payoff and group payoff			0.019		0.020
			(0.013)		(0.013)
own payoff and reciprocity			−0.011***		−0.011***
			(0.003)		(0.003)
group payoff and reciprocity			0.001		0.001
			(0.012)		(0.012)
own payoff, reciprocity, and group payoff			−0.011***		−0.011***
			(0.003)		(0.003)
other motives			0.179***		0.176***
			(0.015)		(0.015)
difficulty = 2			−0.016		−0.015
			(0.012)		(0.011)
difficulty = 3			−0.009		−0.008
			(0.012)		(0.012)
difficulty = 4			−0.015		−0.014
			(0.015)		(0.015)
Constant	–	–	–	–	–
Observations	4,187	4,187	4,153	4,187	4,153
Log Likelihood	−1,141.922	−1,041.278	−861.967	−1,030.113	−855.206
Note:					*p<0.1; **p<0.05; ***p<0.01

All columns report marginal effects, with robust standard errors in parentheses. *Zero contribution* is a binary indicator variable which takes the value 1 if the participant did not contribute, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Signal choice* and *posterior* are categorical variables with "no info treatment" as the omitted reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, with the level 1 (not difficult) as the omitted reference category. The varying number of observations is caused by participants who did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

Table 17: Alternative model: Censored regression on the sample with $0 < g_i \leq 10$.

	Dependent variable:				
	contributions				
	Tobit				
	(1)	(2)	(3)	(4)	(5)
info	−0.889***				
	(0.147)				
prior = 0.25	0.003	0.010	0.119	0.166	0.231
	(0.157)	(0.157)	(0.144)	(0.155)	(0.143)
prior = 0.75	0.420***	0.424***	0.430***	0.243	0.297**
	(0.159)	(0.159)	(0.145)	(0.157)	(0.144)
acquired signal σ_H		−0.594***	−0.433**		
		(0.185)	(0.170)		
acquired signal σ_L		−0.989***	−0.814***		
		(0.159)	(0.147)		
no signal acquired		−1.224***	−0.403	−1.226***	−0.443*
		(0.283)	(0.268)	(0.280)	(0.266)
posterior = 1				0.909***	0.587***
				(0.241)	(0.221)
posterior = 0				−1.045***	−0.831***
				(0.306)	(0.292)
posterior increased				−0.444**	−0.309*
				(0.198)	(0.181)
posterior reduced				−1.624***	−1.289***
				(0.163)	(0.152)
own payoff			−1.479***		−1.403***
			(0.214)		(0.211)
reciprocity			−3.536***		−3.400***
			(0.135)		(0.135)
own payoff and group payoff			1.000***		0.902***
			(0.302)		(0.296)
own payoff and reciprocity			−4.415***		−4.190***
			(0.548)		(0.595)
group payoff and reciprocity			−1.660***		−1.524***
			(0.423)		(0.415)
own payoff, reciprocity, and group payoff			−0.871		−0.874
			(0.809)		(0.769)
other motives			−1.847***		−1.748***
			(0.191)		(0.188)
difficulty = 2			−0.544***		−0.563***
			(0.181)		(0.178)
difficulty = 3			−1.002***		−0.981***
			(0.183)		(0.181)
difficulty = 4			−0.811***		−0.767***
			(0.265)		(0.262)
Constant	8.186***	8.180***	9.677***	8.164***	9.623***
	(0.159)	(0.158)	(0.203)	(0.157)	(0.200)
Observations	3,859	3,859	3,831	3,859	3,831
Log Likelihood	−8,303.484	−8,299.542	−7,909.705	−8,235.291	−7,868.041
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The model is estimated on the subsample of those who contributed $0 < g_i \leq 10$, such that the sample is truncated from below and censored from above. The dependent variable is the contribution level. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Signal choice* and *posterior* are categorical variables with "no info treatment" as the omitted reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, with the level 1 (not difficult) as the omitted reference category. The varying number of observations is caused by participants who did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

Table 18: Alternative model: Two-limit Tobit model on the entire sample.

	Dependent variable:				
	contributions				
	Tobit				
	(1)	(2)	(3)	(4)	(5)
info	−1.168***				
	(0.181)				
prior = 0.25	−0.309	−0.263	−0.067	−0.083	0.054
	(0.191)	(0.189)	(0.171)	(0.187)	(0.170)
prior = 0.75	0.221	0.252	0.290*	0.029	0.132
	(0.194)	(0.190)	(0.171)	(0.188)	(0.170)
acquired signal σ_H		−0.552**	−0.420**		
		(0.223)	(0.202)		
acquired signal σ_L		−0.896***	−0.796***		
		(0.191)	(0.175)		
no signal acquired		−3.762***	−2.434***	−3.738***	−2.466***
		(0.346)	(0.316)	(0.343)	(0.314)
posterior = 1				1.251***	0.698***
				(0.291)	(0.265)
posterior = 0				−1.601***	−1.247***
				(0.371)	(0.341)
posterior increased				−0.181	−0.134
				(0.236)	(0.214)
posterior reduced				−1.605***	−1.291***
				(0.196)	(0.181)
own payoff			−3.048***		−2.943***
			(0.263)		(0.259)
reciprocity			−4.312***		−4.170***
			(0.164)		(0.165)
own payoff and group payoff			0.831**		0.715**
			(0.354)		(0.347)
own payoff and reciprocity			−4.658***		−4.392***
			(0.570)		(0.622)
group payoff and reciprocity			−1.707***		−1.575***
			(0.477)		(0.468)
own payoff, reciprocity, and group payoff			−0.948		−0.970
			(0.902)		(0.859)
other motives			−3.793***		−3.663***
			(0.237)		(0.235)
difficulty = 2			−0.424**		−0.454**
			(0.214)		(0.211)
difficulty = 3			−0.927***		−0.917***
			(0.217)		(0.214)
difficulty = 4			−0.693**		−0.663**
			(0.314)		(0.311)
Constant	7.999***	7.950***	10.031***	7.942***	9.981***
	(0.192)	(0.189)	(0.240)	(0.187)	(0.237)
Observations	4,187	4,187	4,153	4,187	4,153
Log Likelihood	−9,311.650	−9,248.869	−8,780.779	−9,189.193	−8,744.930
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the contribution level. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Signal choice* and *posterior* are categorical variables with "no info treatment" as the omitted reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, with the level 1 (not difficult) as the omitted reference category. The varying number of observations is caused by participants who did not answer the question about the contribution motives or the question about the difficulty of the questionnaire.

C.3 Model Selection

To select the best model between the 3-part model, the 2-part model, and the simple two-limit Tobit model, we compared the models according to their value of the log-Likelihood function. Moreover, to select the best specification of explanatory variables we compared the models according to the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Note that the log-Likelihood of the 3-part and 2-part models is calculated by adding up the log-Likelihood of the separate parts. Table 19 displays the values of the log-Likelihood and the information criteria for the specifications of explanatory variables we employed. Column 1 is the basic specification containing only prior beliefs and the information treatment dummy as explanatory variables. Instead of the information treatment, columns 2 and 3 employ the signal choice, while columns 4 and 5 employ the posterior beliefs. Columns 3 and 5 add contribution motives and difficulty as control variables.

Table 19 shows that the 3-part model clearly provides the best model fit for each specification. Concerning the specification of explanatory variables, including signal choices or posterior beliefs improves the model fit compared to the model with the information treatment dummy. Adding contribution motives and difficulty as control variables further improves the model fit. The preferred model is the 3-part model in column 5, which contains prior and posterior beliefs as main explanatory variables, and contribution motives and difficulty as control variables.

Table 19: Model comparison

		Model specification				
		(1)	(2)	(3)	(4)	(5)
log-Likelihood	3-part model	−9,083.882	−8,967.124	−8,322.329	−8,885.242	−8,270.821
	2-part model	−9,445.405	−9,340.820	−8,771.672	−9,265.404	−8,723.246
	two-limit Tobit	−9,311.650	−9,248.869	−8,780.779	−9,189.193	−8,744.930
AIC	3-part model	18,177.760	17,948.250	16,678.660	17,788.480	16,579.640
	2-part model	18,900.810	18,695.640	17,577.340	18,548.810	17,484.490
	two-limit Tobit	18,633.300	18,511.740	17,595.560	18,396.380	17,527.860
BIC	3-part model	18,209.460	17,992.630	16,786.300	17,845.540	16,699.940
	2-part model	18,932.510	18,740.020	17,684.980	18,605.870	17,604.790
	two-limit Tobit	18,665.000	18,556.120	17,703.190	18,453.440	17,648.160

Comparison of model fit according to the value of the log-Likelihood function, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The 3-part model consists of a probit model for zero contributions, a probit for full contributions and a truncated normal model for the contribution level on the subsample of those who contributed $0 < g_i < 10$, which is truncated from below and above. The 2-part model consists of a probit model for zero contributions, and a censored regression model for the contribution level on the subsample of those who contributed $0 < g_i \leq 10$, which is truncated from below and censored from above. The two-limit Tobit model is a censored regression model for contributions on the entire sample. The model specification includes *info* and *prior* as explanatory variables in column 1, *prior* and *signal choice* in column 2, *prior*, *signal choice*, *motives* and *difficulty* in column 3, *prior* and *posterior* in column 4, and *prior*, *posterior*, *motives* and *difficulty* in column 5.

C.4 Regression Tables: Additional Results

Table 20: OLS regression for the willingness to voluntarily contribute to environmental protection, measured by 3 variables.

	Dependent variable:				
	willingness to contribute to environmental protection				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	−0.135**	−0.097	−0.263***	−0.198***	−0.178***
	(0.066)	(0.070)	(0.061)	(0.065)	(0.066)
acquired signal σ_L	0.132**	0.107*			
	(0.059)	(0.062)			
no signal acquired	0.014	0.089	−0.136	−0.037	0.004
	(0.101)	(0.107)	(0.097)	(0.104)	(0.106)
contributions	0.029***	0.029***	0.020**	0.020**	0.018*
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
difficult = 2		−0.016		−0.030	−0.030
		(0.074)		(0.094)	(0.094)
difficult = 3		0.120		0.106	0.108
		(0.077)		(0.095)	(0.095)
difficult = 4		0.039		0.087	0.094
		(0.112)		(0.128)	(0.128)
no comprehension					−0.096
					(0.065)
female		0.360***		0.376***	0.376***
		(0.051)		(0.060)	(0.060)
age		0.003		0.003	0.004*
		(0.002)		(0.002)	(0.002)
income		−0.00000		0.00000	0.00000
		(0.00002)		(0.00002)	(0.00002)
academic education		0.502***		0.551***	0.543***
		(0.056)		(0.067)	(0.068)
Constant	−0.211***	−0.691***	−0.023	−0.609***	−0.592***
	(0.072)	(0.145)	(0.070)	(0.169)	(0.169)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,892	2,450	2,154	1,820	1,820
R^2	0.011	0.064	0.011	0.069	0.070
Adjusted R^2	0.010	0.060	0.009	0.064	0.065
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the first principle component of three variables capturing the willingness to contribute to environmental protection: *lifestyle changes*, *support carbon tax*, and *sustainable activities*. Higher levels of the dependent variable represent higher willingness to contribute to environmental protection. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the info treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 21: OLS regression for the willingness to voluntarily contribute to COVID-19 containment, measured by 4 variables.

	Dependent variable:				
	willingness to contribute to COVID-19 containment				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	0.149	0.080	−0.058	−0.061	−0.051
	(0.107)	(0.115)	(0.093)	(0.100)	(0.101)
acquired signal σ_L	0.205**	0.133			
	(0.092)	(0.097)			
no signal acquired	0.117	−0.030	−0.078	−0.165	−0.145
	(0.144)	(0.152)	(0.132)	(0.142)	(0.147)
contributions	0.038***	0.021*	0.043***	0.025*	0.024*
	(0.012)	(0.013)	(0.013)	(0.014)	(0.014)
difficult = 2		0.111		0.196	0.195
		(0.120)		(0.150)	(0.150)
difficult = 3		0.196		0.210	0.210
		(0.120)		(0.148)	(0.149)
difficult = 4		0.118		0.310*	0.316*
		(0.170)		(0.187)	(0.188)
no comprehension					−0.052
					(0.095)
female		0.162**		0.186**	0.187**
		(0.077)		(0.087)	(0.087)
age		0.021***		0.019***	0.020***
		(0.003)		(0.003)	(0.003)
income		0.0001***		0.0001***	0.0001***
		(0.00002)		(0.00003)	(0.00003)
academic education		0.255***		0.183*	0.178*
		(0.083)		(0.097)	(0.097)
Constant	−0.374***	−1.928***	−0.201**	−1.803***	−1.794***
	(0.111)	(0.224)	(0.100)	(0.254)	(0.255)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,377	2,080	1,779	1,550	1,550
R^2	0.006	0.051	0.007	0.049	0.049
Adjusted R^2	0.005	0.046	0.005	0.043	0.043
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the first principle component of four variables capturing the willingness to voluntarily contribute to COVID-19 containment via usage of the corona warning app: *app installed*, *app test results*, *app compliance test*, and *app compliance quarantine*. Higher levels of the dependent variable represent higher willingness to contribute to COVID-19 containment. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly. Other control variables include gender, age, income, and education.

Table 22: OLS regression for the support for a carbon tax.

	Dependent variable:				
	support for carbon tax				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	−0.085	−0.024	−0.162***	−0.090	−0.065
	(0.068)	(0.073)	(0.062)	(0.066)	(0.068)
acquired signal σ_L	0.078	0.069			
	(0.059)	(0.063)			
no signal acquired	0.080	0.206**	−0.009	0.120	0.172*
	(0.095)	(0.099)	(0.090)	(0.094)	(0.097)
contributions	0.024***	0.022***	0.019**	0.017*	0.015
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
difficult = 2		0.005		−0.028	−0.027
		(0.075)		(0.095)	(0.095)
difficult = 3		0.104		0.069	0.072
		(0.077)		(0.094)	(0.094)
difficult = 4		0.063		0.063	0.072
		(0.109)		(0.124)	(0.125)
no comprehension					−0.121*
					(0.065)
female		0.191***		0.212***	0.211***
		(0.051)		(0.060)	(0.060)
age		0.001		0.002	0.003
		(0.002)		(0.002)	(0.002)
income		0.00000		0.00000	0.00000
		(0.00002)		(0.00002)	(0.00002)
academic education		0.657***		0.692***	0.681***
		(0.056)		(0.066)	(0.066)
Constant	2.858***	2.466***	2.968***	2.493***	2.513***
	(0.071)	(0.141)	(0.066)	(0.162)	(0.162)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,899	2,456	2,159	1,825	1,825
R^2	0.006	0.070	0.005	0.073	0.075
Adjusted R^2	0.004	0.066	0.004	0.068	0.069
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the answer to the question whether the participants supports or opposes a carbon tax. It is measured on a scale from 1 to 5 and re-coded such that higher values refer to higher levels of support. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 23: OLS regression for lifestyle changes to protect the climate.

	Dependent variable:				
	lifestyle changes				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	−0.102*	−0.065	−0.143***	−0.091*	−0.107*
	(0.057)	(0.062)	(0.051)	(0.055)	(0.057)
acquired signal σ_L	0.043	0.029			
	(0.051)	(0.055)			
no signal acquired	0.021	−0.025	−0.033	−0.063	−0.094
	(0.079)	(0.087)	(0.074)	(0.083)	(0.086)
contributions	0.007	0.012*	0.002	0.006	0.007
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
difficult = 2		−0.069		−0.056	−0.056
		(0.062)		(0.078)	(0.078)
difficult = 3		0.064		0.078	0.076
		(0.065)		(0.079)	(0.079)
difficult = 4		−0.009		0.053	0.047
		(0.095)		(0.107)	(0.107)
no comprehension					0.075
					(0.055)
female		0.291***		0.274***	0.275***
		(0.044)		(0.051)	(0.051)
age		0.002		0.001	0.001
		(0.001)		(0.002)	(0.002)
income		−0.00005***		−0.00004***	−0.00004***
		(0.00001)		(0.00002)	(0.00002)
academic education		0.064		0.072	0.078
		(0.048)		(0.056)	(0.056)
Constant	2.546***	2.456***	2.623***	2.513***	2.500***
	(0.061)	(0.125)	(0.056)	(0.141)	(0.142)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,899	2,456	2,159	1,825	1,825
R^2	0.003	0.031	0.004	0.028	0.029
Adjusted R^2	0.002	0.027	0.002	0.023	0.023
Note:				*p<0.1; **p<0.05; ***p<0.01	

Robust standard errors in parentheses. The dependent variable is the answer to the question whether the participants changed their lifestyle in the past six months to protect the climate. It is measured on a scale from 1 to 5 and re-coded such that higher values refer to higher levels of lifestyle changes. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 24: OLS regression for sustainable activities.

	Dependent variable:				
	sustainable activities				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	−0.085	−0.102	−0.223***	−0.212***	−0.178***
	(0.058)	(0.063)	(0.054)	(0.058)	(0.058)
acquired signal σ_L	0.141***	0.116**			
	(0.052)	(0.056)			
no signal acquired	−0.080	0.010	−0.237***	−0.120	−0.051
	(0.094)	(0.098)	(0.092)	(0.095)	(0.097)
contributions	0.028***	0.023***	0.019**	0.016*	0.013
	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)
difficult = 2		0.030		0.014	0.014
		(0.067)		(0.085)	(0.085)
difficult = 3		0.080		0.062	0.066
		(0.069)		(0.085)	(0.085)
difficult = 4		0.032		0.057	0.069
		(0.098)		(0.114)	(0.114)
no comprehension					−0.163***
					(0.058)
female		0.248***		0.279***	0.278***
		(0.046)		(0.054)	(0.054)
age		0.002		0.003*	0.004**
		(0.002)		(0.002)	(0.002)
income		0.00004***		0.0001***	0.0001***
		(0.00001)		(0.00002)	(0.00002)
academic education		0.362***		0.418***	0.405***
		(0.051)		(0.060)	(0.060)
Constant	3.424***	2.900***	3.616***	2.975***	3.004***
	(0.066)	(0.132)	(0.066)	(0.156)	(0.156)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,899	2,454	2,160	1,824	1,824
R^2	0.013	0.054	0.012	0.063	0.067
Adjusted R^2	0.012	0.049	0.011	0.058	0.061
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the answer to the multiple-choice question which activities related to sustainability they pursued at least once in the past six months. It is measured on a scale from 1 to 8, where higher values refer to higher number of activities pursued. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 25: Probit regression for the probability of having the corona warning app installed between June 19 and July 10, 2020.

	Dependent variable:				
	app installed				
	probit				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	0.003	−0.029	−0.032	−0.014	0.003
	(0.070)	(0.077)	(0.063)	(0.069)	(0.071)
acquired signal σ_L	0.035	−0.018			
	(0.061)	(0.067)			
no signal acquired	−0.107	−0.057	−0.139	−0.044	−0.008
	(0.093)	(0.104)	(0.087)	(0.098)	(0.102)
contributions	0.032***	0.021**	0.033***	0.023**	0.021**
	(0.008)	(0.009)	(0.009)	(0.010)	(0.010)
difficult = 2		−0.037		−0.013	−0.012
		(0.074)		(0.093)	(0.093)
difficult = 3		−0.025		−0.010	−0.009
		(0.077)		(0.093)	(0.093)
difficult = 4		0.111		0.216*	0.227*
		(0.110)		(0.124)	(0.124)
no comprehension					−0.091
					(0.067)
female		−0.008		−0.003	−0.001
		(0.053)		(0.062)	(0.062)
age		−0.003*		−0.003	−0.003
		(0.002)		(0.002)	(0.002)
income		0.0001***		0.0001***	0.0001***
		(0.00002)		(0.00002)	(0.00002)
academic education		0.159***		0.130*	0.123*
		(0.057)		(0.067)	(0.067)
Constant	−0.283***	−0.486***	−0.257***	−0.526***	−0.513***
	(0.072)	(0.147)	(0.067)	(0.168)	(0.168)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,730	2,374	2,035	1,762	1,762
Log Likelihood	−1,875.901	−1,592.717	−1,396.374	−1,183.573	−1,182.641
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant installed the corona warning app at some point between June 19 and July 10, 2020. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 26: OLS regression for willingness to enter positive test results in the corona warning app.

	Dependent variable:				
	app test results				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	0.059	0.004	−0.071	−0.075	−0.060
	(0.095)	(0.103)	(0.084)	(0.091)	(0.092)
acquired signal σ_L	0.127	0.075			
	(0.082)	(0.088)			
no signal acquired	0.102	−0.004	−0.010	−0.077	−0.045
	(0.128)	(0.138)	(0.119)	(0.130)	(0.134)
contributions	0.038***	0.028**	0.047***	0.035***	0.034***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
difficult = 2		0.067		0.102	0.101
		(0.106)		(0.135)	(0.135)
difficult = 3		0.136		0.125	0.126
		(0.107)		(0.133)	(0.133)
difficult = 4		0.073		0.267	0.275
		(0.156)		(0.170)	(0.170)
no comprehension					−0.080
					(0.086)
female		0.104		0.109	0.111
		(0.070)		(0.081)	(0.080)
age		0.014***		0.013***	0.014***
		(0.002)		(0.003)	(0.003)
income		0.0001***		0.0001**	0.0001**
		(0.00002)		(0.00003)	(0.00003)
academic education		0.216***		0.188**	0.181**
		(0.075)		(0.089)	(0.089)
Constant	3.720***	2.696***	3.794***	2.747***	2.763***
	(0.100)	(0.201)	(0.091)	(0.231)	(0.232)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,683	2,337	2,010	1,744	1,744
R^2	0.006	0.029	0.008	0.029	0.030
Adjusted R^2	0.004	0.024	0.007	0.024	0.024
Note:			*p<0.1; **p<0.05; ***p<0.01		

Robust standard errors in parentheses. The dependent variable the answer to the question whether the participant would enter their test results in the corona warning app if they got tested positively for the virus. It is measured on a scale from 0 to 5, and re-coded such that higher levels indicate higher willingness to enter test results, while a value of 0 means that the participant did not want to install the app. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 27: OLS regression for compliance with the corona warning app's request to go into home quarantine.

	Dependent variable:				
	app compliance quarantine				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	0.081	0.042	0.009	0.002	0.012
	(0.091)	(0.097)	(0.081)	(0.086)	(0.087)
acquired signal σ_L	0.070	0.034			
	(0.079)	(0.083)			
no signal acquired	0.123	−0.033	0.067	−0.065	−0.045
	(0.125)	(0.133)	(0.117)	(0.125)	(0.128)
contributions	0.031***	0.020*	0.038***	0.026**	0.025**
	(0.010)	(0.011)	(0.012)	(0.012)	(0.012)
difficult = 2		0.019		0.085	0.085
		(0.101)		(0.130)	(0.130)
difficult = 3		0.094		0.121	0.122
		(0.102)		(0.128)	(0.128)
difficult = 4		0.082		0.227	0.232
		(0.147)		(0.162)	(0.163)
no comprehension					−0.052
					(0.082)
female		0.172***		0.174**	0.175**
		(0.066)		(0.077)	(0.077)
age		0.025***		0.024***	0.024***
		(0.002)		(0.002)	(0.002)
income		0.0001**		0.00004*	0.00004*
		(0.00002)		(0.00002)	(0.00002)
academic education		0.162**		0.111	0.106
		(0.072)		(0.084)	(0.085)
Constant	3.366***	1.811***	3.387***	1.846***	1.856***
	(0.096)	(0.186)	(0.088)	(0.215)	(0.216)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,683	2,338	2,009	1,744	1,744
R^2	0.004	0.062	0.006	0.059	0.059
Adjusted R^2	0.002	0.057	0.004	0.053	0.053
Note:				*p<0.1; **p<0.05; ***p<0.01	

Robust standard errors in parentheses. The dependent variable the answer to the question whether the participant would comply with the corona warning app's request to go into home quarantine. It is measured on a scale from 0 to 5, and re-coded such that higher levels indicate higher willingness to comply, while a value of 0 means that the participant did not want to install the app. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 28: OLS regression for compliance with the corona warning app's request to get tested.

	Dependent variable:				
	app compliance test				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	0.079	0.031	−0.057	−0.056	−0.041
	(0.094)	(0.101)	(0.083)	(0.089)	(0.090)
acquired signal σ_L	0.134*	0.084			
	(0.081)	(0.086)			
no signal acquired	0.118	−0.031	−0.013	−0.126	−0.094
	(0.127)	(0.135)	(0.118)	(0.126)	(0.130)
contributions	0.035***	0.023**	0.037***	0.023*	0.022*
	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)
difficult = 2		0.047		0.104	0.103
		(0.104)		(0.132)	(0.132)
difficult = 3		0.152		0.168	0.169
		(0.105)		(0.130)	(0.131)
difficult = 4		0.041		0.194	0.202
		(0.152)		(0.167)	(0.168)
no comprehension					−0.079
					(0.084)
female		0.148**		0.150*	0.152*
		(0.068)		(0.079)	(0.079)
age		0.021***		0.021***	0.021***
		(0.002)		(0.003)	(0.003)
income		0.0001***		0.0001**	0.0001**
		(0.00002)		(0.00003)	(0.00003)
academic education		0.181**		0.136	0.128
		(0.074)		(0.088)	(0.088)
Constant	3.616***	2.237***	3.738***	2.319***	2.335***
	(0.099)	(0.194)	(0.090)	(0.223)	(0.224)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,683	2,338	2,010	1,745	1,745
R^2	0.005	0.047	0.005	0.045	0.046
Adjusted R^2	0.004	0.043	0.004	0.040	0.040
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable the answer to the question whether the participant would comply with the corona warning app's request to get tested. It is measured on a scale from 0 to 5, and re-coded such that higher levels indicate higher willingness to comply, while a value of 0 means that the participant did not want to install the app. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the *info* treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 29: Alternative specification: OLS regression for the willingness to voluntarily contribute to environmental protection, measured by 5 variables.

	Dependent variable:				
	willingness to contribute to environmental protection				
	(1)	(2)	(3)	(4)	(5)
acquired signal sigma H	−0.079	−0.042	−0.240***	−0.172**	−0.146*
	(0.080)	(0.086)	(0.074)	(0.080)	(0.081)
acquired signal sigma L	0.164**	0.135*			
	(0.072)	(0.076)			
no signal acquired	0.071	0.131	−0.110	−0.024	0.029
	(0.123)	(0.133)	(0.118)	(0.128)	(0.131)
contributions	0.028***	0.032***	0.020*	0.023*	0.021*
	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)
difficult = 2		−0.081		−0.098	−0.098
		(0.092)		(0.116)	(0.116)
difficult = 3		0.115		0.097	0.100
		(0.095)		(0.117)	(0.117)
difficult = 4		0.073		0.110	0.119
		(0.141)		(0.160)	(0.160)
no comprehension					−0.127
					(0.079)
female		0.341***		0.355***	0.354***
		(0.063)		(0.074)	(0.074)
age		0.0004		0.001	0.002
		(0.002)		(0.002)	(0.002)
income		−0.00005**		−0.00004*	−0.00004*
		(0.00002)		(0.00002)	(0.00002)
academic education		0.645***		0.694***	0.683***
		(0.070)		(0.084)	(0.085)
Constant	−0.237***	−0.491***	−0.019	−0.376*	−0.354*
	(0.088)	(0.176)	(0.086)	(0.207)	(0.208)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	2,891	2,449	2,154	1,820	1,820
R^2	0.007	0.056	0.006	0.059	0.060
Adjusted R^2	0.005	0.052	0.005	0.054	0.055
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the first principle component of five variables capturing the willingness to contribute to environmental protection: *lifestyle changes*, *support carbon tax*, *sustainable activities*, *importance emission reductions*, and *would demonstrate/demonstrated.* Higher levels of the dependent variable represent higher willingness to contribute to environmental protection. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the info treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

Table 30: OLS regression for the willingness to voluntarily contribute to environmental protection, measured by 8 variables.

	Dependent variable:				
	willingness to contribute to environmental protection				
	(1)	(2)	(3)	(4)	(5)
acquired signal σ_H	−0.058	−0.017	−0.363***	−0.299**	−0.272*
	(0.137)	(0.147)	(0.132)	(0.143)	(0.147)
acquired signal σ_L	0.306**	0.276**			
	(0.129)	(0.133)			
no signal acquired	0.136	0.306	−0.175	0.010	0.059
	(0.231)	(0.240)	(0.228)	(0.239)	(0.246)
contributions	0.050***	0.057***	0.047**	0.050**	0.049**
	(0.017)	(0.018)	(0.020)	(0.022)	(0.022)
difficult = 2		−0.0002		0.046	0.052
		(0.153)		(0.198)	(0.199)
difficult = 3		0.233		0.200	0.209
		(0.159)		(0.202)	(0.202)
difficult = 4		−0.036		−0.031	−0.015
		(0.243)		(0.273)	(0.275)
no comprehension					−0.105
					(0.145)
female		0.570***		0.556***	0.556***
		(0.111)		(0.134)	(0.134)
age		0.003		0.005	0.005
		(0.004)		(0.004)	(0.004)
income		−0.0001**		−0.0001**	−0.0001**
		(0.00003)		(0.00004)	(0.00004)
academic education		0.870***		0.827***	0.817***
		(0.120)		(0.146)	(0.147)
Constant	−0.440***	−1.014***	−0.115	−0.752**	−0.735**
	(0.148)	(0.289)	(0.158)	(0.335)	(0.336)
Info treatment subsample	No	No	Yes	Yes	Yes
Observations	1,110	961	819	712	712
R^2	0.015	0.093	0.014	0.081	0.081
Adjusted R^2	0.011	0.082	0.011	0.068	0.067
Note:					*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. The dependent variable is the first principle component of eight variables capturing the willingness to contribute to environmental protection: *lifestyle changes*, *support carbon tax*, *sustainable activities*, *importance emission reductions*, *would demonstrate/demonstrated*, *environmentally friendly products*, *energy consumption*, and *donation atmosfair*. Higher levels of the dependent variable represent higher willingness to contribute to environmental protection. Columns 1 and 2 present the regression results for the entire sample. The omitted reference category for information acquisition is "*no info* treatment". Columns 3 – 5 present the regression results for the subsample of those in the info treatment. The omitted reference category for information acquisition is "acquired signal σ_L". *Contributions* is the level of contribution to the public good in the experiment, and takes values from 0 to 10 Euro. The control variable *difficulty* captures the perceived difficulty of the entire questionnaire, and *comprehension* captures whether the participant answered the comprehension question correctly.

D Robustness Checks

In this appendix, we provide several robustness checks to our regression analysis.

First, we repeat the analysis using only the subsample of those participants who did not indicate that they found the questionnaire difficult. The question has four levels, ranging from 1 (not difficult) to 4 (very difficult), and we drop those from the sample who answered 3 (difficult) or 4 (very difficult). This leaves us with a reduced sample size of 2,356 participants. Table 31 and 32 report the marginal effects of the probit estimations for the information stage. Table 33 reports the three-part model for the contribution stage.

Second, we utilize the response times contained in our data set, which capture how much time a participant spent on each question page, including the reading time for the instructions. Since very short response times might indicate a lack of interest, while very long response times might indicate confusion, we drop from the sample the bottom 10% and top 10% with respect to the time spent on the instructions for the Voluntary Contribution Mechanism. The remaining sample contains 3,358 participants. Table 34 and 35 report the marginal effects of the probit estimations for the information stage. Table 36 reports the three-part model for the contribution stage.

Third, we repeat the analysis for the information stage with the subsample of those participants who answered the comprehension question about the information revelation process correctly. The size of the remaining sample is 1,879. Table 37 and 38 report the marginal effects of the respective probit estimations. Because only those in the *info* treatment answered the comprehension question, we cannot use this restriction as a robustness check for the analysis of the contribution stage.

Table 31: Robustness check: Probit Model for the decision to acquire information, on the subset of those who did not find the questionnaire difficult.

	Dependent variable:			
	acquired information			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.026	−0.021	−0.023	−0.023
	(0.020)	(0.020)	(0.019)	(0.019)
prior = 0.75	−0.012	−0.010	−0.003	−0.003
	(0.019)	(0.019)	(0.018)	(0.018)
own payoff		−0.069**	−0.058**	−0.058**
		(0.027)	(0.025)	(0.025)
reciprocity		−0.118***	−0.079***	−0.079***
		(0.025)	(0.021)	(0.021)
own payoff and group payoff		0.068***	0.074***	0.074***
		(0.009)	(0.010)	(0.010)
own payoff and reciprocity		0.068***	0.074***	0.074***
		(0.009)	(0.010)	(0.010)
group payoff and reciprocity		−0.116	−0.109	−0.109
		(0.087)	(0.071)	(0.071)
own payoff, reciprocity, and group payoff		0.068***	0.074***	0.074***
		(0.009)	(0.010)	(0.010)
other motives		−0.156***	−0.146***	−0.146***
		(0.030)	(0.028)	(0.028)
no comprehension			−0.151***	−0.151***
			(0.015)	(0.015)
difficulty = 2				−0.002
				(0.017)
Constant				
Observations	1,598	1,589	1,589	1,589
Log Likelihood	−575.936	−528.418	−477.021	−477.014
Note:				*p<0.1; **p<0.05; ***p<0.01

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those in the *info* treatment, excluding those who indicated that they found the questionnaire difficult or very difficult. The dependent variable *acquired information* is a binary indicator variable which takes the value 1 if the participant chose to acquire either of the two signals, and the value 0 if the participant did not acquire any signal. *Prior* is a categorical variable with 0.5 as the reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives.

Table 32: Robustness check: Probit Model for the decision to acquire signal σ_H among those who acquire information, on the subset of those who did not find the questionnaire difficult.

	Dependent variable:			
	acquired signal σ_H			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.022	−0.019	−0.014	−0.014
	(0.032)	(0.032)	(0.032)	(0.032)
prior = 0.75	−0.049	−0.046	−0.048	−0.048
	(0.032)	(0.032)	(0.031)	(0.031)
own payoff		0.097**	0.102**	0.101**
		(0.043)	(0.042)	(0.042)
reciprocity		0.051	0.035	0.035
		(0.036)	(0.036)	(0.036)
own payoff and group payoff		0.078	0.115**	0.115**
		(0.054)	(0.053)	(0.053)
own payoff and reciprocity		−0.060	−0.076	−0.075
		(0.204)	(0.195)	(0.196)
group payoff and reciprocity		−0.017	0.019	0.019
		(0.121)	(0.131)	(0.131)
own payoff, reciprocity, and group payoff		−0.063	0.001	0.001
		(0.201)	(0.212)	(0.212)
other motives		−0.018	−0.005	−0.004
		(0.041)	(0.041)	(0.041)
no comprehension			0.189***	0.189***
			(0.026)	(0.026)
difficulty=2				−0.007
				(0.028)
Constant				
Observations	1,411	1,405	1,405	1,405
Log Likelihood	−932.189	−924.791	−900.547	−900.513
Note:				*p<0.1; **p<0.05; ***p<0.01

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those who acquired information, excluding those who indicated that they found the questionnaire difficult or very difficult. The dependent variable is a binary indicator variable which takes the value 1 if the participant acquired signal σ_H, and the value 0 if the participant acquired signal σ_L. *Prior* is a categorical variable with 0.5 as the reference category. *Own payoff*, *reciprocity* and *further motives* belong to the same categorical variable which captures the motives behind the contribution decision, with *group payoff* as omitted reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives.

Table 33: Robustness check: Three-Part Model for contributions, on the subset of those who did not find the questionnaire difficult.

	Dependent variable:								
	zero contribution			contributions			full contribution		
	probit			*Tobit*			*probit*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
info	0.027**			−0.635***			−0.050**		
	(0.011)			(0.108)			(0.021)		
prior = 0.25	0.029**	0.023*	0.022*	−0.020	0.048	0.109	−0.012	0.001	0.012
	(0.013)	(0.012)	(0.012)	(0.129)	(0.121)	(0.121)	(0.024)	(0.023)	(0.023)
prior = 0.75	0.017	0.014	0.015	0.142	0.169	0.097	0.042*	0.045**	0.027
	(0.012)	(0.011)	(0.012)	(0.131)	(0.124)	(0.124)	(0.024)	(0.023)	(0.023)
acquired signal sigma H		0.006			−0.536***			−0.028	
		(0.012)			(0.134)			(0.026)	
acquired signal sigma L		−0.002			−0.632***			−0.045**	
		(0.011)			(0.115)			(0.022)	
no signal acquired		0.167***	0.167***		−0.951***	−0.967***		−0.035	−0.038
		(0.027)	(0.027)		(0.243)	(0.243)		(0.040)	(0.040)
posterior = 1			−0.002			0.066			0.103***
			(0.018)			(0.191)			(0.033)
posterior = 0			0.045*			−0.955***			−0.047
			(0.023)			(0.245)			(0.043)
posterior increased			−0.012			−0.391***			−0.021
			(0.013)			(0.144)			(0.028)
posterior reduced			−0.002			−0.816***			−0.111***
			(0.011)			(0.123)			(0.024)
Constant				5.838***	6.268***	6.267***			
				(0.110)	(0.138)	(0.137)			
Motives	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Difficulty	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	2,356	2,345	2,345	1,361	1,353	1,353	2,356	2,345	2,345
Log Likelihood	−597.493	−445.437	−442.119	−2,851.381	−2,743.034	−2,730.719	−1,521.987	−1,358.922	−1,338.370
Note:									*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. Columns 1-3 and 7-9 report marginal effects. The sample excludes those who indicated that they found the questionnaire difficult or very difficult. *Zero contribution* is a binary indicator variable which takes the value 1 if the participant did not contribute, and 0 otherwise. *Contributions* is the level of contributions for the subset of participants who contributed an amount g_i with $0 < g_i < 10$. *Full contribution* is a binary indicator variable which takes the value 1 if the participant contributed the entire endowment, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Signal choice* and *posterior* are categorical variables with "no info treatment" as the omitted reference category. The control variable *motives* captures the difference contribution motives, and *difficulty* captures the perceived difficulty of the entire questionnaire.

Table 34: Robustness check: Probit Model for the decision to acquire information, on the subset of those with neither too short nor too long response times.

	Dependent variable:			
	acquired information			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.012	−0.007	−0.006	−0.007
	(0.016)	(0.015)	(0.015)	(0.015)
prior = 0.75	−0.0004	−0.0002	0.003	0.003
	(0.016)	(0.015)	(0.015)	(0.015)
own payoff		−0.028	−0.026	−0.026
		(0.019)	(0.019)	(0.019)
reciprocity		−0.114***	−0.088***	−0.086***
		(0.019)	(0.017)	(0.017)
own payoff and group payoff		0.069***	0.074***	0.075***
		(0.008)	(0.008)	(0.008)
own payoff and reciprocity		−0.014	0.001	−0.002
		(0.087)	(0.077)	(0.080)
group payoff and reciprocity		−0.116*	−0.121*	−0.120*
		(0.065)	(0.062)	(0.064)
own payoff, reciprocity, and group payoff		0.069***	0.074***	0.075***
		(0.008)	(0.008)	(0.008)
other motives		−0.155***	−0.133***	−0.133***
		(0.023)	(0.021)	(0.021)
no comprehension			−0.135***	−0.132***
			(0.012)	(0.012)
difficulty = 2				−0.008
				(0.019)
difficulty = 3				−0.007
				(0.018)
difficulty = 4				−0.057**
				(0.027)
Constant				
Observations	2,507	2,495	2,495	2,486
Log Likelihood	−903.743	−832.472	−768.560	−762.929
Note:				*p<0.1; **p<0.05; ***p<0.01

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those in the *info* treatment, excluding the bottom 10% and top 10% with respect to the time spent on the instructions for the Voluntary Contribution Mechanism. The dependent variable *acquired information* is a binary indicator variable which takes the value 1 if the participant chose to acquire either of the two signals, and the value 0 if the participant did not acquire any signal. *Prior* is a categorical variable with 0.5 as the reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives.

Table 35: Robustness check: Probit Model for the decision to acquire signal σ_H among those who acquire information on the subset of those with neither too short nor too long response times.

	Dependent variable:			
	acquired signal σ_H			
	probit			
	(1)	(2)	(3)	(4)
prior = 0.25	−0.025	−0.024	−0.025	−0.026
	(0.025)	(0.025)	(0.025)	(0.025)
prior = 0.75	−0.017	−0.015	−0.021	−0.022
	(0.025)	(0.025)	(0.024)	(0.024)
own payoff		0.116***	0.117***	0.121***
		(0.034)	(0.033)	(0.033)
reciprocity		0.049*	0.034	0.041
		(0.028)	(0.028)	(0.028)
own payoff and group payoff		0.053	0.075*	0.072
		(0.045)	(0.045)	(0.044)
own payoff and reciprocity		0.043	0.032	0.048
		(0.163)	(0.146)	(0.144)
group payoff and reciprocity		−0.001	0.021	0.020
		(0.088)	(0.094)	(0.093)
own payoff, reciprocity, and group payoff		−0.055	−0.022	−0.016
		(0.123)	(0.127)	(0.125)
other motives		−0.026	−0.024	−0.025
		(0.031)	(0.030)	(0.030)
no comprehension			0.169***	0.173***
			(0.020)	(0.020)
difficulty = 2				0.009
				(0.031)
difficulty = 3				−0.071**
				(0.031)
difficulty = 4				−0.046
				(0.042)
Constant				
Observations	2,214	2,207	2,207	2,199
Log Likelihood	−1,427.314	−1,414.192	−1,381.272	−1,368.495
Note:		*p<0.1; **p<0.05; ***p<0.01		

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those who acquired information, excluding the bottom 10% and top 10% with respect to the time spent on the instructions for the Voluntary Contribution Mechanism. The dependent variable is a binary indicator variable which takes the value 1 if the participant acquired signal σ_H, and the value 0 if the participant acquired signal σ_L. *Prior* is a categorical variable with 0.5 as the reference category. *Own payoff*, *reciprocity* and *further motives* belong to the same categorical variable which captures the motives behind the contribution decision, with *group payoff* as omitted reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 4 is reduced because some participants did not answer the question about the contribution motives.

Table 36: Robustness check: Three-Part Model for contributions on the subset of those with neither too short nor too long response times.

	Dependent variable:								
	zero contribution			contributions			full contribution		
	probit			*Tobit*			*probit*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
info	0.028***			−0.628***			−0.081***		
	(0.009)			(0.091)			(0.019)		
prior = 0.25	0.021**	0.012	0.012	0.037	0.105	0.162*	−0.012	0.002	0.015
	(0.011)	(0.010)	(0.009)	(0.102)	(0.097)	(0.097)	(0.019)	(0.019)	(0.019)
prior = 0.75	0.010	0.008	0.011	0.084	0.117	0.076	0.018	0.024	0.011
	(0.010)	(0.009)	(0.010)	(0.103)	(0.096)	(0.096)	(0.020)	(0.019)	(0.019)
acquired signal sigma H		0.009			−0.422***			−0.026	
		(0.011)			(0.112)			(0.023)	
acquired signal sigma L		−0.0004			−0.637***			−0.063***	
		(0.009)			(0.096)			(0.019)	
no signal acquired		0.156***	0.156***		−1.019***	−1.026***		−0.046	−0.050
		(0.021)	(0.021)		(0.185)	(0.185)		(0.032)	(0.032)
posterior = 1			−0.008			−0.034			0.076***
			(0.014)			(0.159)			(0.028)
posterior = 0			0.060***			−0.754***			−0.047
			(0.021)			(0.208)			(0.037)
posterior increased			−0.012			−0.313***			−0.020
			(0.011)			(0.119)			(0.025)
posterior reduced			0.001			−0.779***			−0.118***
			(0.010)			(0.100)			(0.020)
Constant				5.848***	6.274***	6.268***			
				(0.095)	(0.131)	(0.131)			
Motives	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Difficulty	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	3,358	3,331	3,331	2,066	2,047	2,047	3,358	3,331	3,331
Log Likelihood	−816.598	−604.496	−596.635	−4,271.504	−4,111.645	−4,097.144	−2,089.464	−1,870.752	−1,843.865
Note:									*p<0.1; **p<0.05; ***p<0.01

Robust standard errors in parentheses. Columns 1-3 and 7-9 report marginal effects. The sample excludes the bottom 10% and top 10% with respect to the time spent on the instructions for the Voluntary Contribution Mechanism. *Zero contribution* is a binary indicator variable which takes the value 1 if the participant did not contribute, and 0 otherwise. *Contributions* is the level of contributions for the subset of participants who contributed an amount g_i with $0 < g_i < 10$. *Full contribution* is a binary indicator variable which takes the value 1 if the participant contributed the entire endowment, and 0 otherwise. *Prior* is a categorical variable with 0.5 as the omitted reference category. *Signal choice* and *posterior* are categorical variables with "no info treatment" as the omitted reference category. The control variable *motives* captures the difference contribution motives, and *difficulty* captures the perceived difficulty of the entire questionnaire.

Table 37: Robustness check: Probit Model for the decision to acquire information on the subset of those who answered the comprehension question correctly.

	Dependent variable:		
	acquired information		
	probit		
	(1)	(2)	(3)
prior = 0.25	−0.013	−0.012	−0.014
	(0.013)	(0.012)	(0.013)
prior = 0.75	−0.008	−0.008	−0.009
	(0.012)	(0.012)	(0.012)
own payoff		0.006	0.007
		(0.015)	(0.015)
reciprocity		−0.029*	−0.027*
		(0.016)	(0.016)
own payoff and group payoff		0.039***	0.039***
		(0.011)	(0.011)
own payoff and reciprocity		0.047***	0.047***
		(0.007)	(0.007)
group payoff and reciprocity		−0.059	−0.060
		(0.060)	(0.060)
own payoff, reciprocity, and group payoff		0.047***	0.047***
		(0.007)	(0.007)
other motives		−0.034*	−0.035*
		(0.019)	(0.019)
difficulty = 2			0.007
			(0.016)
difficulty = 3			−0.001
			(0.016)
difficulty = 4			−0.032
			(0.027)
Constant			
Observations	1,879	1,875	1,869
Log Likelihood	−387.146	−377.233	−375.217
Note:	*p<0.1; **p<0.05; ***p<0.01		

All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those in the *info* treatment, excluding those who did not answer the comprehension question correctly. The dependent variable *acquired information* is a binary indicator variable which takes the value 1 if the participant chose to acquire either of the two signals, and the value 0 if the participant did not acquire any signal. *Prior* is a categorical variable with 0.5 as the reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff*. The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 3 is reduced because some participants did not answer the question about the contribution motives.

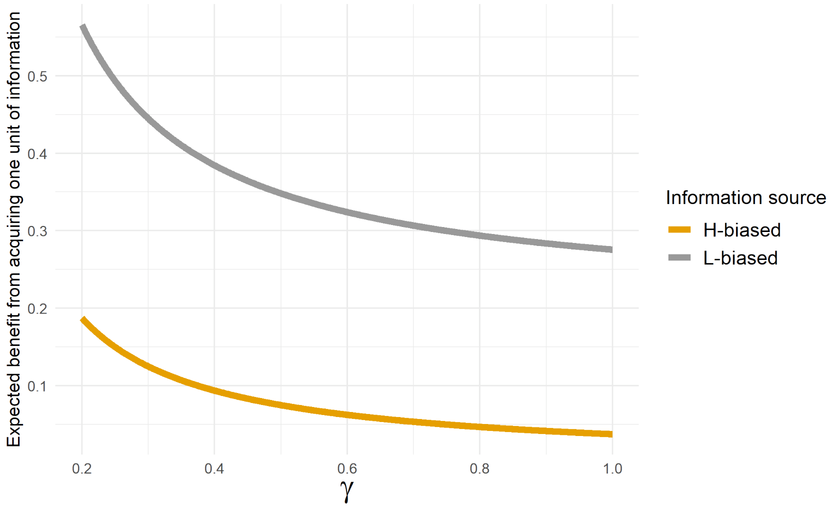
Table 38: Robustness check: Probit Model for the decision to acquire signal σ_H among those who acquire information on the subset of those who answered the comprehension question correctly.

	Dependent variable:		
	acquired signal σ_H		
	probit		
	(1)	(2)	(3)
prior = 0.25	−0.018	−0.015	−0.018
	(0.026)	(0.026)	(0.026)
prior = 0.75	−0.030	−0.027	−0.030
	(0.026)	(0.026)	(0.026)
own payoff		0.075**	0.082**
		(0.035)	(0.035)
reciprocity		0.063**	0.068**
		(0.032)	(0.032)
own payoff and group payoff		0.038	0.031
		(0.044)	(0.043)
own payoff and reciprocity		−0.145	−0.145
		(0.133)	(0.130)
group payoff and reciprocity		0.155	0.153
		(0.102)	(0.102)
own payoff, reciprocity, and group payoff		−0.067	−0.059
		(0.112)	(0.114)
other motives		−0.033	−0.035
		(0.032)	(0.032)
difficulty = 2			−0.005
			(0.034)
difficulty = 3			−0.069**
			(0.033)
difficulty = 4			−0.100**
			(0.046)
Constant			
Observations	1,780	1,776	1,770
Log Likelihood	−1,065.574	−1,055.703	−1,046.086
Note:			*p<0.1; **p<0.05; ***p<0.01

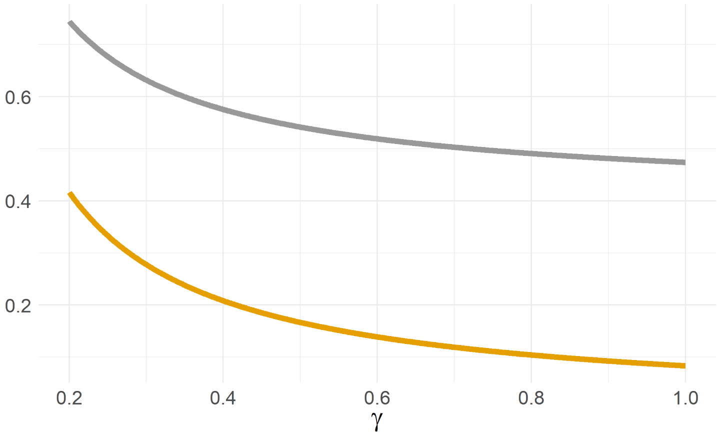
All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those who acquired information, excluding those who did not answer the comprehension question correctly. The dependent variable is a binary indicator variable which takes the value 1 if the participant acquired signal σ_H, and the value 0 if the participant acquired signal σ_L. *Prior* is a categorical variable with 0.5 as the reference category. *Own payoff*, *reciprocity* and *further motives* belong to the same categorical variable which captures the motives behind the contribution decision, with *group payoff* as omitted reference category. The omitted reference category of the categorical variable capturing contribution motives is *group payoff.* The control variable *comprehension* captures whether the participant answered the comprehension question correctly, and *difficulty* captures the perceived difficulty of the entire questionnaire. The number of observations in columns 2 – 3 is reduced because some participants did not answer the question about the contribution motives.

E Additional Figures

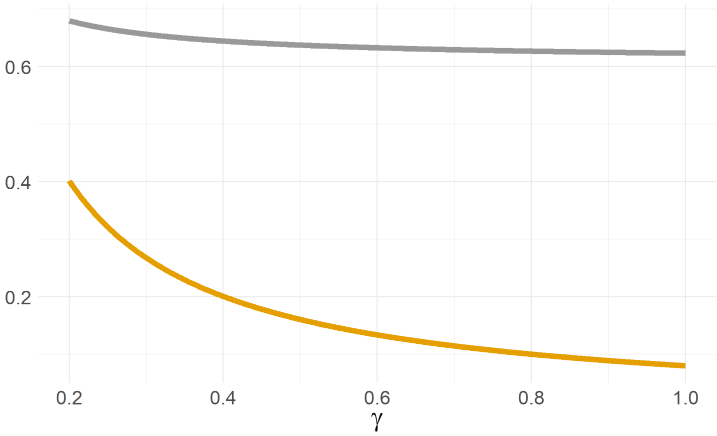
Figure 16: Net expected benefit from acquiring one unit of information from either source for type L.



(a) $\mu = 0.25$



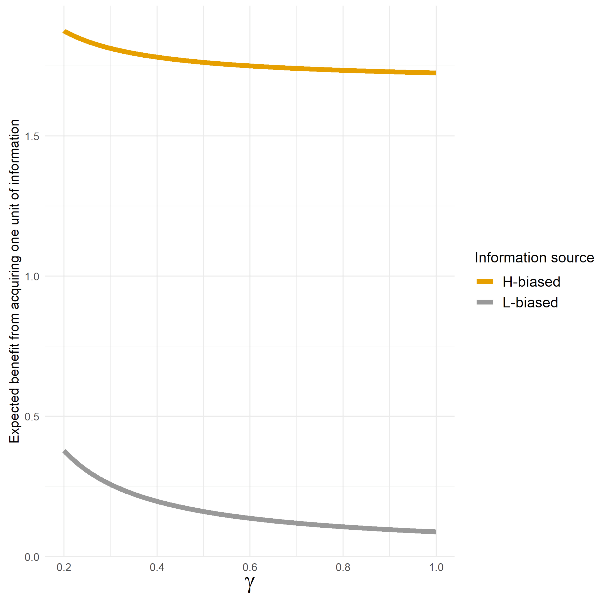
(b) $\mu = 0.5$



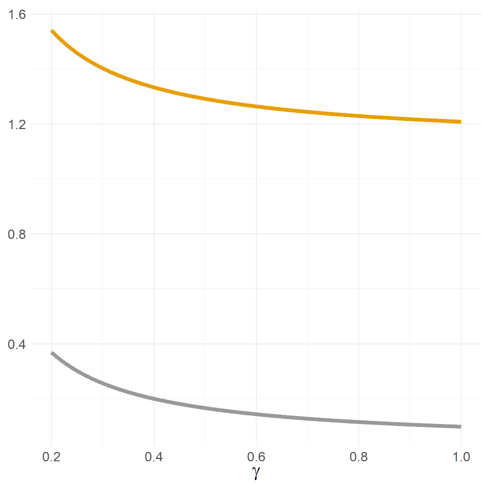
(c) $\mu = 0.75$

We assume $\alpha = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$

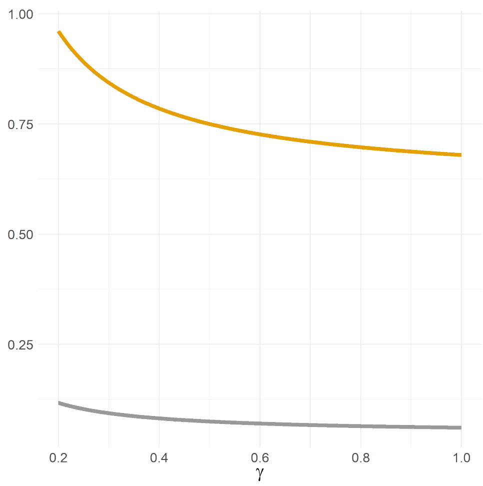
Figure 17: Net expected benefit from acquiring one unit of information from either source for type H.



(a) $\mu = 0.25$



(b) $\mu = 0.5$



(c) $\mu = 0.75$

We assume $\alpha = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$.

F Overview of Additional Variables

To study the question of whether the behaviour observed in the experiment correlates with willingness to contribute to real-world public goods, we complement the data from our experiment with socio-demographic variables and other relevant data from available GIP waves. As control variables, we include gender, age and education from wave 52. Age is reported in 14 brackets for the year of birth and we re-code the variable to use the mid-point of each bracket as a proxy for age. Education is reported in 12 levels but, for our purposes, we re-code it into a binary indicator variable for academic education which takes the value one if the participant has a Bachelor degree or higher, and zero otherwise. In the control variables, we also include income from wave 49, which was fielded in September 2020. Average monthly net income is reported in 15 brackets and again we use the mid-point of each bracket as a proxy. In households where either another person than the participant answering the questionnaire or more than one person contributes to the household income, we use the household instead of personal income.

For the question of whether the contribution types observed in the experiment correlate with the actual public good contributions, we exploit several questions from previous waves and the Mannheim Corona Study. Table 39 presents an overview of all the questions. The original questionnaire documentation in German can be found on the GIP website or via the GIP data archive at the GESIS-Leibniz Institute for the Social Sciences.

To find suitable questions that capture willingness to contribute to environmental protection, we searched the GIP documentation for terms like "environment", "climate", and "sustainability". Among the large number of hits, we focused only on those questions that fulfil the following criteria: First, they concern an individual (as opposed to collective or governmental) willingness to contribute. Second, the contribution is at least to some extent costly to the individual. Third, the contribution is voluntary. Therefore, we discarded all questions that ask about personal opinions, e.g. general attitudes towards climate change or assessment of the tasks of the government concerning environmental protection. In our main specification, we exploit the three questions that best fit the above-mentioned criteria. The first question elicits the support of a carbon tax in a simple yes/no manner. The second question asks whether the participants recently changed their lifestyle to protect the climate, on a scale from 1 to 5. These two questions come from wave 41 (May 2019). The third question asks whether the participants pursued any of eight sustainability-related activities, such as donating to an environmental organization. This question was fielded in wave 48 (July 2020). We assign one point to each activity pursued and sum up the points. For the activity of flying, we assign a point when the answer is negative. All three variables are coded such that higher values indicate a higher willingness to contribute.

In an alternative specification, we add two more variables. The first question asks whether participants find it important to reduce emissions from vehicles, even at the expense of economic growth. This question was fielded in wave 48 as well, and while it does not exactly concern individual contributions, it still captures a certain willingness to pay for environmental protection. The other variable aggregates three questions concerning demonstrations for climate protection. While demonstrating is not a direct contribution, participating is costly in terms of time, and can express a strong opinion. One question concerns participation in such demonstrations in the past 6 months and is asked twice, in waves 41 (May 2019) and 44 (November 2019). We assign one point for each time the participants answered "yes". The third question asks for the intention to participate in such a demonstration on a scale from 1 to 3. We aggregate these three questions to one variable by adding up the answers.

Three more questions capture the behaviour of interest, but they were asked as part of experiments, such that not all participants received the questions. This results in a greatly reduced sample size, but we nevertheless include these variables in an additional specification to check that our results are not sensitive to the choice of the variables. The first question concerns purchases of environmentally friendly products, and the second question concerns the reduction of energy consumption. As part of the experiment, both questions are phrased in two slightly different ways, but because they still capture the same concept, we aggregate the answers to one variable for environmentally friendly goods and one for energy consumption. These questions were asked in wave 38 (November 2018). In wave 44, some participants received an additional amount of 4 euros for answering the questionnaire, and could decide how much of this they wanted to keep for themselves, and how much to donate to the climate protection organization 'atmosfair'.

For the question of whether the contribution types observed in the experiment correlate with the willingness to contribute to the containment of COVID-19, we exploit several questions from the Mannheim Corona Study (MCS). The contributions to the containment of COVID-19 include reducing social contacts, going into home quarantine, getting tested, and getting vaccinated. However, most of these contributions are not strictly voluntary. For instance, during the lockdown social contacts were largely prohibited by law, and home quarantine could be prescribed by the health department. Therefore, to capture individual, voluntary contributions, we focus on the usage of the corona warning app. Installing the app is voluntary, and whether somebody who is warned (about a contact to a positively tested person) by the app gets tested or quarantines cannot be monitored by the authorities. The corona warning app was introduced in Germany on June 16, 2020. In week 13 of the MCS which was fielded from June 12 to June 19, 2020, participants were asked whether they would install the app, and if so, whether they would enter a positive test result, and whether they would comply with the app's request to get tested or to go into home quarantine. The answers were reported on a scale from 1 to 5 and we assign a value of zero if the participants answered that they would not install the app in any case. In addition, the participants were asked whether they had installed the app in the three following weeks (June 20 to July 10, 2020). We aggregate the answers to an additional indicator variable which takes the value 1 if the participants answered that they had installed the app in either of the three weeks.

Table 39: Overview of the additional questions used from previous waves of the GIP or from the Mannheim Corona Study, in alphabetical order.

Variable	Wave	Question	Answer options	Filter
app installed	CW14, CW15, CW16 [48]	Did you or did someone for you install the official corona warning app on your smartphone or not?	1: app installed, 2: app not installed, 3: app installed but since then uninstalled again 4: I do not use a smartphone.	–
app compliance test	CW13	Would you comply with the corona warning app's request to get tested for the virus?	1: yes, in any case, ... 5: no, in any case.	The participants did not receive this question if they previously answered that they do not own a smartphone or that they would be in any case unwilling to install the corona warning app.
app test results	CW13	If you got tested positively for the virus, would you enter it in corona warning app?	1: yes, in any case, ... 5: no, in any case.	The participants did not receive this question if they previously answered that they do not own a smartphone or that they would be in any case unwilling to install the corona warning app.

[48] CW refers to the respective week of the Mannheim Corona Study.

app compliance quarantine	CW13	Would you comply with the corona warning app's request to go into home quarantine as a precaution?	1: yes, in any case, ... 5: no, in any case.	The participants did not receive this question if they previously answered that they do not own a smartphone or that they would be in any case unwilling to install the corona warning app.
demonstrated	41, 44	Did you participate in a demonstration against climate change in the past 6 months?	0: yes 1: no	–
donation atmosfair	44	Please fill in here the amount you want to donate to the climate protection organization atmosfair.	0 € - 4 €	Part of an experiment, such that 2/3 of the participants were randomly selected to receive this question.
energy consumption I	38	To what extent to you find it personally acceptable to restrict your energy consumption in order to stop climate change?	0: not acceptable at all, ..., 10: completely acceptable	Part of an experiment, such that 1/3 of the participants were randomly selected to receive this question. The other 1/3 received the question *energy consumption II*.

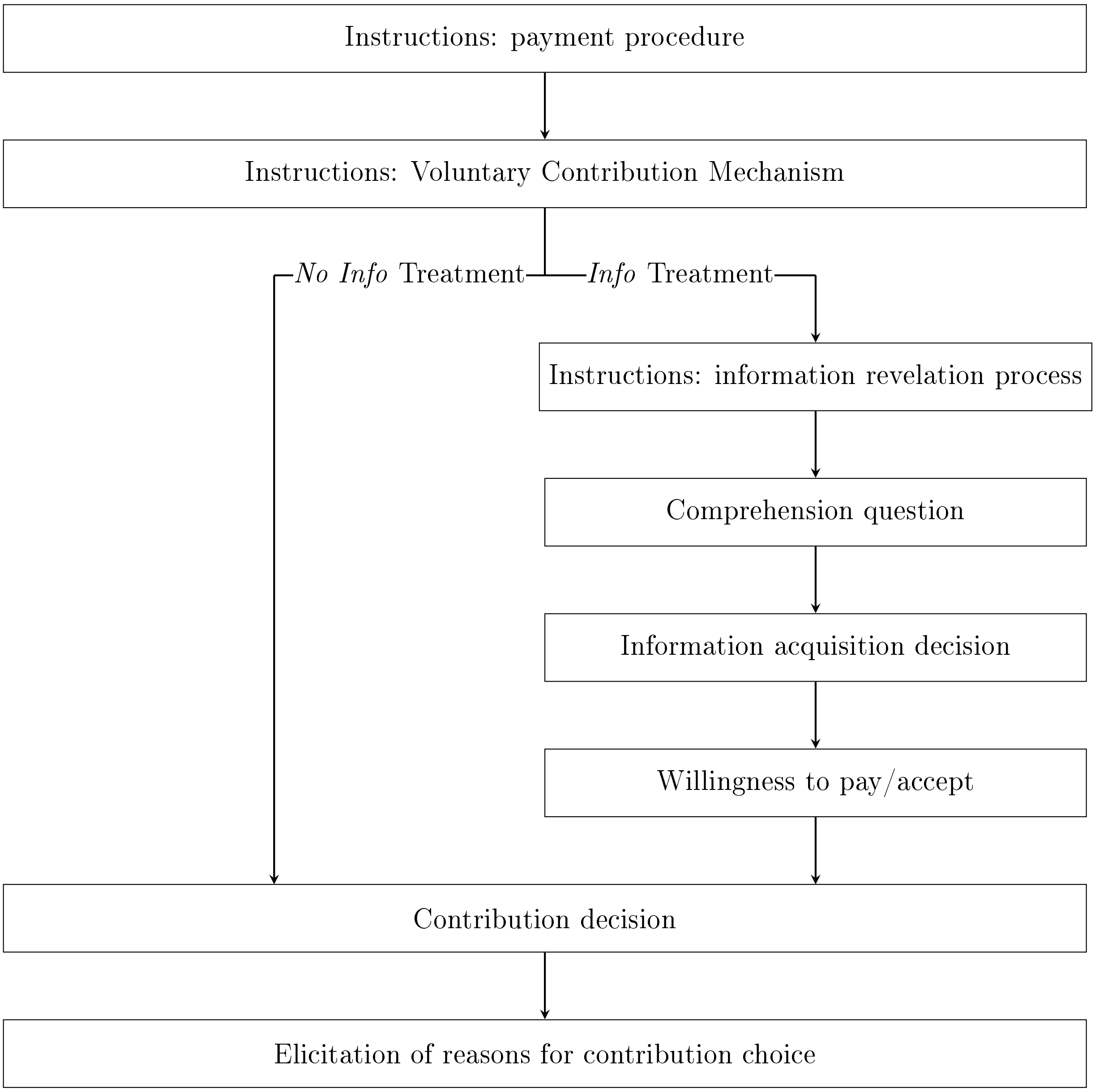
energy consumption II	38	How often in your daily life do you do something to reduce your energy consumption?	0: never, ..., 10: always	Part of an experiment, such that 1/3 of the participants were randomly selected to receive this question. If they received this question they also received *environmentally friendly products II*, not *I*.
environmentally friendly products I	38	To what extent do you find it personally acceptable to pay higher prices for environmentally friendly products?	0: not acceptable at all, ..., 10: completely acceptable	Part of an experiment, such that 1/3 of the participants were randomly selected to receive this question. The other 1/3 received the question *environmentally friendly products II*.
environmentally friendly products II	38	How often when buying products do you pay attention to these products being environmentally friendly?	0: never, ..., 10: always	Part of an experiment, such that 1/3 of the participants were randomly selected to receive this question.
importance emission reductions	48	Please indicate how much you agree with the following statement: It is very important to reduce the emission of carbon dioxide (CO_2) and pollutants by vehicles, even at the expense of economic growth.	1: do not agree at all, ... 7: agree entirely	–

lifestyle changes	41	Did you change your lifestyle in the past 6 months to protect the climate?	1: very much, ..., 5: not at all	–
support carbon tax	41	Do you oppose the introduction of a carbon tax or do you agree with it?	1: agree fully, ..., 5: oppose strongly	–
sustainable activities	48	Which of the following activities did you perform at least once in the past 6 months? Please select all applicable activities.	a: paying attention to the sustainability of a product during the purchase. b: Worked for an environmental project in a voluntary capacity. c: Participated in a demonstration for more environmental and/or climate protection. d: Brought own bag to shopping. e: Signed a petition for more environmental and/or climate protection. f: Donated to an environmental organization. g: Bought regional organic products. h: Went on a flight.	–

would demonstrate	41	Would you participate in such a demonstration for climate protection in the near future if it took place near your residence?	1: yes, in any case 2: probably 3: no	–

G Experimental Instructions

G.1 Overview of the Experimental Procedure



G.2 English Translation of the Instructions and Questions

Instructions for the payment procedure

What follows is about making an investment decision. You are a member of a group of four participants who all have the same investment possibility. Your own payoff depends on the decisions of all group members. Randomly drawn participants of the study will receive their payoffs as real amounts of money. We will randomly draw 50 groups of 4 participants each, that is 200 participants in total, and we will transfer their payoffs to the drawn participants. All other participants will not receive any money. Nobody can be drawn more than once. We estimate that approximately 4000 people will take part in this study. All decisions will of course remain anonymous. We will notify the participants who were drawn in June 2021.

Instructions for the Voluntary Contribution Mechanism.
Example for the *info* treatment and a prior of 0.75

The payoff you will receive when you are drawn depends on your own investment decision as well as on the investment decisions of the three other group members.

You and the three other group members each have a budget of 10 € in a virtual account. You can decide how much of your budget you want to invest into a group project, and how much you want to keep in your virtual account.

Your payoff results from the remaining budget on your virtual account and the revenue from the group project.

You and the other three group members will all receive the same revenue from the group project. The level of the revenue is determined by the sum of all investments in the group project. Moreover, the level of the revenue depends on whether the group project is a GOLD or a SILVER project. Initially, the type of the project is known to nobody. You will later have the opportunity to potentially find out the type of the project.

If the group project is GOLD, the revenue for each group member is one half (50%) of the sum of all investments in the project. If the group project is SILVER, the revenue for each group member is one tenth (10%) of the sum of all investments in the project. Let's consider an example in which the sum of all investments in the group project is 40 €. Then, you and all other group members will receive a revenue of 50% of 40 € = 20 € if the project is GOLD, or alternatively a revenue of 10% of 40 € = 4 € if the project is SILVER.

Among 100 groups, 75 groups have a GOLD project and 25 groups have a SILVER project.

Instructions for the information revelation process (*info* treatment)

Before you make your investment decision, you now have the chance to potentially find out whether the group project is a GOLD or SILVER project.

Below, you can see four envelopes. You may open one of the envelopes once. Every envelope contains a card which is either gold or silver. Only in the case of one of the four envelope the true type of the group project can be inferred with certainty.

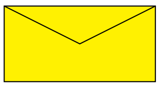
Only if the group project is GOLD, exactly one of the two silver envelopes contains a gold card and hence reveals the type of the group project. Otherwise, the silver envelopes always contain a silver card.

Only if the group project is SILVER, exactly one of the two gold envelopes contains a silver card and hence reveals the type of the group project. Otherwise the gold envelopes always contain a gold card.

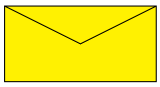
Only if you find a gold card in a silver envelope, you can be completely certain that the group project is a GOLD project. If you find a gold card in a gold envelope, you can be more certain that it is a GOLD project than without this information, but you cannot be completely certain.

Only if you find a silver card in a gold envelope, you can be completely certain that the group project is a SILVER project. If you find a silver card in a silver envelope, you can be more certain that it is a SILVER project than without this information, but you cannot be completely certain.

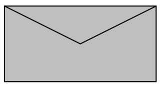
If you open one of the envelopes, you will receive specific information about how you can interpret the color of the card and how certain you can be about the type of your group project.



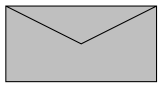
Gold Envelope 1



Gold Envelope 2



Silver Envelope 1



Silver Envelope 2

Comprehension question (*info* treatment)

With this question, we want to check your understanding of the instructions. If you do not know the answer to this question, please go back to the previous page and read the instructions again carefully.

Is the following statement true or false?

"Only if you find a card which does not have the same color as the envelope in which it was located, you can be completely certain that the color of the card reveals the type of the group project."

- ◯ False
- ◯ True
- ◯ I don't know.

Information acquisition decision (*info* treatment)

Gold Envelope 1 | Gold Envelope 2 | Silver Envelope 1 | Silver Envelope 2

Please decide now which of the four envelopes you want to open. If you do not want to open an envelope, please select "No envelope".

Which envelope do you want to open?

- ◯ Gold Envelope 1
- ◯ Gold Envelope 2
- ◯ Silver Envelope 1
- ◯ Silver Envelope 2
- ◯ No envelope

If the participant chose to open a silver envelope (*info* treatment): Willingness to pay

You decided to open a silver envelope. Before we will show you the content of the envelope you chose, we have one additional question which is not going to affect your payoff. Suppose that it would have cost something to open an envelope.

Please state the highest amount, between 0€ and 10€, that you would have been willing to pay to open a silver envelope.

____€

If the participant chose not to open an envelope (*info* treatment): Willingness to accept

You decided not to open an envelope. Before moving on to the next question, we have one additional question which is not going to affect your payoff. Suppose that you would have received money for opening an envelope.

Please indicate the smallest amount, between 0€ and 10€, that we would have had to pay you so that you ...

... would have opened a gold envelope: ____€

... would have opened a silver envelope: ____€

Contribution decision (*no info* treatment)

Please make your investment decision now. You can invest an amount between 0€ and 10€ in the group project. The share of your budget that you do not invest in the group project remains in your virtual account.

Please fill in here which amount you want to invest in the group project:

____€

If the participant opened a silver envelope and received a silver card: Contribution decision (*info* treatment)

You opened the silver envelope 1. The envelope contains a silver card. You are now less certain than before that the group project is a GOLD project. Among 100 groups in which someone found a silver card in a silver envelope, 60 groups have a GOLD project and 40 groups have a SILVER project.

Please make your investment decision now. You can invest an amount between 0 € and 10 € in the group project. The share of your budget that you do not invest in the group project remains in your virtual account.

Please fill in here which amount you want to invest into the group project:

____ €

☐ I want to read the instructions again.

If the participant opened a silver envelope and received a gold card: Contribution decision (*info* treatment)

You opened the silver envelope 1. The envelope contains a gold card. The group project is a GOLD project with certainty.

Please make your investment decision now. You can invest an amount between 0 € and 10 € in the group project. The share of your budget that you do not invest in the group project remains in your virtual account.

Please fill in here which amount you want to invest into the group project:

____ €

☐ I want to read the instructions again.

Motives for the contribution choice

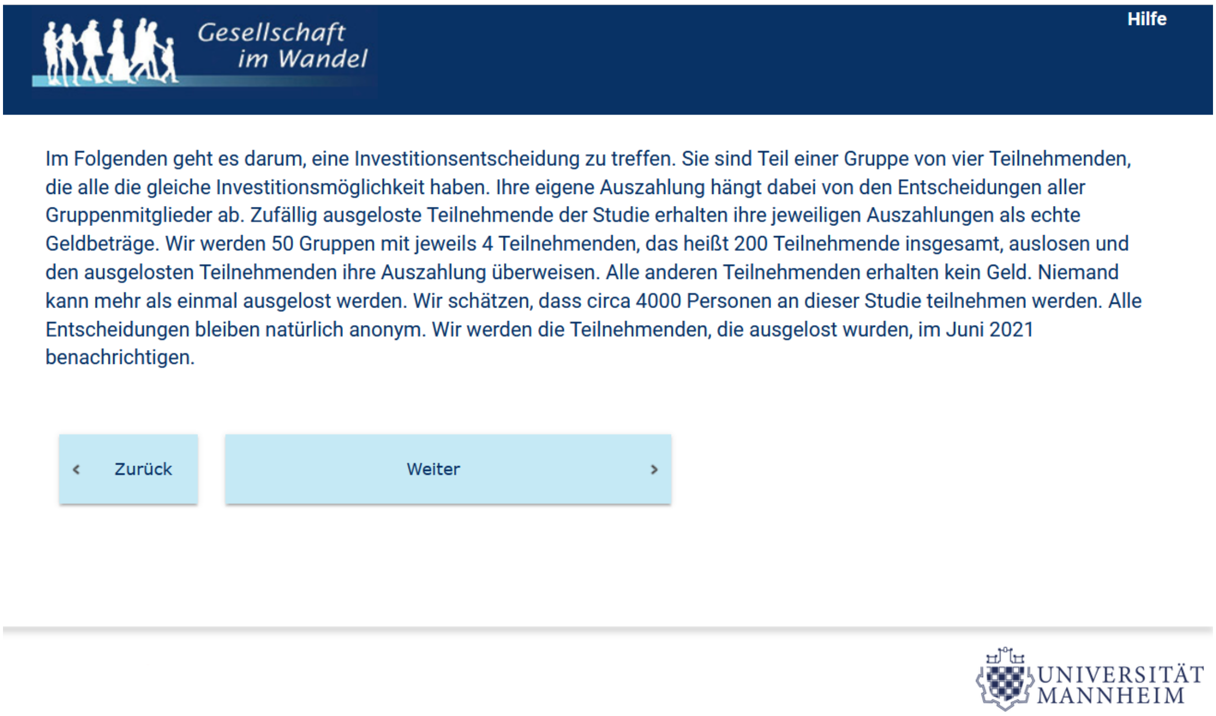
Which of the following motives can explain your personal investment decision?

Please indicate all motives.

- ☐ I want to invest neither more nor less than the other group members.
- ☐ I want to achieve a total payoff as high as possible for my entire group.
- ☐ I want to achieve a payoff as high as possible for myself.
- ☐ I had a different motive, namely: ____

G.3 Screenshots of the Original Instructions and Questions

Figure 18: Instructions for the payment procedure.



Gesellschaft im Wandel

Hilfe

Im Folgenden geht es darum, eine Investitionsentscheidung zu treffen. Sie sind Teil einer Gruppe von vier Teilnehmenden, die alle die gleiche Investitionsmöglichkeit haben. Ihre eigene Auszahlung hängt dabei von den Entscheidungen aller Gruppenmitglieder ab. Zufällig ausgeloste Teilnehmende der Studie erhalten ihre jeweiligen Auszahlungen als echte Geldbeträge. Wir werden 50 Gruppen mit jeweils 4 Teilnehmenden, das heißt 200 Teilnehmende insgesamt, auslosen und den ausgelosten Teilnehmenden ihre Auszahlung überweisen. Alle anderen Teilnehmenden erhalten kein Geld. Niemand kann mehr als einmal ausgelost werden. Wir schätzen, dass circa 4000 Personen an dieser Studie teilnehmen werden. Alle Entscheidungen bleiben natürlich anonym. Wir werden die Teilnehmenden, die ausgelost wurden, im Juni 2021 benachrichtigen.

‹ Zurück

Weiter ›

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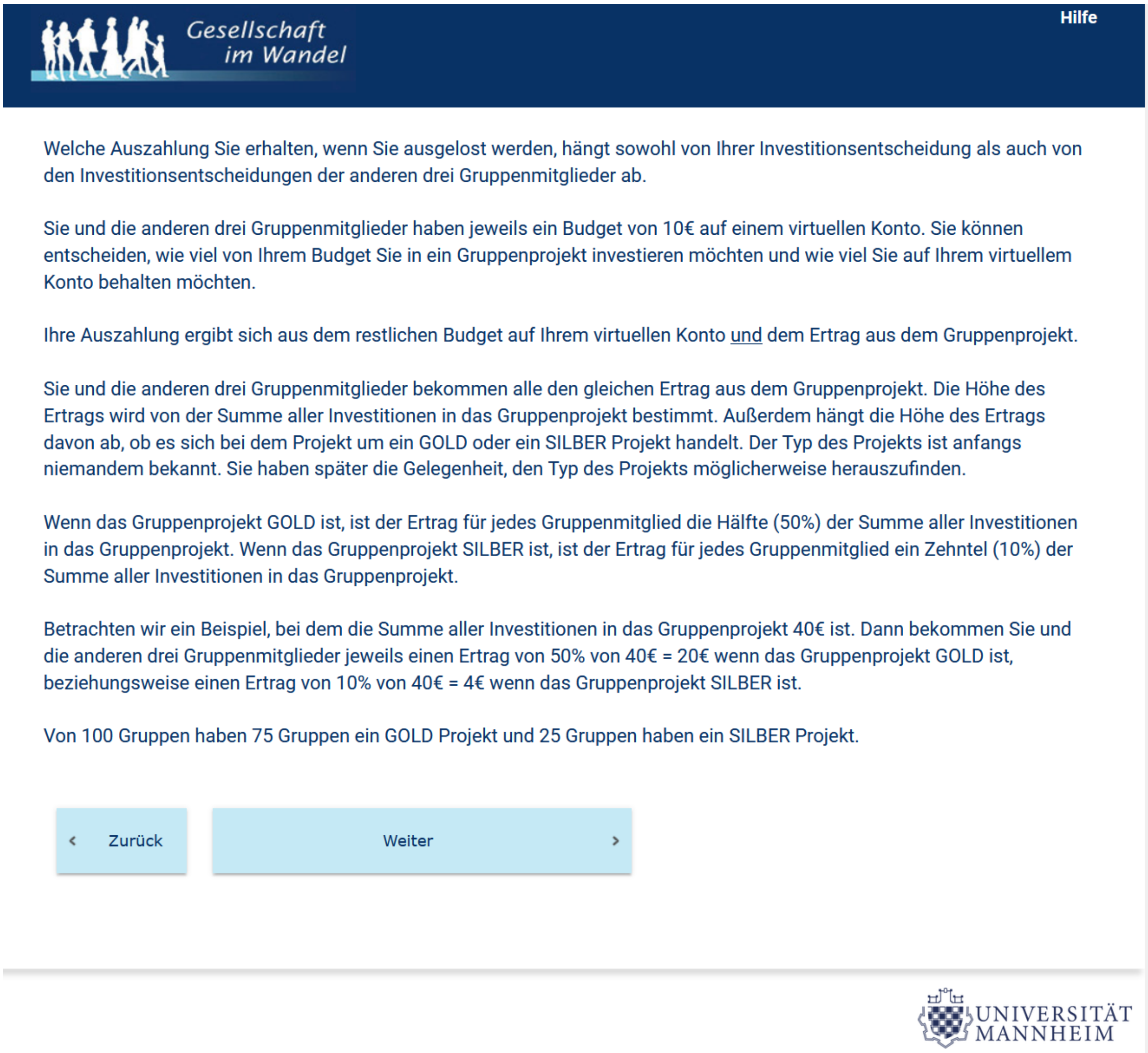
Figure 19: Instructions for the Voluntary Contribution Mechanism. Example for the *info* treatment and a prior of $\mu = 0.75$.



Gesellschaft im Wandel

Hilfe

Welche Auszahlung Sie erhalten, wenn Sie ausgelost werden, hängt sowohl von Ihrer Investitionsentscheidung als auch von den Investitionsentscheidungen der anderen drei Gruppenmitglieder ab.

Sie und die anderen drei Gruppenmitglieder haben jeweils ein Budget von 10€ auf einem virtuellen Konto. Sie können entscheiden, wie viel von Ihrem Budget Sie in ein Gruppenprojekt investieren möchten und wie viel Sie auf Ihrem virtuellem Konto behalten möchten.

Ihre Auszahlung ergibt sich aus dem restlichen Budget auf Ihrem virtuellen Konto und dem Ertrag aus dem Gruppenprojekt.

Sie und die anderen drei Gruppenmitglieder bekommen alle den gleichen Ertrag aus dem Gruppenprojekt. Die Höhe des Ertrags wird von der Summe aller Investitionen in das Gruppenprojekt bestimmt. Außerdem hängt die Höhe des Ertrags davon ab, ob es sich bei dem Projekt um ein GOLD oder ein SILBER Projekt handelt. Der Typ des Projekts ist anfangs niemandem bekannt. Sie haben später die Gelegenheit, den Typ des Projekts möglicherweise herauszufinden.

Wenn das Gruppenprojekt GOLD ist, ist der Ertrag für jedes Gruppenmitglied die Hälfte (50%) der Summe aller Investitionen in das Gruppenprojekt. Wenn das Gruppenprojekt SILBER ist, ist der Ertrag für jedes Gruppenmitglied ein Zehntel (10%) der Summe aller Investitionen in das Gruppenprojekt.

Betrachten wir ein Beispiel, bei dem die Summe aller Investitionen in das Gruppenprojekt 40€ ist. Dann bekommen Sie und die anderen drei Gruppenmitglieder jeweils einen Ertrag von 50% von 40€ = 20€ wenn das Gruppenprojekt GOLD ist, beziehungsweise einen Ertrag von 10% von 40€ = 4€ wenn das Gruppenprojekt SILBER ist.

Von 100 Gruppen haben 75 Gruppen ein GOLD Projekt und 25 Gruppen haben ein SILBER Projekt.

Zurück

Weiter

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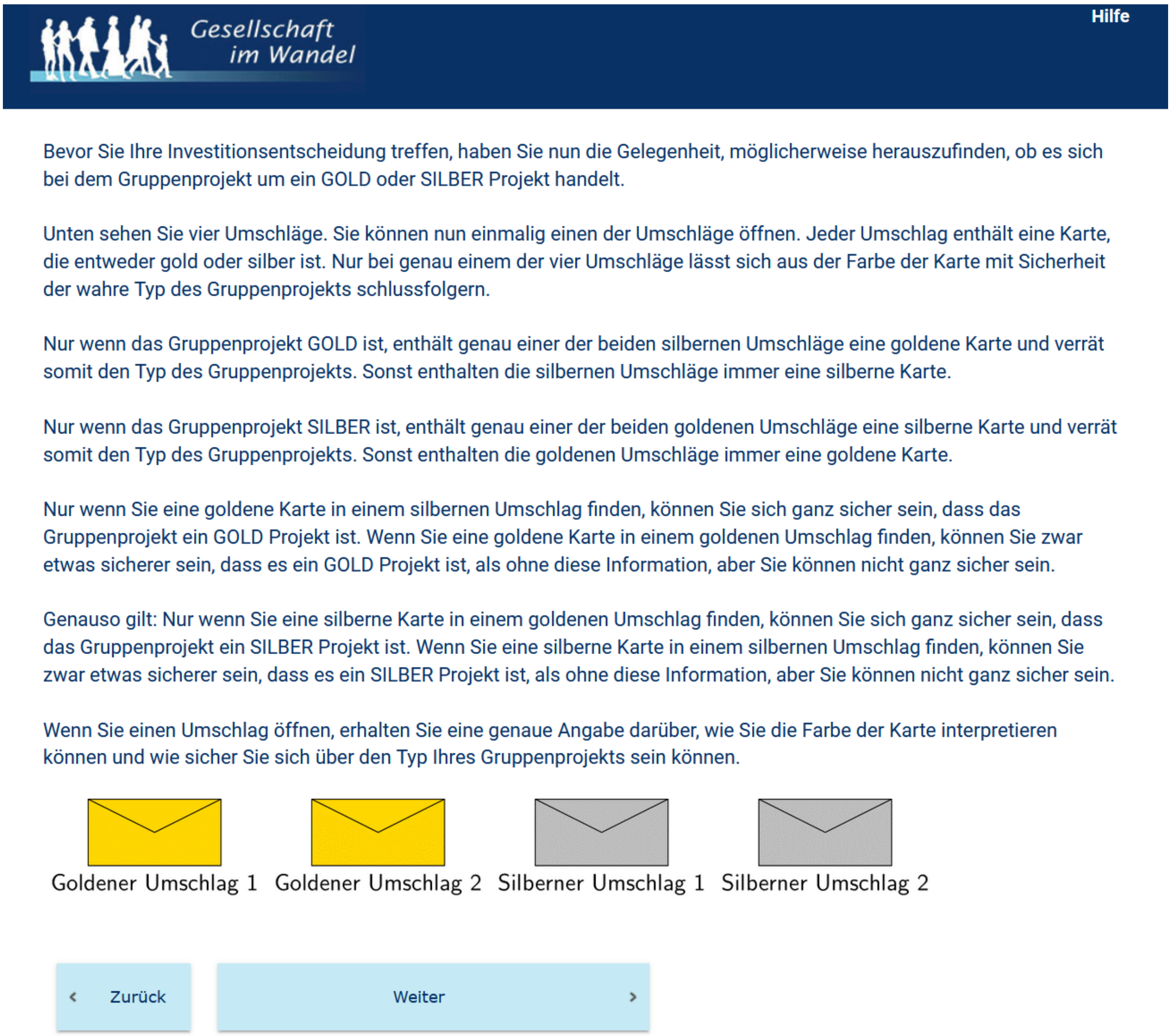
Figure 20: Instructions for the information revelation process (*info* treatment).



Gesellschaft im Wandel

Hilfe

Bevor Sie Ihre Investitionsentscheidung treffen, haben Sie nun die Gelegenheit, möglicherweise herauszufinden, ob es sich bei dem Gruppenprojekt um ein GOLD oder SILBER Projekt handelt.

Unten sehen Sie vier Umschläge. Sie können nun einmalig einen der Umschläge öffnen. Jeder Umschlag enthält eine Karte, die entweder gold oder silber ist. Nur bei genau einem der vier Umschläge lässt sich aus der Farbe der Karte mit Sicherheit der wahre Typ des Gruppenprojekts schlussfolgern.

Nur wenn das Gruppenprojekt GOLD ist, enthält genau einer der beiden silbernen Umschläge eine goldene Karte und verrät somit den Typ des Gruppenprojekts. Sonst enthalten die silbernen Umschläge immer eine silberne Karte.

Nur wenn das Gruppenprojekt SILBER ist, enthält genau einer der beiden goldenen Umschläge eine silberne Karte und verrät somit den Typ des Gruppenprojekts. Sonst enthalten die goldenen Umschläge immer eine goldene Karte.

Nur wenn Sie eine goldene Karte in einem silbernen Umschlag finden, können Sie sich ganz sicher sein, dass das Gruppenprojekt ein GOLD Projekt ist. Wenn Sie eine goldene Karte in einem goldenen Umschlag finden, können Sie zwar etwas sicherer sein, dass es ein GOLD Projekt ist, als ohne diese Information, aber Sie können nicht ganz sicher sein.

Genauso gilt: Nur wenn Sie eine silberne Karte in einem goldenen Umschlag finden, können Sie sich ganz sicher sein, dass das Gruppenprojekt ein SILBER Projekt ist. Wenn Sie eine silberne Karte in einem silbernen Umschlag finden, können Sie zwar etwas sicherer sein, dass es ein SILBER Projekt ist, als ohne diese Information, aber Sie können nicht ganz sicher sein.

Wenn Sie einen Umschlag öffnen, erhalten Sie eine genaue Angabe darüber, wie Sie die Farbe der Karte interpretieren können und wie sicher Sie sich über den Typ Ihres Gruppenprojekts sein können.

Goldener Umschlag 1 Goldener Umschlag 2 Silberner Umschlag 1 Silberner Umschlag 2

‹ Zurück

Weiter ›

Figure 21: Comprehension question (*info* treatment).

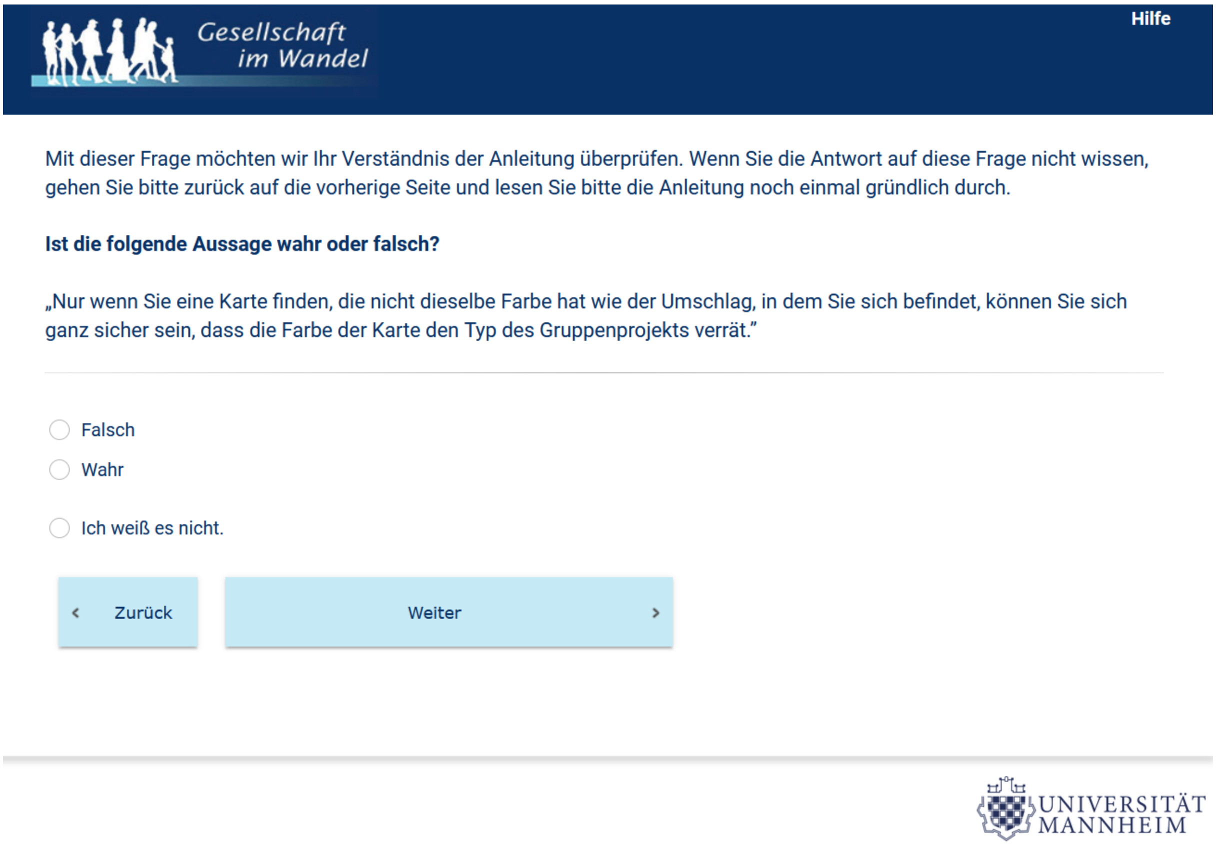


Figure 22: Information acquisition decision (*info* treatment).

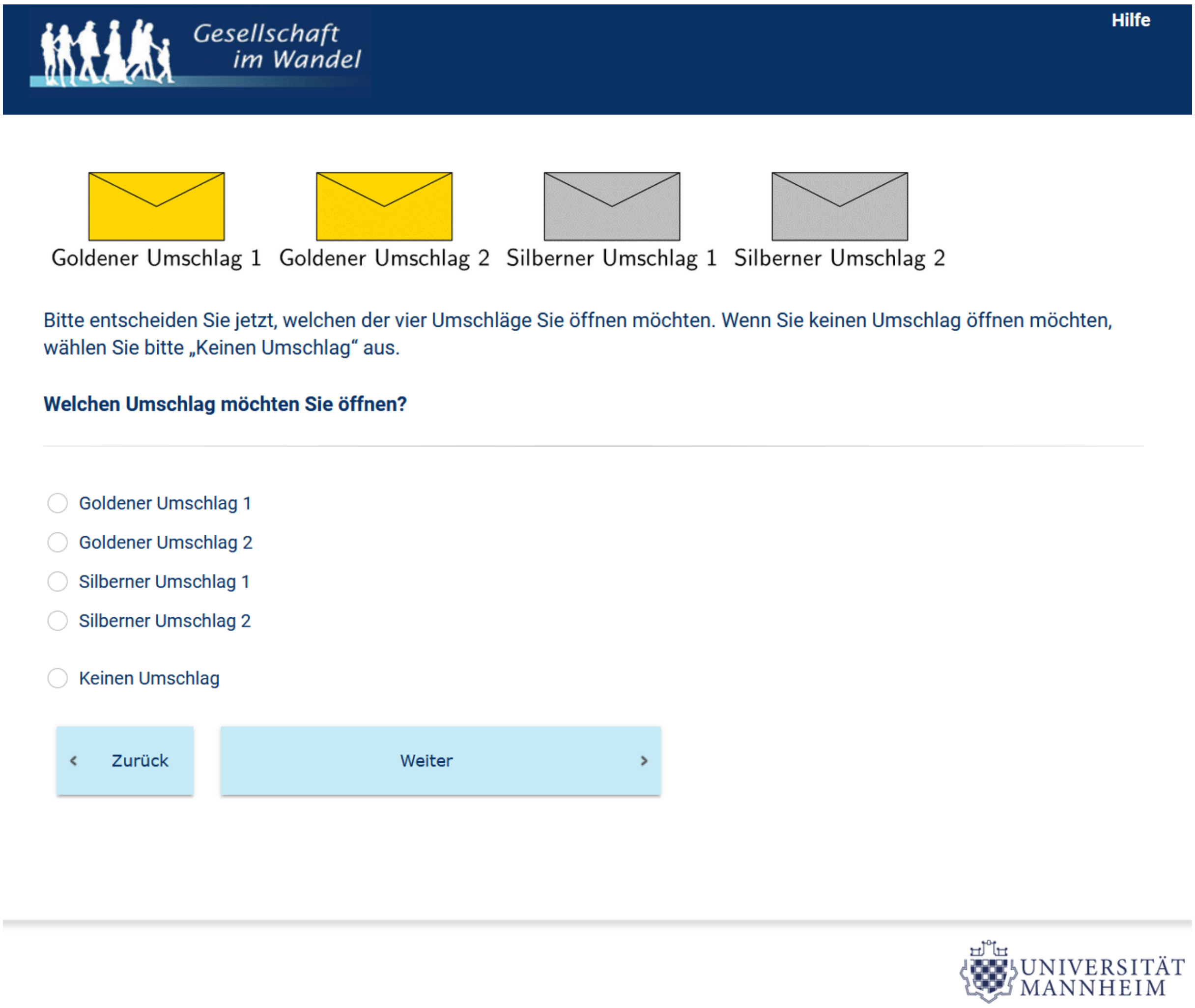


Figure 23: If the participant chose to open a silver envelope (*info* treatment): Willingness to pay question.

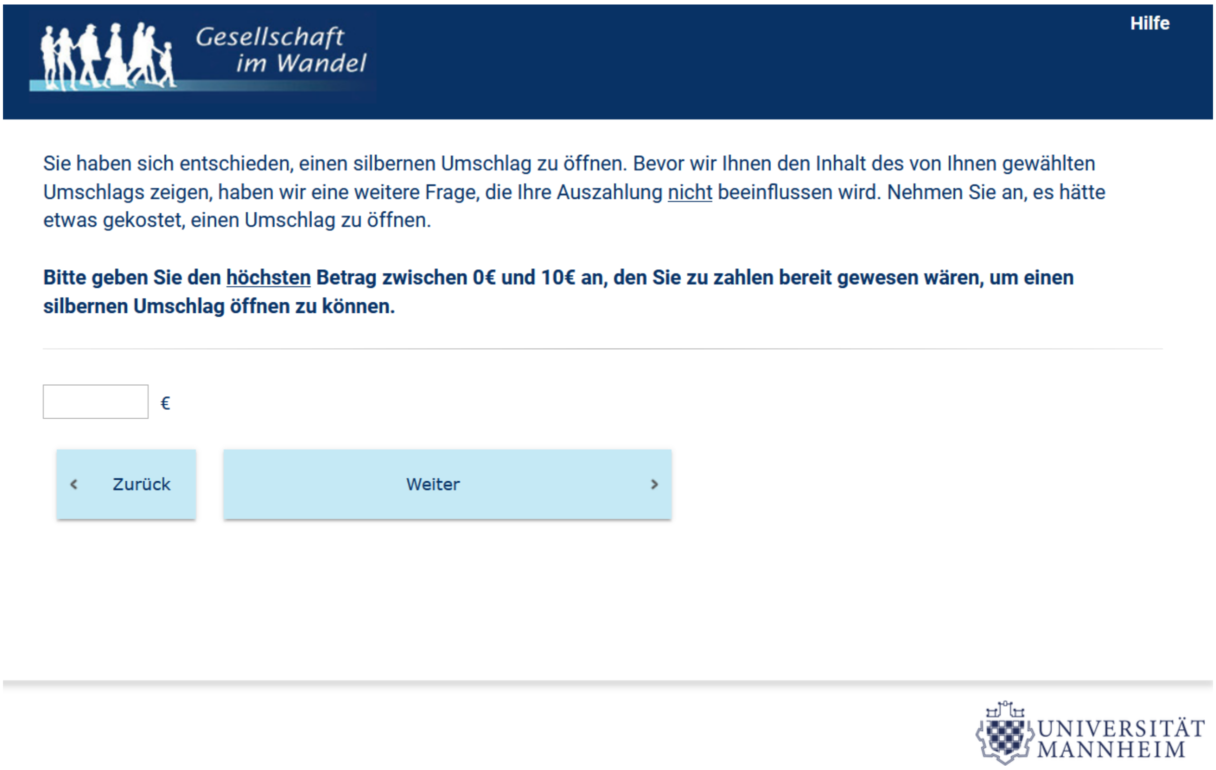


Figure 24: If the participant chose not to open an envelope (*info* treatment): Willingness to accept question.

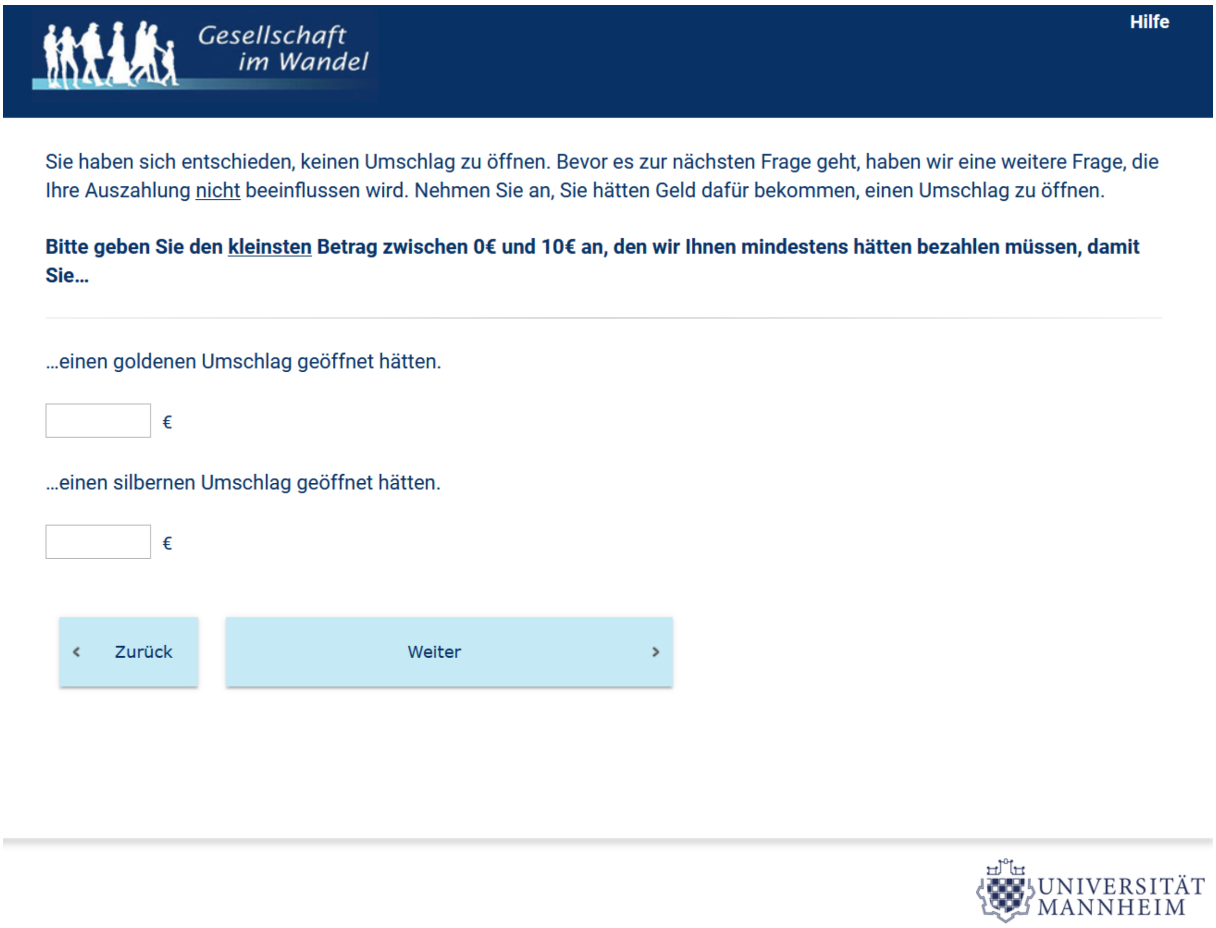


Figure 25: Contribution decision (*no info* treatment).

Figure 26: If the participant opened a silver envelope and received a silver card: Contribution decision (*info* treatment).

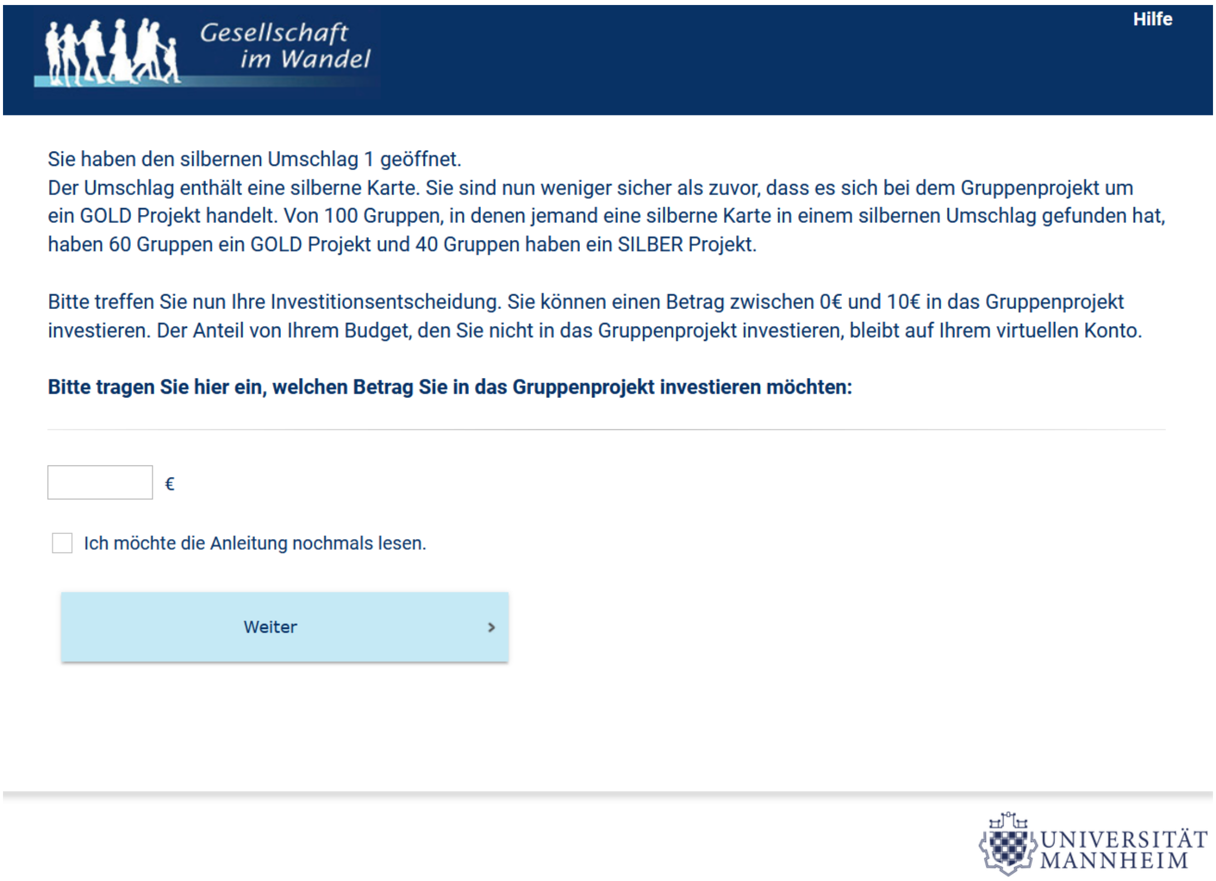
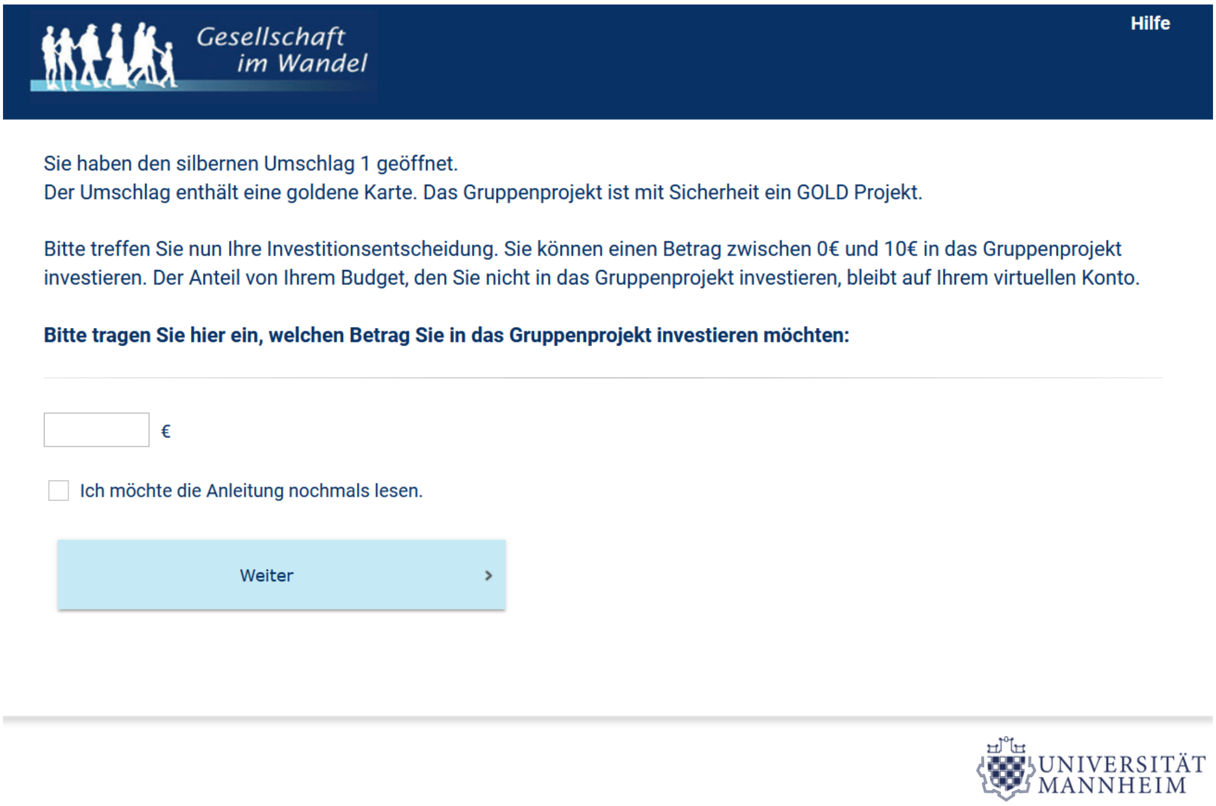


Figure 27: If the participant opened a silver envelope and received a gold card: Contribution decision (*info* treatment).



Gesellschaft im Wandel

Hilfe

Sie haben den silbernen Umschlag 1 geöffnet.
Der Umschlag enthält eine goldene Karte. Das Gruppenprojekt ist mit Sicherheit ein GOLD Projekt.

Bitte treffen Sie nun Ihre Investitionsentscheidung. Sie können einen Betrag zwischen 0€ und 10€ in das Gruppenprojekt investieren. Der Anteil von Ihrem Budget, den Sie nicht in das Gruppenprojekt investieren, bleibt auf Ihrem virtuellen Konto.

Bitte tragen Sie hier ein, welchen Betrag Sie in das Gruppenprojekt investieren möchten:

€

Ich möchte die Anleitung nochmals lesen.

Weiter

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Figure 28: Question about the motives for the contribution choice.

Gesellschaft im Wandel

Hilfe

Welche der folgenden Beweggründe können Ihre persönliche Investitionsentscheidung erklären?

Bitte geben Sie alle Beweggründe an.

- Ich möchte weder mehr noch weniger investieren als die anderen Gruppenmitglieder.
- Ich möchte eine möglichst hohe Gesamtauszahlung für meine ganze Gruppe erzielen.
- Ich möchte eine möglichst hohe Auszahlung für mich selbst erzielen.
- Ich hatte einen anderen Beweggrund, und zwar:

Zurück

Weiter

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4 Information Design under Asymmetric Awareness

joint with Yulia Evsyukova and Niccolò Lomys

4.1 Introduction

The effectiveness—as well as the content—of communication depends on the interpretation of the communication content. There are many reasons why agents may misinterpret communication. One important channel is disagreement on what agents are talking about. Two agents may communicate having in mind different frames of the world. In particular, we study situations where the information designer has a finer understanding of the world than the information receiver. This means that the information designer conceives possibilities that the information receiver is unaware of. An agent with a superior awareness of the world can exploit it to mislead an unaware agent. What is the effect of this exploitation on the information content? Is there an incentive to increase awareness? Answering these questions sheds light on what contingencies remain hidden in communication. These results have a wide range of applicability, including product quality and labelling, the design of a scientific paper, the management of public panic events, the disclosure of information about financial assets, the provision of surprising evidence during a trial, and many others.

To answer these questions, we extend the classical Bayesian Persuasion (BP) framework (Kamenica and Gentzkow, 2011) to account for asymmetric awareness of the state space. Sender (he) of information has to persuade Receiver (she) to take some action. One of the underlying assumptions of the classical framework is that the two agents conceive the same possible states of the world. Such an assumption, however, is not necessarily realistic. In many contexts, economic agents hold heterogeneous world-views: they understand reality differently. This heterogeneity may be the result of either framing or unawareness. Respectively, an agent may have a superior capacity to disentangle events that can appear indivisible to others; or have better knowledge of possible events. Our model allows us to account for both explanations. In this paper, we study the consequences of framing or asymmetric awareness for information design. In particular, we assume that Sender knows perfectly the state space, whereas Receiver is aware only of a subset of states or has a coarse framing of the state space. For tractability, we restrict attention to three states, and Receiver is only aware of two states.

Receiver can choose between two actions. Sender has a preferred action which is independent of the state of the world. In the first stage, Sender chooses the degree of awareness or the framing that Receiver will have when processing information. In particular, Sender decides whether to expand or refine the set of states that Receiver conceives. In the second stage, taking as given Receiver's awareness or framing, Sender designs information about the state of the world to persuade Receiver to take Sender's preferred action. Given the information provided by Sender, Receiver updates her belief and takes the optimal action given such belief. Receiver has state-dependent preferences: she wants to match her action with the state. Receiver holds prior beliefs about the state of the world that could differ from Sender's prior beliefs. Receiver's interpretation of information depends on the states she conceives. Sender always commits to a complete information design; but if he does not expand or refine Receiver's awareness, she does not conceive the part of the information design associated with the state she is not aware of. Moreover, Receiver's preferences and beliefs can change if Sender decides to expand her awareness or refine her framing. Sender's incentive to expand or refine Receiver's conceivable states depends on preferences/beliefs dynamics as well as on optimal information design.

In the second stage, the persuasion game is similar to the standard one in Kamenica and Gentzkow (2011). However, there are some caveats. When Receiver is only partially aware or has a coarse framing, Sender can exploit this fact to conceal the third state. In particular, Sender will recommend his preferred action with probability one under the third state. Indeed, Receiver does not conceive the third state and the corresponding part of information design. Thus, she cannot discount this part of the design when evaluating the credibility of the recommendation. When Receiver is fully aware, the optimal information design depends on how the discovery of a new state impacts Receiver's preferences. When the effect is positive from the perspective of Sender, he can keep recommending his preferred action with probability one under the third state. Otherwise, Sender faces a trade-off between persuading under two averse states. Sender's problem has a bang-bang solution: he focuses on persuasion under one state and leaves persuasion under the other one as a residual task. Whether Sender finds it optimal to focus on the already established averse state or on the newly discovered (by Receiver) one, depends on Sender's prior beliefs of the states as well as on Receiver's prior beliefs and preferences. Indeed, the latter affect Sender's ability to persuade Receiver under the two averse states. Finally, depending on Receiver's prior beliefs and preferences, Sender may be able to recommend his preferred action with probability one under at least one averse state or may be not.

In the first stage, Sender decides which Receiver's degree of awareness he finds more convenient to persuade in the second stage. A first result is that growing awareness can be optimal only if persuasion would be necessary without it. In other words, Sender increases awareness only if this helps him to persuade. If Receiver takes Sender's preferred action already in her small world, there is no purpose for growing awareness from the perspective of Sender. Instead, when Sender has to persuade, he can decide to change Receiver's framing of the world.

A first scenario that makes growing awareness optimal for Sender is when it makes persuasion unnecessary. In other words, the change in Receiver's beliefs and preferences induced by growing awareness is enough to make Sender's preferred action the default one of Receiver. We identify three channels that could make growing awareness optimal for Sender. First of all, growing awareness induces a change in Receiver's prior beliefs. The discovery of a new state makes Receiver assign positive probability to it. Sender's decision is affected by the prior belief that Receiver assigns to the new state, and how this changes the relative likelihood of the existing two. Sender benefits from a shift in prior beliefs that reduces preferences' misalignment between him and Receiver. In particular, Sender can exploit growing awareness when it increases the relative likelihood of his favorable state i.e., the state where the optimal action by Receiver coincides with Sender's preferred action. Instead, the effect of the prior belief assigned to the new state is ambiguous. It depends on whether under the newly discovered state Sender's preferred action is more appealing for Receiver than the alternative, which is the second channel for growing awareness. When Sender's preferred action is optimal for Receiver under that state, then Sender's incentive to increases awareness is higher when Receiver over-reacts to growing awareness - that is Receiver assigns a high probability to the new state. At the contrary, when the alternative action is optimal for Receiver under the new state, Sender's incentive is higher if Receiver under-reacts - that is she assigns a low probability to the new state. Finally, growing awareness could also change Receiver's preferences about the world she was already aware of. Sender has incentive to increase awareness when this makes his preferred action more appealing.

The same channels can explain Sender's decision to increase awareness even when persuasion is optimal before and after growing awareness. In this case, Sender chooses to increase awareness if the value of persuasion increases as a consequence or, in other words, the value of awareness is positive. Sender's incentive to increase awareness depends crucially on whether under the new state Sender's preferred action is better than the alternative for Receiver. If this is the case, growing awareness is optimal unless Receiver's prior beliefs or preferences change in a way that is averse to Sender. Growing awareness can be optimal even if the discovery of a new state makes Sender's preferred action less appealing. This requires a positive change (from the perspective of Sender) in Receiver's prior beliefs or preferences. In addition, it must be the case that either Receiver under-reacts to the newly discovered state or that she over-reacts because Sender assigns a small (objective) probability to the third state.

We consider an application to sale of a good, motivated by the Volkswagen's Dieselgate, and we show that our model can be used to analyse pricing decisions when Seller (i.e., Sender) and Buyer (i.e., Receiver) have asymmetric awareness about the possible quality of a product. In particular, the price chosen by Seller depends on the expected quality of the product. Seller can increase Buyer's awareness to manipulate such expectation and increase profits, by charging a higher price and increasing the chance to sell the good.

We study some refinements of the baseline model to test the robustness of our predictions. Following Karni and Vierø (2013), we assume that Receiver's prior beliefs with different degrees of awareness must satisfy a common ratio assumption. In other words, the relative likelihood of the two initial states is not affected by increasing awareness. Our results do not change qualitatively: growing awareness requires either a change in preferences or that the new state makes Sender's preferred action more appealing (and this channel is stronger when Receiver over-reacts).

Following the literature on framing, we assume that Receiver's prior beliefs satisfy sub-additivity. This means that, when Sender makes Receiver aware that a state consists of two sub-states, the sum of the probabilities assigned by Receiver to these sub-states is larger than the probability assigned to the original state. Sub-additivity imposes a constraint on the feasible beliefs after growing awareness and affects Sender's incentives. In particular, it matters what state is refined: Sender has less of an incentive to increase awareness when the state that is refined (hence has higher total probability after growing awareness) is the one where his preferred action is less appealing.

We also show that our results are robust when introducing some structure on the change of preferences induced by growing awareness. In particular, we assume that preferences under partial awareness are the sum of two components which are separated under full awareness. In this scenario, the effects of changes in preferences and changes in prior beliefs are tightly connected. In particular, Sender benefits from growing awareness if Receiver assigns higher prior belief to the sub-state where Sender's preferred action is relatively more appealing.

Finally, we explore the possibility that Sender cannot conceal the information design under the third state. In particular, we assume that Receiver understands the information generated under the third state as being generated under one of the states she is already aware of. We show that the analysis and the results are not substantially different from the baseline model, with one caveat. The effect of this alternative assumption depends on the framing. In particular, when the refined state is the one where Sender and Receiver share the same preferences, then the analysis (and hence the incentives) are identical to the baseline. Instead, growing awareness is more appealing when the state that is refined is the one where Sender's preferred action differs from Receiver's optimal action.

Road Map. In Section 4.2, we discuss the related literature. In Section 4.3, we present the model. In Section 4.4, we analyse the optimal information design. In Section 4.5, we study Sender's incentive to increase Receiver's awareness. In Section 4.6, we apply of our framework to the sale of a good. In Section 4.7, we consider some refinements of the baseline model. In Section 4.8, we conclude.

4.2 Related Literature

Our work contributes to the literature on Bayesian persuasion, pioneered by Kamenica and Gentzkow (2011) describing an optimal information revelation strategy of a sender who tries to persuade a receiver to take a certain action, assuming that the agents share a common prior. In Alonso and Camara (2016) Sender and Receiver hold different prior beliefs with a common support. The authors prove existence of an optimal mechanism, showing that some difference in prior beliefs can make persuasion beneficial in cases in which it would be useless under a common prior. The closest paper to ours is Galperti (2019) who proposes a model in which the priors of Sender and Receiver have different supports: whereas the ex ante beliefs of Sender are interior, Receiver deems some states impossible. The paper indicates conditions under which Sender finds it beneficial to change Receiver's worldview, providing evidence in the form of a signal. Our study is different in several important aspects. First, we consider the case when Sender and Receiver have asymmetric awareness, so that the latter is unaware about some states rather than assigning them zero probably. Second, in contrast to Galperti (2019), in our model Receiver might change her preferences as a result of growing awareness, which provides an additional channel for Sender to affect the decision of the agent. They also differ in the way Receiver reacts to unexpected information: while, in Galperti (2019) the agents adopts an arbitrary interior prior, we analyze two distinct ways of how the agent might extend her awareness proposed in existing literature.

Our work draws upon literature on growing awareness. The concept of *reversed Bayesianism* has been suggested by Karni and Vierø (2013) as a way to accommodate belief formation under growing awareness. In their approach, relative weights of any states in the expanded state space should be the same as the relative weights of pre-images of these states in the original state space, conditional on having non-zero probability in both. In one of our refinements, we incorporate this approach.

Our paper is also related to the literature on framing. As mentioned in the introduction, one interpretation of our set-up is that, initially, Receiver perceives the state space in the form of a coarse partition, grouping some of the states in an event and seeing no distinction between them. The seminal paper Tversky and Koehler (1994) proposes a theory of sub-additive beliefs, suggesting that people might perceive a joint probability of two disjoint events to be lower when they are presented together (coarse partition), in comparison to the case in which these events are presented separately (fine partition). A number of studies provide experimental evidence in favour of the theory (e.g., Fischhoff et al. (1978), Fox and Clemen (2005), and Sonnemann et al. (2013)). In one of our refinements, we allow Receiver to be subject to sub-additivity in her belief formation process. In this case, Sender can effectively manipulate her prior, using partitions as frames to affect the choice of Receiver. Drawing upon Tversky and Koehler (1994), Ahn and Ergin (2010) use an axiomatic approach to introduce partition-dependent expected utility representation. Burkovskaya (2020), Burkovskaya and Li (2020) also propose a model in which preference of the agent might depend on how the events are grouped together (i.e., on the partition), indicating either event risk-loving or event risk-aversion. However, in the set-up the agent is aware out all the states in the state space. Mullainathan et al. (2008) consider a different approach to coarse thinking, in which Receiver might group the events into categories. Depending on the categorisation, Sender can affect Receiver's choice in this situation even with useless information, as Receiver might mistakenly assign the situation to the category, for which the message is useful.

Finally, the paper relates to a growing literature that studies contracting problems under asymmetric awareness. Filiz-Ozbay (2012) and Auster (2013),Zhao (2011) study a principal-agent model in which the principal holds superior awareness about the state space. von Thadden and Zhao (2012), von Thadden and Zhao (2014) study a principal-agent model in which the principal is better informed about the action space. Auster and Pavoni (2021) and Lei and Zhao (2021) incorporate asymmetric awareness in the context of delegation.

4.3 Model

Primitives. There are two agents, called Sender (he, S) and Receiver (she, R). Agents' payoffs depend on some payoff-relevant state $\omega \in \Omega \coloneqq \{\omega_1, \omega_2, \omega_3\}$ and on Receiver's action $a \in A \coloneqq \{a_1, a_2\}$. Sender has state-independent preferences: without loss of generality, we assume that he prefers action a_1 to action a_2 independently of the state of the world, so that his preferences are represented by a payoff function $u_S \colon A \times \Omega \to \mathbb{R}$, defined pointwise as

$$u_S(a,\omega) \coloneqq \begin{cases} 1 & \text{if } a = a_1 \\ 0 & \text{if } a = a_2 \end{cases}.$$

Sender is aware of all states, whereas Receiver is unaware of state ω_3 at the beginning of the game. Let $\Omega_R^0 \coloneqq \{\omega_1, \omega_2\}$ be the set of all states that Receiver is initially aware of. Sender can increase Receiver's awareness: in this case, Receiver conceives the whole set of states Ω. Receiver's preferences are state-dependent, and vary depending on the Receiver's awareness. In particular, at the beginning of the game, Receiver's preferences are represented by a payoff function $u_R^0 \colon A \times \Omega_R^0 \to \mathbb{R}$, defined pointwise as:

$$u_R^0(a,\omega) \coloneqq \begin{cases} 1 & \text{if } a = a_1 \wedge \omega = \omega_1 \\ \alpha_0 & \text{if } a = a_2 \wedge \omega = \omega_2 \\ -\beta_0 & \text{if } (a = a_1 \wedge \omega = \omega_2) \vee (a = a_2 \wedge \omega = \omega_1) \end{cases}.$$

where $\alpha_0, \beta_0 > 0$. We normalize the payoff from correctly matching action a_1 with state ω_1 to 1. The parameter α_0 represents the relative attractiveness of action a_2 when correctly matched with state ω_2. The parameter β_0 represents mismatching costs.

If Receiver becomes aware of all states (see below), then her preferences are represented by a payoff function $u_R \colon A \times \Omega \to \mathbb{R}$, defined pointwise as

$$u_R(a,\omega) \coloneqq \begin{cases} 1 & \text{if } a = a_1 \wedge \omega = \omega_1 \\ \alpha & \text{if } a = a_2 \wedge \omega = \omega_2 \\ -\beta & \text{if } (a = a_1 \wedge \omega = \omega_2) \vee (a = a_2 \wedge \omega = \omega_1) \\ \gamma & \text{if } a = a_1 \wedge \omega = \omega_3 \\ 0 & \text{if } a = a_2 \wedge \omega = \omega_3 \end{cases}.$$

where $\alpha, \beta > 0$ and $\gamma \in \mathbb{R}$. Parameters α, β have the same interpretations of (but could differ from) parameters α_0, β_0. We normalize the payoff from taking action a_2 under state ω_3 to 0. Thus, the parameter γ represents the relative attractiveness of taking action a_1 under state ω_3. When γ is positive (negative), Receiver prefers action a_1 (a_2) to action a_2 (a_1) when the state is ω_3.

Sender's full-support prior belief is $\mu_S \in \Delta_{++}(\Omega)$ and Receiver's full-support prior belief is $\mu_R^0 \in \Delta_{++}(\Omega_R^0)$. If Receiver becomes aware of all states, Receiver's full-support prior belief is $\mu_R \in \Delta_{++}(\Omega_R)$. Sender knows everything about the game. In particular, he knows that Receiver is initially unaware, which state Receiver is unaware of, Receiver's preferences and prior. Receiver only knows the part of the game within her awareness. In particular, initially Receiver is unaware of her unawareness and is unaware of Sender's superior awareness. Otherwise, the game is common knowledge within Receiver's awareness.

Designing Receiver's Awareness and Information Structures. Sender can expand (or refine) Receiver awareness and design the information structure with the goal of steering Receiver's behavior. In particular, the interaction takes place according to the following stages.

1. Sender decides whether to expand Receiver's awareness from Ω_R^0 to Ω by describing to Receiver the state ω_3. Let $\Omega_R' \in \{\Omega_R^0, \Omega\}$ denote Receiver's *awareness structure* after Sender's choice.

2. If $\Omega_R' = \Omega_R^0$, Receiver's knowledge of the game remains unchanged.

   If $\Omega_R' = \Omega$, Receiver conceives the full set of states Ω and her utility function becomes u_R. Moreover, Receiver forms a new full-support prior belief μ_R.

   We denote by $\mu_R' \in \{\mu_R^0, \mu_R\}$ and $u_R' \in \{u_R^0, u_R\}$ Receiver's prior beliefs and utility function after Sender's choice of Receiver's awareness structure $\Omega_R' \in \{\Omega_R^0, \Omega\}$.

3. Sender provides evidence about the state ω by designing an *information structure*

$$\pi \coloneqq \big(Z, \{\pi(\cdot|\omega)\}_{\omega\in\Omega}\big),$$

   where Z is a finite set of signals and $\{\pi(\cdot|\omega)\}_{\omega\in\Omega}$ is a family of probability distributions on Z. When $\Omega_R' = \Omega$, Sender publicly commits to π. When $\Omega_R' = \Omega_R^0$, Sender publicly commits only to $\tilde{\pi} \coloneqq \big(Z, \{\pi(\cdot|\omega)\}_{\omega\in\Omega_R^0}\big)$, which is obtained by removing $\pi(\cdot|\omega_3)$ from from $\{\pi(\cdot|\omega)\}_{\omega\in\Omega}$. Let Π denote the set of all possible information structures.

4. Signal z from π publicly realizes. We denote by $p_R^z \in \Delta(\Omega_R')$ Receiver's posterior belief after observing signal realization z.

5. Receiver takes an action $a \in A$ and payoffs realize.

Within their awareness, agents are (subjective) expected utility maximizers and process information according to Bayes' rule. To avoid issues about awareness of unawareness and informed-principal problems (i.e., that Receiver may start reasoning about her unawareness and Sender's possibly superior awareness), we assume that Sender can "certify" that all possible states are those in Ω when he expands Receiver's awareness from Ω_R^0 to Ω.

Equilibrium Notion. The equilibrium notion is perfect Bayesian equilibrium (hereafter, PBE). We restrict attention to Sender-preferred language-invariant PBE, and refer to it simply as equilibrium. A PBE is Sender-preferred if Receiver selects an action that maximizes Sender's (subjective) expected utility whenever she is indifferent between actions; a PBE is language invariant if Receiver's action depends only on her posterior belief induced by the observed signal realization.

Value of Awareness. Receiver's action $a\colon \Delta(\Omega'_R) \to A$ in any equilibrium must satisfy

$$a(p^z_R) \in \arg\max_{a\in A} \sum_{\omega\in\Omega'_R} u'_R(a,\omega)p^z_R(\omega).$$

Sender's preferences are state-independent. Therefore, his utility depends only on Receiver's action, not on (his posterior beliefs about) the state of the world. In particular, for any signal realization z and corresponding Receiver's posterior belief p^z_R, Sender's utility is $u_S(a(p^z_R),\omega) = 1\{a(p^z_R) = a_1\}$. Let $v_S(\pi;\Omega'_R,\mu_S,\mu'_R)$ be Sender's expected payoff from information structure π when Receiver's awareness structure is Ω'_R and agents' prior beliefs are (μ_S,μ'_R). That is,

$$v_S(\pi;\Omega'_R,\mu_S,\mu'_R) \coloneqq \mathbb{E}^\pi\big[u_S(p^z_R)\big],$$

where $\mathbb{E}^\pi$ is the expectation taken over the distribution of posterior beliefs p^z_R induced by π given prior beliefs (μ_S,μ'_R). Receiver's action $a(p^z_R)$ is a function of her posterior belief p^z_R. Sender can manipulate p^z_R through the design of the information structure π. The posterior beliefs that Sender can induce must satisfy Bayesian plausibility. In other words, it must hold that Receiver's expectation of her posterior belief equals her prior belief. Formally,

$$\mathbb{E}^\pi\big[p^z_R\big] = \mu'_R$$

Let $\overline{v}_S(\Omega'_R,\mu_S,\mu'_R)$ be Sender's expected payoff under the optimal information structure when Receiver's awareness structure is Ω'_R and agents' prior beliefs are (μ_S,μ'_R). That is,

$$\overline{v}_S(\Omega'_R,\mu_S,\mu'_R) \coloneqq \max_{\pi\in\Pi} v_S(\pi;\Omega'_R,\mu_S,\mu'_R).$$

The value of expanding (or refining) Receiver's awareness is denoted by V_S and defined by

$$V_S \coloneqq \overline{v}_S(\Omega,\mu_S,\mu_R) - \overline{v}_S\big(\Omega^0_R,\mu_S,\mu^0_R\big).$$

Sender expands (or refines) Receiver's awareness, that is $\Omega'_R = \Omega$, if and only if $V_S \geq 0$.

Discussion. We refer to Kamenica and Gentzkow (2011) for a discussion of the standard assumptions of the BP framework. Here, we discuss the additional assumption of our paper, namely asymmetric awareness. First of all, it is necessary to remark the relationship between awareness and framing. Growing awareness can take two forms: expansion and refinement. Expansion means that Sender makes Receiver aware of the existence of a third state ω_3 which has no relationship with the states ω_1 and ω_2 that Receiver was already aware of. Instead, refinement means that Sender makes Receiver aware that either ω_1 or ω_2 are more complex that what Receiver has conceived. For instance, ω_2 can be decomposed in two sub-states ω_{2a} and ω_{2b}. Our model can account for refinement by labelling ω_{2a} as ω_2 and ω_{2b} as ω_3, and refinement can be interpreted as changing Receiver's framing of the world. There is one possible caveat. We assume that Sender commits to π but Receiver observes only the part of information design that she can conceive. This is a natural assumption with expansion because Sender and Receiver give the same interpretation to states ω_1 and ω_2. The same assumption holds with refinement if Receiver, in her initial unawareness, identifies one sub-state as the whole state. Then, Sender can hide the information design under the second sub-state. Consider the following example. Sender is a doctor and Receiver is his patient. Receiver is ill and given the symptoms she is aware that she could have either disease x or disease y. Depending on the disease, Sender can prescribe either drug a_x or drug a_y that are effective only with either disease x or disease y, respectively. Sender wants to prescribe drug a_x, independently of Receiver's disease. Sender knows that disease y has two variants y_a and y_b, each one with specific markers requiring different analysis. Variant y_a is the most common and Receiver identifies it with disease y. Sender can hide that he is not testing for the specific markers of variant y_b. Therefore, our model is suitable to study this application. In different applications, our assumption may fail to hold. In any case, given Receiver's unawareness of state ω_3, she cannot understand π in the same way as Sender does. In Section 4.7.4, we study the case where Receiver understands the information design under ω_2 as a combination of the information design under ω_{2a} and ω_{2b}.

4.4 Optimal Information Structure

In this section, we analyze the optimal information design by Sender. The first step is to study Receiver's optimal action, which varies according to her awareness.

Lemma 5. *If Sender does not modify Receiver's awareness, that is $\Omega'_R = \Omega^0_R$, the optimal action is $a\colon \Delta(\Omega^0_R) \to A$ such that*

$$a(p_R) = \begin{cases} a_1 & \text{if } p_R(\omega_1) \geq \bar{p}_0 \\ a_2 & \text{otherwise} \end{cases}$$

where $\bar{p}_0 \coloneqq \frac{\alpha_0+\beta_0}{1+\alpha_0+2\beta_0}$.

By Lemma 5, Receiver takes Sender's preferred action a_1 if and only if her posterior belief that the true state is ω_1 is above a threshold $\bar{p}_0$. Such a threshold depends on Receiver's preferences. In particular, $\frac{\partial \bar{p}_0}{\partial \alpha_0} > 0$ means that the threshold for taking a_1 increases the higher the relative attractiveness of action a_2. Instead, the effect of matching costs on the threshold depends on the value of α_0, that is $\frac{\partial \bar{p}_0}{\partial \beta_0} > 0$ if and only if $\alpha_0 < 1$.

Lemma 6. *If Sender has decided to expand (or refine) Receiver's awareness, that is $\Omega'_R = \Omega$, the optimal action is $a\colon \Delta(\Omega) \to A$ such that*

$$a(p_R) = \begin{cases} a_1 & \text{if } p_R(\omega_1) + \lambda p_R(\omega_3) \geq \bar{p} \\ a_2 & \text{otherwise} \end{cases}$$

where $\bar{p} \coloneqq \frac{\alpha+\beta}{1+\alpha+2\beta}$ and $\lambda \coloneqq \frac{\alpha+\beta+\gamma}{1+\alpha+2\beta}$.

There are two important differences in this case. First, the threshold $\bar{p}$ could differ from $\bar{p}_0$, because the parameters governing preferences could change following growing awareness. Second, the posterior belief regarding state ω_3 matters and its contribution to satisfy the threshold depends on γ.

For a given degree of Receiver's awareness Ω'_R, the information design problem of Sender can be analysed following Kamenica and Gentzkow (2011). In particular, there exists a straightforward information structure (i.e., with only two signals $Z = \{z_1, z_2\}$) that is equivalent to any optimal information structure. Moreover, if persuasion is optimal, then the posterior beliefs induced by the optimal information structure are characterized by the following expressions:

$$p_R^{z_1}(\omega_1) = \bar{p}_0, \quad p_R^{z_2}(\omega_1) = 0 \quad \text{when } \Omega'_R = \Omega^0_R \text{ and } \mu^0_R(\omega_1) < \bar{p}_0 \tag{27}$$

$$p_R^{z_1}(\omega_1) + \lambda p_R^{z_1}(\omega_3) = \bar{p}, \quad p_R^{z_2}(\omega_1) = 0 \quad \text{when } \Omega'_R = \Omega \text{ and } \mu_R(\omega_1) < \bar{p} \tag{28}$$

Signal z_1 is Sender's recommendation to take action a_1, and it makes Receiver indifferent between a_1 and a_2. Signal z_2 recommends the worst action from the perspective of Sender, thus Receiver can be certain that this is the correct action after observing z_2. The intuition is simple because Sender's utility is a step function: it is zero if the posterior belief is lower than $\bar{p}_0$ or $\bar{p}$, whereas above the thresholds the utility is one. Because posterior beliefs in expectation must equal Receiver's prior beliefs, Sender wants to achieve his preferred action with the lowest posterior beliefs that makes it optimal for Receiver. At the same time, a zero posterior belief after signal z_2 allows to maximize the probability of the posterior belief associated with signal z_1.

Using conditions (27)-(28), we recover the design of the optimal information structure. The following two propositions summarize our findings:

Proposition 13. *When Receiver is partially aware and persuasion is optimal, that is $\Omega'_R = \Omega^0_R$ and $\mu^0_R(\omega_1) < \bar{p}_0$, Sender's optimal information structure is characterized as follows:*

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)}, \quad \pi(z_1|\omega_3) = 1;$$

Sender's expected utility under the optimal information structure is:

$$\overline{v}_S(\Omega^0_R, \mu_S, \mu^0_R) = 1 - \mu_S(\omega_2)\left[1 - \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)}\right] \tag{29}$$

By Proposition 13, when Receiver is not aware of ω_3, Sender conceals it and exploits unawareness to increase the probability to persuade. Instead, the probability to persuade under state ω_2 depends on Receiver preferences over actions as well as on her prior beliefs about states ω_1 and ω_2.

Proposition 14. *When Receiver is fully aware and persuasion is optimal, that is $\Omega'_R = \Omega$ and $\mu_R(\omega_1) + \lambda\mu_R(\omega_3) < \bar{p}$, Sender's optimal information structure and his expected utility under the optimal information structure depends on γ. If $\gamma \geq 0$, the optimal information structure is:*

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = \frac{(1+\beta)\mu_R(\omega_1) + \gamma\mu_R(\omega_3)}{(\alpha+\beta)\mu_R(\omega_2)}, \quad \pi(z_1|\omega_3) = 1$$

and Sender's expected utility is:

$$\overline{v}_S(\Omega, \mu_S, \mu_R) = 1 - \mu_S(\omega_2)\left[1 - \frac{(1+\beta)\mu_R(\omega_1) + \gamma\mu_R(\omega_3)}{(\alpha+\beta)\mu_R(\omega_2)}\right] \tag{30}$$

If $\gamma < 0$, Sender finds it optimal to focus on persuasion under state ω_3 if the following condition holds:

$$\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} \geq -\left(\frac{\gamma}{\alpha+\beta}\right)\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} \tag{31}$$

There are four cases to consider:

1. *If (31) holds and additionally it holds that*

   $$\frac{\mu_R(\omega_1)}{\mu_R(\omega_3)} \geq -\frac{\gamma}{1+\beta} \tag{32}$$

   then the same results as with $\gamma \geq 0$ hold.

2. *If (31) holds but (32) does not hold, then the optimal information structure is:*

   $$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = 0, \quad \pi(z_1|\omega_3) = -\left(\frac{1+\beta}{\gamma}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_3)}$$

   and Sender's expected utility is:

   $$\overline{v}_S(\Omega, \mu_S, \mu_R) = \mu_S(\omega_1) - \mu_S(\omega_3)\left(\frac{1+\beta}{\gamma}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_3)} \tag{33}$$

3. *If* (31) *does not hold and it holds that*

$$\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} \geq \frac{\alpha+\beta}{1+\beta} \tag{34}$$

then the optimal information structure is:

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = 1, \quad \pi(z_1|\omega_3) = -\frac{(1+\beta)\mu_R(\omega_1) - (\alpha+\beta)\mu_R(\omega_2)}{\gamma\mu_R(\omega_3)}$$

and Sender's expected utility is:

$$\overline{v}_S(\Omega, \mu_S, \mu_R) = 1 - \mu_S(\omega_3)\left[1 - \frac{(\alpha+\beta)\mu_R(\omega_2) - (1+\beta)\mu_R(\omega_1)}{\gamma\mu_R(\omega_3)}\right] \tag{35}$$

4. *If* (31) *and* (34) *do not hold then the optimal information structure is:*

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = \left(\frac{1+\beta}{\alpha+\beta}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)}, \quad \pi(z_1|\omega_3) = 0$$

and Sender's expected utility is:

$$\overline{v}_S(\Omega, \mu_S, \mu_R) = \mu_S(\omega_1) + \mu_S(\omega_2)\left(\frac{1+\beta}{\alpha+\beta}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} \tag{36}$$

Proposition 14 has two main implications. When γ is positive, persuasion is necessary only under state ω_2. Therefore, Sender benefits from pooling ω_1 with ω_3. Instead, when γ is negative, Sender has to persuade under both ω_2 and ω_3. Moreover, persuading under ω_2 makes it more difficult to persuade under ω_3 and the other way around. Sender focuses on persuasion under either of the states, depending on his own assessment of the likelihood of the two as well as on Receiver's beliefs, as stated by condition (31). Finally, Sender's ability to persuade under both states requires Receiver to be a believer i.e., to assign higher prior belief to state ω_1 relative to either state ω_2 - see condition (34) - or state ω_3 - see condition (32).

4.5 Optimal Awareness/Framing

In this section, we examine Sender's incentives to expand (or refine) Receiver's awareness. In particular, drawing from the results in Propositions 13 and 14, we establish whether the value of expanding (or refining) Receiver's awareness V_S is positive or not.

First of all, the value of awareness can be strictly positive, that is $V_S > 0$, only if $\mu_R^0(\omega_1) < \bar{p}_0$. In other words, it can be optimal for Sender to increase awareness only when, in the small world of Receiver, persuasion is optimal. Therefore, the possibility to expand or refine Receiver's awareness becomes an additional instrument for Sender to increase his chance to persuade her.

The first scenario where Sender increases Receiver's awareness is when this choice is sufficient to induce Receiver to take Sender's preferred action a_1, in other words, when $\mu_R(\omega_1) + \lambda\mu_R(\omega_3) \geq \bar{p}$. The following proposition states this result.

Proposition 15. *The value of awareness V_S is strictly greater than zero if the following conditions hold:*

$$(1+\beta_0)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} - (\alpha_0+\beta_0) < 0 \tag{37}$$

$$(1+\beta)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} + \gamma\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} - (\alpha+\beta) \geq 0 \tag{38}$$

A necessary condition for (37)-(38) to hold is the following:

$$(1+\beta_0)\left(\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right) + \Delta_\beta\left(\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - 1\right) + \gamma\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} - \Delta_\alpha \geq 0 \tag{39}$$

where $\Delta_\alpha = \alpha - \alpha_0$ and $\Delta_\beta = \beta - \beta_0$.

By Proposition 15, Sender always finds it optimal to increase awareness if this is enough to make Receiver, who is a sceptic in her small world, a believer within her richer awareness. Moreover, condition (39) highlights the four channels that can make growing awareness optimal (see Figure 29):

1. Receiver's prior beliefs become more favorable from the perspective of Sender, that is $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} > \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}$.

2. A change in the cost β for Receiver of mismatching action and state. An increase (decrease) in this cost i.e., $\Delta_\beta > 0$ ($\Delta_\beta < 0$) can make growing awareness more appealing if Receiver is a believer (sceptic), that is, $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} > 1$ $\left(\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} < 1\right)$.

3. Under the novel contingency ω_3, action a_1 is more appealing than action a_2. In other words, $\gamma > 0$. This effect is stronger, the higher $\mu_R(\omega_3)$, that is, Receiver's prior of ω_3 after growing awareness. In this case, Sender benefits from Receiver's overreaction.

4. In the new world of Receiver, action a_2 is generically less appealing, that is $\Delta_\alpha < 0$.

Even if persuasion is still necessary after growing awareness, that is condition (38) does not hold, Sender might have an incentive to increase Receiver's awareness. In order to investigate these incentives, we compare Sender's utility in the different scenarios considered in Propositions 13 and 14. The following propositions present the results of our analysis, case by case.

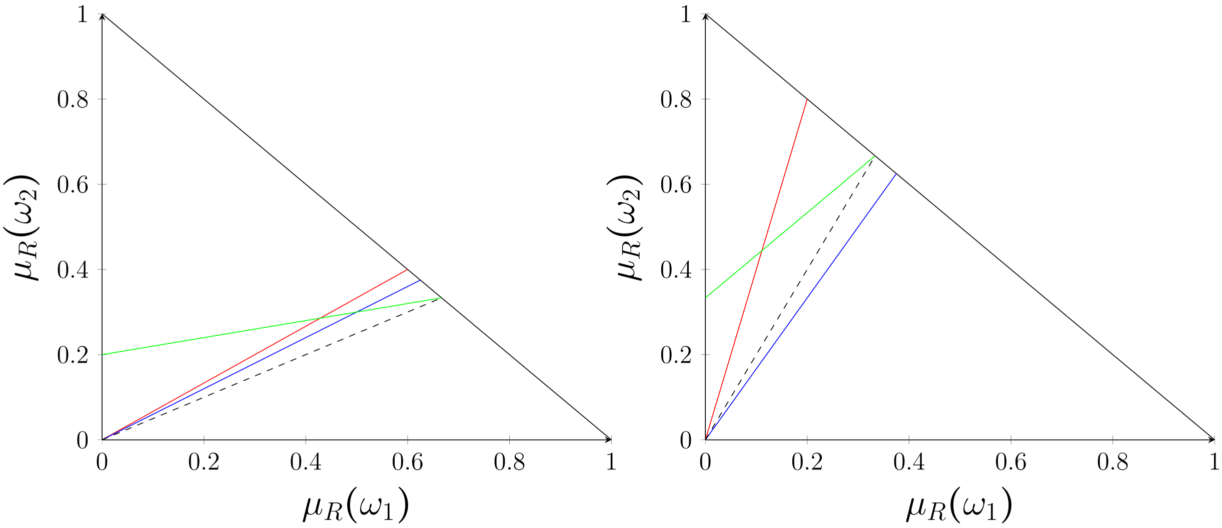
Proposition 16. *If $\gamma \geq 0$ but (38) does not hold, Sender finds it optimal to increase awareness if and only if the following condition holds:*

$$(1+\beta_0)(\alpha_0+\beta_0)\left(\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right) + \Delta_\beta\left[(\alpha_0+\beta_0)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - (1+\beta_0)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right] + \gamma(\alpha_0+\beta_0)\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} - \Delta_\alpha(1+\beta_0)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} \geq 0 \tag{40}$$

When γ is positive, Sender has incentives to pool ω_1 and ω_3, because being in state ω_3 makes action a_1 more appealing. Therefore, the information design before and after growing awareness are very similar. Thus, the incentives to increase awareness depend exclusively on the trade-off between the advantage of making Receiver aware of state ω_3 and the effect of the change in Receiver's preferences and beliefs on Sender's ability to persuade under stage ω_2. This trade-off is expressed by the condition (40), which is similar but weaker than condition (38). Also the four channels previously identified work in a similar way. See Figure 30 as an example.

When γ is negative, growing awareness seems to be not appealing because Sender cannot conceal ω_3 and, at the same time, being in state ω_3 makes it harder for Sender to persuade Receiver to take action a_1. Nevertheless, growing awareness can be optimal. The trade-off that Sender faces depends on condition (31), namely whether Sender prefers to persuade marginally under state ω_2 or under state ω_3. The following two propositions state Sender's optimal behavior.

Figure 29: Example for Proposition 15



(a) $\alpha_0 = 2$ and $\beta_0 = 0$

(b) $\alpha_0 = \frac{1}{2}$ and $\beta_0 = 0$

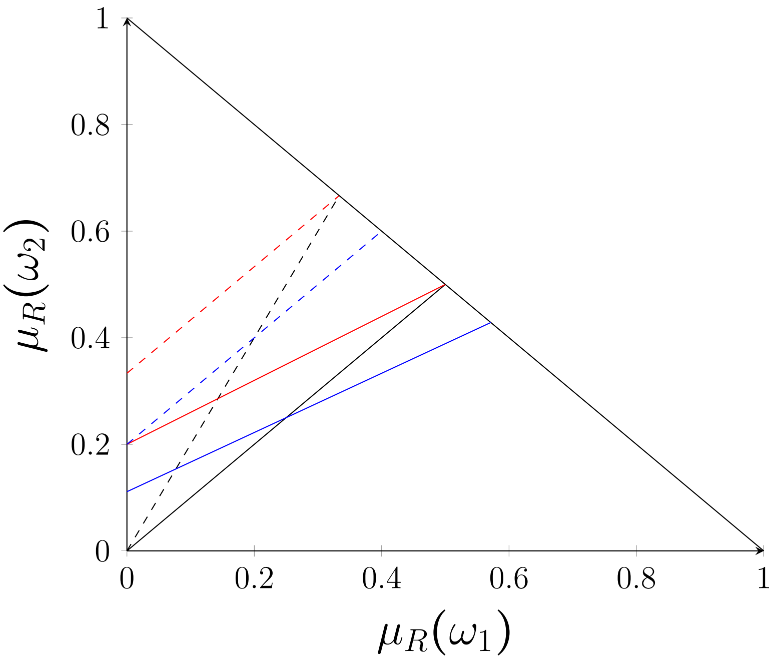
A necessary condition for growing awareness is $\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} < 2$ in Figure 29a and $\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} < \frac{1}{2}$ in Figure 29b. Without considering the effect of the change in preferences, growing awareness is optimal for beliefs μ_R that are below the black dashed lines. The red lines represent the effect of a negative Δ_α. In particular, we assume $\alpha = \frac{3}{2}$ in Figure 29a and $\alpha = \frac{1}{4}$ in Figure 29b. This expands the space of new beliefs that support growing awareness. The effect is stronger the lower Receiver's prior belief of state ω_3. Instead, the green lines represent the effect of a positive γ. In particular, we assume $\gamma = \frac{1}{2}$ in Figure 29a and $\gamma = \frac{1}{4}$ in Figure 29b. This expands the space of new beliefs that support growing awareness. The effect is stronger the higher Receiver's prior belief of state ω_3. Finally, the blue lines represent the effect of a positive Δ_β. In particular, we assume $\beta = \frac{1}{2}$ in Figure 29a and $\beta = \frac{1}{4}$ in Figure 29b. The effect of Δ_β varies depending on α_0. An increase in β expands (shrinks) the space of new beliefs that support growing awareness when $\alpha_0 > 1$ ($\alpha_0 < 1$). Indeed, in the black dashed line, Receiver is a believer (sceptic) in Figure 29a (29b).

Proposition 17. *If $\gamma < 0$, (38) does not hold and (31)-(32) are satisfied, Sender finds it optimal to increase Receiver's awareness if and only if (40) holds. When (32) does not hold, growing awareness is never optimal.*

Condition (31) is satisfied if Sender finds it optimal to pool state ω_3 (rather than state ω_2) with state ω_1. Therefore, (31) requires Receiver to have a sufficiently small belief that the true state is ω_3, relative to the objective belief hold by Sender. In particular, we say that Receiver under-reacts to state ω_3 if $\mu_R(\omega_3) < \mu_S(\omega_3)$. Therefore, Receiver's under-reaction is likely to lead to growing awareness. Instead, condition (32) represents the possibility by Sender to pool all states together. In particular, this is possible if $\mu_R(\omega_3)$ is small enough. In other words, (32) requires Receiver to be a believer, that is to attribute higher belief to ω_1 than to ω_3. The higher $\mu_R(\omega_3)$, the higher the cost of pooling ω_1 and ω_3, in terms of persuasion power under state ω_2, because the effect of γ is multiplicative in $\mu_R(\omega_3)$. Both conditions (31)-(32) imply that an excessive reaction of Receiver to growing awareness in terms of prior belief of state ω_3 can discourage Sender to increase awareness. See Figure 31. Finally, when condition (32) does not hold, Sender prefers to separate state ω_1 and stage ω_2, because he finds it optimal to pool ω_1 and state ω_3 as much as possible. In this case, growing awareness cannot be optimal because, under partial awareness, Sender can conceal state ω_3 (being sure to persuade under ω_3) and persuade under state ω_2 with positive probability.

If condition (31) does not hold, Sender prefers to separate marginally ω_1 and ω_3 in

Figure 30: Example for Proposition 16



We assume that $\alpha_0 = 1$, $\beta_0 = 0$ and $\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} = \frac{1}{2}$. We identify the region of beliefs μ_R such that Proposition 16 applies, for different parameter choices. In particular, we compare beliefs that satisfy condition (40) (dashed line) with those that satisfy also condition (38) (solid line). As a benchmark, the black lines represent the case where only beliefs vary, that is $\gamma = \Delta_\alpha = \Delta_\beta = 0$. Then, we fix $\gamma = \frac{1}{4}$. The red lines corresponds to the case $\Delta_\alpha = \Delta_\beta = 0$. Instead, the blue lines correspond to the case $\Delta_\alpha = \Delta_\beta = \frac{1}{2}$.

order to pool ω_1 and ω_2. Even if this reduces the probability to persuade under state ω_3 (as opposed to concealing under partial awareness), growing awareness can be optimal. The next proposition states this result.

Proposition 18. *If $\gamma < 0$ whereas (38) and (31) do not hold, Sender's incentive to increase Receiver's awareness depends on condition (34). When the latter holds, Sender finds it optimal to increase Receiver's awareness if and only if*

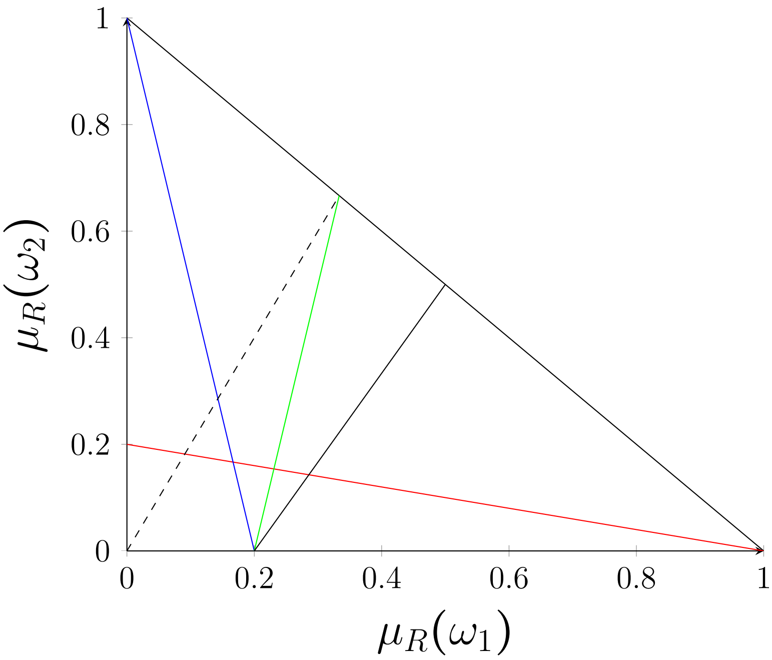
$$\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} \leq \left[\frac{1 - \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right) \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}}{1 - \left(\frac{(1+\beta_0+\Delta_\beta)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - (\alpha_0+\beta_0+\Delta_\alpha+\Delta_\beta)}{-\gamma \frac{\mu_R(\omega_3)}{\mu_R(\omega_2)}} \right)} \right] \tag{41}$$

Otherwise, Sender finds it optimal to increase Receiver's awareness if and only if

$$\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} \leq \left(\frac{1+\beta}{\alpha+\beta}\right) \frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right) \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} \tag{42}$$

Condition (34) is satisfied if Receiver is a believer after growing awareness, that is the discovery of ω_3 changes Receiver's beliefs and preferences in a way that even if states ω_1 and ω_2 are pooled Receiver's optimal action is still a_1. In this case, Sender can exploit this fact to pool ω_1 with ω_3 to some extent. If this is not the case, increasing awareness can be optimal only if the change in Receiver's preferences or priors makes persuasion much easier under state ω_2 and compensate for the lack of persuasion under state ω_3. Conditions (41)-(42), as well as (31) being violated, require $\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)}$ to be small enough. In other words, Sender can benefit from growing awareness only if his prior belief regarding state ω_3 is sufficiently small. See Figure 32 as an example.

Figure 31: Example for Proposition 17

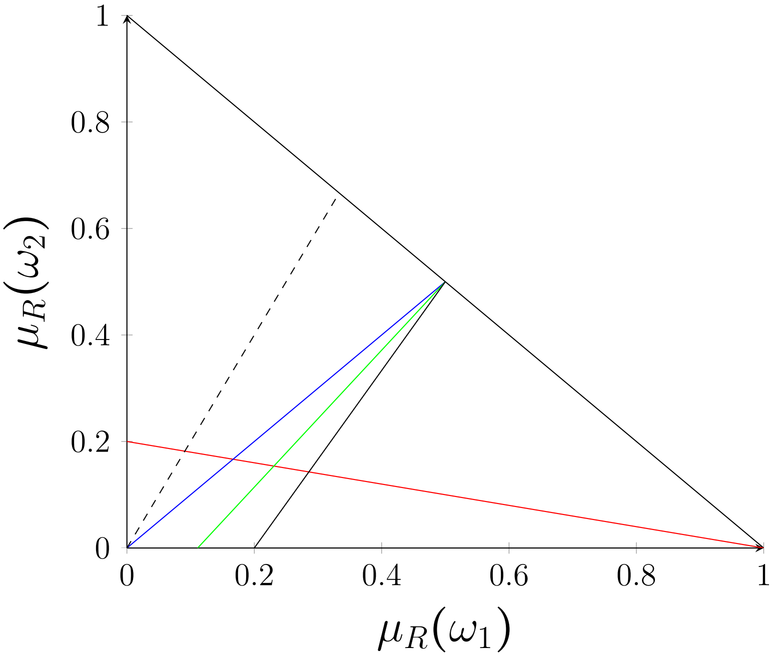


We assume that $\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} = 1$, $\alpha_0 = 1$ and $\beta_0 = 0$. We rule out any change in preferences, that is $\Delta_\alpha = \Delta_\beta = 0$, and we consider feasible changes in prior beliefs that lead to growing awareness when $\gamma = -\frac{1}{4}$ and $\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} = \frac{1}{2}$. The red line represents condition (31), whereas the blue line represents condition (32). Therefore, the feasible prior beliefs are those above the two lines. The green line represents condition (40): growing awareness is optimal below the green line. In the absence of any change in preferences, a negative γ can be compensated by a change in priors. In particular, it must be the case that $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} > \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}$. Indeed, the green line lies below the black dashed line that represents prior beliefs such that $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} = \frac{1}{2}$. Finally, the black solid line represents condition (38), which is sufficient but not necessary for growing awareness.

4.6 An Application: Volkswagen's Diesel-gate

During 2015, Volkswagen was discovered to have faked emissions test of its cars: this scandal is known as Diesel-gate. Using this as a starting point, we study the problem of a car producer that must decide whether to make consumers aware that its cars can be polluting. In this example, $\Omega = \{$"good car", "good but polluting car", "bad car"$\}$ whereas $\Omega_R^0 = \{$"good car", "bad car"$\}$. Therefore, consumer's frame does not include the possibility that a car can be polluting, despite being technically a good car. The car producer decides upon changing consumer's awareness depending on the induced changes in preferences and beliefs. An average consumers is likely to value a good car less if it is a polluting one. In other words, we assume $\gamma < 0$. At the same time, it is reasonable to assume that there is no change in matching costs ($\Delta_\beta = 0$) and that the payoff from buying a good car increases as soon as the consumer becomes aware that this is certified as not polluting ($\Delta_\alpha < 0$). Unless this positive effect of certification is sufficient to justify the increase in awareness, the key role is played by changes in beliefs. One possible explanation for hiding the possibility that a car is polluting is that opening this possibility can harm the car producer's reputation. In other words, it can lead to $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} < \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}$. Finally, the decision to increase awareness depends on how much probability consumers attaches to the event that the car is polluting, that is $\mu_R(\omega_3)$. The car producer benefits from an under-reaction in general: revealing the possibility that the car is polluting is only meant to exclude this possibility and certify that the car has a higher quality. By contrast, the

Figure 32: Example for Proposition 18



We assume that $\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} = 1$, $\alpha_0 = 1$ and $\beta_0 = 0$. We rule out any change in preferences, that is $\Delta_\alpha = \Delta_\beta = 0$, and we consider feasible changes in prior beliefs that lead to growing awareness when $\gamma = -\frac{1}{4}$ and $\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} = \frac{1}{2}$. The red line represents condition (31). Since it is violated, we consider beliefs below the red line. The blue line represents condition (34). Therefore, the feasible prior beliefs are below it. The green line represents condition (41): growing awareness is optimal below the green line, which lies below the black dashed line that represents prior beliefs such that $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} = \frac{1}{2}$. Instead, the black solid line represents condition (38), which is sufficient but not necessary for growing awareness. Finally, given the parameters that were chosen, condition (42) cannot hold.

car producer can benefit from an over-reaction only if the event that the car is polluting absorbs all the negative considerations about the car. In other words, $\mu_R(\omega_2)$ is small. Hence, it is easy to persuade to buy the car, once the car provider obtains the certification that the car is not polluting.

Going beyond this particular example, our model can be used to study any situation where a buyer interacts with a seller that has superior awareness. Seller provides a product with uncertain quality $\omega \in \Omega \coloneqq \{\omega_H, \omega_M, \omega_L\}$, where $\omega_H > 0 > \omega_L$ and $\omega_H > \omega_M > \omega_L$. Buyer is initially unaware of quality ω_M, that is $\Omega_R^0 \coloneqq \{\omega_H, \omega_L\}$. The timing is the following: Seller decides whether to make Buyer aware of ω_M. Then, Sender designs information about product's quality. Given posterior beliefs, Seller chooses the price of the product. Finally, Buyer decides whether to buy, that is $A = \{a_1, a_2\} = \{\text{buy, not buy}\}$. Buyer has valuation v for the product, which is Buyer's private information. Seller knows that $v \sim U[0,1]$. Buyer's utility depends on her awareness Ω_R'. In particular, when $\Omega_R' = \Omega_R^0$:

$$u_R^0(a,\omega) \coloneqq \begin{cases} v + \omega_H - p_0 & \text{if } a = a_1 \wedge \omega = \omega_H \\ 0 & \text{if } a = a_2 \wedge \omega = \omega_H \\ v & \text{if } a = a_1 \wedge \omega = \omega_L \\ p_0 - \omega_L & \text{if } a = a_2 \wedge \omega = \omega_L \end{cases}.$$

where p_0 is the price charged by Seller if $\Omega_R' = \Omega_R^0$. If we normalize $\omega_H = 1$ and set $\alpha_0 = p_0 - \omega_L$, $\beta_0 = 0$, we are back to our initial model. Buyer chooses a_1 if and only if $v + E_0(\omega) - p_0 \geq 0$, where E_0 is Buyer's expected quality if $\Omega_R' = \Omega_R^0$. Instead, when $\Omega_R' = \Omega$:

$$u_R(a,\omega) \coloneqq \begin{cases} v+\omega_H-p & \text{if } a=a_1 \wedge \omega=\omega_H \\ 0 & \text{if } a=a_2 \wedge \omega=\omega_H \\ v & \text{if } a=a_1 \wedge \omega=\omega_L \\ p-\omega_L & \text{if } a=a_2 \wedge \omega=\omega_L \\ v+\omega_M-p & \text{if } a=a_1 \wedge \omega=\omega_M \\ 0 & \text{if } a=a_2 \wedge \omega=\omega_M \end{cases}.$$

where p is the price charged by Seller if $\Omega'_R = \Omega$. If we set $\alpha = p - \omega_L$, $\beta = 0$ and $\gamma = \omega_M$, we are back to our initial model. Buyer chooses a_1 if and only if $v + E(\omega) - p \geq 0$, where E is Buyer's expected quality if $\Omega'_R = \Omega$. Let $E' \in \{E_0, E\}$ and $p' \in \{p_0, p\}$ be, respectively, product's expected quality and price as a function of Buyer's awareness Ω'_R. In particular, $E'(\omega) = \sum_{\omega\in\Omega'_R} p_R(\omega)\omega$, where p_R are Buyer's posterior beliefs. We define Seller's profit Π as follows:

$$\Pi(p_R, p') = (1 + E'(\omega) - p')p'$$

Therefore, the optimal price is $p' = \frac{1+E'(\omega)}{2}$ and corresponding profits are $\Pi(p_R) = \frac{[1+E'(\omega)]^2}{4}$. Therefore, the goal of Seller, when designing information and choosing whether to increase Buyer's awareness, is to maximize $E'(\omega)$. Seller's choices depend on how beliefs are affected by growing awareness and by the value of ω_M (that is γ). As a final remark, $\Delta_\alpha = p - p_0 > 0$ because Seller increases awareness only if this increases $E'(\omega)$, but this endogenous Δ_α does not offset the benefit of growing awareness.

4.7 Refinements

4.7.1 Reverse Bayesianism

Following Karni and Vierø (2013), in this section we assume that the ratio of prior beliefs of states ω_1 and ω_2 must stay constant following growing awareness, that is $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} = \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} = c \in \mathbb{R}_+$. In other words, the discovery of a new state of the world (ω_3) does not affect the relative likelihood of those already conceived (ω_1 and ω_2). This assumption eliminates one channel that can make growing awareness optimal for Sender: see condition (39). In particular, Receiver is neither more believer or more sceptic after growing awareness. As a consequence, the incentive to increase awareness must come from a positive (from the perspective of Sender) change in preferences. Condition (37) is a necessary condition for growing awareness and imposes an upper bound on the value of c, that is $c < \frac{\alpha_0+\beta_0}{1+\beta_0}$. Moreover, it is possible to express the prior belief of state ω_2 as a function of the prior belief of state ω_3, that is $\mu_R(\omega_2) = \frac{1-\mu_R(\omega_3)}{1+c}$. Then, condition (38) can be rewritten as follows:

$$\gamma(1+c)\frac{\mu_R(\omega_3)}{1-\mu_R(\omega_3)} + \Delta_\beta(c-1) - \Delta_\alpha \geq \underbrace{\alpha_0 + \beta_0 - c(1-\beta_0)}_{\geq 0} \tag{43}$$

If this condition is satisfied, the change in preferences justify growing awareness, because it is sufficient to make persuasion unnecessary. In particular, it is necessary that either γ is positive (whose effect is proportional to the prior belief that the true state is ω_3) or there is a decrease in α. Finally, the effect of a change in β depends on c. When condition (43) fails, as we have shown before, we need to analyse the trade-off for Sender between persuasion under partial awareness and persuasion under full awareness. Reverse Bayesianism has an effect on this trade-off. In particular, condition (40) becomes

$$c\left[\Delta_\beta(\alpha_0 - 1) - \Delta_\alpha(1+\beta_0)\right] + \gamma(\alpha_0+\beta_0)(1+c)\frac{\mu_R(\omega_3)}{1-\mu_R(\omega_3)} \geq 0 \tag{44}$$

where changes in preferences play the same role as in (43). Condition (44) applies when $\gamma \geq 0$ or condition (31) holds. When $\gamma < 0$ and condition (31) fails, condition (41) becomes:

$$\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} \leq \left[\frac{1 - \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right) c}{1 - \left(\frac{(1+\beta_0+\Delta_\beta)c - (\alpha_0+\beta_0+\Delta_\alpha+\Delta_\beta)}{-\gamma(1+c)\frac{\mu_R(\omega_3)}{1-\mu_R(\omega_3)}} \right)} \right] \tag{45}$$

Because of reverse Bayesianism, condition (45) requires $\frac{\alpha+\beta}{1+\beta} \leq c \leq \frac{\alpha_0+\beta_0}{1+\beta_0}$, that is $\Delta_\alpha < 0$ and/or $\Delta_\beta < 0$ ($\Delta_\beta > 0$) if $\alpha < 1$ ($\alpha > 1$). Otherwise, condition (42) applies, and it becomes:

$$\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} \leq c \left(\frac{\Delta_\beta(\alpha_0 - 1) - \Delta_\alpha(1+\beta_0)}{(\alpha+\beta)(\alpha_0+\beta_0)} \right) \tag{46}$$

that requires at least $\Delta_\alpha \leq \Delta_\beta \left(\frac{\alpha_0-1}{1+\beta_0}\right)$. In other words, when $\gamma < 0$ and reverse Bayesianism applies, the only channels left for growing awareness are adjustments in α and β. Table 40 summarizes some examples with the relevant threshold values for γ. We assume that $\mu_S(\omega_1) = \mu_S(\omega_2) = \mu_S(\omega_3) = \frac{1}{3}$.

Table 40: Values of γ that make growing awareness optimal for Sender

α_0	β_0	c	Δ_α	Δ_β	(43)	(44)	(45) and (46)
1	0	$\frac{1}{2}$	0	0	$\gamma \geq \frac{1-\mu_R(\omega_3)}{3\mu_R(\omega_3)}$	$\gamma \geq 0$	$\varnothing$
1	0	$\frac{1}{2}$	$-\frac{1}{4}$	0	$\gamma \geq \frac{1-\mu_R(\omega_3)}{6\mu_R(\omega_3)}$	$\gamma \geq -\left(\frac{1-\mu_R(\omega_3)}{12\mu_R(\omega_3)}\right)$	$\varnothing$
1	0	$\frac{1}{2}$	$-\frac{3}{4}$	0	$\gamma \geq -\left(\frac{1-\mu_R(\omega_3)}{6\mu_R(\omega_3)}\right)$	$\varnothing$	$\gamma \in \left(-\frac{1-\mu_R(\omega_3)}{3\mu_R(\omega_3)}, -\frac{1-\mu_R(\omega_3)}{6\mu_R(\omega_3)}\right)$
1	0	$\frac{1}{2}$	0	$\frac{1}{4}$	$\gamma \geq \frac{5}{12}\left(\frac{1-\mu_R(\omega_3)}{3\mu_R(\omega_3)}\right)$	$\gamma \geq 0$	$\varnothing$
1	0	$\frac{1}{4}$	0	0	$\gamma \geq \frac{2}{5}\left(\frac{1-\mu_R(\omega_3)}{3\mu_R(\omega_3)}\right)$	$\gamma \geq 0$	$\varnothing$

4.7.2 Sub-Additivity

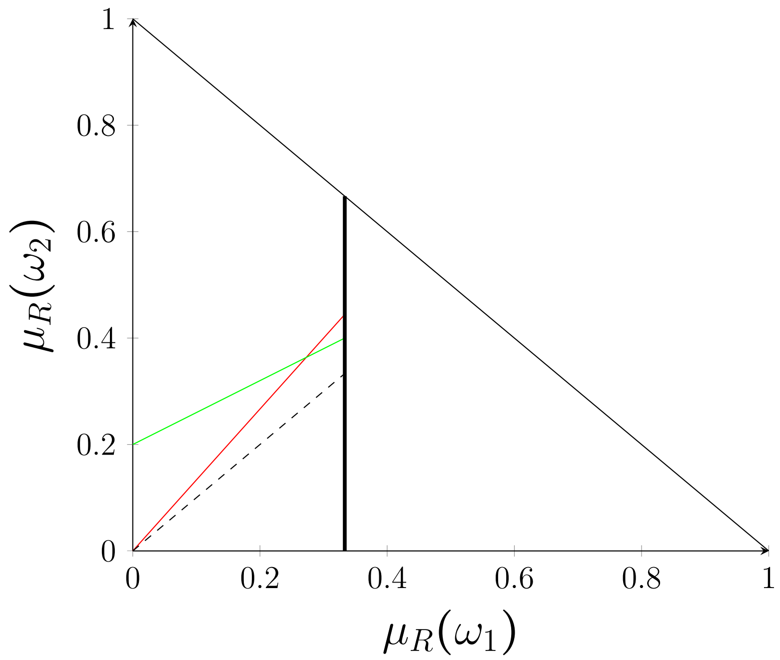
When growing awareness can be interpreted as a change in Receiver's frame (from a coarse one to a finer one), the prior beliefs can change because of partition dependence. In particular, there is large evidence that beliefs satisfy a sub-additivity property: a "bundle" of two events has lower probability for Receiver than the two events considered separately.

There are two cases to study: state ω_3 could be either a refinement of state ω_1 (that is $\omega_3 = \omega_{1b}$) or a refinement of state ω_2 (that is $\omega_3 = \omega_{2b}$). Sub-additivity imposes different restrictions on beliefs in these two cases:

$$\mu_R^0(\omega_1) \leq \mu_R(\omega_1) + \mu_R(\omega_3) \iff \mu_R^0(\omega_2) \geq \mu_R(\omega_2) \tag{47}$$
$$\mu_R^0(\omega_2) \leq \mu_R(\omega_2) + \mu_R(\omega_3) \iff \mu_R^0(\omega_1) \geq \mu_R(\omega_1) \tag{48}$$

These conditions are weaker than the one imposed by Reverse Bayesianism. In particular, the relative likelihood of state ω_1 compared to stage ω_2 can be both higher or lower after growing awareness. The restriction is on the level of the belief regarding one state: the state that is not refined is associated with a lower belief after the refinement than prior to it. This has important consequences on the decision to increase awareness. In particular, when ω_1 is refined and (47) holds, the set of feasible beliefs shrinks in a way that there are fewer beliefs such that growing awareness is not optimal. At the opposite, when ω_2 is refined and (48) holds, there are fewer beliefs that support growing awareness. Therefore, it does matter for Sender's decision what state is refined, and Sender has less incentives to refine ω_2 than ω_1, ceteris paribus. Figure 33 shows an example.

Figure 33: The effect of sub-additivity



In this graph, we assume $\alpha_0 = 1$ and $\beta_0 = 0$. Therefore, a necessary condition for growing awareness is $\mu_R^0(\omega_1) < \frac{1}{2}$. We assume $\mu_R^0(\omega_1) = \frac{1}{3}$. The black dashed line represents beliefs μ_R such that $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} = 1$. Without considering the effect of a change in preferences, growing awareness is optimal below the dashed line. The red line represents the effect of a negative Δ_α. In particular, we assume $\alpha = \frac{3}{4}$. Instead, the green line represents the effect of a positive γ. In particular, we assume $\gamma = \frac{1}{4}$. The black solid vertical line at $\mu_R(\omega_1) = \frac{1}{3}$ represents the constraint imposed by sub-additivity, in particular condition (48). Sub-additivity shrinks the set of beliefs that lead to growing awareness, as beliefs at the right of the black solid line are not feasible.

4.7.3 Preferences Correlation

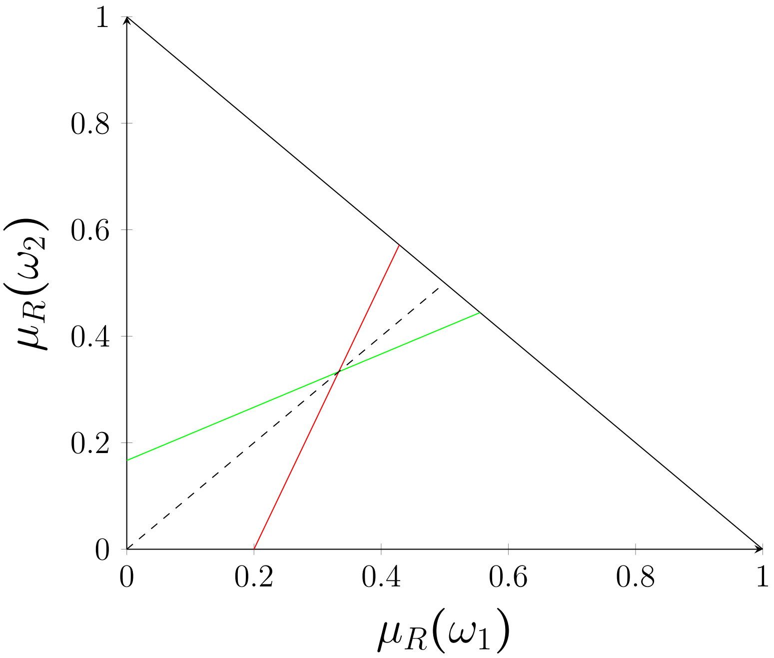
In the previous sections, we focused on restrictions about how beliefs evolve with growing awareness. In this section, we keep beliefs free and instead impose a restriction on preferences. In particular, we assume that $\gamma = \Delta_\alpha$. This is equivalent to $\alpha_0 = \alpha - \gamma$. In other words, the preference parameter under partial awareness (α_0) is the sum of two components (α and $-\gamma$) that are unbundled after growing awareness. The interpretation is the following: when the discovery of ω_3 is associated with a positive payoff ($\gamma > 0$), this makes ω_2 relatively less appealing. Instead, when $\gamma < 0$, the new state ω_3 partially absorbs the negative aspects of state ω_2, making it more appealing. Using this restriction and imposing for simplicity $\beta_0 = 0$ and $\Delta_\beta = 0$, conditions (37)-(38) become:

$$\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} < \alpha_0 \tag{49}$$

$$\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} + \gamma\left(\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} - 1\right) \geq \alpha_0 \tag{50}$$

In this case, the effect of a change in preferences depends on whether $\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} \geq 1$. Sender benefits from the discovery of ω_3 if the state (either ω_2 or ω_3) under which action a_1 becomes relatively more attractive (ω_3 if $\gamma > 0$) is also the state to which Receiver attributes higher prior belief between the two. In line with the previous results, Sender benefits also when the ratio $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)}$ gets larger, that is it becomes easier to persuade under ω_2 following growing awareness. See Figure 34 as an example.

Figure 34: Desired prior beliefs when changes in preferences are correlated.



We assume $\alpha_0 = 1$. The black dashed line represents beliefs μ_R such that $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} = 1$. This is a sufficient condition for growing awareness, without a change in preferences (i.e., $\gamma = 0$). The green line represents the effect of a positive γ. In particular, we assume $\gamma = \frac{1}{4}$. Growing awareness is optimal below the green line. The higher $\mu_R(\omega_3)$, the more appealing growing awareness. The red line represents the effect of a negative γ. In particular, we assume $\gamma = -\frac{1}{4}$. Growing awareness is optimal below the red line. The higher $\mu_R(\omega_3)$ is, the less appealing growing awareness becomes.

When condition (50) does not hold, if $\gamma > 0$ or (31) holds, the trade-off is represented by (40), that becomes:

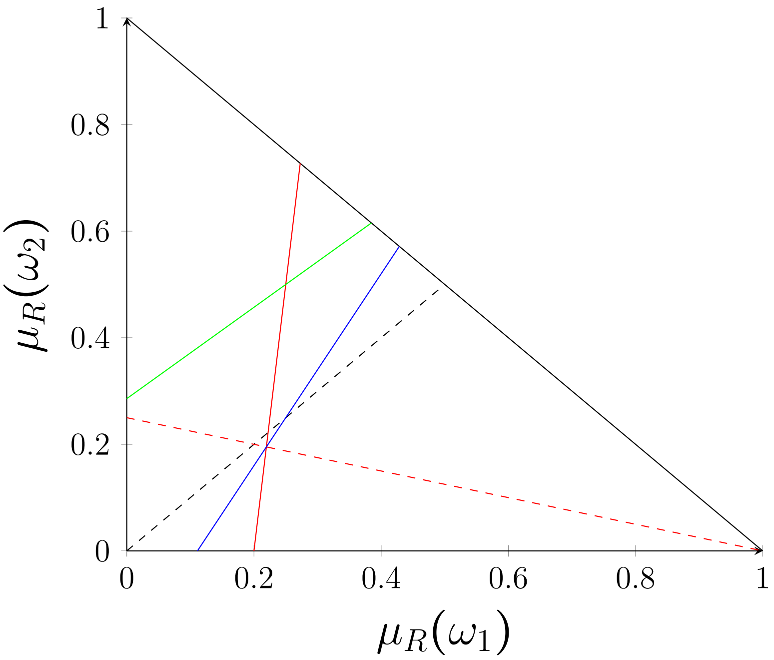
$$\alpha_0\left(\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right) + \gamma\left(\alpha_0\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} - \frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right) \geq 0 \tag{51}$$

In this case, the effect of γ depends on whether $\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} \geq \frac{\mu_R^0(\omega_1)}{\alpha_0\mu_R^0(\omega_2)}$, and this threshold is smaller than one by condition (49). Finally, when $\gamma < 0$ and (31) does not hold (that requires Receiver to over-react to the discovery of state ω_3), condition (41) becomes:

$$\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} \leq \left[\frac{1 - \frac{\mu_R^0(\omega_1)}{\alpha_0\mu_R^0(\omega_2)}}{1 - \left(\frac{\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - (\alpha_0+\gamma)}{-\gamma\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)}}\right)}\right] \tag{52}$$

The effect of a change in γ depends on whether $\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} \geq 1$, and clearly for this condition to hold $\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)}$ must be sufficiently small. Note that instead condition (42) does not depend on γ. See Figure 35 as an example.

Figure 35: Growing awareness when changes in preferences are correlated.



We assume $\alpha_0 = 1$, $\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} = \frac{1}{2}$ and $\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)} = 1$. The black dashed line represents beliefs μ_R such that $\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} = 1$. The green line represents the effect of a positive γ. In particular, we assume $\gamma = \frac{1}{4}$. Growing awareness is optimal below the green line. When $\gamma < 0$, in particular we assume $\gamma = -\frac{1}{4}$, the trade-off depends on whether condition (31) holds. The red dashed line represents (31), which holds above it. The red solid line represents the effect of a negative γ when (31) holds, that is condition (51). Growing awareness is optimal below the red solid line (if above the red dashed line). Finally, the blue solid line represents the effect of a negative γ when (31) does not hold, that is condition (52). Growing awareness is optimal below the blue solid line (if below the red dashed line).

4.7.4 Alternative Interpretation of Framing

In this section, we relax the assumption that Receiver observes only $\tilde{\pi}$, the restriction of Sender's information structure to those states that Receiver conceives given her awareness. Because Receiver is not aware of ω_3, she cannot understand the information structure as Sender does. Here, we examine what happens if Receiver understands the information generating process under either ω_1 or ω_2 as the combination of the true information generating process under the selected state and state ω_3. There are two cases to consider:

1. According to Receiver's worldview, ω_1 and ω_3 are bundled together, thus:

$$\tilde{\pi}(z|\omega_1) = \frac{\pi(z|\omega_1) + \pi(z|\omega_3)}{2}, \quad \tilde{\pi}(z|\omega_2) = \pi(z|\omega_2)$$

2. According to Receiver's worldview, ω_2 and ω_3 are bundled together, thus:

$$\tilde{\pi}(z|\omega_1) = \pi(z|\omega_1), \quad \tilde{\pi}(z|\omega_2) = \frac{\pi(z|\omega_2) + \pi(z|\omega_3)}{2}$$

In this first scenario, our results are robust. Under partial awareness, Sender finds it optimal to conceal ω_3 (Proposition 13). Even if Receiver conceives evidence generated under state ω_3 as being generated in state ω_1, this does not affect Sender's problem. The second scenario is more interesting because by concealing ω_3 Sender reduces the credibility of his recommendation under state ω_2. This is because Receiver conceives evidence generated under state ω_3 as being generated in state ω_2. Hence, if Sender uses the information structure described in Proposition 13, his recommendation z_1 to take action a_1 does not persuade Receiver. The following proposition describes the optimal information structure in the second scenario.

Proposition 19. *When $\tilde{\pi}(z|\omega_1) = \pi(z|\omega_1)$ and $\tilde{\pi}(z|\omega_2) = \frac{\pi(z|\omega_2)+\pi(z|\omega_3)}{2}$, Sender prefers to persuade marginally under state ω_2 than under state ω_3 if and only if $\mu_S(\omega_2) \geq \mu_S(\omega_3)$. The optimal information structure depends on whether the following condition holds:*

$$\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} \geq \frac{1}{2} \tag{53}$$

There are four cases to consider:

1. *If $\mu_S(\omega_2) \geq \mu_S(\omega_3)$ and (53) holds, then the optimal information structure is:*

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = 1, \quad \pi(z_1|\omega_3) = 2\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} - 1$$

and Sender's expected utility is:

$$\overline{v}_S(\Omega,\mu_S,\mu_R) = 1 - 2\mu_S(\omega_3)\left[1 - \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right] \tag{54}$$

2. *If $\mu_S(\omega_2) \geq \mu_S(\omega_3)$ and (53) does not hold, then the optimal information structure is:*

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = 2\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}, \quad \pi(z_1|\omega_3) = 0$$

and Sender's expected utility is:

$$\overline{v}_S(\Omega,\mu_S,\mu_R) = \mu_S(\omega_1) + 2\mu_S(\omega_2)\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} \tag{55}$$

3. *If $\mu_S(\omega_2) < \mu_S(\omega_3)$ and (53) holds, then the optimal information structure is:*

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = 2\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} - 1, \quad \pi(z_1|\omega_3) = 1$$

and Sender's expected utility is:

$$\overline{v}_S(\Omega,\mu_S,\mu_R) = 1 - 2\mu_S(\omega_2)\left[1 - \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right] \tag{56}$$

4. *If $\mu_S(\omega_2) < \mu_S(\omega_3)$ and (53) does not hold, then the optimal information structure is:*

$$\pi(z_1|\omega_1) = 1, \quad \pi(z_1|\omega_2) = 0, \quad \pi(z_1|\omega_3) = 2\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}$$

and Sender's expected utility is:

$$\overline{v}_S(\Omega,\mu_S,\mu_R) = \mu_S(\omega_1) + 2\mu_S(\omega_3)\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)} \tag{57}$$

Proposition 19 illustrates the effects on the optimal information structure of Sender's inability to conceal state ω_3. The change in the optimal information structure has an impact on Sender's trade-off about growing awareness. We argue that, whereas the parameter's values that make Sender indifferent changes and growing awareness becomes more appealing, our results do not change qualitatively: changes in preferences and beliefs play the same role as before. For instance, we consider the case where $\mu_S(\omega_2) < \mu_S(\omega_3)$ and (53) holds. Comparing (56) and (29), we observe that the value of keeping Receiver in the dark is lower. Therefore, the incentive to increase awareness (for instance, the comparison with (30)) is stronger. The new prior beliefs μ_R as well as preferences parameters α, β, γ are not affected by this alternative $\tilde{\pi}$. What matters are prior beliefs and preferences before growing awareness. When (53) does not hold - that is, Receiver in his small world is extremely sceptical of action a_1 - growing awareness is very appealing. As a final remark, these considerations attain the scenario where ω_3 is a refinement of ω_2, which suggests that in this case the incentives to increase awareness are stronger than when ω_3 is a refinement of ω_1. This finding is in contrast with Section 4.7.2, and suggests that the design of the optimal framing of Receiver is not trivial.

4.8 Conclusion

In this paper, we examine the relationship between the design of information and the level of awareness of the agents in an economy. We show how the designer of information (Sender) can exploit asymmetric awareness of the states of the world to increase the chance to persuade the user of information (Receiver). We also study whether Sender can have an incentive to expand or refine Receiver's awareness. We find that this depends on how the discovery of a new state influences Receiver's prior beliefs and preferences. In particular, growing awareness is beneficial for Sender if it makes unnecessary or easier for him to persuade Receiver. This could happen because under the new state it is optimal for Receiver to take Sender's preferred action; or because growing awareness makes Sender's preferred action more appealing; or, finally, because it changes Receiver's prior beliefs of the states in a way that increases the likelihood that Sender's preferred action is also optimal for Receiver.

This paper is a first attempt to deal with the problem of awareness in information design, and therefore there are a number of directions that can be explored in further research. First of all, we assume that Sender has full knowledge of the game, in particular of how prior beliefs and preferences change as a consequence of growing awareness. One extension could be an analysis of the same problem when Sender is uncertain about Receiver's reaction to growing awareness. A second direction is competition. Whereas competition when two rival senders provide information about the same state of the world would lead to full revelation, it could be interesting to study the problem of two senders providing information about two different states which are both relevant for Receiver's decision. Finally, it would be interesting to explore a setting with multiple and heterogeneous receivers. In particular, it may be reasonable to assume that only some receivers are partially aware, whereas others have full awareness. If Sender has to design public information, he must deal with persuasion of Receivers having heterogeneous prior beliefs and as well as interpretations of the information design.

H Proofs

Proof of Lemma 5

When $\Omega'_R = \Omega^0_R$, Receiver's expected utility given posterior belief p_R is:

$$\mathbb{E}\left[u^0_R(a,\omega)\right] = \begin{cases} p_R(\omega_1) - \beta_0 p_R(\omega_2) & \text{if } a = a_1 \\ \alpha_0 p_R(\omega_2) - \beta_0 p_R(\omega_1) & \text{if } a = a_2 \end{cases}$$

Therefore, Receiver finds it optimal action a_1 if and only if

$$p_R(\omega_1) - \beta_0 p_R(\omega_2) \geq \alpha_0 p_R(\omega_2) - \beta_0 p_R(\omega_1) \iff (1+\beta_0) p_R(\omega_1) \geq (\alpha_0 + \beta_0) p_R(\omega_2)$$

or equivalently

$$p_R(\omega_1) \geq \frac{\alpha_0 + \beta_0}{1 + \alpha_0 + 2\beta_0} = \bar{p}_0$$

.

Proof of Lemma 6

When $\Omega'_R = \Omega$, Receiver's expected utility given posterior belief p_R is:

$$\mathbb{E}\left[u_R(a,\omega)\right] = \begin{cases} p_R(\omega_1) + \gamma p_R(\omega_3) - \beta p_R(\omega_2) & \text{if } a = a_1 \\ \alpha p_R(\omega_2) - \beta p_R(\omega_1) & \text{if } a = a_2 \end{cases}$$

Therefore, Receiver finds it optimal action a_1 if and only if

$$p_R(\omega_1) + \gamma p_R(\omega_3) - \beta p_R(\omega_2) \geq \alpha p_R(\omega_2) - \beta p_R(\omega_1) \iff (1+\beta) p_R(\omega_1) + \gamma p_R(\omega_3) \geq (\alpha+\beta) p_R(\omega_2)$$

or equivalently

$$(1 + \alpha + 2\beta) p_R(\omega_1) + (\alpha + \beta + \gamma) p_R(\omega_3) \geq (\alpha + \beta) \iff p_R(\omega_1) + \lambda p_R(\omega_3) \geq \bar{p}$$

Proof of Proposition 13

It follows from (27) and Bayesian plausibility that

$$\pi(z_1)\bar{p}_0 = \mu^0_R(\omega_1)$$

where $\pi(z_1)$ is the unconditional probability of observing signal z_1. Simple algebra shows that

$$\pi(z_1|\omega_1) + \pi(z_1|\omega_2)\frac{\mu^0_R(\omega_2)}{\mu^0_R(\omega_1)} = \frac{1}{\bar{p}_0}$$

Noting that (27) implies that $\pi(z_2|\omega_1) = 0$ and hence $\pi(z_1|\omega_1) = 1$, it follows:

$$\pi(z_1|\omega_2) = \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)}$$

Finally, when $\Omega'_R = \Omega^0_R$, Receiver only observes $\tilde{\pi}$. Therefore, the information structure under state ω_3 is irrelevant for Receiver's beliefs updating and hence her decision. Sender's payoff corresponds to the probability that Receiver takes action a_1 which, in turn, corresponds to the probability of observing signal z_1. Since the probability of signal z_1, given by

$$\sum_{\omega\in\Omega} \pi(z_1\,|\,\omega)\mu_S(\omega),$$

is strictly increasing in $\pi(z_1\,|\,\omega_3)$, it follows immediately that it is optimal to set $\pi(z_1\,|\,\omega_3) = 1$.

Proof of Proposition 14

It follows from (28) and Bayesian plausibility that

$$\pi(z_1)\left[\left(\frac{\alpha+\beta}{1+\beta}\right)p_R^{z_1}(\omega_2)-\left(\frac{\gamma}{1+\beta}\right)p_R^{z_1}(\omega_3)\right]=\mu_R(\omega_1)$$

Noting that $p_R^{z_1}(\omega)=\frac{\pi(z_1|\omega)\mu_R(\omega)}{\pi(z_1)}$, it follows that

$$\pi(z_1|\omega_2)=\left(\frac{1+\beta}{\alpha+\beta}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)}+\left(\frac{\gamma}{\alpha+\beta}\right)\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)}\pi(z_1|\omega_3) \tag{58}$$

Note that (28) implies that $\pi(z_2|\omega_1)=0$ and hence $\pi(z_1|\omega_1)=1$.

When $\gamma\geq 0$, $\pi(z_1|\omega_3)=1$ because Sender's payoff is strictly increasing in $\pi(z_1\,|\,\omega_3)$ and, at the same time, the higher is $\pi(z_1|\omega_3)$ the higher can be $\pi(z_1|\omega_2)$.

When $\gamma<0$, Sender faces a trade-off between pooling ω_2 and pooling ω_3. His expected utility is:

$$v_S(\Omega,\mu_S,\mu_R)=\mu_S(\omega_1)+\mu_S(\omega_2)\pi(z_1|\omega_2)+\mu_S(\omega_3)\pi(z_1|\omega_3)$$

Using (58), we can write:

$$v_S(\Omega,\mu_S,\mu_R)=\mu_S(\omega_1)+\mu_S(\omega_2)\left[\left(\frac{1+\beta}{\alpha+\beta}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)}+\left(\frac{\gamma}{\alpha+\beta}\right)\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)}\pi(z_1|\omega_3)\right]+\mu_S(\omega_3)\pi(z_1|\omega_3)$$

Taking the derivative with respect to $\pi(z_1|\omega_3)$ we find:

$$\frac{\partial v_S(\Omega,\mu_S,\mu_R)}{\partial\pi(z_1|\omega_3)}=\mu_S(\omega_2)\left(\frac{\gamma}{\alpha+\beta}\right)\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)}+\mu_S(\omega_3)$$

Therefore, Sender finds it optimal to increase marginally $\pi(z_1|\omega_3)$ if and only if

$$\frac{\partial v_S(\Omega,\mu_S,\mu_R)}{\partial\pi(z_1|\omega_3)}\geq 0\iff\frac{\mu_S(\omega_3)}{\mu_S(\omega_2)}\geq-\left(\frac{\gamma}{\alpha+\beta}\right)\frac{\mu_R(\omega_3)}{\mu_R(\omega_2)} \tag{59}$$

Since condition (59) does not depend on $\pi(z_1|\omega_3)$, we have a bang-bang solution: Sender focuses on persuasion either under state ω_2 or under state ω_3. If (59) holds, then $\pi(z_1|\omega_3)=\min\left\{1,-\left(\frac{1+\beta}{\gamma}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_3)}\right\}$, depending on whether $\pi(z_1|\omega_2)$ is greater or equal to zero, which implies condition (32). If (59) does not hold, then $\pi(z_1|\omega_3)=\max\left\{0,-\frac{(1+\beta)\mu_R(\omega_1)-(\alpha+\beta)\mu_R(\omega_2)}{\gamma\mu_R(\omega_3)}\right\}$, depending on whether $\pi(z_1|\omega_2)$ is smaller or equal to one, which implies condition (34).

Proof of Proposition 15

Simple algebra shows that $\mu_R^0(\omega_1)<\bar{p}_0$ and $\mu_R(\omega_1)+\lambda\mu_R(\omega_3)\geq\bar{p}$ are equivalent to (37) and (38), respectively. Condition (39) is equivalent to the difference between (38) and (37) being positive. It is a necessary condition because the expression in (38) is positive whereas the expression in (37) is negative. Instead, it is not sufficient because even if (39) holds true, (38) may not hold.

Proof of Proposition 16

Condition (40) follows directly from the comparison of (30) and (29). In particular,

$$V_S=\overline{v}_S(\Omega,\mu_S,\mu_R)-\overline{v}_S(\Omega_R^0,\mu_S,\mu_R^0)=\mu_S(\omega_2)\left[\frac{(1+\beta)\mu_R(\omega_1)+\gamma\mu_R(\omega_3)}{(\alpha+\beta)\mu_R(\omega_2)}-\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu_R^0(\omega_1)}{\mu_R^0(\omega_2)}\right]$$

Therefore, $V_S\geq 0$ if and only if (40) holds true.

Proof of Proposition 17

The first part of this proposition follows directly from the comparison of (30) and (29), as in Proposition 16. Instead, when (32) does not hold, from Propositions 13-14 we have to compare (33) and (29), that is:

$$V_S = \overline{v}_S(\Omega, \mu_S, \mu_R) - \overline{v}_S(\Omega^0_R, \mu_S, \mu^0_R) = -\mu_S(\omega_2)\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)} - \mu_S(\omega_3)\left[1+\left(\frac{1+\beta}{\gamma}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_3)}\right]$$

Because (32) does not hold, it follows that $\frac{1+\beta}{\gamma}\frac{\mu_R(\omega_1)}{\mu_R(\omega_3)} \in (-1, 0)$. Therefore, $V_S < 0$.

Proof of Proposition 18

From Propositions 13-14, when (34) holds, we have to compare (35) and (29):

$$V_S = \overline{v}_S(\Omega, \mu_S, \mu_R) - \overline{v}_S(\Omega^0_R, \mu_S, \mu^0_R) =$$

$$= \mu_S(\omega_2)\left[1-\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)}\right] - \mu_S(\omega_3)\left[1-\frac{(\alpha+\beta)\mu_R(\omega_2)-(1+\beta)\mu_R(\omega_1)}{\gamma\mu_R(\omega_3)}\right]$$

Therefore, $V_S \geq 0$ is equivalent to (41). Instead, when (34) does not hold, we have to compare (36) and (29):

$$V_S = \overline{v}_S(\Omega, \mu_S, \mu_R) - \overline{v}_S(\Omega^0_R, \mu_S, \mu^0_R) =$$

$$\mu_S(\omega_2)\left[\left(\frac{1+\beta}{\alpha+\beta}\right)\frac{\mu_R(\omega_1)}{\mu_R(\omega_2)} - \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)}\right] - \mu_S(\omega_3)$$

Therefore, $V_S \geq 0$ is equivalent to (42).

Proof of Proposition 19

It follows from (27) and Bayesian plausibility that

$$\tilde{\pi}(z_1)\left(\frac{\alpha_0+\beta_0}{1+\beta_0}\right)p^{z_1}_R(\omega_2) = \mu^0_R(\omega_1)$$

Simple algebra shows that

$$\tilde{\pi}(z_1|\omega_2) = \left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)}$$

Therefore, the optimal information structure is subject to the following constraint:

$$\pi(z_1|\omega_2) + \pi(z_1|\omega_3) = 2\left(\frac{1+\beta_0}{\alpha_0+\beta_0}\right)\frac{\mu^0_R(\omega_1)}{\mu^0_R(\omega_2)} \tag{60}$$

Note that (28) implies that $\pi(z_2|\omega_1) = 0$ and hence $\pi(z_1|\omega_1) = 1$. Therefore, Sender's expected utility is:

$$v_S(\Omega, \mu_S, \mu_R) = \mu_S(\omega_1) + \mu_S(\omega_2)\pi(z_1|\omega_2) + \mu_S(\omega_3)\pi(z_1|\omega_3)$$

and, substituting (60) in the expected utility, clearly Sender finds it optimal to increase marginally $\pi(z_1|\omega_2)$ if and only $\mu_S(\omega_2) \geq \mu_S(\omega_3)$. Finally, by (60) it follows that Sender can pool all states together only if condition (53) holds.

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