Essays on Individual and Collective Decision Making

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Für Mama und Papa und Evi.

Preface

This dissertation consists of three self-contained chapters.

Chapter 1
Can Compulsory Voting Reduce Information Acquisition?

An election with full turnout is supposed to achieve a policy outcome which perfectly reflects the majority's preference. This result requires all voters to be perfectly informed about their preference and to vote accordingly. I study a private values model with costly information acquisition and costly voting, showing that incentivizing participation through an abstention fine does not necessarily incentivize information acquisition. While a small abstention fine always increases information acquisition compared to Voluntary Voting, a high abstention fine that achieves full turnout increases information acquisition only if voting costs are sufficiently high. If voting costs are low, the opposite is true: Less individuals acquire information under Compulsory Voting with full turnout than under Voluntary Voting. The incentives to acquire information further decrease if uninformed voters are biased. Moreover, I show that expected social welfare under Compulsory Voting is lower than under Voluntary Voting and decreases in the bias of uninformed voters.

Chapter 2
Selective Exposure Reduces Voluntary Contributions
Experimental Evidence from the German Internet Panel

With Federico Innocenti.

Can strategic information acquisition harm the provision of a public good? We investigate this question 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 information treatment, participants can choose between two information sources with opposite biases. 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%. Moreover, 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 show that participants' behavior in our experiment is consistent with their attitudes towards actual public goods.

Chapter 3
The Value of Choice
Evidence from an Incentivized Survey Experiment

With Hans Peter Grüner.

Do people have a preference for making choices themselves, or do they prefer to choose a preselected alternative? If consumers value choice, recommender systems which facilitate choices might trigger consumers not to choose the recommendation – even when the other alternatives are less preferred. We conduct an incentivized survey experiment with a large sample from the German population, where participants choose between three lotteries. In the main treatment, participants make a choice between a preselected lottery and a two-element choice set, from which they then make an additional choice. We find that participants' choices exhibit a bias towards the preselected alternative, and estimating a structural model reveals that the mean willingness to pay to make an additional choice is negative. Nevertheless, about 41% of the sample are estimated to have a positive value of choice. We show that measurable individual characteristics correlate with the preference for choice. Linking choices to the Big Five personality traits reveals that the preference for the preselected alternative increases in Openness. Moreover, we link participants' preferences for choice to their political attitudes, showing that right-wing participants are more likely to prefer the preselected alternative than center-left participants.

Contents

Chapter 1

Can Compulsory Voting Reduce Information Acquisition?

1.1 Introduction

Maximizing turnout through Compulsory Voting is supposed to achieve a policy outcome which accurately reflects all citizens' preferences, thereby maximizing the quality of the collective decision (Lijphart, 1997; Chapman, 2019; Börgers, 2004). If casting a ballot is costly, high turnout results in high participation costs. Thus, the decision between making participation in an election voluntary or compulsory entails a trade-off between the quality and the social costs of the collective decision (cf. e.g. Börgers, 2004). If however voting costs are sufficiently small, the trade-off between the quality and the costs of the collective decision seemingly disappears. Therefore, why not reduce voting costs and make participation compulsory?

High turnout can achieve a high quality of the collective decision only if the participating voters are sufficiently informed about the political alternatives to form a preference. Acquiring such information however is costly, such that some citizens might not have enough relevant knowledge to correctly assess which alternative they prefer.[1] It has been argued that the obligation to vote can increase political interest and involvement, thereby increasing information acquisition (Lijphart, 1997; de Leon and Rizzi, 2016). In that case, maximizing turnout indeed maximizes the quality of the collective decision. If Compulsory Voting does not incentivize information acquisition, uninformed individuals might feel

[1]Voters typically rely on mass media to acquire information about politicians, parties, and policy issues. Due to the spread of the Internet, the costs of accessing this information have decreased substantially. The opportunity costs of information acquisition however increase as other sources of entertainment become available over the Internet (Gavazza et al., 2018). Moreover, not only the availability of information matters for becoming informed, but also personal motivation and cognitive ability (Barabas et al., 2014).

compelled to vote without being able to tell the alternatives apart.[2] With the participation of uninformed voters the share of random votes increases until, eventually, “the election outcome itself will not be more likely to reflect the interests of the majority than, say, a fair coin toss” (Martinelli, 2006, p. 226). Therefore, Compulsory Voting might reduce the quality of the collective decision compared to Voluntary Voting, where uninformed individuals can abstain.

In this paper, I address the following question: If voters are initially uninformed about the available alternatives and if information acquisition is costly, should participation in an election be voluntary or compulsory? I specifically investigate how the introduction of an abstention fine affects an individual’s incentives to acquire information, and expected social welfare.

I study a private values model with two alternatives and costly voting. Initially, all individuals are uninformed about which alternative they prefer, but they can acquire a costly, perfectly informative signal that reveals their preferred alternative. I explicitly model Compulsory Voting by introducing an abstention fine that sanctions non-voters. An individual’s rational decision to cast an informed vote is driven by the probability that her vote will be decisive for the outcome. Thus, my model applies to collective decisions in small electorates – as for example in clubs, boards of companies, or committees in universities, parties or parliaments.

I first consider a benchmark model where an individual is ex ante equally likely to favor each alternative, i.e. preferences are neutral. I assume that uninformed individuals who participate in the election are unbiased and vote for each alternative with equal probability. I show that, as long as the abstention fine is sufficiently small, uninformed individuals abstain from the election, such that Compulsory Voting increases information acquisition by increasing participation from informed voters only. If however the abstention fine is sufficiently high, uninformed individuals participate in the election by casting a random vote, and full turnout is reached. Then, Compulsory Voting increases information acquisition only if the voting costs are sufficiently high. In that case, even individuals with low information costs abstain under Voluntary Voting. Those individuals however acquire information and vote as soon as the abstention fine fully compensates their voting costs. If voting costs are small, Compulsory Voting reduces information acquisition compared to Voluntary Voting. In that case, even individuals with high information costs participate

[2] When uninformed individuals participate in an election, they might choose to spoil their ballot. With electronic voting however it is impossible to cast an invalid vote. And even when it is possible, casting an invalid vote is often not perceived as a legitimate voting choice (Ambrus et al., 2017). Thus, when they are compelled to participate, uninformed citizens might cast a valid vote by randomly selecting one of the alternatives.

under Voluntary Voting. Because Compulsory Voting with full turnout however reduces the expected benefits of acquiring information, those individuals no longer acquire information, and cast an uninformed vote instead. In the limit with zero voting costs, it is impossible to incentivize information acquisition through an abstention fine.

Similar to Börgers (2004), I find that because of the negative externality of voting, Compulsory Voting reduces expected social welfare: By increasing turnout, Compulsory Voting reduces the probability that an individual's vote will be decisive for the outcome, thereby reducing her expected benefits of voting. When Compulsory Voting increases information acquisition compared to Voluntary Voting, it increases both voting and information costs, such that the reduction in expected benefits and the increase in expected participation costs imply a reduction in expected social welfare. If Compulsory Voting reduces information acquisition compared to Voluntary Voting, expected information costs however decrease. I show that nevertheless, the reduction in benefits outweighs the reduction in information costs, again implying a reduction in expected social welfare.

I generalize the model to cover two important extensions (appendix 1.B). First, in the neutral preferences setting, I allow for biased uninformed voters who choose one of the alternatives with higher probability. The results from the benchmark model are robust to this generalization. Moreover, I show that the probability of acquiring information under Compulsory Voting with full participation is strictly decreasing in the bias of uninformed voters. Therefore, an increase in the bias of uninformed voters has a detrimental effect on expected social welfare under Compulsory Voting with full participation.

Second, I study the non-neutral preferences setting, where one alternative is expected to be favored by a strict majority of voters. Then, uninformed individuals who participate in the election endogenously prefer to cast a valid vote, and their weakly dominant strategy is to vote for the ex ante preferred alternative, i.e. they are fully biased. I show that under Compulsory Voting with full participation, there exists an equilibrium in which all individuals remain uninformed, independent of their information and voting costs. Then, the ex ante preferred alternative wins the election, and expected social welfare is strictly lower than under Voluntary Voting.

1.2 Related Literature

My model is related to three strands of literature: The literature on costly voting with private values, the literature on endogenous information acquisition of voters, as well as the literature on compulsory voting with an explicit fine on abstention.

The observation that voting is costly dates back to early work by Downs (1957); Tullock (1967), and Riker and Ordeshook (1968). Palfrey and Rosenthal (1983, 1985) point out that, if voting is costly, the decision whether to vote or not becomes a “strategic calculus of voting”: A rational individual votes only if the expected benefits of voting exceed its costs.

For my benchmark model, I follow Börgers (2004). He compares Voluntary Voting to Compulsory Voting with full turnout, but does not consider explicitly how participation is enforced. Börgers' main result is that there is a *negative externality of voting*: By voting, an individual reduces the probability of being pivotal and hence also the expected benefits of voting for all other voters. Börgers shows that due to this negative externality of voting, participation is inefficiently high already under Voluntary Voting, such that Compulsory Voting further reduces expected social welfare. In his conclusion, Börgers claims that his results remain unchanged if the voting costs are reinterpreted as the costs of information acquisition. He assumes that uninformed individuals abstain under Voluntary Voting and that Compulsory Voting forces all individuals to become informed, but points out that mandatory information acquisition would not be implementable. I explicitly address this point by analyzing the incentives to acquire costly information under Voluntary and Compulsory Voting. I show that although Compulsory Voting might reduce information acquisition, the negative externality of voting still leads to lower expected social welfare under Compulsory Voting than under Voluntary Voting.

While voters always exert a negative externality of voting on other voters, there can be a positive externality of voters on non-voters if the assumption of neutral preferences is relaxed: If one alternative is ex ante preferred by the majority of voters (Taylor and Yildirim, 2010; Krasa and Polborn, 2009) or if preferences are correlated (Goeree and Großer, 2007), the members of the majority have an incentive to free-ride on other voters, such that participation becomes inefficiently low. Goeree and Großer (2007) show that, for correlated preferences, providing information about the electorate's preference increases participation among the minority group and therefore reduces welfare.

For the generalized version of my model that allows for non-neutral preferences, I mostly follow Taylor and Yildirim (2010). They especially formalize the *underdog effect*: Members of the expected minority are more likely to vote than voters of the expected majority. They show that, nevertheless, the ex ante preferred alternative remains more likely to win the election. They however only consider Voluntary Voting. I add costly information acquisition and an explicit abstention fine to their model.

Another strand of the costly voting literature is concerned with the design of optimal voting rules (e.g. Gerardi and Yariv, 2008; Gershkov and Szentes, 2009; Kartal, 2015).

For the comparison between Voluntary and Compulsory Voting, Grüner and Tröger (2019) show that in the neutral preference setting, the standard voluntary simple majority rule is always optimal. Moreover, they show that Voluntary Voting Pareto-dominates Compulsory Voting with full participation if participation costs are sufficiently small.

Endogenous information acquisition is mainly studied in *common* value models in which the election serves as an information aggregation mechanism. Early contributions to this literature include the papers related to the Condorcet Jury Theorem which assume that information as well as voting is costless (Austen-Smith and Banks, 1996; Feddersen and Pesendorfer, 1996, 1997). This implicitly means that voting is considered as compulsory and that all individuals vote. If acquiring political information is costly, independent of whether the information signal is perfectly informative (Mukhopadhaya, 2003; Persico, 2004) or whether it is imperfectly informative with increasing quality at increasing costs (Martinelli, 2006, 2007), information is a public good and the incentive to free-ride on other voters leads to underinvestment in information. This is fundamentally different from the mechanisms involved in the private value setting. Moreover, none of these papers study the voters' participation decision.

Only few papers exist that explicitly model the incentives for participation under Compulsory Voting. Krasa and Polborn (2009) introduce a subsidy for voters in a costly voting model with private values and non-neutral preferences. They show that, because voters of the majority exert a positive externality on non-voters with the same preference, turnout is inefficiently low under Voluntary Voting. Therefore, a subsidy for voting increases expected welfare and improves the quality of the collective decision.

Tyson (2016) addresses a research question that is very similar to mine – though in a *common* value framework. He studies endogenous information acquisition when both voting and information acquisition are costly. He shows that an abstention tax leads to a higher level of informed voting but also creates an incentive for uninformed voters to participate in the election. He however assumes that these uninformed voters spoil their ballot, while I assume that they cast a valid vote by randomly picking one of the two alternatives.[3] Because invalid votes do not affect the collective decision, Tyson finds that incentivizing voting increases the probability that the correct alternative is chosen collectively.

[3] Jakee and Sun (2006) also suppose that uninformed voters vote randomly because they cannot tell the two alternatives apart. However, they take an expressive voting approach, which contrasts with my rational choice framework.

To the best of my knowledge, there exists no work on endogenous information acquisition of voters in a purely *private* value setting. Thus, I contribute to the literature by analyzing the effects of an abstention fine on the participation and information acquisition decision of voters both in the neutral and the non-neutral preference setting. I introduce a novel perspective on the effect of information under Compulsory Voting – in the neutral preference setting by assuming that uninformed voters cast a valid, potentially biased vote, and in the non-neutral preference setting by showing that participation and bias of uninformed voters arise endogenously.

1.3 The Model

There are $n \geq 3$ individuals $i \in \{1, 2, ..., n\}$ who have to make a collective policy decision x from the set of alternatives $X = \{A, B\}$. The outcome is determined by simple majority rule. In case of a tie, both alternatives are chosen with equal probability.

Let $r_i \in X$ denote the alternative which is strictly preferred by individual i.[4] The preference r_i of individual i is assumed to be stochastically independent of the preference r_j of individual $j \neq i$. Ex ante, an individual is equally likely to favor each alternative, i.e. preferences are *neutral*.[5]

The individuals are initially uninformed about their preferred alternative r_i and they do not automatically observe r_i at the interim stage. If they want to learn which alternative they prefer, they can acquire a costly, perfectly informative signal that reveals r_i. Let c_i denote the stochastic information costs of individual i. For each i, the information costs c_i are drawn independently from the cumulative distribution function (CDF) G which is the same for all individuals and has the support $[\underline{c}, \overline{c}]$ where $0 \leq \underline{c} < \overline{c}$. Let g denote the probability density function (PDF) associated with G and assume that g is positive on all of the support. The information costs c_i of individual i are assumed to be stochastically independent of her preferred alternative r_i, and of the information costs c_j of individual $j \neq i$.

Let ε denote the voting costs, i.e. the costs of casting a ballot, which are deterministic and the same for all individuals. The voting costs are assumed to be known by each individual when they make their decision to acquire information. Therefore, the information acquisition decision and the voting decision can be treated as a bundle.[6]

[4] I rule out the possibility that an individual is indifferent between the two alternatives.

[5] I consider the setting with non-neutral preferences using the generalized version of the model in appendix section 1.B.2.

[6] In contrast to that, I assume in the generalized version of the model in appendix 1.B that the voting costs are unknown at the information stage, such that the information acquisition decision and the

In order to incentivize participation, abstention is sanctioned with a fine f. I will call the case without a fine "Voluntary Voting", and the case where $f > 0$ "Compulsory Voting".

If individual i's preferred alternative r_i is chosen collectively, her utility is normalized to 1. If the other alternative is chosen, i's utility is normalized to zero. I assume that voters do not receive any intrinsic utility from the voting act itself.[7] Table 1.1 summarizes the ex post payoff of an individual i , where $\mathbb{1}\{x = r_i\}$ is an indicator function that takes the value 1 if the collective outcome x is equal to i's preferred alternative r_i and zero otherwise.

For an informed individual, it is a weakly dominant strategy to vote sincerely for her preferred alternative. Therefore, *if* an individual is informed, she participates and votes for her favored alternative. For an uninformed invidiual, I assume that *if* she participates, she casts a valid vote by selecting one of the two alternatives randomly, and that no individual casts an invalid vote.[8] Moreover, I assume that uninformed voters are unbiased, meaning that *if* they vote, they select each alternative with the same probability.[9]

Table 1.1: Ex post payoff.

	Participate	Abstain
Informed	$\mathbb{1}\{x = r_i\} - (c_i + \varepsilon)$	$\mathbb{1}\{x = r_i\} - c_i - f$
Uninformed	$\mathbb{1}\{x = r_i\} - \varepsilon$	$\mathbb{1}\{x = r_i\} - f$

The timing of the game can be summarized as follows:

1. For each individual $i \in \{1, 2, ..., n\}$, nature draws the information costs $c_i \in [\underline{c}, \overline{c}]$ according to the PDF g. Nature also draws i's preferred alternative r_i from the set of alternatives X with $Pr(r_i = A) = Pr(r_i = B) = \frac{1}{2}$.

voting decision can no longer be treated as a bundle but need to be considered sequentially.

[7] For the framework where voters receive intrinsic utility from fulfilling their civic duty of participating in the election see e.g. Feddersen and Sandroni (2006).

[8] The results of my analysis continue to hold even if some voters spoil their ballot, as long as some uninformed voters still cast a valid vote: Because an invalid vote does not affect the outcome of the election, it does not affect the probability of being pivotal for other voters. As long as uninformed voters cast a valid vote with a positive probability, they however affect the probability of being pivotal for other voters. Note that in the non-neutral preferences setting (appendix section 1.B.2), uninformed *endogenously* prefer to cast a valid vote over spoiling their ballot.

[9] I allow for biased uninformed voters who select one alternative with higher probability in the generalized version of the model in appendix section 1.B.1.

2. Each individual privately observes her information costs c_i and the voting costs ε, but not her preference r_i.

3. *Information stage*: All individuals simultaneously decide whether to acquire information or not. The decision is private information. If individual i acquires information, she privately observes her preference r_i.

4. *Voting stage*: All individuals simultaneously decide whether to vote or abstain.

5. The collective policy outcome $x \in X$ is realized by simple majority rule.

6. Payoffs are realized.

Individual i acquires information if her expected payoff of casting an informed vote is both higher than her expected payoff of casting a random vote and higher than her expected payoff of abstaining. The expected payoff of voting depends on the probability of being pivotal, which in turn depends on how many other voters participate. Individual i is pivotal only if her vote creates or breaks a tie. In both cases, she gains $\frac{1}{2}$ in expected utility. Let $\Pi(p)$ denote the probability that individual i is pivotal if all others participate with probability p and let $B(p)$ denote the expected benefit from casting an informed, pivotal vote, which is

$$B(p) = \frac{1}{2}\Pi(p) \tag{1.1}$$

where $B(p) \leq \frac{1}{2}$ for all $p \in [0, 1]$. From the perspective of individual i, it does not matter whether the other individuals who participate are informed or not: If they are informed, they vote for their preferred alternative and i knows that they favor each alternative with probability 1/2. If they are not informed, they also vote for each alternative with probability 1/2. Therefore, from Börgers (2004), the probability that individual i is pivotal is

$$\Pi(p) = \sum_{l=0}^{n-1} \binom{n-1}{l} p^l (1-p)^{n-1-l} \pi(l) \tag{1.2}$$

where

$$\pi(l) = \begin{cases} \binom{l}{\frac{l-1}{2}} \frac{1}{2}^l & \text{if } l \text{ is odd} \\ \binom{l}{\frac{l}{2}} \frac{1}{2}^l & \text{if } l \text{ is even} \end{cases} \tag{1.3}$$

is the probability that i is pivotal, conditional on $l \leq n-1$ other voters participating. Börgers (2004) shows that $\Pi(p)$ is differentiable and strictly decreasing in p for all $p \in (0,1)$. Intuitively, the higher the probability with which each individual participates, the less likely it is that i will be pivotal.

If all other individuals participate in the election, the benefit of casting an informed, pivotal vote is

$$B(1) = \begin{cases} \binom{n-1}{\frac{n-1}{2}} \left(\frac{1}{2}\right)^n & \text{if } n \text{ is odd} \\ \binom{n-1}{\frac{n}{2}-1} \left(\frac{1}{2}\right)^n & \text{if } n \text{ is even.} \end{cases} \tag{1.4}$$

Next, let's derive the expected benefit of casting an uninformed vote. If individual i does not know which alternative she prefers but participates anyway by voting randomly, her expected benefit of being pivotal is zero. If an even number of voters other than i participate, i is pivotal only if her vote breaks a tie. Because she votes randomly, i picks her preferred alternative with probability 1/2; this alternative is chosen collectively and her expected utility *in*creases by 1/2. She however also picks the other alternative with probability 1/2; this alternative is chosen collectively and her expected utility *de*creases by 1/2. Thus her expected benefit of voting is zero. If an odd number of voters other than i participates, i is pivotal only if her vote creates a tie. If without her, i's preferred alternative was chosen collectively, she creates a tie only if she votes for the other alternative, which she does with probability 1/2. Her expected utility *de*creases by 1/2. If without her the alternative i prefers less was chosen, she creates a tie only if she votes for her preferred alternative, which she does with probability 1/2. Her expected utility *in*creases by 1/2. Thus the expected benefit of voting randomly is again zero.

1.4 Results

To characterize the equilibrium, we need to consider two different cases: first, the case of a small abstention fine (or no abstention fine) $0 \leq f < \varepsilon$, where only informed individuals participate, and second, the case of a high abstention fine $f > \varepsilon$, which achieves full participation.[10]

[10] In the case where $f = \varepsilon$, uninformed individuals are indifferent between abstaining and participating. However, if we suppose that the voting costs ε are a random variable which is drawn from a continuous probability function, this is a probability zero event and therefore does not need to be considered.

1.4.1 Voluntary Voting and Compulsory Voting with a Small Abstention Fine

Let $0 \leq f < \varepsilon$. Because the expected benefit of casting an uninformed vote is zero, uninformed individuals abstain. Thus, an individual i with information costs c_i acquires information about her preferred alternative and votes accordingly if and only if

$$c_i \leq B(p) - \varepsilon + f \tag{1.5}$$

and remains uninformed and abstains otherwise.[11] Hence, individual i acquires information only if her information costs are sufficiently low, which yields the following equilibrium result:

Proposition 1.1. *The unique symmetric Bayesian Nash equilibrium under Voluntary Voting with $f = 0$ or under Compulsory Voting with a small abstention fine $0 < f < \varepsilon$ has the following properties:*

(i) If $\overline{c}+\varepsilon-f \leq B(1)$, all individuals acquire information about their preferred alternative r_i and vote for this alternative.

(ii) If $\underline{c} + \varepsilon - f \geq \frac{1}{2}$, all individuals remain uninformed and abstain.

(iii) Otherwise, i.e. if $\underline{c}+\varepsilon-f < \frac{1}{2}$ and $\overline{c}+\varepsilon-f > B(1)$, there exists a unique equilibrium cutoff value $c^* \in (\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f)$ such that an individual i with information costs c_i acquires information about her preferred alternative r_i and casts her vote accordingly if and only if $c_i \leq c^* - \varepsilon + f$, and abstains otherwise.

Let p^* denote the equilibrium probability that individual i casts an informed vote, where

$$p^* \equiv Pr(c_i \leq c^* - \varepsilon + f) = G(c^* - \varepsilon + f). \tag{1.6}$$

The effects of the voting costs ε and of the abstention fine f on the equilibrium probability of casting an informed vote are straightforward:

Remark 1. *Let $0 \leq f < \varepsilon$. Then the equilibrium probability of casting an informed vote is*

(i) weakly decreasing in the voting costs ε and

(ii) weakly increasing in the abstention fine f.

In an interior equilibrium, both relationships are strict.

[11] Note that if condition 1.5 holds with equality, individual i is indifferent between getting informed or not. I assume here that in that case, i acquires information. Because this is a probability zero event, it does not matter for the further analysis.

Intuitively, an increase in the voting costs ε makes it more likely that the participation costs of individual i, which are her information costs c_i plus the voting costs ε, exceed the benefits of casting an informed, pivotal vote and therefore make it *less* likely for her to become informed. An increase in the abstention fine f however makes it more expensive for i to remain uninformed and abstain and therefore makes it *more* likely for her to become informed and vote accordingly.

From remark 1 follows directly that the probability of casting an informed vote is strictly higher under Compulsory Voting with a small abstention fine $0 < f < \varepsilon$ than under Voluntary Voting. Because casting an uninformed vote is strictly dominated by abstaining under Compulsory Voting with a small abstention fine $0 < f < \varepsilon$, incentivizing participation at the same time incentivizes information acquisition.

1.4.2 Compulsory Voting with a High Abstention Fine

Let $f > \varepsilon$. Now, uninformed individuals participate, and we have full turnout. Thus, an individual i with information costs c_i acquires information about her preferred alternative and votes accordingly if and only if

$$c_i \leq B(1) \tag{1.7}$$

and remains uninformed but casts a random vote otherwise. Thus, we have the following equilibrium result:

Proposition 1.2. *The unique symmetric Bayesian Nash equilibrium under Compulsory Voting with a high abstention fine $f > \varepsilon$ has the following properties:*

(i) If $\bar{c} \leq B(1)$, all individuals acquire information about their preferred alternative r_i and vote for this alternative.

(ii) If $\underline{c} \geq B(1)$, all individuals remain uninformed but cast a random vote.

(iii) Otherwise, if $\underline{c} < B(1) < \bar{c}$, all individuals participate, but an individual i with information costs c_i acquires information about her preferred alternative r_i and votes accordingly if and only if $c_i \leq B(1)$, and remains uninformed but casts a random vote otherwise.

The probability that individual i acquires information in equilibrium is given by

$$q^* \equiv Pr(c_i \leq B(1)) = G(B(1)).$$

Note that because all individuals participate as soon as $f > \varepsilon$, neither the voting costs

ε nor the level of the abstention fine f affect the probability of acquiring information anymore.

The following proposition shows that – in contrast to a small abstention fine $0 < f < \varepsilon$ – a high abstention fine $f > \varepsilon$ does not necessarily incentivize information acquisition, which is the central result of this analysis.

Proposition 1.3. *Let $\underline{c} < B(1) < \overline{c}$. There exists a unique voting costs threshold $\tilde{\varepsilon} \in (0, \frac{1}{2} - \underline{c})$ such that for all $\varepsilon < \tilde{\varepsilon}$, Compulsory Voting with a high abstention fine $f > \varepsilon$ strictly reduces the probability of acquiring information, while for all $\varepsilon > \tilde{\varepsilon}$ it strictly increases the probability of acquiring information compared to Voluntary Voting.*

The effect of a high abstention fine $f > \varepsilon$ on information acquisition depends on the voting costs: Compulsory Voting with a high abstention fine $f > \varepsilon$ increases the probability that an individual acquires information only if the voting costs are high, but reduces the probability that an individual acquires information if the voting costs are low. In the latter case there are some individuals who would have acquired information under Voluntary Voting, but rationally decide not to acquire information anymore under Compulsory Voting. Moreover, it follows from proposition 1.3 that, in the limit, as $\varepsilon \to 0$, it is never possible to incentivize information acquisition with an abstention fine. Instead, Compulsory Voting then always reduces the probability that an individual acquires information compared to Voluntary Voting.

Intuitively, the result from proposition 1.3 can be explained as follows. High voting costs $\varepsilon > \tilde{\varepsilon}$ allow only individuals with sufficiently low information costs to participate in the election under Voluntary Voting. However as soon as the high abstention fine $f > \varepsilon$ is introduced, the voting costs do not play a role in the voting decision anymore, as they are fully compensated for by not having to pay the abstention fine. Now consider a marginal individual whose information costs are low but, in sum with the voting costs, are just too high for her to vote under Voluntary Voting. Then, under Compulsory Voting, the expected benefits of casting an informed vote – despite being reduced due to the negative externality of voting – exceed the information costs. Hence the marginal individual acquires information and votes accordingly. As a result, with sufficiently high voting costs, there are some individuals who abstain under Voluntary Voting, but cast an informed vote under Compulsory Voting.

In contrast to that, low voting costs $\varepsilon < \tilde{\varepsilon}$ allow even individuals with high information costs to participate in the election under Voluntary Voting. Now consider a marginal individual whose information costs are high, but just sufficiently low so that this individuals acquires information and votes under Voluntary Voting. Under Compulsory Voting, however, full participation reduces the expected benefit of casting an informed vote, and her information costs exceed the expected benefit of casting an informed vote. Hence, this marginal individual will not acquire information under Compulsory Voting anymore. As a result, with sufficiently low voting costs, there are some individuals who acquired information and voted accordingly under Voluntary Voting, but remain uninformed and cast a random vote under Compulsory Voting.

Figure 1.1 shows the effects of an abstention fine f on the equilibrium probability of acquiring information for different voting costs and illustrates the results from remark 1 and proposition 1.3.

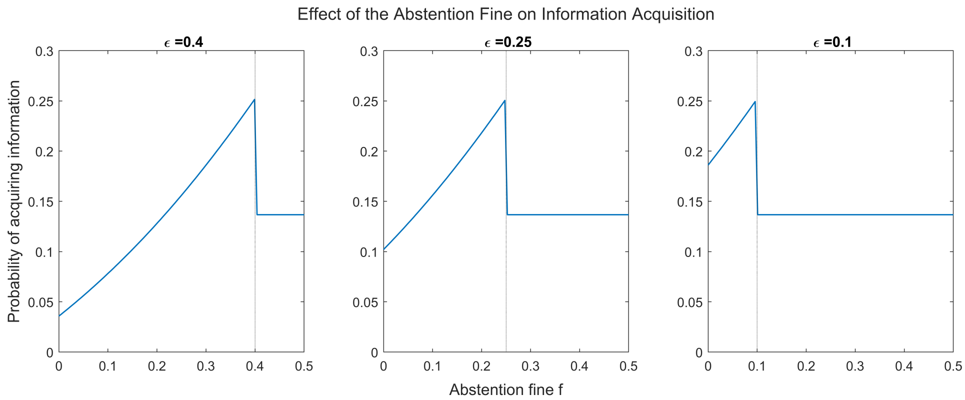


Figure 1.1: The effect of an abstention fine $0 \leq f \leq 0.5$ on the equilibrium probability of acquiring information for different voting costs $\varepsilon \in \{0.4, 0.25, 0.1\}$. The information costs are uniformly distributed on the interval $[0, 1]$. There are $n = 9$ individuals in the electorate.

1.4.3 Welfare

To analyze how the introduction of an abstention fine affects expected social welfare, we again need to distinguish the two cases of a small abstention fine $0 < f < \varepsilon$ and a high abstention fine $f > \varepsilon$.

Recall that if $f < \varepsilon$, only informed voters participate. Then, the expected utility of an individual consists of the expected utility given that the individual acquires information and votes accordingly, plus the expected utility given that the individual does not acquire information and abstains. Hence, expected utility is given by (adapted from Börgers, 2004)

$$U(p^*) = \int_{\underline{c}}^{c^*-\varepsilon+f} \left[\frac{1}{2} + B(p^*) - c - \varepsilon\right] g(c)\mathrm{d}c + \int_{c^*-\varepsilon+f}^{\overline{c}} \left[\frac{1}{2} - f\right] g(c)\mathrm{d}c$$
$$= \frac{1}{2} + \left[B(p^*) - \varepsilon\right] p^* - \int_{\underline{c}}^{c^*-\varepsilon+f} cg(c)\mathrm{d}c - f(1-p^*). \tag{1.8}$$

Under the assumption that the expected revenue generated from the abstention fine is re-distributed to the individuals, expected social welfare can be written as

$$W(p^*) = n\left(\frac{1}{2} + \left[B(p^*) - \varepsilon\right] p^* - \int_{\underline{c}}^{c^*-\varepsilon+f} cg(c)\mathrm{d}c\right). \tag{1.9}$$

Proposition 1.4. *Let $0 \leq f < \varepsilon$. Then expected social welfare is weakly decreasing in the abstention fine f. In an interior equilibrium, it is strictly decreasing.*

This result is in line with the result by Börgers (2004), and relies on the same intuition:[12] Due to the negative externality of voting, the expected benefits of acquiring information and voting are decreasing as participation increases in response to an increase in the abstention fine. At the same time, both information and voting costs increase. Thus, smaller expected benefits and higher participation costs imply a reduction in expected social welfare.

If $f > \varepsilon$, all individuals vote, but not all acquire information. Then, the expected utility of an individual consists of the expected utility given that the individual acquires information and votes accordingly, plus the expected utility given that the individual does not acquire information and casts a random vote. Hence expected utility is given by (again adapted from Börgers, 2004)

$$U(q^*) = \int_{\underline{c}}^{B(1)} \left[\frac{1}{2} + B(1) - c - \varepsilon\right] g(c)\mathrm{d}c + \int_{B(1)}^{\overline{c}} \left[\frac{1}{2} - \varepsilon\right] g(c)\mathrm{d}c$$
$$= \frac{1}{2} - \varepsilon + B(1)q^* - \int_{\underline{c}}^{B(1)} cg(c)\mathrm{d}c. \tag{1.10}$$

[12] Börgers however does not consider an explicit abstention fine, but considers Compulsory Voting to be an exogenous increase in the voting cost threshold to $\overline{c}$, such that all individuals vote. Then, however, if $\overline{c} > c^*$, some individuals vote although their costs exceed the expected benefits of doing so. This yields an additional negative effect in Börgers' model, which does not occur in my case, where the abstention fine endogenously increases the equilibrium voting cost threshold.

Because under full participation, no individual pays the abstention fine, expected social welfare if $f > \varepsilon$ can be simply written as $W(q^*) = nU(q^*)$.

Proposition 1.5. *Whenever Voluntary Voting does not achieve full turnout, the introduction of a high abstention fine $f > \varepsilon$ strictly reduces expected social welfare compared to Voluntary Voting.*

Because Compulsory Voting with $f > \varepsilon$ induces full turnout, the expected benefits of casting a pivotal, informed vote are smaller under Compulsory Voting with $f > \varepsilon$ than under Voluntary Voting, as long as there is less than full turnout under Voluntary Voting.[13] Moreover, the overall voting costs are higher.

However, recall that Compulsory Voting with a high abstention fine $f > \varepsilon$ does not necessarily increase the probability of acquiring information compared to Voluntary Voting, but might instead reduce information acquisition if the voting costs are sufficiently small (proposition 1.3). Therefore, the information costs however are affected differently:

On the one hand, if Compulsory Voting with $f > \varepsilon$ increases the probability of acquiring information compared to Voluntary Voting, it also increases the information costs. Then the same logic applies as for the intuition of proposition 1: Smaller expected benefits and higher participation costs imply a reduction in expected social welfare.

If on the other hand, Compulsory Voting with $f > \varepsilon$ reduces the probability of acquiring information compared to Voluntary Voting, it also reduces information costs. Proposition 2 however shows that the reduction in benefits always outweighs the reduction in information costs, such that welfare overall decreases.

1.5 Extensions

The benchmark model analyzed in the previous section does not cover two important cases. First, uninformed voters might be biased towards one of the two alternatives. Second, one alternative might be ex ante more likely to be favored by each individual. I present a generalized version of the model that covers these two extensions in appendix 1.B. Moreover, the model allows for stochastic voting costs $k_i \in [\underline{k}, \overline{k}]$ which can have a different distribution than the information costs c_i. In the following, I summarize the main results from the extended model and refer the reader to appendix 1.B for details.

[13] Note that if Voluntary Voting already achieves full turnout, the introduction of the abstention fine affects neither turnout nor information acquisition, and expected social welfare remains constant.

1.5.1 Neutral Preferences With Biased Uninformed Voters

In the first generalization of my model I continue to study neutral preferences, where each alternative is ex ante equally likely to be favored by the majority. I assume that uninformed voters who participate in the election cast a valid ballot by voting randomly. In particular, I assume that uninformed voters vote for alternative A with probability λ, which is common knowledge. If $\lambda = \frac{1}{2}$, they are unbiased, while if $\lambda > \frac{1}{2}$ they are biased towards alternative A. In the latter case, uninformed voters who participate in the election create an ex ante expected advantage for alternative A. Then the probability of being pivotal is lower for A-voters than for B-voters. Therefore, informed individuals who favor B are more like to participate than those who favor A – which is the underdog effect (cf. e.g. Taylor and Yildirim, 2010).

I show that – as in the benchmark case – Compulsory Voting with a marginal abstention fine $0 < f < \underline{k}$ which does not necessarily lead to full participation increases the probability of acquiring information. A high abstention fine $f \geq \overline{k}$, which always leads to full participation, only increases the probability of acquiring information if voting costs are high. If voting costs are sufficiently low, it however reduces the probability of acquiring information compared to Voluntary Voting. In particular, as the voting costs approach the degenerate distribution where $\underline{k} = \overline{k} = 0$, it is impossible to incentivize information acquisition through an abstention fine. Moreover, the probability of acquiring information under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ is decreasing in the bias λ of the uninformed voters. In particular, I find that if uninformed voters are fully biased, i.e. if $\lambda = 1$, not acquiring information is an equilibrium.

Moreover, I show that a marginal abstention fine $0 < f < \underline{k}$ reduces expected social welfare because the increase in turnout from informed voters reduces the expected benefits of acquiring information. With a high abstention fine $f \geq \overline{k}$, uninformed voters exert an additional negative externality on informed voters. Therefore, expected social welfare under Compulsory Voting with a high abstention fine is lower than under Voluntary Voting, and decreasing in the bias λ of the uninformed voters.

1.5.2 Non-Neutral Preferences

In the second generalization of my model I study non-neutral preferences, where alternative A is ex ante more likely to be favored by the majority. In particular, each individual favors alternative A with probability $\alpha \in \left(\frac{1}{2}, 1\right)$. I show that it is a weakly dominant strategy for uninformed voters who participate in the election to vote for alternative A with probability 1. While in the neutral preferences setting I exogenously assumed that uninformed voters cast a valid vote, this behavior now arises endogenously in the non-neutral preferences setting. Moreover, uninformed voters are endogenously biased towards alternative A. Although uninformed voters derive a positive expected benefit from casting a pivotal vote already under Voluntary Voting, their benefit is always lower than the expected benefit from casting a pivotal, informed vote. Therefore, uninformed voters are less likely to participate than informed voters.

As in the case with neutral preferences and fully biased uninformed voters, I show that under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ that leads to full participation, not acquiring information is an equilibrium. In that case, alternative A wins the election with certainty, and hence the expected benefits of acquiring information are reduced to zero. At the same time, information costs are reduced to zero as well. I show that nevertheless, expected social welfare is strictly lower under Compulsory Voting with full participation from uninformed voters only than under Voluntary Voting.

1.6 Conclusion

The most important result of my analysis is that – in contrast to the prevailing view in the literature – Compulsory Voting with full participation does not necessarily achieve a collective outcome that accurately reflects the majority's preferences. If individuals are initially uninformed about their preferred alternative and acquiring this information is costly, this result would require that incentivizing participation through an abstention fine also incentivizes information acquisition. I show that, while a small abstention fine that does not achieve full turnout always increases information acquisition, a high abstention fine that achieves full turnout does so only if the voting costs are sufficiently high. If the voting costs however are low, the opposite is true: Then, a high abstention fine that achieves full turnout reduces information acquisition compared to Voluntary Voting. In particular, in the limit with zero voting costs, it is impossible to incentivize information acquisition through an abstention fine. If uninformed voters are biased, the incentives to acquire information are reduced further. As a result, the preference of the majority cannot necessarily be inferred from the outcome of the collective decision anymore.

Moreover, I show that due to the negative externality of voting, expected social welfare under Compulsory Voting is lower than under Voluntary Voting. Even in the limit with zero voting costs, when Compulsory Voting does not increase voting costs, but even reduces expected information costs by reducing information acquisition, the reduction in the expected benefits of voting outweighs the reduction in expected costs. Under Compulsory Voting with full participation, expected social welfare is further reduced when the bias of uninformed voters increases.

Therefore – coming back to my initial thought experiment – I show that, compared to Voluntary Voting, nearly costless but mandatory elections have a detrimental effect both on the quality of the collective decision and on expected social welfare.

Future research could allow for a correlation between information costs and preferences. This might be the case if less educated individuals, for whom it is more costly to acquire policy-specific information, have systematically different policy preferences than more educated individuals. Then, under Voluntary Voting where only informed individuals participate in the election, the outcome of the election is biased towards the preference of those with low information costs. Compulsory Voting might make participation between voters with different preferences more balanced and achieve a policy outcome that reflects the preferences of the entire electorate, not just of the subgroup of individuals with low information costs.

Appendix to Chapter 1

1.A Proofs for the Benchmark Model

Proof of Proposition 1.1.

(i) and (ii) follow directly from everything that has been stated before.

(iii) Let $\underline{c} + \varepsilon - f < \frac{1}{2}$ and $\overline{c} + \varepsilon - f > B(1)$. A *voting strategy* takes the form $\sigma : [\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f] \to \{0, 1\}$ where $\sigma_i = 0$ means that individual i abstains and $\sigma_i = 1$ means that i casts an informed vote for her favored alternative r_i. An equilibrium voting strategy must be a cutoff strategy (as in Börgers, 2004) and there must be a common cutoff value $\hat{c}$ such that, for all individuals $i \in \{1, ..., n\}$, $\sigma_i = 1$ if $c_i \leq \hat{c} - \varepsilon + f$, and $\sigma_i = 0$ otherwise. For any cutoff value $\hat{c}$, the probability that individual i votes as implied by the cutoff voting strategy, is

$$p(\hat{c}) \equiv Pr(c_i \leq \hat{c} - \varepsilon + f) = G(\hat{c} - \varepsilon + f).$$

Note that $p(\hat{c}) \in [0, 1]$ where $p(\hat{c}) = 1$ if $\hat{c} \geq \overline{c} + \varepsilon - f$ and $p(\hat{c}) = 0$ if $\hat{c} \leq \underline{c} + \varepsilon - f$. Through the equilibrium voting probability $p(\hat{c})$, the equilibrium benefit of voting $B(p(\hat{c}))$ is fixed and defines the cost threshold for which each individual participates. A value $\hat{c}$ is a threshold for an equilibrium cutoff voting strategy if and only if $B(p(\hat{c})) = \hat{c}$ for $\hat{c} \in (\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f)$ or $B(p(\hat{c})) \leq \hat{c}$ if $\hat{c} = \underline{c} + \varepsilon - f$ or $B(p(\hat{c})) \geq \hat{c}$ if $\hat{c} = \overline{c} + \varepsilon - f$. For existence and uniqueness of such an equilibrium threshold, we need to show that $B(p(\hat{c}))$ is differentiable and strictly decreasing in $\hat{c}$ on the interval $(\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f)$ (Börgers, 2004). Then, the function $B(p(\hat{c}))$ intersects with the 45° line exactly once on the interval $(\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f)$, so that we have exactly one point where $B(p(\hat{c})) = \hat{c}$. We already know that $B(p)$ is strictly decreasing in p and that $p = G(\hat{c} - \varepsilon + f)$. We can conclude from the fact that p is strictly increasing in $\hat{c}$ because $\frac{\partial G(\hat{c} - \varepsilon + f)}{\partial \hat{c}} = g(\hat{c} - \varepsilon + f) > 0$ for $\hat{c}$ in $(\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f)$ that $B(p(\hat{c}))$ is indeed strictly decreasing in $\hat{c}$ on this interval.

□

Proof of Remark 1.

Let $0 \leq f < \varepsilon$.

(i) Consider an increase in the voting costs, such that $\varepsilon' > \varepsilon$. Let $p^{*\prime}$ denote the equilibrium probability of voting under the increased voting costs ε', and $c^{*\prime}$ the corresponding equilibrium information cost cutoff value. I want to show that $p^{*\prime} \leq p^*$, with strict inequality if $p^* \in (0,1)$. If $p^* = 1$, it is obvious that $p^{*\prime} \leq p^*$. Therefore, consider now the remaining two cases $p^* = 0$ and $p^* \in (0,1)$.

First, consider $p^* = 0$. Then $c^* = \underline{c} + \varepsilon - f \geq \frac{1}{2}$. Then, for any $\varepsilon' > \varepsilon$ we have $\underline{c} + \varepsilon' - f > \frac{1}{2}$, such that $p^{*\prime} = 0$ as well.

Second, consider $p^* \in (0,1)$, i.e. $c^* \in (\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f)$. Recall that then $c^* = B(p^*)$. I now want to show that $c^{*\prime} > c^*$. Suppose for a contradiction that $c^{*\prime} \leq c^*$. By the equilibrium definition of c^* and $B(\cdot)$ strictly decreasing, this is equivalent to $p^{*\prime} \geq p^*$, which, by the equilibrium definition of p is equivalent to $G(c^{*\prime} - \varepsilon' + f) \geq G(c^* - \varepsilon + f)$. By $G(\cdot)$ strictly increasing, this is equivalent to $c^{*\prime} - c^* \geq \varepsilon' - \varepsilon$. The left-hand side of this inequality is strictly negative, while the right-hand side is strictly positive, which yields a contradiction. Hence, we must have that $c^{*\prime} > c^*$. By the equilibrium definition of c^* and $B(\cdot)$ strictly decreasing, this is equivalent to $p^{*\prime} < p^*$.

(ii) Next, I need to show that the equilibrium probability of casting an informed vote, p^*, is weakly increasing in the abstention fine f, with strict inequality of $p^* \in (0,1)$. If $p^* = 0$, it is obvious that $p^{*\prime} \geq p^*$ for any $f' > f$. Therefore, consider now the remaining two cases $p^* = 1$ and $p^* \in (0,1)$.

First, consider $p^* = 1$. Then $c^* = \overline{c} + \varepsilon - f \leq B(1)$. Then, for any $f' > f$ we have $\underline{c} + \varepsilon - f' < B(1)$, such that $p^{*\prime} = 1$ as well.

Second, consider $p^* \in (0,1)$, i.e. $c^* \in (\underline{c} + \varepsilon - f, \overline{c} + \varepsilon - f)$. Recall that then $c^* = B(p^*)$. In equilibrium,

$$\frac{\mathrm{d}p^*}{\mathrm{d}f} = g(c^* - \varepsilon + f) \left[\frac{\mathrm{d}c^*}{\mathrm{d}f} + 1 \right]$$

where, again from the implicit definition of c^*,

$$\frac{\mathrm{d}c^*}{\mathrm{d}f} = \frac{\partial B(p)}{\partial p} \left[\frac{\partial G(c^* - \varepsilon + f)}{\partial c^*} \frac{\mathrm{d}c^*}{\mathrm{d}f} + \frac{\partial G(c^* - \varepsilon + f)}{\partial f} \right].$$

Rearranging,

$$\begin{aligned}\frac{\mathrm{d}c^*}{\mathrm{d}f} &= \frac{\frac{\partial B(p)}{\partial p}\frac{\partial G(c^*-\varepsilon+f)}{\partial f}}{1-\frac{\partial B(p)}{\partial p}\frac{\partial G(c^*-\varepsilon+f)}{\partial c^*}} \\ &= \frac{\frac{\partial B(p)}{\partial p}g(c^*-\varepsilon+f)}{1-\frac{\partial B(p)}{\partial p}g(c^*-\varepsilon+f)}\end{aligned}$$

such that from $\frac{\partial B(p)}{\partial p} < 0$ and $g(c) > 0$ for $c \in (\underline{c}, \overline{c})$, we have $\frac{\mathrm{d}c^*}{\mathrm{d}f} \in (-1, 0)$. Therefore, $\frac{\mathrm{d}p^*}{\mathrm{d}f} > 0$ for all $c^* \in (\underline{c}+\varepsilon-f, \overline{c}+\varepsilon-f)$.

□

Proof of Proposition 1.2.

(i) and (ii) follow directly from everything that has been stated before.

(iii) Let $\underline{c} < B(1) < \overline{c}$. A *voting strategy* takes the form $\sigma : [\underline{c}, \overline{c}] \to \{0, 1\}$ where $\sigma_i = 1$ means that individual i acquires information and hence votes for her favored alternative, and $\sigma_i = 0$ means that individual i remains uninformed and randomly votes for each alternative with equal probability.

The equilibrium voting strategy is a cutoff strategy with a common cutoff value $\hat{c}$ such that $\sigma_i = 1$ if $c_i \leq \hat{c}$ and $\sigma_i = 0$ otherwise. In particular, a value $\hat{c}$ is a threshold for an equilibrium cutoff voting strategy if and only if $B(1) = \hat{c}$ for $\hat{c} \in (\underline{c}, \overline{c})$ or $B(1) \leq \hat{c}$ if $\hat{c} = \underline{c}$ or $B(1) \geq \hat{c}$ if $\hat{c} = \overline{c}$. If $\underline{c} < B(1) < \overline{c}$, the function $B(1)$ crosses the 45° line exactly once on the interval $(\underline{c}, \overline{c})$ because $B(1)$ is simply a constant function. Therefore, we can conclude immediately that the equilibrium cutoff value exists and is unique.

□

Proof of Proposition 1.3.

Consider a high abstention fine $f > \varepsilon$ and let $\underline{c} < B(1) < \overline{c}$. Let p^{*V} denote the equilibrium probability of acquiring information under Voluntary Voting and q^* the equilibrium probability of acquiring information under Compulsory Voting. I need to show that there exists a unique $\tilde{\varepsilon} \in (0, \frac{1}{2} - \underline{c})$ such that for $\varepsilon < \tilde{\varepsilon}$, $q^* < p^{*V}$ while for $\varepsilon > \tilde{\varepsilon}$, $q^* > p^{*V}$.

First, consider $\varepsilon = 0$.[14] Then, by $\underline{c} < B(1) < \frac{1}{2}$ and $\overline{c} > B(1)$, $c^{*V} \in (\underline{c}+\varepsilon, \overline{c}+\varepsilon)$ and hence $c^{*V} = B(p^{*V})$. Note that because because B is strictly decreasing in p^{*V} and $p^{*V} < 1$, we have $B(p^{*V}) > B(1)$. Because G is strictly increasing, it follows directly that $p^{*V} = G(B(p^{*V})) > G(B(1)) = q^*$.

[14]Note that for $\varepsilon = 0$, uninformed voters are indifferent between casting a random vote and abstaining. Here, I assume that all uninformed voters abstain.

Second, consider $\varepsilon = \frac{1}{2} - \underline{c}$. Then, $p^{*V} = 0$. Because $\underline{c} < B(1)$, it follows that $q^* = G(B(1)) > 0 = p^{*V}$.

Moreover, recall from remark 1 that p^{*V} is strictly decreasing in ε, while q^* is unaffected by ε. Therefore, because $p^{*V} > q^*$ at $\varepsilon = 0$ and $p^{*V} < q^*$ at $\varepsilon = \frac{1}{2} - \underline{c}$, we can conclude that there exists a unique $\tilde{\varepsilon} \in (0, \frac{1}{2} - \underline{c})$ where $p^{*V} = q^*$, and hence for all $\varepsilon < \tilde{\varepsilon}$, $q^* < p^{*V}$ while for all $\varepsilon > \tilde{\varepsilon}$, $q^* > p^{*V}$.

□

Proof of Proposition 1.4.

Let $0 \leq f < \varepsilon$. Let $p^* = G(c^* - \varepsilon + f)$ denote the probability of acquiring information (and voting) for $f < \varepsilon$. I need to show that expected social welfare is weakly decreasing in the abstention fine f, and strictly increasing if $p^* \in (0, 1)$. Note that if $p^* = 1$, an increase in the abstention fine f does not affect the probability of acquiring information (and voting), and therefore expected social welfare remains unaffected as well. Therefore, consider now the remaining two cases $p^* = 0$ and $p^* \in (0, 1)$.

First, consider $p^* \in (0, 1)$. Then, we have from Remark 1 that $\frac{\mathrm{d}p^*}{\mathrm{d}f} > 0$. Moreover, recall that then $c^* = B(p^*)$.

$$
\begin{aligned}
\frac{\mathrm{d}W(p^*)}{\mathrm{d}f} &= n\Bigg[\left[B(p^*) - (c^* - \varepsilon + f) - \varepsilon\right] g(c^* - \varepsilon + f)\frac{\mathrm{d}(c^* - \varepsilon + f)}{\mathrm{d}f} \\
&\qquad + \int_{\underline{c}}^{c^*-\varepsilon+f} \frac{\partial B(p^*)}{\partial p^*}\frac{\mathrm{d}p^*}{\mathrm{d}f} g(c)\mathrm{d}c\Bigg] \\
&= n\left[-fg(c^* - \varepsilon + f)\frac{\mathrm{d}(c^* - \varepsilon + f)}{\mathrm{d}f} + \frac{\partial B(p^*)}{\partial p^*}\frac{\mathrm{d}p^*}{\mathrm{d}f}p^*\right] \\
&= n\left[\left(\frac{\partial B(p^*)}{\partial p^*}p^* - f\right)\frac{\mathrm{d}p^*}{\mathrm{d}f}\right]
\end{aligned}
$$

where the second line follows from $c^* = B(p^*)$ and $p^* = G(c^* - \varepsilon + f)$, and the third line follows from the fact that $\frac{\mathrm{d}p^*}{\mathrm{d}f} = g(c^* - \varepsilon + f)\frac{\mathrm{d}(c^* - \varepsilon + f)}{\mathrm{d}f}$. Because $\frac{\partial B(p^*)}{\partial p^*} < 0$ and $\frac{\mathrm{d}p^*}{\mathrm{d}f} > 0$ for all $p^* \in (0, 1)$, it follows that $\frac{\mathrm{d}W(p^*)}{\mathrm{d}f} < 0$.

Second, consider $p^* = 0$. Then $c^* = \underline{c} + \varepsilon - f \geq \frac{1}{2}$ and $\left.\frac{\mathrm{d}p^*}{\mathrm{d}f}\right|_{p^*=0} \geq 0$. Then

$$
\left.\frac{\mathrm{d}W(p^*)}{\mathrm{d}f}\right|_{p^*=0} = n\left[\left(\frac{1}{2} - \underline{c} - \varepsilon\right)\left.\frac{\mathrm{d}p^*}{\mathrm{d}f}\right|_{p^*=0}\right]
$$

where $\underline{c} + \varepsilon - f \geq \frac{1}{2}$ implies $\frac{1}{2} - \underline{c} - \varepsilon \leq 0$. Hence $\left.\frac{\mathrm{d}W(p^*)}{\mathrm{d}f}\right|_{p^*=0} \leq 0$.

□

Proof of Proposition 1.5.

Let $p^{*V} = G(c^{*V} - \varepsilon)$ denote the the probability of acquiring information (and voting) under Voluntary Voting. I want to show that, as long as $p^{*V} < 1$, expected social welfare compared is strictly lower under Compulsory Voting with a high abstention fine $f > \varepsilon$ than under Voluntary Voting. Let $q^* = G(B(1))$ denote the probability of acquiring information under Compulsory Voting with $f > \varepsilon$. I need to distinguish the three cases, where $q^* \in (0,1)$, $q^* = 0$ and $q^* = 1$.

(i) Consider $\underline{c} < B(1) < \bar{c}$ such that $q^* \in (0,1)$. Note that $B(1) < \bar{c}$ implies $p^{*V} < 1$. Therefore, either $p^{*V} = 0$ and $c^{*V} \geq B(p^{*V})$, or $p^{*V} \in (0,1)$ and $c^{*V} = B(p^{*V})$. Then,

$$U(q^*) - U(p^{*V}) = B(1)q^* - B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) - \int_{\underline{c}}^{B(1)} cg(c)\mathrm{d}c + \int_{\underline{c}}^{c^{*V}-\varepsilon} cg(c)\mathrm{d}c$$

Recall from proposition 3 that there exists a unique voting costs threshold $\tilde{\varepsilon} \in (0, \frac{1}{2} - \underline{c})$ such that for all $\varepsilon < \tilde{\varepsilon}$, we have $q^* < p^{*V}$, while for all $\varepsilon > \tilde{\varepsilon}$, we have $q^* > p^{*V}$. Therefore, we need to distinguish these two cases.

First, consider $q^* > p^{*V}$, which is equivalent to $c^{*V} - \varepsilon < B(1)$. Therefore,

$$\begin{aligned}
U(q^*) - U(p^{*V}) &= B(1)q^* - B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) - \int_{c^{*V}-\varepsilon}^{B(1)} cg(c)\mathrm{d}c \\
&= B(1)q^* - B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) - \left[B(1)q^* - (c^{*V}-\varepsilon)p^{*V}\right] + \int_{c^{*V}-\varepsilon}^{B(1)} G(c)\mathrm{d}c \\
&= \left[c^{*V} - B(p^{*V})\right]p^{*V} - \varepsilon + \int_{c^{*V}-\varepsilon}^{B(1)} G(c)\mathrm{d}c \\
&< B(1) - c^{*V}
\end{aligned}$$

where the second-to-last line follows from the fact that either $p^{*V} = 0$ or $c^{*V} = B(p^{*V})$ and from $G(c) \leq 1$ for all c. Because $B(1) < B(p^{*V}) \leq c^{*V}$ it follows that $U(q^*) - U(p^{*V}) < 0$.

Second, consider $q^* < p^{*V}$, which is equivalent to $B(1) < c^{*V} - \varepsilon$. Therefore,

$$\begin{aligned}
U(q^*) - U(p^{*V}) &= B(1)q^* - B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) + \int_{B(1)}^{c^{*V}-\varepsilon} cg(c)\mathrm{d}c \\
&= B(1)q^* - B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) + \left[(c^{*V}-\varepsilon)p^{*V} - B(1)q^*\right] - \int_{B(1)}^{c^{*V}-\varepsilon} G(c)\mathrm{d}c \\
&= \left[c^{*V} - B(p^{*V})\right]p^{*V} - \varepsilon - \int_{B(1)}^{c^{*V}-\varepsilon} G(c)\mathrm{d}c.
\end{aligned}$$

Because either $p^{*V} = 0$ or $c^{*V} = B(p^{*V})$, it follows that $U(q^*) - U(p^{*V}) < 0$.

(ii) Consider $\underline{c} > B(1)$ such that $q^* = 0$. Hence $q^* \leq p^{*V}$. Note that $\underline{c} > B(1)$ implies $B(1) < \overline{c}$ and hence $p^{*V} < 1$. Therefore, again, either $p^{*V} = 0$ and $c^{*V} \geq B(p^{*V})$, or $p^{*V} \in (0,1)$ and $c^{*V} = B(p^{*V})$. Thus,

$$\begin{aligned} U(0) - U(p^{*V}) &= -B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) + \int_{\underline{c}}^{c^{*V}-\varepsilon} cg(c)\mathrm{d}c \\ &= -B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) + (c^{*V}-\varepsilon)p^{*V} - \int_{\underline{c}}^{c^{*V}-\varepsilon} G(c)\mathrm{d}c \\ &= \left[c^{*V} - B(p^{*V})\right]p^{*V} - \varepsilon - \int_{\underline{c}}^{c^{*V}-\varepsilon} G(c)\mathrm{d}c. \end{aligned}$$

As before, because either $p^{*V} = 0$ or $c^{*V} = B(p^{*V})$, it follows that $U(q^*) - U(p^{*V}) < 0$.

(iii) Consider $\overline{c} < B(1)$ such that $q^* = 1$. Hence $q^* \geq p^{*V}$. If $p^{*V} = 1$ then obviously $U(q^*) = U(p^{*V})$. Thus, consider $p^{*V} < q^*$. Then,

$$\begin{aligned} U(1) - U(p^{*V}) &= B(1) - B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) - \int_{c^{*V}-\varepsilon}^{\overline{c}} cg(c)\mathrm{d}c \\ &= B(1) - B(p^{*V})p^{*V} - \varepsilon(1-p^{*V}) - \left[\overline{c} - (c^{*V}-\varepsilon)p^{*V}\right] + \int_{c^{*V}-\varepsilon}^{\overline{c}} G(c)\mathrm{d}c \\ &= B(1) - \left[c^{*V} - B(p^{*V})\right]p^{*V} - \varepsilon - \overline{c} + \int_{c^{*V}-\varepsilon}^{\overline{c}} G(c)\mathrm{d}c \\ &< B(1) - c^{*V} \end{aligned}$$

where the second-to-last line follows, as before, from the fact that either $p^{*V} = 0$ or $c^{*V} = B(p^{*V})$ and from $G(c) \leq 1$ for all c. Then, again, because $B(1) < B(p^{*V}) \leq c^{*V}$ it follows that $U(q^*) - U(p^{*V}) < 0$.

All in all, we have $U(q^*) < U(p^{*V})$ for any individual in all cases, as long as p^{*V}. Therefore, we can conclude that $W(q^*) < W(p^{*V})$, i.e. expected social welfare is strictly lower under Compulsory Voting with a high abstention fine $f > \varepsilon$ compared to Voluntary Voting.

□

1.B The Extended Model

To study biased voters in the neutral preferences setting as well as the case of non-neutral preferences, I will now present a generalized version of my model.

As in the benchmark model, there are $n \geq 3$ individuals $i \in \{1, 2, ..., n\}$ who have to make a collective policy decision x from the set of alternatives $X = \{A, B\}$. The outcome is determined by simple majority rule. In case of a tie, both alternatives are chosen with equal probability.

Let $r_i \in X$ denote the alternative favored by individual $i \in \{1, 2, ..., n\}$. Let $\alpha \in (0, 1)$ denote the probability that an individual favors alternative A and $1 - \alpha$ the probability that an individual favors alternative B. Without loss of generality, suppose that $\alpha \geq \frac{1}{2}$. On the one hand, if $\alpha = \frac{1}{2}$, both alternatives are ex ante equally likely to be favored by the majority, and the preferences of the electorate are said to be *neutral.* On the other hand if $\alpha > \frac{1}{2}$, alternative A is ex ante expected to be favored by the majority of voters, and the preferences of the electorate are *non-neutral.*

Let c_i denote the stochastic information costs of individual i. For each i, the information costs c_i are drawn independently from the CDF G which has the support $[\underline{c}, \overline{c}]$ where $0 \leq \underline{c} < \overline{c}$. Let g denote the PDF associated with G and assume that g is positive on all of the support. I continue to assume that information acquisition is a binary decision, i.e. individual i can either acquire a perfectly informative signal about her preferred alternative r_i, or remain uninformed such that she only knows that she, as well as all other individuals, favors alternative A with probability α.

Let k_i denote the stochastic voting costs, i.e. the costs of casting a ballot, of individual i. The voting costs are not yet known to the individual when she makes her information acquisition decision. For each i, the voting costs k_i are drawn independently from the CDF H which is the same for all individuals and has the support $[\underline{k}, \overline{k}]$ with $0 \leq \underline{k} < \overline{k}$. Assume that $\underline{k} < \frac{1}{2}$ to rule out trivial equilibria where nobody votes. Let h denote the PDF associated with H and assume that h is positive on all of the support. The voting costs k_i of individual i are assumed to be stochastically independent of her preferred alternative r_i, her information costs c_i and of the voting costs k_j of individual $j \neq i$.

As in the benchmark model, ex post utility is normalized to 1 if an individual's preferred alternative is chosen collectively, and to zero otherwise. If an individual who knows her preferred alternative casts a ballot, voting against her preferred alternative is a weakly dominated strategy. Hence informed voters vote sincerely for their preferred alternative. Uninformed individuals can participate in the election although they do not know which alternative they favor: They are assumed to cast a valid vote by voting for alternative A with probability λ, which is common knowledge.

The timing of the game can be summarized as follows:

1. For each individual $i \in \{1, 2, ..., n\}$, nature draws the information costs $c_i \in [\underline{c}, \overline{c}]$ according to the PDF g and the voting costs $k_i \in [\underline{k}, \overline{k}]$. Nature also draws i's preferred alternative r_i from the set of alternatives $X = \{A, B\}$ with $Pr(r_i = A) = \alpha \geq \frac{1}{2}$.

2. Each individual privately observes her information cost c_i, but she neither observes her preference r_i nor her voting costs k_i.

3. *Information stage*: All individuals simultaneously decide whether to acquire information or not. The decision is private information. If individual i acquires information she privately observes her preference r_i.

4. Each individual privately observes her voting costs k_i.

5. *Voting stage*: All individuals simultaneously decide whether to vote or abstain.

6. The collective policy outcome $x \in X$ is realized by simple majority rule.

7. Payoffs are realized.

Note that at the voting stage, we have three different political groups of individuals: Those who are informed and favor alternative A, those who are informed and favor B and those who are uninformed (denoted by U). Let $\theta \in \Theta \equiv \{A, B, U\}$ denote the political group an individual belongs to. Individuals of the same group face an identical decision problem so that, as common in the literature, I can focus on type-symmetric strategies. A voting strategy must be a cutoff strategy with (potentially different) cutoff values $\hat{k}_\theta \in [\underline{k}, \overline{k}]$ for each group $\theta \in \{A, B, U\}$. Then, an individual i in group θ casts a ballot if and only if her voting costs k_i are sufficiently low, i.e. if $k_i \leq \hat{k}_\theta$, and abstains otherwise. The voting cost cutoff values pin down the voting probabilities

$$p_\theta = Pr(k_i \leq \hat{k}_\theta) = H(\hat{k}_\theta)$$

for each group $\theta \in \{A, B, U\}$. Note that $p_\theta \in [0, 1]$ with $p_\theta = 0$ if $\hat{k}_\theta \leq \underline{k}$ and $p_\theta = 1$ if $\hat{k}_\theta \geq \overline{k}$.

At the information stage, all individuals face an identical decision problem. An information acquisition strategy must be a cutoff strategy with a common cutoff value $\hat{c} \in [\underline{c}, \overline{c}]$ for all individuals such that an individual i acquires information if and only if her information costs c_i are sufficiently low, i.e. if $c_i \leq \hat{c}$, and remains uninformed otherwise. The information cost cutoff value then implies the probability of acquiring information for all individuals, which is given by

$$q \equiv Pr(c_i \leq \hat{c}) = G(\hat{c})$$

where $q \in [0,1]$ with $q = 0$ if $\hat{c} \leq \underline{c}$ and $q = 1$ if $\hat{c} \geq \bar{c}$.

In the following, I will solve the game using a backward induction logic.

The Voting Stage

First, let's derive the expected benefit of casting an informed vote. Individual i is pivotal only if her vote creates or breaks a tie. In both cases, she gains $\frac{1}{2}$ in expected utility. The probability of being pivotal depends on the other individuals' expected behavior and, because alternative A is ex ante preferred by the majority, on whether individual i votes for A or for B. Let $\Pi_A(\mathbf{p}, q)$ denote the probability that an individual who votes for A is pivotal and $\Pi_B(\mathbf{p}, q)$ the probability that an individual who votes for B is pivotal if all other individuals participate with probabilities $\mathbf{p} \equiv (p_A, p_B, p_U)$ and if all others acquire information with probability q. Let $\mathcal{B}_A(\mathbf{p}, q)$ denote the expected benefit from casting a pivotal vote for A, which is

$$\mathcal{B}_A(\mathbf{p}, q) = \frac{1}{2}\Pi_A(\mathbf{p}, q) \tag{1.11}$$

and let $\mathcal{B}_B(\mathbf{p}, q)$ denote the expected benefit from casting a pivotal vote for B, which is

$$\mathcal{B}_B(\mathbf{p}, q) = \frac{1}{2}\Pi_B(\mathbf{p}, q). \tag{1.12}$$

Next, let's derive the expected benefit of casting an uninformed vote. In general, since an uninformed voter does not have any information about which alternative she favors, she can vote randomly for A or B. Let $\lambda \in [0,1]$ denote the probability with which an uninformed voter votes for alternative A. Then, if an uninformed voter i casts a pivotal vote for A, she knows that with probability α, she actually favors A and her expected utility increases by $\frac{1}{2}$. With probability $1-\alpha$, she however favors B and her expected utility decreases by $\frac{1}{2}$. Similarly, if i casts a pivotal vote for B she knows that with probability α, she actually favors A and her expected utility decreases by $\frac{1}{2}$. With probability $1-\alpha$, she however favors B and her expected utility increases by $\frac{1}{2}$. Let $\mathcal{B}_U(\mathbf{p}, q)$ denote the expected benefit of casting an uninformed, pivotal vote, which is

$$\begin{aligned}\mathcal{B}_U(\mathbf{p},q) &= \lambda\Pi_A(\mathbf{p},q)[\alpha\frac{1}{2}+(1-\alpha)(-\frac{1}{2})]+(1-\lambda)\Pi_B(\mathbf{p},q)[\alpha(-\frac{1}{2})+(1-\alpha)\frac{1}{2}]\\ &= (\alpha-\frac{1}{2})(\lambda\Pi_A(\mathbf{p},q)-(1-\lambda)\Pi_B(\mathbf{p},q)). \end{aligned} \tag{1.13}$$

Two observations follow from equation 1.13: First, in the neutral preference setting ($\alpha = \frac{1}{2}$), the expected benefit of casting an uninformed vote is zero for all λ. Second, in the non-neutral preference setting ($\alpha > \frac{1}{2}$), the expected benefit of casting an uninformed vote $\mathcal{B}_U(\mathbf{p},q)$ is increasing in λ. In this case, it is optimal for any uninformed voter who participates in the election to vote for A with probability $\lambda = 1$. Thus, in contrast to the neutral preference setting, where I exogenously assume uninformed voters to be biased, this bias arises endogenously in the non-neutral setting. Moreover, if the probability of being pivotal is positive, the expected benefit of casting a pivotal vote for A is positive and an uninformed individual strictly prefers to cast a valid vote for A over spoiling her ballot. This is in contrast to the neutral preference setting, where uninformed voters are indifferent between casting a valid or an invalid vote, and in contrast to Tyson (2016), who assumes that uninformed voters always spoil their ballot.

Because $\mathcal{B}_U(\mathbf{p},q) = 0$ for all λ if $\alpha = \frac{1}{2}$, and because $\lambda = 1$ if $\alpha > \frac{1}{2}$, the expected benefit of casting an uninformed vote can be written as

$$\mathcal{B}_U(\mathbf{p},q) = (\alpha-\frac{1}{2})\Pi_A(\mathbf{p},q). \tag{1.14}$$

Next, I need to calculate the probability $\Pi(\mathbf{p},q)$ that individual i is pivotal. Given the voting probabilities $\mathbf{p}$ and the information acquisition probability q, let $\phi_A(\mathbf{p},q)$ denote the ex ante expected probability that an individual votes for alternative A, and $\phi_B(\mathbf{p},q)$ the ex ante expected probability that an individual votes for alternative B. If preferences are neutral, we have $\phi_A(\mathbf{p},q) = \frac{1}{2}qp_A + \lambda(1-q)p_U$ and $\phi_B(\mathbf{p},q) = \frac{1}{2}qp_B + (1-\lambda)(1-q)p_U$. If preferences are non-neutral, we have $\phi_A(\mathbf{p},q) = \alpha qp_A + (1-q)p_U$ and $\phi_B(\mathbf{p},q) = (1-\alpha)qp_B$ because all uninformed vote for alternative A.

The ex ante expected probability that an individual abstains is $1-\phi_A-\phi_B$.

A voter is pivotal if her vote either creates a tie or breaks a tie. Hence, given the voting probabilities $\mathbf{p}$ and the information acquisition probability q, the probability that an A-vote is pivotal is given by (following Taylor and Yildirim, 2010)

$$\begin{aligned}\Pi_A(\mathbf{p},q) = &\sum_{l=0}^{\lfloor\frac{n-1}{2}\rfloor}\binom{n-1}{l,l,n-1-2l}\phi_A^l\phi_B^l(1-\phi_A-\phi_B)^{n-1-2l}\\ &+\sum_{l=0}^{\lfloor\frac{n-2}{2}\rfloor}\binom{n-1}{l,l+1,n-2-2l}\phi_A^l\phi_B^{l+1}(1-\phi_A-\phi_B)^{n-2-2l}.\end{aligned} \tag{1.15}$$

Analogously, the probability that a B-vote is pivotal is given by

$$\begin{aligned}\Pi_B(\mathbf{p},q) = &\sum_{l=0}^{\lfloor\frac{n-1}{2}\rfloor}\binom{n-1}{l,l,n-1-2l}\phi_A^l\phi_B^l(1-\phi_A-\phi_B)^{n-1-2l}\\ &+\sum_{l=0}^{\lfloor\frac{n-2}{2}\rfloor}\binom{n-1}{l,l+1,n-2-2l}\phi_A^{l+1}\phi_B^{l}(1-\phi_A-\phi_B)^{n-2-2l}.\end{aligned} \tag{1.16}$$

From Taylor and Yildirim (2010), we have $\Pi_A - \Pi_B = sign(\phi_B - \phi_A)$.

Given the probability that her vote will be pivotal, an individual casts a ballot if and only if her expected payoff from voting exceeds her expected payoff from abstaining. Thus, an individual with voting costs k_i in group $\theta \in \{A, B, U\}$ votes if and only if

$$k_i \leq \mathcal{B}_\theta(\mathbf{p},q) + f \equiv \varphi_\theta(\mathbf{p},q) \tag{1.17}$$

and abstains otherwise.[15]

In any symmetric pure strategy Bayesian Nash equilibrium, the equilibrium voting cost cutoff value k_θ^* for the group of voters $\theta \in \{A, B, U\}$ must satisfy

$$\begin{aligned} k_\theta^* &= \varphi_\theta(\mathbf{p}^*,q) \text{ if } k_\theta^* \in (\underline{k},\overline{k})\\ \text{or } k_\theta^* &\geq \varphi_\theta(\mathbf{p}^*,q) \text{ if } k_\theta^* = \underline{k}\\ \text{or } k_\theta^* &\leq \varphi_\theta(\mathbf{p}^*,q) \text{ if } k_\theta^* = \overline{k}.\end{aligned} \tag{1.18}$$

where $\mathbf{p}^* = (p_A^*, p_B^*, p_U^*)$ are the equilibrium voting probabilities implied by the equilibrium voting cost cutoffs, and q is the information acquisition probability implied by some information cost cutoff $\hat{c}$.

Because the CDF H is strictly increasing on all of the support, finding equilibrium

[15]Note that an individual in group $\theta \in \{A, B, U\}$ is indifferent between voting and abstaining if equation 1.17 holds with equality. However, since the voting costs k_i are a continuous random variable, this is a probability zero event and can be ignored for the following analysis.

voting cost cutoff values $(k_A^*, k_B^*, k_U^*) \in [\underline{k}, \overline{k}]^3$ is equivalent to finding equilibrium voting probabilities $(p_A^*, p_B^*, p_U^*) = (H(k_A^*), H(k_B^*), H(k_U^*)) \in [0,1]^3$. Hence, using that $H'(y) > 0$ for all $y \in (\underline{k}, \overline{k})$ and that $H(y) = 0$ for $y \leq \underline{k}$ and $H(y) = 1$ for $y \geq \overline{k}$, we can re-write the above conditions in one single condition: In any symmetric pure strategy Bayesian Nash equilibrium, the equilibrium probabilities of voting for all groups of voters $\theta \in \{A, B, U\}$ need to satisfy

$$p_\theta^* = H(\varphi_\theta(\mathbf{p}^*, q)) \tag{1.19}$$

for any information acquisition probability $q \in [0,1]$.

The Information Stage

At the information stage, an individual acquires information if her expected payoff of doing so, given the respective probability of casting an informed vote after learning whether she favors A or B, exceeds the expected payoff of remaining uninformed, given the probability of casting an uninformed vote.

For any information cost cutoff $\hat{c}$ and a corresponding vector of equilibrium voting cost cutoffs (k_A^*, k_B^*, k_U^*), an individual i with information costs c_i acquires information about her preferred alternative, if and only if

$$\begin{aligned}
&\alpha \left[\int_{\underline{k}}^{k_A^*} \left(\frac{1}{2} \Pi_A(\mathbf{p}^*, q) - y \right) h(y) dy + \int_{k_A^*}^{\overline{k}} (-f) h(y) dy \right] \\
&+ (1-\alpha) \left[\int_{\underline{k}}^{k_B^*} \left(\frac{1}{2} \Pi_B(\mathbf{p}^*, q) - y \right) h(y) dy + \int_{k_B^*}^{\overline{k}} (-f) h(y) dy \right] - c_i \\
\geq &\int_{\underline{k}}^{k_U^*} \left(\left(\alpha - \frac{1}{2} \right) \Pi_A(\mathbf{p}^*, q) - y \right) h(y) dy + \int_{k_U^*}^{\overline{k}} (-f) h(y) dy.
\end{aligned} \tag{1.20}$$

The first line is the expected payoff if individual i acquires information and finds out that she prefers alternative A: If her voting costs are below k_A^*, she casts her vote for A and, if she is pivotal, gains $\frac{1}{2}$ in expected utility, but also pays the voting costs k_i. If her voting costs are above k_A^*, she abstains and pays the fine f. Analogously, the second line is the expected payoff if i acquires information and finds out that she prefers alternative B. The third line is the expected payoff if i remains uninformed.

Using integration by parts, this condition can be re-written such that an individual i with information costs c_i acquires information about her preferred alternative, if and only if

$$
\begin{aligned}
c_i \leq \alpha & \left[\left(\frac{1}{2}\Pi_A - k_A^* + f \right) p_A^* + \int_{\underline{k}}^{k_A^*} H(y)dy \right] \\
& + (1-\alpha) \left[\left(\frac{1}{2}\Pi_B - k_B^* + f \right) p_B^* + \int_{\underline{k}}^{k_B^*} H(y)dy \right] \\
& - \left((\alpha - \frac{1}{2})\Pi_A - k_U^* + f \right) p_U^* - \int_{\underline{k}}^{k_U^*} H(y)dy
\end{aligned} \tag{1.21}
$$

and remains uninformed otherwise. Let $\Phi(\mathbf{p}^*, q)$ denote the right-hand side of condition 1.21, which can be interpreted as the expected benefit of acquiring information. Note that if $k_A^*, k_B^*, k_U^* \in (\underline{k}, \overline{k})$, condition 1.21 can be further simplified to

$$
c_i \leq \alpha \int_{\underline{k}}^{k_A^*} H(y)dy + (1-\alpha) \int_{\underline{k}}^{k_B^*} H(y)dy - \int_{\underline{k}}^{k_U^*} H(y)dy. \tag{1.22}
$$

In any symmetric pure strategy Bayesian Nash equilibrium, the equilibrium information cost cutoff c^* must satisfy

$$
\begin{aligned}
c^* = \Phi(\mathbf{p}^*, q) &\text{ if } c^* \in (\underline{c}, \overline{c}) \\
\text{or } c^* \geq \Phi(\mathbf{p}^*, q) &\text{ if } c^* = \underline{c} \\
\text{or } c^* \leq \Phi(\mathbf{p}^*, q) &\text{ if } c^* = \overline{c}.
\end{aligned} \tag{1.23}
$$

Because the CDF G is strictly increasing on all of the support, finding the equilibrium information cost cutoff value $c^* \in [\underline{c}, \overline{c}]$ is equivalent to finding the equilibrium information acquisition probability $q^* = G(c^*) \in [0, 1]$. Hence, using that $G'(y) > 0$ for all $y \in (\underline{c}, \overline{c})$ and that $G(y) = 0$ for $y \leq \underline{c}$ and $G(y) = 1$ for $y \geq \overline{c}$, we can re-write the above conditions in one single condition: In any symmetric pure strategy Bayesian Nash equilibrium, the equilibrium probability q^* of acquiring information needs to satisfy

$$
q^* = G(\Phi(\mathbf{p}^*, q^*)) \tag{1.24}
$$

given the equilibrium voting probabilities $\mathbf{p}^*$.

Proposition 1.6 shows the existence of an equilibrium in this generalized model.

Proposition 1.6. *There exists a type-symmetric pure-strategy Bayesian Nash equilibrium, in which the following conditions are satisfied simultaneously for the equilibrium probabilities of voting, $\boldsymbol{p}^* = (p_A^*, p_B^*, p_U^*)$, and the equilibrium probability of acquiring information, q^*:*

$$\begin{aligned} q^* &= G(\Phi(\boldsymbol{p}^*, q^*)) \\ p_A^* &= H(\varphi_A(\boldsymbol{p}^*, q^*)) \\ p_B^* &= H(\varphi_B(\boldsymbol{p}^*, q^*)) \\ p_U^* &= H(\varphi_U(\boldsymbol{p}^*, q^*)). \end{aligned}$$

Welfare

The expected utility of an individual consists of the expected utility given that the individual acquires information, plus the expected utility given that the individual does not acquire information. In both cases, she can either cast a vote (informed or uninformed), or abstain. Hence, expected utility given the equilibrium probabilities of voting, $\mathbf{p}^* = (p_A^*, p_B^*, p_U^*)$, and the equilibrium probability of acquiring information, q^*, is given by

$$\begin{aligned} U(\mathbf{p}^*, q^*) = {} & \alpha Pr(A \text{ wins}) + (1-\alpha) Pr(B \text{ wins}) \\ & + \int_{\underline{c}}^{c^*} \Bigg[\alpha \left[\int_{\underline{k}}^{k_A^*} \left(\frac{1}{2} \Pi_A(\mathbf{p}^*, q^*) - k \right) h(k) \mathrm{d}k - \int_{k_A^*}^{\overline{k}} f h(k) \mathrm{d}k \right] \\ & +(1-\alpha) \left[\int_{\underline{k}}^{k_B^*} \left(\frac{1}{2} \Pi_B(\mathbf{p}^*, q^*) - k \right) h(k) \mathrm{d}k - \int_{k_B^*}^{\overline{k}} f h(k) \mathrm{d}k \right] - c \Bigg] g(c) \mathrm{d}c \\ & + \int_{c^*}^{\overline{c}} \left[\int_{\underline{k}}^{k_U^*} \left(\left(\alpha - \frac{1}{2} \right) \Pi_A(\mathbf{p}^*, q^*) - k \right) h(k) \mathrm{d}k - \int_{k_U^*}^{\overline{k}} f h(k) \mathrm{d}k \right] g(c) \mathrm{d}c \end{aligned} \tag{1.25}$$

where the first line represents the individual's expected utility if she casts a vote but is not pivotal, or if she abstains. Intuitively, with probability α, she favors A, and hence she will get a payoff of 1 only if A wins and 0 otherwise. With probability $1-\alpha$, she favors B, and hence she will get a payoff of 1 only if B wins and 0 otherwise. The second and third line represent her expected utility if she acquires information while the fourth line represents her expected utility if she remains uninformed. Note that expected utility can be rewritten as

$$
\begin{aligned}
U(\mathbf{p}^*, q^*) = {} & \alpha Pr(A \text{ wins}) + (1-\alpha) Pr(B \text{ wins}) \\
& + q^* \left[\alpha p_A^* \frac{1}{2} \Pi_A(\mathbf{p}^*, q^*) + (1-\alpha) p_B^* \frac{1}{2} \Pi_B(\mathbf{p}^*, q^*) \right] \\
& + (1-q^*) p_U^* \left(\alpha - \frac{1}{2} \right) \Pi_A(\mathbf{p}^*, q^*) \\
& - q^* \left[\alpha \int_{\underline{k}}^{k_A^*} k h(k) \mathrm{d}k + (1-\alpha) \int_{\underline{k}}^{k_B^*} k h(k) \mathrm{d}k \right] \\
& - (1-q^*) \int_{\underline{k}}^{k_U^*} k h(k) \mathrm{d}k \\
& - q^* \left[\alpha (1-p_A^*) + (1-\alpha) p_B^* \right] f - (1-q^*)(1-p_U^*) f \\
& - \int_{\underline{c}}^{c^*} c g(c) \mathrm{d}c.
\end{aligned}
\tag{1.26}
$$

Moreover, we have (adapted from Taylor and Yildirim, 2010)

$$
\begin{aligned}
Pr(A \text{ wins}) = {} & \frac{1}{2} \sum_{l=0}^{\lfloor \frac{n}{2} \rfloor} \binom{n}{l, l, n-2l} \phi_A^l \phi_B^l (1-\phi_A-\phi_B)^{n-2l} \\
& + \sum_{l=1}^{\lfloor \frac{n+1}{2} \rfloor} \sum_{l'=0}^{l-1} \binom{n}{l, l', n-l-l';} \phi_A^l \phi_B^{l'} (1-\phi_A-\phi_B)^{n-l-l'} \\
& + \sum_{l=\lfloor \frac{n+1}{2} \rfloor + 1}^{n} \sum_{l'=0}^{n-l} \binom{n}{l, l', n-l-l';} \phi_A^l \phi_B^{l'} (1-\phi_A-\phi_B)^{n-l-l'}
\end{aligned}
\tag{1.27}
$$

where, for ease of notation, $\phi_A \equiv \phi_A(\mathbf{p}^*, q^*)$ and $\phi_B \equiv \phi_B(\mathbf{p}^*, q^*)$, and $Pr(B \text{ wins}) = 1 - Pr(A \text{ wins})$. Under the assumption that the expected revenue generated from the abstention fine is re-distributed to the individuals, expected social welfare can be written as

$$
\begin{aligned}
W(\mathbf{p}^*, q^*) = n \Bigg(& \alpha Pr(A \text{ wins}) + (1-\alpha) Pr(B \text{ wins}) \\
& + q^* \left[\alpha p_A^* \frac{1}{2} \Pi_A(\mathbf{p}^*, q^*) + (1-\alpha) p_B^* \frac{1}{2} \Pi_B(\mathbf{p}^*, q^*) \right] \\
& + (1-q^*) p_U^* \left(\alpha - \frac{1}{2} \right) \Pi_A(\mathbf{p}^*, q^*) \\
& - q^* \left[\alpha \int_{\underline{k}}^{k_A^*} k h(k) \mathrm{d}k + (1-\alpha) \int_{\underline{k}}^{k_B^*} k h(k) \mathrm{d}k \right] \\
& - (1-q^*) \int_{\underline{k}}^{k_U^*} k h(k) \mathrm{d}k - \int_{\underline{c}}^{c^*} c g(c) \mathrm{d}c \Bigg) .
\end{aligned}
\tag{1.28}
$$

1.B.1 Neutral Preferences

In the neutral-preferences setting with $\alpha = \frac{1}{2}$, each individual is ex ante equally likely to favor alternative A or B. Recall that the expected benefit for uninformed voters of casting a pivotal vote is zero when preferences are neutral (follows directly from equation 1.13). Because voting is costly, uninformed voters strictly prefer to abstain under Voluntary Voting. Under Compulsory Voting, uninformed voters participate if and only if their voting costs are smaller than the abstention fine, i.e. if $k_i < f$. Therefore, the equilibrium probability of voting for an uninformed individual is $p_U^* = H(f)$, which is positive if the abstention fine is sufficiently high, i.e. if $f \geq \underline{k}$. I assume that uninformed voters who participate in the election cast a valid vote by randomly selecting one of the two alternatives with probability $\lambda \in [\frac{1}{2}, 1]$.[16] If $\lambda = \frac{1}{2}$, I will say that the uninformed voters are unbiased. If $\lambda > \frac{1}{2}$, I will say that the uninformed voters are biased towards alternative A.

Equilibrium Properties

To understand the effect of an abstention fine on the probability of acquiring information later, it is important to first derive some basic properties of voting behavior in equilibrium.

Remark 2. *The type-symmetric pure-strategy Bayesian Nash equilibrium under neutral preferences ($\alpha = \frac{1}{2}$) has the following properties:*

(i) If uninformed voters are unbiased ($\lambda = \frac{1}{2}$), then $0 < p_A^* = p_B^*$ in equilibrium.

[16] Note that in the non-neutral preference setting (section 1.B.2), uninformed voters endogenously prefer to cast a valid vote over spoiling their ballot.

(ii) If uninformed voters are biased ($\lambda > \frac{1}{2}$), then

(a) if $f \leq \underline{k}$, $p_U^* = 0$ and $p_A^* = p_B^* > 0$.

(b) if $f \in (\underline{k}, \overline{k})$, $0 < p_U^* < p_A^* \leq p_B^* \leq 1$, and if $p_A^* < 1$, then $p_A^* < p_B^*$.

(c) if $f \geq \overline{k}$, $p_U^* = p_A^* = p_B^* = 1$.

Intuitively, if either uninformed voters are unbiased, or if they are biased but don't participate, there is no ex ante expected majority for either of the two alternatives, such that A- and B- voters are equally likely to vote in equilibrium (as in Börgers, 2004). If however biased, uninformed voters participate in the election, there is an ex ante expected majority for alternative A, such that the probability of being pivotal is lower for A-voters than for B-voters. Therefore, informed individuals who favor B are more like to participate than those who favor A – which is the underdog effect (cf. e.g. Taylor and Yildirim, 2010).

Proposition 1.7. *The type-symmetric pure-strategy Bayesian Nash equilibrium under neutral preferences ($\alpha = \frac{1}{2}$) is unique if $\frac{1-\lambda}{\lambda} \geq 1 - \frac{1}{\lfloor \frac{n}{2} \rfloor}$.*

Note that proposition 1.7 implies that, if uninformed voters are unbiased, i.e. if $\lambda = \frac{1}{2}$, the equilibrium is unique, which is the result from Börgers (2004). This uniqueness result can be extended to the case where uninformed voters are biased only if the bias λ is sufficiently close to $\frac{1}{2}$, such that voting probabilities remain sufficiently symmetric. To show this, I draw on the result from Taylor and Yildirim (2010) for the case with non-neutral preferences, which says that there exists at most one equilibrium that satisfies $1 \geq \frac{\phi_B^*}{\phi_A^*} \geq 1 - \frac{1}{\lfloor \frac{n}{2} \rfloor}$. If uninformed voters are biased and participate, the expected probability that an individual votes for A, ϕ_A^*, is always higher than the ex ante expected probability that an individual votes for B, ϕ_B^*. Then, A-voters always impose a negative externality of voting on all other individuals. B-voters however might impose a positive externality of voting on other voters with the same preference, which can cause the existence of multiple equilibria (Taylor and Yildirim, 2010). This positive externality arises only if the gap in voting probabilities is sufficiently large, which in the neutral preference setting is possible only if the bias of the uninformed voters is sufficiently large. If the bias of the uninformed voters is not too large, i.e. if λ is sufficiently close to $\frac{1}{2}$, the gap in voting probabilities is small and B-voters impose a negative externality of voting on all other individuals. Then, equilibrium voting behavior is sufficiently symmetric for the equilibrium to remain unique. Thus, I find that the uniqueness result from the symmetric setting with unbiased uninformed voters is robust to small perturbations in the bias of uninformed voters.

Information Acquisition

In the following, I will compare the probability of acquiring information under Voluntary and Compulsory Voting. In particular, I will analyze how the probability of acquiring information is affected on the one hand by the introduction of a marginal abstention fine $0 < f < \underline{k}$ which does not necessarily lead to full turnout, and on the other hand by the introduction of a high abstention fine $f \geq \overline{k}$ which leads to full turnout.

First, consider the introduction of a marginal abstention fine $0 < f < \underline{k}$. Recall from remark 2 that then, $p_U^* = 0$ and $p_A^* = p_B^* > 0$ for all $\lambda \geq \frac{1}{2}$. Therefore, let $p_I^* \equiv p_A^* = p_B^*$ denote the equilibrium probability of voting for an informed individual.

Proposition 1.8. *Consider neutral preferences ($\alpha = \frac{1}{2}$). If $0 \leq f < \underline{k}$, the probability of acquiring information weakly increases in the abstention fine f. It increases strictly if $q^* \in (0,1)$ and $p_I^* \in (0,1)$.*

This result relies on the fact that, as long as $f < \underline{k}$, uninformed individuals strictly prefer to abstain. Then, the incentives to acquire information are driven by the probability of voting for informed individuals only. If $p_I^* = 1$ at $f = 0$, i.e. all informed individuals vote under Voluntary Voting, the introduction of a marginal abstention fine does not affect the probability of voting for informed individuals, p_I^*, and hence it cannot affect the probability of acquiring information either. If however $p_I^* < 1$ at $f = 0$, then the introduction of a marginal abstention fine incentivizes participation of informed individuals, and therefore incentivizes information acquisition as well.

Next, for the comparison between Voluntary Voting and Compulsory Voting with a high abstention fine $f \geq \overline{k}$, let's start with some observations about the probability of casting a pivotal vote under Compulsory Voting with $f \geq \overline{k}$. Recall from remark 2 that $f \geq \overline{k}$ leads to full participation, i.e. $p_A^* = p_B^* = p_U^* = 1$. Then, the voting probabilities are

$$\phi_A(\mathbf{1}, q^*) = \frac{1}{2}q^* + \lambda(1 - q^*)$$

and

$$\phi_B(\mathbf{1}, q^*) = \frac{1}{2}q^* + (1 - \lambda)(1 - q^*)$$

and the probabilities of being pivotal are given by

$$\Pi_A(\mathbf{1}, q^*) = \begin{cases} \binom{n-1}{\frac{n-1}{2}} \phi_A^{\frac{n-1}{2}} \phi_B^{\frac{n-1}{2}} & \text{if } n \text{ odd} \\ \binom{n-1}{\frac{n}{2}-1} \phi_A^{\frac{n}{2}-1} \phi_B^{\frac{n}{2}} & \text{if } n \text{ even} \end{cases} \tag{1.29}$$

and

$$\Pi_B(\mathbf{1},q^*) = \begin{cases} \binom{n-1}{\frac{n-1}{2}}\phi_A^{\frac{n-1}{2}}\phi_B^{\frac{n-1}{2}} & \text{if } n \text{ odd} \\ \binom{n-1}{\frac{n}{2}-1}\phi_A^{\frac{n}{2}}\phi_B^{\frac{n}{2}-1} & \text{if } n \text{ even} \end{cases} \tag{1.30}$$

where, for ease of notation, $\phi_A = \phi_A(\mathbf{1},q^*)$ and $\phi_B = \phi_B(\mathbf{1},q^*)$. Moreover, the expected benefit of acquiring information is

$$\Phi(\mathbf{1},q^*) = \frac{1}{4}\left(\Pi_A(\mathbf{1},q^*) + \Pi_B(\mathbf{1},q^*)\right). \tag{1.31}$$

Now, first note that if $q^* = 0$, $\phi_A(\mathbf{1},0) = \lambda$ and $\phi_B(\mathbf{1},0) = 1-\lambda$. Thus, if $\frac{1}{2} \leq \lambda < 1$, we have $0 < \Pi_A(\mathbf{1},0) \leq \Pi_B(\mathbf{1},0)$, and hence $\Phi(\mathbf{1},0) > 0$. However if $\lambda = 1$, we have $\Pi_A(\mathbf{1},0) = \Pi_B(\mathbf{1},0) = 0$, and hence $\Phi(\mathbf{1},0) = 0$.

Second, note that if $q^* = 1$, $\phi_A(\mathbf{1},1) = \phi_B(\mathbf{1},1) \equiv \phi(\mathbf{1},1) = \frac{1}{2}$. Hence $\Pi_A(\mathbf{1},1) = \Pi_B(\mathbf{1},1) \equiv \Pi(\mathbf{1},1)$ which is given by

$$\Pi(\mathbf{1},1) = \begin{cases} \binom{n-1}{\frac{n-1}{2}}\frac{1}{2}^{n-1} & \text{if } n \text{ odd} \\ \binom{n-1}{\frac{n}{2}-1}\frac{1}{2}^{n-1} & \text{if } n \text{ even} \end{cases} \tag{1.32}$$

where $\Pi(\mathbf{1},1) > 0$ such that $\Phi(\mathbf{1},1) = \frac{1}{2}\Pi(\mathbf{1},1) > 0$.

Let's continue with some observations about the expected benefit of casting an informed vote under Voluntary Voting. Recall that, under Voluntary Voting, $p_U^* = 0$ and $p_A^* = p_B^* \equiv p_I^* > 0$, and also $\phi_A(p_I^*,q^*) = \phi_B(p_I^*,q^*) \equiv \phi(p_I^*,q^*) = \frac{1}{2}q^*p_I^*$ and $\Pi_A(p_I^*,q^*) = \Pi_B(p_I^*,q^*) \equiv \Pi$. Hence

$$\Phi(p_I^*,q^*) = \left(\frac{1}{2}\Pi(p_I^*,q^*) - k_I^*\right)p_I^* + \int_{\underline{k}}^{k_I^*} H(y)dy. \tag{1.33}$$

If we have full participation under Voluntary Voting, i.e. if $p_I^* = 1$ and $q^* = 1$, then $\phi = \frac{1}{2}$. Thus the probability of being pivotal in that case is given by equation 1.32.

Armed with the characterization of the probabilities of being pivotal and the expected benefit of casting an informed vote, I can now proceed to comparing the probability of acquiring information under Compulsory Voting with full participation to Voluntary Voting.

Proposition 1.9. *Consider neutral preferences ($\alpha = \frac{1}{2}$) and let $\frac{1}{2} \leq \lambda < 1$. Let $\underline{c} < \frac{1}{4}(\Pi_A(\mathbf{1},0) + \Pi_B(\mathbf{1},0))$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1},1)$. Consider voting costs $k_i \in [\underline{k},\overline{k}]$ where $\overline{k}$ =*

$\underline{k}+\kappa$. There exists a unique threshold $\tilde{\underline{k}} \in (0, \frac{1}{2}-\underline{c})$ and $\kappa \in (0, \frac{1}{2}\Pi(\mathbf{1},1)-\underline{c})$ sufficiently small, such that for low voting costs $\underline{k} < \tilde{\underline{k}}$, the probability of acquiring information under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ is strictly lower than under Voluntary Voting, while for high voting costs $\underline{k} > \tilde{\underline{k}}$, it is strictly higher than under Voluntary Voting.

Note that the conditions $\underline{c} < \frac{1}{4}(\Pi_A(\mathbf{1},0)+\Pi_B(\mathbf{1},0))$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1},1)$ ensure that $q^* \in (0,1)$ in any equilibrium under Compulsory Voting with a high abstention fine $f \geq \overline{k}$. Otherwise, if $\underline{c} > \frac{1}{4}(\Pi_A(\mathbf{1},0)+\Pi_B(\mathbf{1},0))$, there exists an equilibrium in which $q^*=0$, and if $\overline{c} < \frac{1}{2}\Pi(\mathbf{1},1)$, there exists an equilibrium in which $q^*=1$ under Compulsory Voting with a high abstention fine $f \geq \overline{k}$. Moreover, $\underline{c} < \frac{1}{4}(\Pi_A(\mathbf{1},0)+\Pi_B(\mathbf{1},0))$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1},1)$ ensure that there exists at least one stable equilibrium.

The result of proposition 1.9 is in line with the result from proposition 1.3 for the benchmark model and follows a similar intuition. Under Voluntary Voting, uninformed individuals abstain, while Compulsory Voting with $f \geq \overline{k}$ leads to full participation even from uninformed voters.

If voting costs are high, participation from informed individuals is low under Voluntary Voting. Then, Compulsory Voting with $f \geq \overline{k}$ increases participation from both informed and uninformed individuals compared to Voluntary Voting. The expected benefit of acquiring information is increasing in the probability of casting an informed vote, but decreasing in the probability of casting an uninformed vote. Therefore, Compulsory Voting with $f \geq \overline{k}$ can increases information acquisition if the increase in participation from informed voters is sufficiently large, i.e. if voting costs are sufficiently high.

If however voting costs are low, participation from informed individuals is already high under Voluntary Voting. Then Compulsory Voting with $f \geq \overline{k}$ cannot increase participation from informed individuals by a lot, and the negative effect of increased participation from uninformed individuals predominates, such that information acquisition decreases compared to Voluntary Voting.

This effect becomes stronger as the bias of uninformed voters increases:

Proposition 1.10. *Consider neutral preferences ($\alpha = \frac{1}{2}$) and let $\frac{1}{2} < \lambda < 1$. Let $\underline{c} < \frac{1}{4}(\Pi_A(\mathbf{1},0)+\Pi_B(\mathbf{1},0))$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1},1)$. Consider a stable equilibrium under Compulsory Voting with a high abstention fine $f \geq \overline{k}$. Then the probability of acquiring information is strictly decreasing in the bias λ of uninformed voters.*

Intuitively, as uninformed voters become more likely to vote for alternative A, the expected majority for A becomes larger under Compulsory Voting with full participation. Therefore, the probability of casting a pivotal vote decreases, which reduces the incentives to acquire information. As a result, there exists an equilibrium in which no individual acquires information under Compulsory Voting with full participation if uninformed voters are fully biased, i.e. $\lambda = 1$:

Proposition 1.11. *Consider neutral preferences ($\alpha = \frac{1}{2}$) and let $\lambda = 1$. Then not acquiring information is an equilibrium under Compulsory Voting with a high abstention fine $f \geq \overline{k}$.*

To illustrate the effect of Compulsory Voting on the equilibrium probability of acquiring information, I solve for the type-symmetric pure-strategy Bayesian Nash equilibrium numerically using a Gauss-Seidel algorithm. The equilibrium is unique in all of my numerical examples.

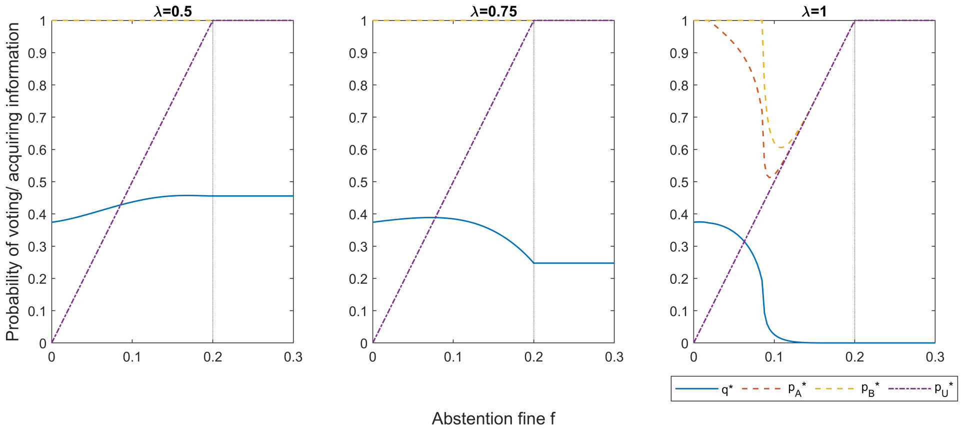
Figure 1.2 displays the effect of introducing Compulsory Voting on the equilibrium probabilities of voting and on the equilibrium probability of acquiring information. I consider unbiased uninformed voters ($\lambda = 0.5$) as well as biased uninformed voters ($\lambda > 0.5$). In panel (a), the voting costs are low, while in panel (b), the voting costs are high, in the sense that the distribution of voting costs in (b) first-order stochastically dominates the distribution in (a).

All figures illustrate the properties of the equilibrium voting probabilities as described in remark 2. The figures in panel (b) are in line with the result from proposition 1.8: A small abstention fine $0 < f < \underline{k}$ increases participation from informed individuals only, and therefore also increases information acquisition. The comparison between the figures for $\lambda = 0.75$ in panel (a) and (b) displays the result from proposition 1.9: For low voting costs (panel (a)), Compulsory Voting with a high abstention fine $f \geq \overline{k}$ reduces the probability of acquiring information compared to Voluntary Voting, while for high voting costs (panel (b)), it increases the probability of acquiring information compared to Voluntary Voting.

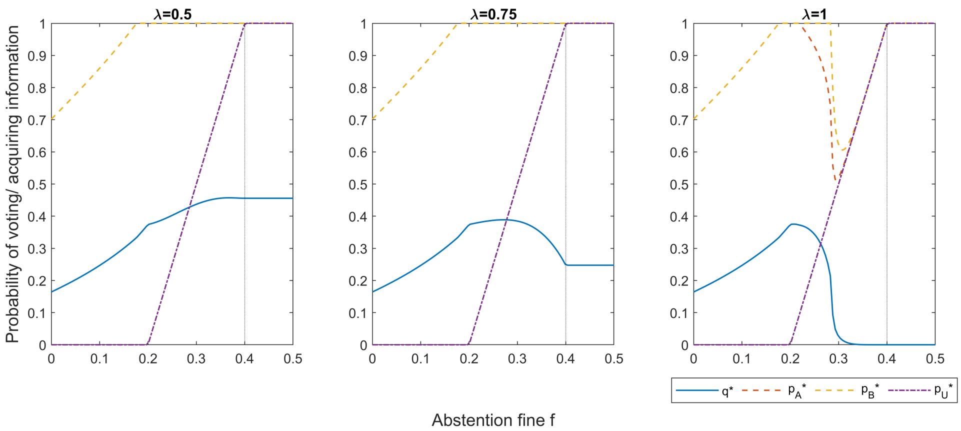
As expected from proposition 1.10, the probability of acquiring information under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ is strictly decreasing in the bias of uninformed voters, λ. Moreover, the figures show that, as expected from proposition 1.11, if uninformed individuals are fully biased ($\lambda = 1$), no individual acquires information under Compulsory Voting with a high abstention fine $f \geq \overline{k}$.

Welfare

In the following, I will analyze how expected social welfare is affected on the one hand by the introduction of a marginal abstention fine $0f < \underline{k}$ which does not necessarily lead to full turnout, and on the other hand by the introduction of a high abstention fine $f \geq \overline{k}$ which leads to full turnout. I will also study the effect of the bias λ of uninformed voters on expected social welfare.



(a) $k_i \sim U[0, 0.2]$



(b) $k_i \sim U[0.2, 0.4]$

Figure 1.2: The effect of an abstention fine f on the equilibrium probabilities of voting, p_A^*, p_B^*, p_U^*, and on the equilibrium probability of acquiring information, q^*, in the neutral preference setting with differing strength $\lambda \geq \frac{1}{2}$ of the bias of uninformed voters towards alternative A. The information costs are uniformly distributed on the interval $[0, 0.3]$. In panel (a) the voting costs are uniformly distributed on the interval $[0, 0.2]$ and in panel (b) the voting costs are uniformly distributed on the interval $[0.2, 0.4]$. The vertical line indicates the upper bound of the voting costs, $\overline{k}$. There are $n = 9$ individuals in the electorate.

First, consider the case of a marginal abstention fine $0 < f < \underline{k}$. Recall from remark 2 that then, $p_U^* = 0$ and $p_A^* = p_B^* > 0$ for all $\lambda \geq \frac{1}{2}$. Therefore, let $p_I^* \equiv p_A^* = p_B^*$ denote the equilibrium probability of voting for an informed individual. Then, expected social welfare is given by

$$W(p_I^*, q^*) = n\left(\frac{1}{2} + q^*\Phi(p_I^*, q^*) - \int_{\underline{c}}^{c^*} cg(c)\mathrm{d}c\right) \tag{1.34}$$

where $\Phi(p_I^*, q^*)$ is the expected benefit of acquiring information as given by equation 1.33.

Proposition 1.12. *Consider neutral preferences ($\alpha = \frac{1}{2}$). If $0 \leq f < \underline{k}$, expected social welfare weakly decreases in the abstention fine f. It decreases strictly if $q^* \in (0,1)$ and $p_I^* \in (0,1)$.*

As in the benchmark model (section 1.4.3), the reduction in social welfare is driven by the negative externality of voting (cf. also Börgers, 2004): Because uninformed individuals abstain and A- and B-voters participate with equal probability, the increase in turnout from informed voters reduces the expected benefit of acquiring information. At the same time, both information and voting costs increase. Thus, again, smaller expected benefits and higher participation costs imply a reduction in expected social welfare.

Next, consider the case of a high abstention fine $f \geq \overline{k}$. Recall from remark 2 that we have full turnout in that case, i.e. $p_U^* = p_A^* = p_B^* = 1$. Hence $\phi_A = \frac{1}{2}q^* + \lambda(1-q^*)$ and $\phi_B = \frac{1}{2}q^* + (1-\lambda)(1-q^*)$. Hence we have $\phi_A \geq \phi_B$ and therefore $\Pi_A \leq \Pi_B$, with strict inequality if $\lambda > \frac{1}{2}$. Then, expected social welfare is given by

$$W(\mathbf{1}, q^*) = n\left(\frac{1}{2} + q^*\Phi(\mathbf{1}, q^*) - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k - \int_{\underline{c}}^{c^*} cg(c)\mathrm{d}c\right) \tag{1.35}$$

where $\Phi(\mathbf{1}, q^*) = \frac{1}{4}(\Pi_A(\mathbf{1}, q^*) + \Pi_B(\mathbf{1}, q^*))$.

Proposition 1.13. *Consider neutral preferences ($\alpha = \frac{1}{2}$) and let $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$. The introduction of a high abstention fine $f \geq \overline{k}$ strictly reduces expected social welfare compared to Voluntary Voting.*

Recall from proposition 1.9 that Compulsory Voting with a high abstention fine $f \geq \overline{k}$ does not necessarily increase the probability of acquiring information compared to Voluntary Voting, but might instead reduce information acquisition if the voting costs are sufficiently small.

If uninformed voters are unbiased ($\lambda = \frac{1}{2}$), the increase in participation from both informed and uninformed voters under Compulsory Voting exerts a negative externality on all other voters. Therefore, and because of full turnout, the expected benefits of casting a pivotal, informed vote are smaller under Compulsory Voting with $f \geq \overline{k}$ than under Voluntary Voting, and the expected voting costs are higher. The expected information costs however can decrease, if the probability of acquiring information decreases compared to Voluntary Voting. However, as in the benchmark case, proposition 1.13 shows that the reduction in benefits always outweighs the reduction in information costs, such that expected social welfare decreases.

If uninformed voters are biased ($\lambda > \frac{1}{2}$), recall that B-voters are more likely to vote than A-voters. The increase in participation from B-voters under Compulsory Voting can exert a positive externality on other voters. At the same time, participation from – informed and uninformed – A-voters increases as well, thereby exerting a negative externality on others. Proposition 1.13 shows that the increase in voting costs and the negative externality from the increase in A-votes outweighs the positive externality from the increase in B-votes and the potential reduction in information costs. Therefore, again, expected social welfare is lower under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ than under Voluntary Voting.

This effect becomes even stronger as the bias λ of uninformed voters increases.

Proposition 1.14. *Consider neutral preferences ($\alpha = \frac{1}{2}$) and let $\frac{1}{2} < \lambda < 1$. Let $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$. Consider a stable equilibrium under Compulsory Voting with a high abstention fine $f \geq \overline{k}$. Then expected social welfare is strictly decreasing in the bias λ of uninformed voters.*

Intuitively, an increase in the bias λ of uninformed voters increases the probability that any individual votes for alternative A under Compulsory Voting with a high abstention fine $f \geq \overline{k}$. Hence, both A- and B-voters are less likely to cast a pivotal vote, and the expected benefits of acquiring information decrease for all voters. We know from proposition 1.10 that then, the probability of acquiring information under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ decreases, thereby reducing expected information costs. However, proposition 1.14 shows that the reduction in expected benefits outweighs the reduction in expected information costs.

1.B.2 Non-Neutral Preferences

In the non-neutral preference setting, each individual favors A with probability $\alpha \in \left(\frac{1}{2}, 1\right)$. Hence, alternative A is ex ante expected to be favored by the majority of individuals. Recall from equation 1.3 that in this case, uninformed voters who participate in the election always vote for alternative A.

Equilibrium Properties

To understand the effect of an abstention fine on the probability of acquiring information later, it is important to first derive some basic properties of voting behavior in equilibrium.

Remark 3. *The type-symmetric pure-strategy Bayesian Nash equilibrium under non-neutral preferences ($\alpha > \frac{1}{2}$) has the following properties:*

(i) if $f \leq \overline{k}$, $0 \leq p_U^* \leq p_A^*$ *and* $0 < p_A^* \leq p_B^*$, *and if* $f > \underline{k}$ *and* $p_A^* < 1$, *then* $0 < p_U^* < p_A^* < p_B^*$.

(ii) if $f \geq \overline{k}$, $p_U^* = p_A^* = p_B^* = 1$.

Intuitively, because there is an ex ante expected majority for alternative A, the probability of being pivotal is lower for A-voters than for B-voters. Therefore, informed individuals who favor B are more like to participate than those who favor A – which again is the underdog effect (cf. Taylor and Yildirim, 2010).

Neither the uniqueness result from the neutral preference setting with biased uninformed voters (proposition 1.7) nor the uniqueness result from Taylor and Yildirim (2010) extend to my setting with non-neutral preferences. Taylor and Yildirim (2010) – whose framework corresponds to the case with $q^* = 1$ in my model – find that the equilibrium is unique as long as the individuals are sufficiently symmetric, i.e. as long as α is sufficiently close to $\frac{1}{2}$. This result relies on the fact that, for α close to $\frac{1}{2}$, the ex ante expected probabilities that an individual votes for A or for B are very close. Similarly, I showed in proposition 1.7 that the uniqueness result for the neutral preference setting continues to hold when allowing uninformed voters to be biased as well, as long as the bias is not too large. This result relies on the same logic requiring voting probabilities to be sufficiently symmetric. In my setting with non-neutral preferences however, uninformed voters are perfectly biased, i.e. they vote for alternative A with probability 1. Under Voluntary Voting, uninformed voters participate in the election if the voting costs are not too high, and they become more likely to participate when an abstention fine is introduced. Thus, they create a large advantage for alternative A, such that the voting probabilities for A and B are always highly asymmetric: Even for small perturbations of α close to $\frac{1}{2}$, uninformed voters cause the ex ante expected probability that an individual votes for A to be much larger than the ex ante expected probability that an individual votes for B.

Information Acquisition

Evaluating the effect of Compulsory Voting with a small abstention fine $0 < f < \underline{k}$ is more difficult in the case with non-neutral preferences than with neutral preferences. The expected benefit of acquiring information (condition 1.21) is increasing in the probability of casting an informed vote, p_A^* and p_B^*, but decreasing in the probability of casting an uninformed vote, p_U^*. If voting costs are sufficiently high, such that $\underline{k} > \alpha - \frac{1}{2}$, uninformed individuals abstain as long as $0 \leq f < \underline{k} - (\alpha - \frac{1}{2})$. Thus, if introducing Compulsory Voting with a small abstention fine $0 < f < \underline{k} - (\alpha - \frac{1}{2})$ incentivizes participation from both A- and B-voters, it immediately follows that it also incentivizes information acquisition, by the same arguments as in the neutral preference setting. Because preferences are non-neutral, there are more individuals who favor A than individuals who favor B, and A-voters impose a negative externality on other voters. Therefore, it is unclear whether introducing Compulsory Voting with $0 < f < \underline{k} - (\alpha - \frac{1}{2})$ incentivizes participation from both A- and B-voters, and whether it incentivizes information acquisition.

For the comparison between Voluntary Voting and Compulsory Voting with a high abstention fine $f \geq \overline{k}$ let's start with some observations about the probability of casting a pivotal vote under Compulsory Voting with $f \geq \overline{k}$. Recall from remark 3 that $f \geq \overline{k}$ leads to full participation, i.e. $p_A^* = p_B^* = p_U^* = 1$. Then, the voting probabilities are

$$\phi_A(\mathbf{1}, q^*) = \alpha q^* + 1 - q^*$$

and

$$\phi_B(\mathbf{1}, q^*) = (1-\alpha) q^*.$$

Moreover, the expected benefit of casting an informed vote under Compulsory Voting with $f \geq \overline{k}$ is given by

$$\begin{aligned}\Phi(\mathbf{1}, q^*) &= \alpha \frac{1}{2} \Pi_A(\mathbf{1}, q^*) + (1-\alpha)\frac{1}{2}\Pi_B(\mathbf{1}, q^*) - (\alpha - \frac{1}{2})\Pi_A(\mathbf{1}, q^*) \\ &= (1-\alpha)\frac{1}{2}\left(\Pi_A(\mathbf{1}, q^*) + \Pi_B(\mathbf{1}, q^*)\right). \end{aligned} \tag{1.36}$$

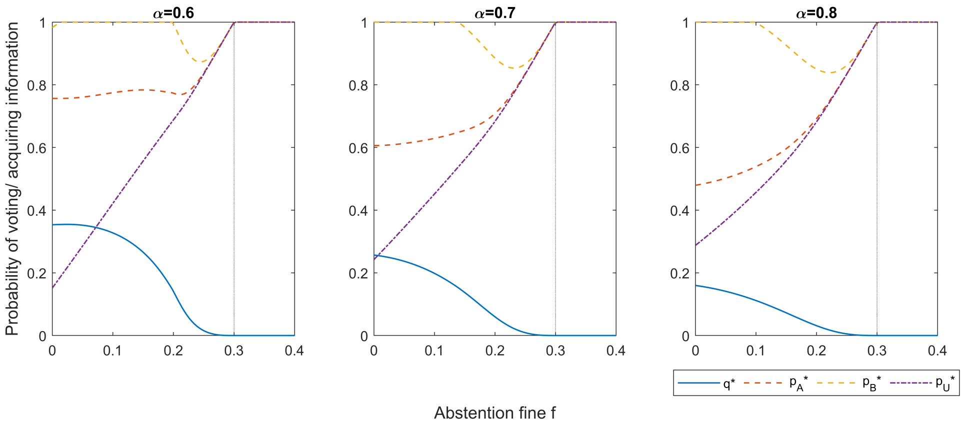
where $\Pi_A(\mathbf{1}, q^*)$ and $\Pi_B(\mathbf{1}, q^*)$ are given by equations 1.29 and 1.30 and $\phi_A(\mathbf{1}, q^*)$ and $\phi_B(\mathbf{1}, q^*)$ as above.

Now, note that if $q^* = 0$, $\phi_A(\mathbf{1}, 0) = 1$ and $\phi_B(\mathbf{1}, 0) = 0$. Thus, $\Pi_A(\mathbf{1}, 0) = \Pi_B(\mathbf{1}, 0) = 0$, and hence $\Phi(\mathbf{1}, 0) = 0$. Therefore, there exists an equilibrium with full participation, in which no individual acquires information. This result is in line with the result from the neutral preference setting with fully biased uninformed voters from proposition 1.11.

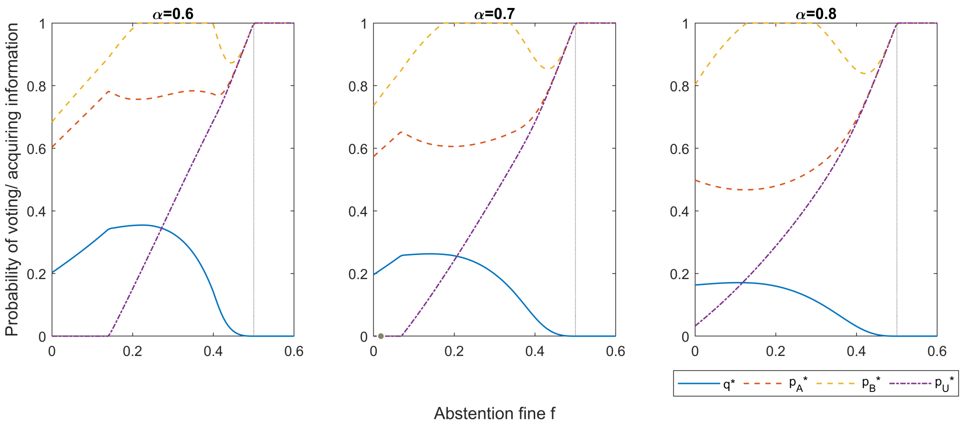
Proposition 1.15. *Consider non-neutral preferences ($\alpha > \frac{1}{2}$). Then not acquiring information is an equilibrium under Compulsory Voting with a high abstention fine $f \geq \overline{k}$.*

To illustrate the effect of introducing Compulsory Voting on the equilibrium probability of acquiring information, I again solve for the type-symmetric pure-strategy Bayesian Nash equilibrium numerically using a Gauss-Seidel algorithm. The equilibrium is unique in all of my numerical examples. Figure 1.3 displays the effect of the abstention fine f on the equilibrium probabilities of voting and on the equilibrium probability of acquiring information for different values of α, i.e. for differing strength of the ex ante preference for alternative A. In panel (a), the voting costs are low, while in panel (b), the voting costs are high, in the sense that the distribution of voting costs in (b) first-order stochastically dominates the distribution in (a).

All figures illustrate the properties of the equilibrium voting probabilities as described in remark 2, as well as the result from proposition 1.15: If $f \geq \overline{k}$, all individuals participate in the election, but no individual ever acquires information. The figures in panel (b) illustrate that, if $\underline{k}$ is sufficiently high such that $p_U^* = 0$ under Voluntary Voting, introducing a small abstention fine $0 < f < \underline{k}$ that increases participation from both A- and B-voters also increases information acquisition.



(a) $k_i \sim U[0, 0.3]$



(b) $k_i \sim U[0.2, 0.5]$

Figure 1.3: The effect of an abstention fine f on the equilibrium probabilities of voting, p_A^*, p_B^*, p_U^*, and on the equilibrium probability of acquiring information, q^*, in the non-neutral preference setting with differing strength $\alpha > \frac{1}{2}$ of the ex ante preference for alternative A. The information costs are uniformly distributed on the interval $[0, 0.3]$. In panel (a) the voting costs are uniformly distributed on the interval $[0, 0.3]$ and in panel (b) the voting costs are uniformly distributed on the interval $[0.2, 0.5]$. The vertical line indicates the upper bound of the voting costs, $\overline{k}$. There are $n = 5$ individuals in the electorate.

Welfare

In the following, I will evaluate how Compulsory Voting with a high abstention fine $f \geq \overline{k}$ that leads to full participation from uninformed voters only affects expected social welfare compared to Voluntary Voting. Because all individuals cast an uninformed vote for alternative A, such that A wins the election with certainty. Then however, the probability of being pivotal for an A-voter is $\Pi_A(\mathbf{1}, 0) = 0$, such that the expected benefits of casting a pivotal vote are zero. Thus, expected social welfare is given by

$$W(\mathbf{1}, 0) = n \left[\alpha - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k \right]. \tag{1.37}$$

Intuitively, because A wins the election with certainty, a share of α of the electorate can expect to get a payoff of 1 from their favored alternative being chosen collectively, however all individuals have to pay the expected voting costs.

Proposition 1.16. *Consider non-neutral preferences ($\alpha > \frac{1}{2}$) and let $\underline{k} > \alpha - \frac{1}{2}$. Introducing a high abstention fine $f \geq \overline{k}$ under which no individual acquires information strictly reduces expected social welfare compared to Voluntary Voting.*

Recall that if $\underline{k} > \alpha - \frac{1}{2}$, uninformed voters abstain under Voluntary Voting. Moreover, because preferences are not neutral, B-voters are more likely to vote than A-voters under Voluntary Voting. Under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ however, all individuals remain uninformed and vote for alternative A. Thus, both the reduction in B-votes and the increase in A-votes exerts a negative externality on others, and the expected benefit of casting a pivotal vote is reduced to zero. At the same time, information costs are reduced to zero as well. Proposition 1.16 shows that the increase in voting costs and the reduction in expected benefits outweighs the positive reduction in information costs. Therefore, again, expected social welfare is lower under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ than under Voluntary Voting.

1.C Proofs for the Extended Model

Proof of Proposition 1.6.

I need to show that there exists a type-symmetric pure-strategy Bayesian Nash equilibrium, in which the following conditions are satisfied simultaneously for the equilibrium probabilities of voting, $\mathbf{p}^* = (p_A^*, p_B^*, p_U^*)$, and the equilibrium probability of acquiring information, q^*:

$$\begin{aligned} q^* &= G(\Phi(\mathbf{p}^*, q^*)) \\ p_A^* &= H(\varphi_A(\mathbf{p}^*, q^*)) \\ p_B^* &= H(\varphi_B(\mathbf{p}^*, q^*)) \\ p_U^* &= H(\varphi_U(\mathbf{p}^*, q^*)) \end{aligned}$$

To show that such an equilibrium exists, define

$$\xi(\mathbf{p}, q) = (G(\Phi(\mathbf{p}, q), H(\varphi_A(\mathbf{p}, q)), H(\varphi_B(\mathbf{p}, q)), H(\varphi_U(\mathbf{p}, q)))\,. \tag{1.38}$$

From conditions 1.19 and 1.24, it is clear that the equilibrium probabilities of voting, $\mathbf{p}^* = (p_A^*, p_B^*, p_U^*)$, and the equilibrium probability of acquiring information, q^*, are a fixed point of ξ. Since ξ maps the compact and convex set $[0,1]^4$ into itself, and since ξ is continuous, we have, by Brouwer's Fixed Point Theorem, such a fixed point of ξ exists.

□

Proof of Remark 2.

(i) Let $\alpha = \frac{1}{2}$ and $\lambda = \frac{1}{2}$. Then $\phi_A(\mathbf{p}^*, q^*) = \frac{1}{2}\left(q^* p_A^* + (1-q^*)p_U^*\right)$ and $\phi_B(\mathbf{p}^*, q^*) = \frac{1}{2}\left(q^* p_B^* + (1-q^*)p_U^*\right)$. First I want to show that $p_A^* = p_B^*$ in equilibrium. Suppose for a contradiction that $p_A^* > p_B^*$. Then, $\phi_A > \phi_B$. Then, because $\Pi_A - \Pi_B = sign(\phi_B - \phi_A)$, we have $\Pi_A < \Pi_B$. Then however, by the equilibrium definition of p_A^* and p_B^*, $p_A^* = H\left(\frac{1}{2}\Pi_A + f\right) \leq H\left(\frac{1}{2}\Pi_B + f\right) = p_B^*$, which is a contradiction. Similarly, we get a contradiction if we assume $p_A^* > p_B^*$. Therefore, $p_A^* = p_B^*$ in equilibrium. Second, I need to show that $p_A^*, p_B^* > 0$. Suppose for a contradiction that $p_A^* = p_B^* \equiv p_I^* = 0$. Then $\phi_A = \phi_B = 0$ and $\Pi_A = \Pi_B = 1$. Then however, by $\underline{k} < \frac{1}{2}$, $p_I^* = H(\frac{1}{2} + f) > H(\underline{k}) = 0$, which is a contradiction. Hence $p_A^*, p_B^* > 0$.

(ii) Let $\alpha = \frac{1}{2}$ and $\lambda > \frac{1}{2}$.

(a) Let $f \leq \underline{k}$. Then $p_U^* = H(f) = 0$. I want to show that $p_A^* = p_B^*$ in equilibrium. To do so, I need to consider two cases: either $q^* = 0$ or $q^* > 0$. First, consider the case where $q^* = 0$. Then $\phi_A = \phi_B = 0$ by $p_U^* = 0$, and $\Pi_A = \Pi_B = 1$. Hence $p_A^* = H(\frac{1}{2} + f) = p_B^*$.

Second, consider the case where $q^* > 0$. Suppose for a contradiction that $p_A^* < p_B^*$ in equilibrium. Then $\phi_A > \phi_B$ and $\Pi_A < \Pi_B$. Then however, $p_A^* = H\left(\frac{1}{2}\Pi_A + f\right) \leq H\left(\frac{1}{2}\Pi_B + f\right) = p_B^*$, which is a contradiction. Similarly, we get a contradiction if we assume $p_A^* > p_B^*$. Therefore, $p_A^* = p_B^*$ in equilibrium. It remains to be shown that $p_A^*, p_B^* > 0$. Suppose for a contradiction that $p_A^* = p_B^* \equiv p_I^* = 0$. Then $\phi_A = \phi_B = 0$ and $\Pi_A = \Pi_B = 1$. Then however, by $\underline{k} < \frac{1}{2}$, $p_I^* = H(\frac{1}{2} + f) > H(\underline{k}) = 0$, which is a contradiction. Hence $p_A^*, p_B^* > 0$.

(b) Let $f \in (\underline{k}, \overline{k})$. Then $p_U^*, p_A^*, p_B^* > 0$ and $p_U^* < 1$. First, $p_U^* < p_A^*$ follows directly from the equilibrium definition of p_U^* and p_A^* and $\Pi_A > 0$: $p_U^* = H(f) < H(\frac{1}{2}\Pi_A + f) = p_A^*$.

Second, I want to show that $p_A^* \leq p_B^*$. Suppose for a contradiction that $p_A^* > p_B^*$. Then, for all $q^* \geq 0$, $\phi_A > \phi_B$ because $\lambda > \frac{1}{2}$ and $p_U^* > 0$. Thus, $\Pi_A < \Pi_B$. Then however, $p_A^* = H(\frac{1}{2}\Pi_A + f) \leq H(\frac{1}{2}\Pi_B + f) = p_B^*$, which is a contradiction. Hence $p_A^* \leq p_B^*$.

Third, I want to show that if $p_A^* < 1$, then $p_A^* < p_B^*$. Suppose for a contradiction that $p_A^* < 1$ but $p_A^* = p_B^*$. Then, for all $q^* \geq 0$, $\phi_A > \phi_B$ because $\lambda > \frac{1}{2}$ and $p_U^* > 0$. Thus, $\Pi_A < \Pi_B$. Then however, $p_A^* = H(\frac{1}{2}\Pi_A + f) < H(\frac{1}{2}\Pi_B + f) = p_B^*$, which is a contradiction.

(c) Let $f \geq \overline{k}$. It follows directly that $p_U^* = H(f) = H(\overline{k}) = 1$ and $p_A^* = H(\frac{1}{2}\Pi_A + f) = H(\overline{k}) = 1$ and $p_B^* = H(\frac{1}{2}\Pi_B + f) = H(\overline{k}) = 1$.

$\square$

Proof of Proposition 1.7.

Let $\alpha = \frac{1}{2}$ and $\lambda \geq \frac{1}{2}$. I want to show that, if $\frac{1-\lambda}{\lambda} \geq 1 - \frac{1}{\lceil \frac{n}{2} \rceil}$, the symmetric pure-strategy Bayesian Nash equilibrium is unique.

Let $\phi_A^* \equiv \phi_A(\mathbf{p}^*, q^*) = \frac{1}{2}q^* p_A^* + \lambda(1 - q^*)p_U^*$ and $\phi_B^* \equiv \phi_B(\mathbf{p}^*, q^*) = \frac{1}{2}q^* p_B^* + (1-\lambda)(1 - q^*)p_U^*$. From Taylor and Yildirim (2010) we have that there exists at most one equilibrium that satisfies $1 \geq \frac{\phi_B^*}{\phi_A^*} \geq 1 - \frac{1}{\lceil \frac{n}{2} \rceil}$.

Now, I want to show that $\frac{\phi_B^*}{\phi_A^*} \geq \frac{1-\lambda}{\lambda}$. Suppose for a contradiction that $\frac{\phi_B^*}{\phi_A^*} < \frac{1-\lambda}{\lambda}$. Plugging in $\phi_A^* = \phi_A(\mathbf{p}^*, q^*)$ and $\phi_B^* = \phi_B(\mathbf{p}^*, q^*)$ as above, this is

$$\frac{\frac{1}{2}q^* p_B^* + (1 - q^*)(1 - \lambda)p_U^*}{\frac{1}{2}q^* p_A^* + (1 - q^*)\lambda p_U^*} < \frac{1 - \lambda}{\lambda}$$

which, rearranging, is equivalent to

$$\frac{p_B^*}{p_A^*} < \frac{1 - \lambda}{\lambda}.$$

This however is a contradiction, because we have $p_B^* \geq p_A^*$ in equilibrium such that $\frac{p_B^*}{p_A^*} \geq 1$ while $\frac{1-\lambda}{\lambda} < 1$ because $\lambda > \frac{1}{2}$.

Therefore we must have that $\frac{\phi_B^*}{\phi_A^*} \geq \frac{1-\lambda}{\lambda}$ always in equilibrium. Then, if $\frac{1-\lambda}{\lambda} \geq 1 - \frac{1}{\lceil \frac{n}{2} \rceil}$, we have $\frac{\phi_B^*}{\phi_A^*} \geq 1 - \frac{1}{\lceil \frac{n}{2} \rceil}$ in any equilibrium, and because at most one equilibrium with this property can exist, we can conclude that the equilibrium is unique.

□

Proof of Proposition 1.8.

Let $\alpha = \frac{1}{2}$ and $\lambda \geq \frac{1}{2}$. Suppose $0 \leq f < \underline{k}$. I need to show that the probability of acquiring information weakly increases in the abstention fine f, and that it increases strictly if $0 < q^* < 1$ and $p_I^* < 1$.

To do so, consider the total differential $\frac{\mathrm{d}q^*}{\mathrm{d}f}$, which is given by (where I most of the time suppress the arguments $(\mathbf{p}^*, q^*)$ for ease of notation)

$$\begin{aligned}\frac{\mathrm{d}q^*}{\mathrm{d}f} &= \frac{\mathrm{d}}{\mathrm{d}f} G(\Phi(\mathbf{p}^*, q^*)) \\ &= g(\Phi(\mathbf{p}^*, q^*)) \left[\frac{\partial \Phi}{\partial p_A^*} \frac{\mathrm{d}p_A^*}{\mathrm{d}f} + \frac{\partial \Phi}{\partial p_B^*} \frac{\mathrm{d}p_B^*}{\mathrm{d}f} + \frac{\partial \Phi}{\partial p_U^*} \frac{\mathrm{d}p_U^*}{\mathrm{d}f} \right].\end{aligned}$$

The total differential $\frac{\mathrm{d}p_A^*}{\mathrm{d}f}$ is given by

$$\begin{aligned}\frac{\mathrm{d}p_A^*}{\mathrm{d}f} &= \frac{\mathrm{d}}{\mathrm{d}f} H(\varphi(\mathbf{p}^*, q^*)) \\ &= h(\varphi(\mathbf{p}^*, q^*)) \left[\frac{1}{2} \frac{\partial \Pi_A}{\partial \phi_A} \left(\frac{\partial \phi_A}{\partial p_A^*} \frac{\mathrm{d}p_A^*}{\mathrm{d}f} + \frac{\partial \phi_A}{\partial p_U^*} \frac{\mathrm{d}p_U^*}{\mathrm{d}f} + \frac{\partial \phi_A}{\partial q^*} \frac{\mathrm{d}q^*}{\mathrm{d}f} \right) \right. \\ &\quad \left. + \frac{1}{2} \frac{\partial \Pi_A}{\partial \phi_B} \left(\frac{\partial \phi_B}{\partial p_B^*} \frac{\mathrm{d}p_B^*}{\mathrm{d}f} + \frac{\partial \phi_B}{\partial p_U^*} \frac{\mathrm{d}p_U^*}{\mathrm{d}f} + \frac{\partial \phi_B}{\partial q^*} \frac{\mathrm{d}q^*}{\mathrm{d}f} \right) + 1 \right]\end{aligned}$$

and the total differential $\frac{\mathrm{d}p_B^*}{\mathrm{d}f}$ is given by

$$\begin{aligned}\frac{\mathrm{d}p_B^*}{\mathrm{d}f} &= \frac{\mathrm{d}}{\mathrm{d}f} H(\varphi(\mathbf{p}^*, q^*)) \\ &= h(\varphi(\mathbf{p}^*, q^*)) \left[\frac{1}{2} \frac{\partial \Pi_B}{\partial \phi_A} \left(\frac{\partial \phi_A}{\partial p_A^*} \frac{\mathrm{d}p_A^*}{\mathrm{d}f} + \frac{\partial \phi_A}{\partial p_U^*} \frac{\mathrm{d}p_U^*}{\mathrm{d}f} + \frac{\partial \phi_A}{\partial q^*} \frac{\mathrm{d}q^*}{\mathrm{d}f} \right) \right. \\ &\quad \left. + \frac{1}{2} \frac{\partial \Pi_B}{\partial \phi_B} \left(\frac{\partial \phi_B}{\partial p_B^*} \frac{\mathrm{d}p_B^*}{\mathrm{d}f} + \frac{\partial \phi_B}{\partial p_U^*} \frac{\mathrm{d}p_U^*}{\mathrm{d}f} + \frac{\partial \phi_B}{\partial q^*} \frac{\mathrm{d}q^*}{\mathrm{d}f} \right) + 1 \right].\end{aligned}$$

Note that from proposition 2 as long as $0 \leq f < \underline{k}$ we have $p_U^* = 0$. Thus, $\phi_A = \phi_B$ and $\Pi_A = \Pi_B$, which implies $\frac{\mathrm{d}p_A^*}{\mathrm{d}f} = \frac{\mathrm{d}p_B^*}{\mathrm{d}f}$. To simplify notation, let $p_I^* \equiv p_A^* = p_B^*$ and $\phi \equiv \phi_A = \phi_B = \frac{1}{2} q^* p_I^*$ and $\Pi \equiv \Pi_A = \Pi_B$.

Rearranging yields

$$\frac{\mathrm{d}p_I^*}{\mathrm{d}f} = \frac{h(\varphi(\mathbf{p}^*, q^*))\left[\frac{1}{2}\frac{\partial \Pi}{\partial \phi}\left(\frac{\partial \phi}{\partial p_U}\frac{\mathrm{d}p_U^*}{\mathrm{d}f} + \frac{\partial \phi}{\partial q}\frac{\mathrm{d}q^*}{\mathrm{d}f}\right) + 1\right]}{1 - h(\varphi(\mathbf{p}^*, q^*))\frac{1}{2}\frac{\partial \Pi}{\partial \phi}\frac{\partial \phi}{\partial p_I}}. \tag{1.39}$$

Moreover, $\frac{\partial \Phi}{\partial p_A^*} = \frac{1}{2}p_A^*\frac{1}{h(k_A^*)}$ and $\frac{\partial \Phi}{\partial p_B^*} = \frac{1}{2}p_B^*\frac{1}{h(k_B^*)}$. Thus we can write that $\frac{\partial \Phi}{\partial p_I^*} = \frac{1}{2}p_I^*\frac{1}{h(k_I^*)}$. Plugging in $\frac{\mathrm{d}p_A^*}{\mathrm{d}f} = \frac{\mathrm{d}p_B^*}{\mathrm{d}f} = \frac{\mathrm{d}p_I^*}{\mathrm{d}f}$, $\frac{\mathrm{d}q^*}{\mathrm{d}f}$ becomes

$$\frac{\mathrm{d}q^*}{\mathrm{d}f} = g(\Phi(\mathbf{p}^*, q^*))\left[2\frac{\partial \Phi}{\partial p_I^*}\frac{\mathrm{d}p_I^*}{\mathrm{d}f} + \frac{\partial \Phi}{\partial p_U^*}\frac{\mathrm{d}p_U^*}{\mathrm{d}f}\right]. \tag{1.40}$$

Plugging in $\frac{\mathrm{d}p_I^*}{\mathrm{d}f}$ from above and rearranging yields

$$\frac{\mathrm{d}q^*}{\mathrm{d}f} = \frac{g(\Phi(\mathbf{p}^*, q^*))\left[2\frac{\partial \Phi}{\partial p_I}h(\varphi(\mathbf{p}^*, q^*))\left(\frac{1}{2}\frac{\partial \Pi}{\partial \phi}\frac{\partial \phi}{\partial p_U^*}\frac{\mathrm{d}p_U^*}{\mathrm{d}f} + 1\right) + \frac{\partial \Phi}{\mathrm{d}p_U}\frac{\mathrm{d}p_U^*}{df}\left(1 - h(\varphi(\mathbf{p}^*, q^*))\frac{1}{2}\frac{\partial \Pi}{\partial \phi}\frac{\partial \phi}{\partial p_I^*}\right)\right]}{1 - h(\varphi(\mathbf{p}^*, q^*))\frac{1}{2}\frac{\partial \Pi}{\partial \phi}\left[\frac{\partial \phi}{\partial p_I^*} + g(\Phi(\mathbf{p}^*, q^*))2\frac{\partial \Phi}{\partial p_I^*}\frac{\partial \phi}{\partial q^*}\right]}$$

In order to evaluate $\frac{\mathrm{d}q^*}{\mathrm{d}f}$ at $f = 0$, recall that $p_U^* = H(f)$ and $\underline{k} > 0$ such that $\frac{\mathrm{d}p_U^*}{\mathrm{d}f}\Big|_{0 \leq f < \underline{k}} = h(f)\Big|_{0 \leq f < \underline{k}} = h(0) = 0$. Thus,

$$\frac{\mathrm{d}q^*}{\mathrm{d}f}\Big|_{0 \leq f < \underline{k}} = \frac{g(\Phi(\mathbf{p}^*, q^*))h(\varphi(\mathbf{p}^*, q^*))2\frac{\partial \Phi}{\partial p_I^*}}{1 - h(\varphi(\mathbf{p}^*, q^*))\frac{1}{2}\frac{\partial \Pi}{\partial \phi}\left[\frac{\partial \phi}{\partial p_I} + g(\Phi(\mathbf{p}^*, q^*))2\frac{\partial \Phi}{\partial p_I}\frac{\partial \phi}{\partial q}\right]}\Big|_{0 \leq f < \underline{k}}. \tag{1.41}$$

To sign $\frac{\mathrm{d}q^*}{\mathrm{d}f}\Big|_{0 \leq f < \underline{k}}$, I now need to derive the signs of its individual parts.

Lemma 1. $\frac{\partial \Pi(\boldsymbol{p}^*, q^*)}{\partial \phi} < 0$ *for all* q^*.

Proof. If $\phi_A(\mathbf{p}^*, q^*) = \phi_B(\mathbf{p}^*, q^*) \equiv \phi(\mathbf{p}^*, q^*)$ the probability of being pivotal is given by

$$\begin{aligned}\Pi(\mathbf{p}^*, q^*) = &\sum_{l=0}^{\lfloor \frac{n-1}{2} \rfloor}\binom{n-1}{l, l, n-1-2l}\phi^{2l}(1-2\phi)^{n-1-2l}\\ &+\sum_{l=0}^{\lfloor \frac{n-2}{2} \rfloor}\binom{n-1}{l, l+1, n-2-2l}\phi^{2l+1}(1-2\phi)^{n-2-2l}.\end{aligned} \tag{1.42}$$

The derivative of Π with respect to ϕ is

$$\begin{aligned}
\frac{\partial \Pi(\mathbf{p}^*, q^*)}{\partial \phi} = & \sum_{l=1}^{\lfloor \frac{n-1}{2} \rfloor} \binom{n-1}{l, l, n-1-2l} 2l \ \phi^{2l-1}(1-2\phi)^{n-1-2l} \\
& - 2 \sum_{l=0}^{\lfloor \frac{n-2}{2} \rfloor} \binom{n-1}{l, l, n-1-2l} (n-1-2l)\phi^{2l}(1-2\phi)^{n-2-2l} \\
& + \sum_{l=0}^{\lfloor \frac{n-2}{2} \rfloor} \binom{n-1}{l, l+1, n-1-2l} (2l+1)\phi^{2l}(1-2\phi)^{n-2-2l} \\
& - 2 \sum_{l=0}^{\lfloor \frac{n-3}{2} \rfloor} \binom{n-1}{l, l+1, n-2-2l} (n-2-2l)\phi^{2l+1}(1-2\phi)^{n-3-2l}.
\end{aligned}$$

Rearranging,

$$\begin{aligned}
\frac{\partial \Pi(\mathbf{p}^*, q^*)}{\partial \phi} = & \, 2 \sum_{l=1}^{\lfloor \frac{n-1}{2} \rfloor} \frac{(n-1)!}{(l-1)!l!(n-1-2l)!} \phi^{2l-1}(1-2\phi)^{n-1-2l} \\
& - 2 \sum_{l=0}^{\lfloor \frac{n-2}{2} \rfloor} \frac{(n-1)!}{l!l!(n-2-2l)!} \phi^{2l}(1-2\phi)^{n-2-2l} \\
& + \sum_{l=0}^{\lfloor \frac{n-2}{2} \rfloor} \frac{(n-1)!}{l!(l+1)!(n-2-2l)!} (2l+1)\phi^{2l}(1-2\phi)^{n-2-2l} \\
& - 2 \sum_{l=0}^{\lfloor \frac{n-2}{2} \rfloor} \frac{(n-1)!}{l!(l+1)!(n-3-2l)!} \phi^{2l+1}(1-2\phi)^{n-3-2l}
\end{aligned}$$

where the first and fourth term cancel out. Therefore,

$$\frac{\partial \Pi(\mathbf{p}^*, q)}{\partial \phi} = \sum_{l=0}^{\lfloor \frac{n-2}{2} \rfloor} \frac{(n-1)!}{l!l!(n-2-2l)!} \phi^{2l}(1-2\phi)^{n-2-2l} \left[\frac{2l+1}{l+1} - 2 \right]$$

which is negative because $\frac{2l+1}{l+1} - 2 = -\frac{1}{l+1} < 0$ for all $l \geq 0$. Hence $\frac{\partial \Pi(\mathbf{p}^*, q^*)}{\partial \phi} < 0$.

□

We also have that $\frac{\partial \phi(\mathbf{p}^*, q^*)}{\partial p_I^*} = \frac{1}{2} q^*$ which is strictly positive if $q^* > 0$, and $\frac{\partial \phi(\mathbf{p}^*, q^*)}{\partial q^*} = \frac{1}{2} p_I^*$ which is strictly positive because $p_I^* > 0$.

Moreover, $\frac{\partial \Phi}{\partial p_I^*} = \frac{1}{2} p_I^* \frac{1}{h(k_I^*)}$ is again strictly positive because $p_I^* > 0$ and $h(y) > 0$ for all

$y \in [\underline{k}, \overline{k}]$.

Thus, taking all parts together, I have shown that $\frac{\mathrm{d}q^*}{\mathrm{d}f}\Big|_{0 \leq f < \underline{k}} \geq 0$, i.e. the probability of acquiring information is non-decreasing in the abstention fine f as long as $0 \leq f < \underline{k}$.

If $0 < q^* < 1$ and $p_I^* < 1$, we can be sure that $g(\Phi(\mathbf{p}^*, q^*)) > 0$ and $h(\varphi(\mathbf{p}^*, q^*)) > 0$, such that $\frac{\mathrm{d}q^*}{\mathrm{d}f}\Big|_{0 \leq f < \underline{k}} > 0$ with strict inequality, i.e. the probability of acquiring information is *strictly* increasing in the abstention fine f as long as $0 \leq f < \underline{k}$.

□

Proof of Proposition 1.9.

Let $\alpha = \frac{1}{2}$. To simplify notation, let q^{*V} denote the probability of acquiring information under Voluntary Voting, and let q^{*C} denote the probability of acquiring information under Compulsory Voting with full participation ($f \geq \overline{k}$). Let $\frac{1}{2} \leq \lambda < 1$ and $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$. Then $\underline{c} < \Phi(\mathbf{1}, q(\underline{c}))$ and $\overline{c} > \Phi(\mathbf{1}, q(\overline{c}))$, which implies $q^{*C} \in (0, 1)$.

Recall that

$$\phi_A(\mathbf{1}, q^{*C}) = \frac{1}{2}q^{*C} + \lambda(1 - q^{*C})$$

and

$$\phi_B(\mathbf{1}, q^{*C}) = \frac{1}{2}q^{*C} + (1 - \lambda)(1 - q^{*C}).$$

Before continuing to the proof of the proposition, I want to show that $\Phi(q(c))$ is weakly increasing in c, therefore implying that the equilibrium is not necessarily unique if $\lambda > \frac{1}{2}$.

Lemma 2. *$\Phi(\mathbf{1}, q(\hat{c}))$ is weakly increasing in $\hat{c}$ on $(\underline{c}, \overline{c})$.*

Proof. The derivative of $\Phi(\mathbf{1}, q(\hat{c}))$ with respect to the information cost cutoff $\hat{c}$ is

$$\frac{\partial \Phi(\mathbf{1}, q(\hat{c}))}{\partial \hat{c}} = \frac{1}{4}\left[\left(\frac{\partial \Pi_A}{\partial \phi_A} + \frac{\partial \Pi_B}{\partial \phi_A}\right)\frac{\partial \phi_A}{\partial q}\frac{\partial q}{\partial \hat{c}} + \left(\frac{\partial \Pi_A}{\partial \phi_B} + \frac{\partial \Pi_B}{\partial \phi_B}\right)\frac{\partial \phi_B}{\partial q}\frac{\partial q}{\partial \hat{c}}\right] \tag{1.43}$$

where, for ease of notation, $\Pi_A = \Pi_A(\mathbf{1}, q(\hat{c}))$, $\Pi_B = \Pi_B(\mathbf{1}, q(\hat{c}))$, $\phi_A = \phi_A(\mathbf{1}, q(\hat{c}))$ and $\phi_B = \phi_B(\mathbf{1}, q(\hat{c}))$.

To sign this expression, we need to consider the individual parts. First, $\frac{\partial q}{\partial \hat{c}} = h(\hat{c}) > 0$ for all $c \in (\underline{c}, \overline{c})$. Second, $\frac{\partial \phi_A(\mathbf{1}, q(\hat{c}))}{\partial q} = \frac{1}{2} - \lambda \leq 0$ and $\frac{\partial \phi_B(\mathbf{1}, q(\hat{c}))}{\partial q} = \lambda - \frac{1}{2} \geq 0$. Third, if n is odd, $\Pi_A(\mathbf{1}, q(\hat{c})) = \Pi_B(\mathbf{1}, q(\hat{c})) \equiv \Pi(\mathbf{1}, q(\hat{c}))$. Then, using $\phi_A = 1 - \phi_B$,

$$\frac{\partial \Pi(\mathbf{1}, q(\hat{c}))}{\partial \phi_A} = \binom{n-1}{\frac{n-1}{2}}\frac{n-1}{2}\phi_A^{\frac{n-1}{2}-1}\phi_B^{\frac{n-1}{2}-1}[\phi_B - \phi_A] \tag{1.44}$$

and

$$\frac{\partial \Pi(\mathbf{1}, q(\hat{c}))}{\partial \phi_B} = \binom{n-1}{\frac{n-1}{2}} \frac{n-1}{2} \phi_A^{\frac{n-1}{2}-1} \phi_B^{\frac{n-1}{2}-1} [\phi_A - \phi_B]. \tag{1.45}$$

Thus, $\frac{\partial \Pi(\mathbf{1}, q(\hat{c}))}{\partial \phi_A} \leq 0$ and $\frac{\partial \Pi(\mathbf{1}, q(\hat{c}))}{\partial \phi_B} \geq 0$ by $\phi_A \geq \phi_B$. If n is even,

$$\frac{\partial \Pi_A(\mathbf{1}, q(\hat{c}))}{\partial \phi_A} + \frac{\partial \Pi_B(\mathbf{1}, q(\hat{c}))}{\partial \phi_A} = \binom{n-1}{\frac{n}{2}-1} \left(\frac{n}{2}-1\right) \phi_A^{\frac{n}{2}-2} \phi_B^{\frac{n}{2}-2} \left[\phi_B^2 - \phi_A^2\right] \tag{1.46}$$

which is weakly negative by $\phi_A \geq \phi_B$, and

$$\frac{\partial \Pi_A(\mathbf{1}, q(\hat{c}))}{\partial \phi_B} + \frac{\partial \Pi_B(\mathbf{1}, q(\hat{c}))}{\partial \phi_B} = \binom{n-1}{\frac{n}{2}-1} \left(\frac{n}{2}-1\right) \phi_A^{\frac{n}{2}-2} \phi_B^{\frac{n}{2}-2} \left[\phi_A^2 - \phi_B^2\right] \tag{1.47}$$

which is weakly positive by $\phi_A \geq \phi_B$. Therefore, putting all parts together, $\frac{\partial \Phi(\mathbf{1}, q(\hat{c}))}{\partial \hat{c}} \geq 0$.

□

If $\lambda = \frac{1}{2}$, we have $\phi_A = \phi_B$ and therefore $\frac{\partial \Phi(\mathbf{1}, q(\hat{c}))}{\partial \hat{c}} = 0$. In that case, the function $\Phi(\mathbf{1}, q(\hat{c}))$ crosses the 45° line exactly once on the interval $(\underline{c}, \overline{c})$, implying that the equilibrium is unique.

If $\lambda > \frac{1}{2}$, we have $\phi_A > \phi_B$ for all $q^{*C} < 1$. Therefore $\frac{\partial \Phi(\mathbf{1}, q(\hat{c}))}{\partial \hat{c}} > 0$. In that case, the function $\Phi(\mathbf{1}, q(\hat{c}))$ crosses the 45° line at least once on the interval $(\underline{c}, \overline{c})$, but the equilibrium is not necessarily unique. Because $\frac{1}{2} \leq \lambda < 1$ and $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$, we know that the function $\Phi(\mathbf{1}, q(\hat{c}))$ crosses the 45° line at least once from above, which yields a stable equilibrium. If the function $\Phi(\mathbf{1}, q(\hat{c}))$ additionally crosses the 45° line at least once from below, this equilibrium is unstable. Then however, there exists another stable equilibrium, because the function $\Phi(\mathbf{1}, q(\hat{c}))$ must cross the 45° line again from above.

Now, consider $k_i \in [\underline{k}, \overline{k}]$ where $\overline{k} = \underline{k} + \kappa$. I need to show that there exists a unique $\underline{k}' \in (0, \frac{1}{2} - \underline{c})$ and $\kappa \in (0, \frac{1}{2}\Pi(\mathbf{1}, 1) - \underline{c})$ such that for all $\underline{k} < \underline{k}'$, we have $q^{*V} > q^{*C}$ while for all $\underline{k} > \underline{k}'$, we have $q^{*V} < q^{*C}$. Note that q^{*C} is not affected by the voting costs, because $p_U^* = p_A^* = p_B^* = 1$ in any case. Thus, we can focus on how the voting costs affect q^{*V}.

First, let $\underline{k} = \frac{1}{2} - \underline{c}$. Then, under Voluntary Voting,

$$\begin{aligned}
\Phi(p_I^{*V}, q^{*V}) &= \left(\frac{1}{2}\Pi(p_I^{*V}, q^{*V}) - k_I^{*V}\right) p_I^* + \int_{\underline{k}}^{k_I^{*V}} H(y)dy \\
&< \frac{1}{2}\Pi(p_I^{*V}, q^{*V}) - \underline{k} \\
&\leq \frac{1}{2} - \underline{k} \\
&= \underline{c}
\end{aligned}$$

where the second line follows from $p_I^{*V} \geq 0$ and $\int_{\underline{k}}^{k_I^{*V}} H(y)dy < k_I^{*V} - \underline{k}$, and the third line follows from $\Pi(p_I^{*V}, q^{*V}) \leq 1$. Hence $q^{*V} = G(\Phi(p_I^{*V}, q^{*V}) = G(\underline{c}) = 0 < q^{*C}$.

Second, let $\underline{k} = 0$ and $\overline{k} = \kappa < \frac{1}{2}\Pi(\mathbf{1}, 1) - \underline{c}$. Recall that, if $p_I^{*V} = 1$ under Voluntary Voting, the probability of being pivotal is $\Pi(1, 1)$ as well, as defined by equation 1.32. Note that because $p_U^{*V} = 0$, ϕ is increasing in q^{*V}. Thus, because $\frac{\partial \Pi}{\partial \phi} < 0$, $\frac{1}{2}\Pi(1, 1) < \frac{1}{2}\Pi(1, q^{*V})$ for all $q^{*V} < 1$. Moreover, for these minimal voting costs we must have $p_I^{*V} = 1$ under Voluntary Voting because $\overline{k} < \frac{1}{2}\Pi(\mathbf{1}, 1)$. Then,

$$\begin{aligned}
\Phi(1, q^{*V}) &= \frac{1}{2}\Pi(1, q^{*V}) - \overline{k} + \int_{\underline{k}}^{\overline{k}} H(y)dy \\
&> \frac{1}{2}\Pi(1, 1) - \overline{k} \\
&> \underline{c}
\end{aligned}$$

where the second line uses $\int_{\underline{k}}^{\overline{k}} H(y)dy > 0$. Hence $q^{*V} = G(\Phi(1, q^{*V})) > G(\underline{c}) = 0$. From the assumption $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$ follows that $q^{*V} < 1$.

I want to show that, for these minimal voting costs, $q^{*V} > q^{*C}$. Suppose for a contradiction that $q^{*V} < q^{*C}$. Then $\phi_A(1, q^{*V}) = \frac{1}{2}q^{*V} < q^{*C} + \lambda(1 - q^{*C}) = \phi_A(\mathbf{1}, q^{*C})$ and $\phi_B(1, q^{*V}) = \frac{1}{2}q^{*V} < q^{*C} + (1 - \lambda)(1 - q^{*C}) = \phi_B(\mathbf{1}, q^{*C})$. But then

$$\begin{aligned}
\Phi(1, q^{*V}) &= \frac{1}{2}\Pi(1, q^{*V}) - \overline{k} + \int_{\underline{k}}^{\overline{k}} H(y)dy \\
&> \frac{1}{2}\Pi(1, q^{*V}) - \overline{k} \\
&> \frac{1}{2}\Pi(1, q^{*C}) - \overline{k} \\
&> \frac{1}{4}(\Pi_A(\mathbf{1}, q^{*C}) + \Pi_B(\mathbf{1}, q^{*C})) - \overline{k} \\
&= \Phi(\mathbf{1}, q^{*C}) - \overline{k}
\end{aligned}$$

where the second line follows from $\int_{\underline{k}}^{\overline{k}} H(y)dy > 0$, the third line follows from $\Pi(1, q)$ being strictly decreasing in q, and the fourth line follows from $\Pi_B(\mathbf{1}, q^{*C}) > \Pi_A(\mathbf{1}, q^{*C})$. Thus, for $\overline{k} = \kappa = 0$, we have $q^{*V} = G(\Phi(1, q^{*V})) > G(\Phi(\mathbf{1}, q^{*C})) = q^{*C}$, which is a contradiction to $q^{*V} < q^{*C}$. By continuity of the expression above, the same holds true for $\kappa > 0$ sufficiently small. Hence we must have that, there exists a $\kappa > 0$ sufficiently small, such that for voting costs $k_i \in [0, \kappa]$, $q^{*V} > q^{*C}$.

To summarize, we so far have that there exists a $\kappa \in (0, \frac{1}{2}\Pi(\mathbf{1}, 1) - \underline{c})$ sufficiently small such that for $k_i \in [0, \kappa]$, $q^{*V} > q^{*C}$, while for $k_i \in [\frac{1}{2} - \underline{c}, \frac{1}{2} - \underline{c} + \kappa]$, $q^{*V} < q^{*C}$. To complete the proof, it remains to be shown that q^{*V} is decreasing as the voting costs increase from $k_i \in [0, \kappa]$ to $k_i \in [\frac{1}{2} - \underline{c}, \frac{1}{2} - \underline{c} + \kappa]$.

Lemma 3. *Under Voluntary Voting, consider an increase in the voting costs by $\delta > 0$, such that $k_i' = k_i + \delta$ for all voters i, and $\underline{k}' = \underline{k} + \delta < \frac{1}{2}$ and $\overline{k}' = \overline{k} + \delta$. Then the probability of acquiring information under Voluntary Voting is weakly decreasing as the voting costs increase.*

Proof. Note that k_i' has the CDF H' with support $[\underline{k} + \delta, \overline{k} + \delta]$ and $H'(y) = H(y - \delta)$.[17] Under the increased voting costs, let $p_I^{*\prime}$ denote the probability that an informed voter votes, with $p_I^{*\prime} = H'(k_I^{*\prime}) = H(\frac{1}{2}\Pi(\mathbf{p}^{*\prime}, q^{*\prime}) - \delta)$, where $p_I^{*\prime} > 0$ by $\underline{k}' < \frac{1}{2}$. Similarly, let $q^{*\prime}$ denote the probability of acquiring information under the increased voting costs.

First, consider the case where $k_I^* < \overline{k}$ under Voluntary Voting (recall that $k_I^* > \underline{k}$ by $\underline{k} < \frac{1}{2}$). I want to show that $k_I^{*\prime} \leq k_I^* + \delta$. Suppose for a contradiction that $k_I^{*\prime} > k_I^* + \delta$. Then $p_I^{*\prime} = H'(k_I^{*\prime}) > H'(k_I^* + \delta) = H(k_I^*) = p_I^*$. Then, by Π strictly decreasing in p_I, $\Pi(p_I^{*\prime}) < \Pi(p_I^*)$. Note that $k_I^* > \underline{k}$ and $k_I^{*\prime} \geq k_I^* + \delta$ imply $k_I^{*\prime} > \underline{k} + \delta$. Then however $k_I^* = \frac{1}{2}\Pi(p_I^*) > \frac{1}{2}\Pi(p_I^{*\prime}) > \frac{1}{2}\Pi(p_I^{*\prime}) - \delta \geq k_I^{*\prime}$, which is a contradiction to $k_I^{*\prime} > k_I^* + \delta$. Therefore, we can conclude that $k_I^{*\prime} \leq k_I^* + \delta$.

Note that $k_I^* < \overline{k}$ and $k_I^{*\prime} \leq k_I^* + \delta$ imply that $k_I^{*\prime} < \overline{k} + \delta$. Moreover, the assumption $\underline{k}' < \frac{1}{2}$ implies $k_I^{*\prime} > \underline{k} + \delta$. Therefore, $k_I^{*\prime} \in (\underline{k} + \delta, \overline{k} + \delta)$. Then, the expected benefit of

[17] Note that the CDF of the increased voting costs, H' first-order stochastically dominates H and, since k_i represents a loss, all individuals strictly prefer H over H'.

acquiring information under the increased voting costs k_i' is

$$
\begin{aligned}
\Phi(k_I^{*\prime}) &= \int_{\underline{k}+\delta}^{k_I^{*\prime}} H'(y)\mathrm{d}y \\
&= \int_{\underline{k}+\delta}^{k_I^{*\prime}} H(y-\delta)\mathrm{d}y \\
&\leq \int_{\underline{k}+\delta}^{k_I^{*}+\delta} H(y-\delta)\mathrm{d}y \\
&= \int_{\underline{k}}^{k_I^{*}} H(y)\mathrm{d}y \\
&= \Phi(k_I^*)
\end{aligned}
$$

where the third line follows from $k_I^{*\prime} \leq k_I^* + \delta$. From G increasing it follows that $G(\Phi(k_I^{*\prime})) \leq G\left(\Phi(k_I^*)\right)$ and hence $q^{*\prime} \leq q^*$.

Second, consider the case where $k_I^* = \overline{k}$ under Voluntary Voting. Then, we need to distinguish two further cases:

(i) $k_I^{*\prime} < \overline{k} + \delta$. Then, the expected benefit of acquiring information under the increased voting costs k_i' is

$$
\begin{aligned}
\Phi(k_I^{*\prime}) &= \int_{\underline{k}+\delta}^{k_I^{*\prime}} H'(y)\mathrm{d}y \\
&= \int_{\underline{k}+\delta}^{k_I^{*\prime}} H(y-\delta)\mathrm{d}y \\
&< \int_{\underline{k}+\delta}^{\overline{k}+\delta} H(y-\delta)\mathrm{d}y \\
&= \int_{\underline{k}}^{\overline{k}} H(y)\mathrm{d}y \\
&\leq \frac{1}{2}\Pi(\mathbf{p}^*, q^*) - \overline{k} + \int_{\underline{k}}^{\overline{k}} H(y)\mathrm{d}y \\
&= \Phi(k_I^*)
\end{aligned}
$$

Again, from G increasing it follows that $G(\Phi(k_I^{*\prime})) \leq G\left(\Phi(k_I^*)\right)$ and hence $q^{*\prime} \leq q^*$.

(ii) $k_I^{*\prime} = \overline{k} + \delta > k_I^*$. Then $p_I^{*\prime} = p_I^* = 1$. Suppose for a contradiction that $q^{*\prime} > q^*$. Then $\phi' = \frac{1}{2}q^{*\prime} > \frac{1}{2}q^* = \phi$, and hence $\Pi(\mathbf{p}^{*\prime}, q^{*\prime}) < \Pi(\mathbf{p}^*, q^*)$. Then however, the expected

benefit of acquiring information under the increased voting costs k_i' is

$$\begin{aligned}\Phi(k_I^{*\prime}) &= \frac{1}{2}\Pi(\mathbf{p}^{*\prime}, q^{*\prime}) - (\overline{k} + \delta) + \int_{\underline{k}+\delta}^{\overline{k}+\delta} H'(y)\mathrm{d}y \\ &< \frac{1}{2}\Pi(\mathbf{p}^{*\prime}, q^{*\prime}) - \overline{k} + \int_{\underline{k}+\delta}^{\overline{k}+\delta} H(y-\delta)\mathrm{d}y \\ &< \frac{1}{2}\Pi(\mathbf{p}^{*}, q^{*}) - \overline{k} + \int_{\underline{k}}^{\overline{k}} H(y)\mathrm{d}y \\ &= \Phi(k_I^*)\end{aligned}$$

where the third line follows from $\Pi(\mathbf{p}^{*\prime}, q^{*\prime}) < \Pi(\mathbf{p}^{*}, q^{*})$. This however implies $G(\Phi(k_I^{*\prime})) \leq G(\Phi(k_I^*))$ which is a contradiction to $q^{*\prime} > q^*$. Therefore, we need to have $q^{*\prime} \leq q^*$ in this case as well.

To summarize, we have in all cases that $\Phi(k_I^{*\prime}) \leq \Phi(k_I^*)$ such that $q^{*\prime} \leq q^*$, i.e. the probability of acquiring information under Voluntary Voting weakly decreases as the voting costs increase from k_i to $k_i' = k_i + \delta$ for all voters i. □

From Lemma 3 it follows that q^{*V} weakly decreases as the voting costs increase from k_i to $k_i' = k_i + \delta$. All in all, I have shown that there exists a $\kappa \in (0, \frac{1}{2}\Pi(\mathbf{1}, 1) - \underline{c})$ sufficiently small such that for $k_i \in [0, \kappa]$, $q^{*V} > q^{*C}$, while for $k_i \in [\frac{1}{2} - \underline{c}, \frac{1}{2} - \underline{c} + \kappa]$, $q^{*V} < q^{*C}$. Moreover, q^{*V} is decreasing as the voting costs increase from $k_i \in [0, \kappa]$ to $k_i \in [\frac{1}{2} - \underline{c}, \frac{1}{2} - \underline{c} + \kappa]$. Therefore, we can conclude that there exists a unique threshold $\tilde{\underline{k}} \in (0, \frac{1}{2} - \underline{c})$, such that $q^{*V} = q^{*C}$ when $k_i \in [\tilde{\underline{k}}, \tilde{\underline{k}} + \kappa]$, and $q^{*V} > q^{*C}$ for all $\underline{k} < \tilde{\underline{k}}$ while $q^{*V} < q^{*C}$ for all $\underline{k} < \tilde{\underline{k}}$.

□

Proof of Proposition 1.10.

Let $\alpha = \frac{1}{2}$ and $\frac{1}{2} < \lambda < 1$. Again, let q^{*C} denote the probability of acquiring information under Compulsory Voting with $f \geq \overline{k}$. Let $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$, which implies $q^{*C} < 1$, and let $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$, which implies $q^{*C} > 0$. The voting probabilities are

$$\phi_A(\mathbf{1}, q^*) = \frac{1}{2}q^* + \lambda(1 - q^*)$$

and

$$\phi_B(\mathbf{1}, q^*) = \frac{1}{2}q^* + (1 - \lambda)(1 - q^*).$$

Now, consider an increase in the bias of uninformed voters, such that $\lambda' > \lambda > \frac{1}{2}$. Let $q^{*C\prime}$ denote the probability of acquiring information under the increased bias λ'. I want to show that, in any stable equilibrium, $q^{*C\prime} < q^{*C}$. To do so, I will show that $\Phi(\mathbf{1}, q(\hat{c}))$ is decreasing in λ for all $\hat{c}$, such that $c^{*\prime} < c^{*}$.

Recall that for any $\hat{c}$, the expected benefit of casting an informed vote under Compulsory Voting with $f \geq \overline{k}$ is

$$\Phi(\mathbf{1}, q(\hat{c})) = \frac{1}{4}\left(\Pi_A(\mathbf{1}, q(\hat{c})) + \Pi_B(\mathbf{1}, q(\hat{c}))\right).$$

Then

$$\frac{\partial \Phi(\mathbf{1}, q(\hat{c}))}{\partial \lambda} = \frac{1}{4}\left[\left(\frac{\partial \Pi_A}{\partial \phi_A} + \frac{\partial \Pi_B}{\partial \phi_A}\right)\frac{\partial \phi_A}{\partial \lambda} + \left(\frac{\partial \Pi_A}{\partial \phi_B} + \frac{\partial \Pi_B}{\partial \phi_B}\right)\frac{\partial \phi_B}{\partial \lambda}\right].$$

From the proof of Lemma 2 (equations 1.44 – 1.47) and because because $\phi_A > \phi_B$, we have $\frac{\partial \Pi_A(\mathbf{1}, q(\hat{c}))}{\partial \phi_A} + \frac{\partial \Pi_B(\mathbf{1}, q(\hat{c}))}{\partial \phi_A} < 0$, and that $\frac{\partial \Pi_A(\mathbf{1}, q(\hat{c}))}{\partial \phi_B k} + \frac{\partial \Pi_B(\mathbf{1}, q(\hat{c}))}{\partial \phi_B} > 0$. Moreover, $\frac{\partial \phi_A}{\partial \lambda} = 1 - q(\hat{c})$ and $\frac{\partial \phi_B}{\partial \lambda} = -(1 - q(\hat{c}))$. Thus, $\Phi(\mathbf{1}, q(\hat{c}))$ is strictly decreasing in λ for all $\hat{c} \in [\underline{c}, \overline{c})$. However, at $\overline{c}$, $\Phi(\mathbf{1}, 1)$ is constant in λ.

Therefore, an increase in λ corresponds to a downwards rotation of $\Phi(\mathbf{1}, q(\hat{c}))$ around $\overline{c}$. This means that for any $\lambda' > \lambda$, we have $\Phi'(\mathbf{1}, q(\hat{c})) < \Phi(\mathbf{1}, q(\hat{c}))$. Hence we can conclude that, in any stable equilibrium, i.e. where the function $\Phi(\mathbf{1}, q(\hat{c}))$ crosses the 45° line from above, the new intersection for $\lambda' > \lambda$ is at $c' < c^{*}$, and hence $q^{*C\prime} < q^{*C}$. If the function does not cross the 45° line anymore because $\Phi'(\mathbf{1}, 0) < \underline{c}$, then $q^{*C\prime} = 0 < q^{*C}$.

□

Proof of Proposition 1.11.

Let $\alpha = \frac{1}{2}$ and $\lambda = 1$. Under Compulsory Voting with $f \geq \overline{k}$, $\phi_A(\mathbf{1}, q^*) = 1 - \frac{1}{2}q^*$ and $\phi_B(\mathbf{1}, q^*) = \frac{1}{2}q^*$. Hence, $\phi_A(\mathbf{1}, 0) = 1$ and $\phi_B(\mathbf{1}, q^*) = 0$. Therefore, $\Pi_A(\mathbf{1}, 0) = \Pi_B(\mathbf{1}, 0) = 0$, which in turn implies $\Phi(\mathbf{1}, 0) = 0$. Therefore, for any $\underline{c} \geq 0$, we have $\Phi(\mathbf{1}, 0) \leq \underline{c}$. Therefore, $q^{*C} = 0$ is an equilibrium.

□

Proof of Proposition 1.12.

Let $\alpha = \frac{1}{2}$. Let $0 \leq f < \underline{k}$. I want to show that expected social welfare weakly decreases in the abstention fine f and decreases strictly if $0 < q^* < 1$ and $p_I^* < 1$. Recall that $0 \leq f < \underline{k}$ implies $p_U^* = 0$. Let $p_I^* \equiv p_A^* = p_B^*$ denote the equilibrium probability of voting for an informed individual. Note that then $\phi \equiv \phi_A = \phi_B = \frac{1}{2}q^* p_I^*$ and therefore $\Pi_A = \Pi_B \equiv \Pi$. Also recall from proposition 1.8 that $\left.\frac{\mathrm{d}q^*}{\mathrm{d}f}\right|_{0 \leq f < \underline{k}} \geq 0$, with strict inequality if $0 < q^* < 1$ and $p_I^* < 1$. Before I proceed to the proof of the proposition, I need to show that the probability of voting is increasing in the abstention fine f as well.

Lemma 4. $\left.\frac{\mathrm{d}p_I^*}{\mathrm{d}f}\right|_{0\leq f<\underline{k}} \geq 0$, *with strict inequality if* $0 < q^* < 1$ *and* $p_I^* < 1$.

Proof. From the proof of proposition 1.8 (equation 1.40), and $\frac{\mathrm{d}p_U^*}{\mathrm{d}f}|_{0\leq f<\underline{k}} = 0$, we have

$$\frac{\mathrm{d}q^*}{\mathrm{d}f} = g(\Phi(\mathbf{p}^*, q^*))2\frac{\partial\Phi}{\partial p_I^*}\frac{\mathrm{d}p_I^*}{\mathrm{d}f}.$$

It is clear that $\frac{\mathrm{d}p_I^*}{\mathrm{d}f} < 0$ leads to a contradiction to $\frac{\mathrm{d}q^*}{\mathrm{d}f} > 0$. Hence, we can conclude that $\left.\frac{\mathrm{d}p_I^*}{\mathrm{d}f}\right|_{0\leq f<\underline{k}} \geq 0$. If $0 < q^* < 1$ and $p_I^* < 1$, we have $\frac{\mathrm{d}q^*}{\mathrm{d}f} > 0$, and hence we must have $\left.\frac{\mathrm{d}p_I^*}{\mathrm{d}f}\right|_{0\leq f<\underline{k}} > 0$ with strict inequality as well.

□

Now, I need to show that expected social welfare is always weakly decreasing in the abstention fine f, and is strictly decreasing if $0 < q^* < 1$ and $p_I^* < 1$. To do so, consider the total differential $\frac{\mathrm{d}W(\mathbf{p}^*,q^*)}{\mathrm{d}f}$, which is given by

$$\begin{aligned}\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f} = n\Bigg[& q^*p_I^*\frac{1}{2}\frac{\partial\Pi}{\partial\phi}\left[\frac{\partial\phi}{\partial q^*}\frac{\mathrm{d}q^*}{\mathrm{d}f} + \frac{\partial\phi}{\partial p_I^*}\frac{\mathrm{d}p_I^*}{\mathrm{d}f}\right] \\ &+ q^*\frac{1}{2}\Pi(\mathbf{p}^*, q^*)\frac{\mathrm{d}p_I^*}{\mathrm{d}f} + p_I^*\frac{1}{2}\Pi(\mathbf{p}^*, q^*)\frac{\mathrm{d}q^*}{\mathrm{d}f} \\ &- \frac{\mathrm{d}q^*}{\mathrm{d}f}\int_{\underline{k}}^{k_I^*} kh(k)\mathrm{d}k - q^*k_I^*h(k_I^*)\frac{\mathrm{d}k_I^*}{\mathrm{d}f} \\ &- c^*g(c^*)\frac{\mathrm{d}c^*}{\mathrm{d}f}\Bigg].\end{aligned}$$

First, consider the case where $0 < q^* < 1$ and $0 < p_I^* < 1$. Then, using that $\frac{\mathrm{d}p_I^*}{\mathrm{d}f} = h(k_I^*)\frac{\mathrm{d}k_I^*}{\mathrm{d}f}$ and $\frac{\mathrm{d}q^*}{\mathrm{d}f} = h(c^*)\frac{\mathrm{d}c^*}{\mathrm{d}f}$, the previous equation can be rewritten as

$$\begin{aligned}\left.\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f}\right|_{\substack{0<q^*<1,\\ 0<p_I^*<1}} &= n\Bigg[q^*p_I^*\frac{1}{2}\frac{\partial\Pi}{\partial\phi}\left[\frac{\partial\phi}{\partial q^*}\frac{\mathrm{d}q^*}{\mathrm{d}f} + \frac{\partial\phi}{\partial p_I^*}\frac{\mathrm{d}p_I^*}{\mathrm{d}f}\right] \\ &\quad + q^*\frac{\mathrm{d}p_I^*}{\mathrm{d}f}\left[\frac{1}{2}\Pi(\mathbf{p}^*, q^*) - k_I^*\right] + p_I^*\frac{\mathrm{d}q^*}{\mathrm{d}f}\left[\frac{1}{2}\Pi(\mathbf{p}^*, q^*) - c^*\right] \\ &\quad - \frac{\mathrm{d}q^*}{\mathrm{d}f}\left[k_I^*p_I^* - \int_{\underline{k}}^{k_I^*} H(k)\mathrm{d}k\right]\Bigg] \\ &= n\left[q^*p_I^*\frac{1}{2}\frac{\partial\Pi}{\partial\phi}\left[\frac{\partial\phi}{\partial q^*}\frac{\mathrm{d}q^*}{\mathrm{d}f} + \frac{\partial\phi}{\partial p_I^*}\frac{\mathrm{d}p_I^*}{\mathrm{d}f}\right] - f\left[q^*\frac{\mathrm{d}p_I^*}{\mathrm{d}f} + p_I^*\frac{\mathrm{d}q^*}{\mathrm{d}f}\right]\right] \qquad (1.48)\end{aligned}$$

where the second equality follows from the fact that $p_I^* < 1$ implies $k_I^* = \frac{1}{2}\Pi(\mathbf{p}^*, q^*) + f$ and $0 < q^* < 1$ implies $c^* = \Phi(\mathbf{p}^*, q^*) = \int_{\underline{k}}^{k_I^*} H(k)\mathrm{d}k$. Then, using that $\frac{\partial \Pi}{\partial \phi} < 0$ and $\frac{\mathrm{d}p_I^*}{\mathrm{d}f} > 0$ and $\frac{\mathrm{d}q^*}{\mathrm{d}f} > 0$ for all $0 < q^* < 1$ and $0 < p_I^* < 1$, we have directly that $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f} < 0$.

To show that otherwise, $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f} \leq 0$, consider three separate cases. Also recall that by $\underline{k} < \frac{1}{2}$, we have $p_I^* > 0$.

(i) $q^* = 0$ and $0 < p_I^* < 1$. Then

$$\left.\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f}\right|_{\substack{q^*=0,\\ 0<p_I^*<1}} = n\left[\frac{\mathrm{d}q^*}{\mathrm{d}f}\left[p_I^*\left(\frac{1}{2}\Pi(\mathbf{p}^*, q^*) - k_I^*\right) - \int_{\underline{k}}^{k_I^*} H(k)\mathrm{d}k\right]\right]$$
$$= n\left[\frac{\mathrm{d}q^*}{\mathrm{d}f}\left[-p_I^* f - \int_{\underline{k}}^{k_I^*} H(k)\mathrm{d}k\right]\right] \tag{1.49}$$

where the second equality follows from the fact that $p_I^* < 1$ implies $k_I^* = \frac{1}{2}\Pi(\mathbf{p}^*, q^*) + f$. Because $\frac{\mathrm{d}q^*}{\mathrm{d}f} \geq 0$, we can conclude that $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f} \leq 0$.

(ii) $q^* = 0$ and $p_I^* = 1$. Then $k_I^* = \overline{k} \leq \frac{1}{2}\Pi(\mathbf{p}^*, q^*) + f$. If this holds with equality, $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f}$ is the same as in equation 1.49. If instead, $\overline{k} < \frac{1}{2}\Pi(\mathbf{p}^*, q^*) + f$ with strict inequality, we have $g(\varphi(\mathbf{p}^*, q^*)) = g(\Pi(\mathbf{p}^*, q^*) + f) = 0$ and hence, from the proof of proposition 1.8 (equation 1.41), $\frac{\mathrm{d}q^*}{\mathrm{d}f} = 0$, such that $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f} = 0$.

(iii) $0 < q^* < 1$ and $p_I^* = 1$. Then $c^* = \Phi(\mathbf{p}^*, q^*) = \int_{\underline{k}}^{k_I^*} H(k)\mathrm{d}k$, but again $k_I^* = \overline{k} \leq \frac{1}{2}\Pi(\mathbf{p}^*, q^*) + f$. If this holds with equality, $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f}$ is the same as in equation 1.48. If instead, $\overline{k} < \frac{1}{2}\Pi(\mathbf{p}^*, q^*) + f$ with strict inequality, we have by the same argument as in (ii) that $\frac{\mathrm{d}q^*}{\mathrm{d}f} = 0$ and, moreover, $\frac{\mathrm{d}p_I^*}{\mathrm{d}f} = 0$, such that $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f} = 0$.

All in all, I have shown that $\frac{\mathrm{d}W(\mathbf{p}^*, q^*)}{\mathrm{d}f} \leq 0$, with strict inequality if $0 < q^* < 1$ and $0 < p_I^* < 1$.

□

Proof of Proposition 1.13.

Let $\alpha = \frac{1}{2}$ and $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$. I want to show that Compulsory Voting with a high abstention fine $f \geq \overline{k}$ strictly reduces expected social welfare compared to Voluntary Voting. Let q^{*V} denote the equilibrium probability of acquiring information under Voluntary Voting, and c^{*V} the corresponding equilibrium information costs threshold. Analogously, let q^{*C} the the equilibrium probability of acquiring information under Compulsory Voting with a high abstention fine $f \geq \overline{k}$, and

c^{*C} the corresponding equilibrium information costs threshold. Recall that if $\frac{1}{2} \leq \lambda < 1$, $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1},0) + \Pi_B(\mathbf{1},0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1},1)$ imply $c^{*C} \in (\underline{c},\overline{c})$. This in turn implies $c^{*C} = \Phi(\mathbf{1},q^{*C}) = \frac{1}{4}\left(\Pi_A(\mathbf{1},q^{*C}) + \Pi_B(\mathbf{1},q^{*C})\right).\frac{1}{2} \leq \lambda < 1$ If $\lambda = 1$, we have from proposition 1.11 that $q^{*C} = 0$ is an equilibrium. Then $q^{*C} \leq q^{*V}$. Moreover, $\overline{c} > \frac{1}{2}\Pi(\mathbf{1},1)$ implies $q^{*C} < 1$ for $\lambda = 1$ as well. Note that because $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1},0) + \Pi_B(\mathbf{1},0)\right) < \frac{1}{2} = \frac{1}{2}\Pi(p_I^{*V},0)$, we also have $c^{*V} > \underline{c}$.

Note that if $q^{*V} = q^{*C} \equiv q^*$, i.e. $c^{*V} = c^{*C} \equiv c^*$, we must have $\Phi(\mathbf{1},q^*) = \Phi(p_I^{*V},q^*)$ and hence $U(\mathbf{1},q^*) - U(\mathbf{p}^{*V},q^*) = -\int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k$ which is clearly negative. Therefore, consider now the remaining two cases.

(i) Suppose $q^{*V} < q^{*C}$. This implies $q^{*V} < 1$, i.e. $c^{*V} \in (\underline{c},\overline{c})$ and hence

$$c^{*V} = \Phi(p_I^{*V},q^{*V}) = \left(\frac{1}{2}\Pi(p_I^{*V},q^{*V}) - k_I^{*V}\right)p_I^{*V} + \int_{\underline{k}}^{k_I^{*V}} H(k)\mathrm{d}k.$$

Then,

$$\begin{aligned}
U(\mathbf{1},q^{*C}) - U(\mathbf{p}^{*V},q^{*V}) &= q^{*C}\Phi(\mathbf{1},q^{*C}) - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k - \int_{c^{*V}}^{c^{*C}} cg(c)\mathrm{d}c - q^{*V}\Phi(p_I^{*V},q^{*V}) \\
&= q^{*C}\Phi(\mathbf{1},q^{*C}) - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k - c^{*C}q^{*C} + c^{*V}q^{*V} + \int_{c^{*V}}^{c^{*C}} G(c)\mathrm{d}c \\
&\quad - q^{*V}\Phi(p_I^{*V},q^{*V}) \\
&< -\overline{k} + \int_{\underline{k}}^{\overline{k}} H(k)\mathrm{d}k + c^{*C} - c^{*V} \\
&= -\overline{k} + \int_{\underline{k}}^{\overline{k}} H(k)\mathrm{d}k + c^{*C} - \left(\frac{1}{2}\Pi(p_I^{*V},q^{*V}) - k_I^{*V}\right)p_I^{*V} - \int_{\underline{k}}^{k_I^{*V}} H(k)\mathrm{d}k \\
&< -\overline{k} + c^{*C} - \frac{1}{2}\Pi(p_I^{*V},q^{*V}) - k_I^{*V} + \int_{k_I^{*V}}^{\overline{k}} H(k)\mathrm{d}k \\
&< c^{*C} - \frac{1}{2}\Pi(p_I^{*V},q^{*V}) \\
&= \frac{1}{4}\left(\Pi_A(\mathbf{1},q^{*C}) + \Pi_B(\mathbf{1},q^{*C})\right) - \frac{1}{2}\Pi(p_I^{*V},q^{*V})
\end{aligned}$$

where I use integration by parts as well as the fact that $G(c) \leq 1$ for all c and $H(k) \leq 1$ for all k. To see that the expression in the last line is strictly negative, first note that $\phi(p_I^{*V},q^{*V}) = \frac{1}{2}q^{*V}p_I^{*V} \leq \frac{1}{2}q^{*V} < \frac{1}{2}q^{*C} + (1-\lambda)(1-q^{*C}) = \phi_B(\mathbf{1},q^{*C}) \leq \phi_A(\mathbf{1},q^{*C})$. Second, recall that (from Taylor and Yildirim, 2010), $\frac{\partial \Pi_B}{\partial \phi_A} < 0$. Third, recall from Lemma 1, that, in the case where $\Pi_A = \Pi_B = \Pi$ we have $\frac{\partial \Pi}{\partial \phi} < 0$ as well. Fourth, recall that $\Pi_A(\mathbf{1}, q^{*C}) \leq \Pi_B(\mathbf{1}, q^{*C})$. Taking all these observations together, we have $\frac{1}{4}\left(\Pi_A(\mathbf{1}, q^{*C}) + \Pi_B(\mathbf{1}, q^{*C})\right) \leq \frac{1}{2}\Pi_B(\mathbf{1}, q^{*C}) < \frac{1}{2}\Pi(p_I^{*V}, q^{*V})$. Therefore, $U(\mathbf{1}, q^{*C}) < U(\mathbf{p}^{*V}, q^{*V})$ if $q^{*V} < q^{*C}$.

(ii) Suppose $q^{*V} > q^{*C}$. Because $0 < q^{*V} \leq 1$ we have

$$c^{*V} \leq \Phi(p_I^{*V}, q^{*V}) = \left(\frac{1}{2}\Pi(p_I^{*V}, q^{*V}) - k_I^{*V}\right) p_I^{*V} + \int_{\underline{k}}^{k_I^{*V}} H(k)\mathrm{d}k,$$

which holds with equality if $c^{*V} \in (\underline{c}, \overline{c})$.

Then,

$$\begin{aligned} U(\mathbf{1}, q^{*C}) - U(\mathbf{p}^{*V}, q^{*V}) &= q^{*C}\Phi(\mathbf{1}, q^{*C}) - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k + \int_{c^{*C}}^{c^{*V}} cg(c)\mathrm{d}c - q^{*V}\Phi(p_I^{*V}, q^{*V}) \\ &= q^{*C}\Phi(\mathbf{1}, q^{*C}) - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k + c^{*V}q^{*V} - c^{*C}q^{*C} - \int_{c^{*C}}^{c^{*V}} G(c)\mathrm{d}c \\ &\quad - q^{*V}\Phi(p_I^{*V}, q^{*V}) \\ &\leq -\int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k - \int_{c^{*C}}^{c^{*V}} G(c)\mathrm{d}c \end{aligned}$$

which is clearly negative. Thus, $U(\mathbf{1}, q^{*C}) < U(\mathbf{p}^{*V}, q^{*V})$ if $q^{*V} > q^{*C}$ as well.

All in all, from $U(\mathbf{1}, q^{*C}) < U(\mathbf{p}^{*V}, q^{*V})$ follows directly that expected social welfare is strictly lower under Compulsory Voting with a high abstention fine $f \geq \overline{k}$ than under Voluntary Voting.

□

Proof of Proposition 1.14.

Let $\alpha = \frac{1}{2}$ and $\frac{1}{2} < \lambda < 1$ and $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$. Consider $f \geq \overline{k}$. I want to show that, for any stable equilibrium, expected social welfare is strictly decreasing in the bias λ of uninformed voters. Recall from proposition 1.9 that $\underline{c} < \frac{1}{4}\left(\Pi_A(\mathbf{1}, 0) + \Pi_B(\mathbf{1}, 0)\right)$ and $\overline{c} > \frac{1}{2}\Pi(\mathbf{1}, 1)$ imply $c^* \in (\underline{c}, \overline{c})$. This in turn implies $c^* = \Phi(\mathbf{1}, q^*)$. Then

$$\begin{aligned} \frac{\mathrm{d}W(\mathbf{1}, q^*)}{\mathrm{d}\lambda} &= n\left(\frac{\mathrm{d}q^*}{\mathrm{d}\lambda}\Phi(\mathbf{1}, q^*) + q^*\frac{\partial\Phi(\mathbf{1}, q^*)}{\partial q^*}\frac{\mathrm{d}q^*}{\mathrm{d}\lambda} - c^*g(c^*)\frac{\mathrm{d}c^*}{\mathrm{d}\lambda}\right) \\ &= n\left(q^*\frac{\partial\Phi(\mathbf{1}, q^*)}{\partial q^*}\frac{\mathrm{d}q^*}{\mathrm{d}\lambda}\right) \end{aligned}$$

where the second equality follows from $c^* = \Phi(\mathbf{1}, q^*)$ and $\frac{\mathrm{d}q^*}{\mathrm{d}\lambda} = \frac{\mathrm{d}G(c^*)}{\mathrm{d}\lambda} = g(c^*)\frac{\mathrm{d}c^*}{\mathrm{d}\lambda}$. From Lemma 2 we have $\frac{\partial\Phi(\mathbf{1},q^*)}{\partial q^*} > 0$ for $\lambda > \frac{1}{2}$. Moreover, recall from proposition 1.10 that q^* is strictly decreasing in λ in any stable equilibrium. Therefore, $\frac{\mathrm{d}W(\mathbf{1},q^*)}{\mathrm{d}\lambda} < 0$.

□

Proof of Remark 3.

Let $\alpha > \frac{1}{2}$. (i) Let $f \leq \overline{k}$. First, I want to show that $p_A^*, p_B^* > 0$. If $f \leq \underline{k}$, first suppose $p_U^* = p_A^* = p_B^* = 0$ for a contradiction. Then $\phi_A = \phi_B = 0$, and $\Pi_A = \Pi_B = 1$. But then $p_A^* = H(\frac{1}{2} + f) > \underline{k} = 0$, which is a contradiction. Next, suppose $p_U^* = p_A^* = 0$, $p_B^* > 0$ for a contradiction. Then $0 = \phi_A < \phi_B$ and $\Pi_A > \Pi_B$. But then $p_A^* = H(\frac{1}{2}\Pi_A + f) > H(\frac{1}{2}\Pi_B + f) = p_B^*$, which is a contradiction. Finally, suppose $p_U^* \leq p_A^*$ and $p_A^* > 0$, while $p_B^* = 0$ for a contradiction. Then $0 = \phi_B < \phi_A$ and $\Pi_B > \Pi_A$. But then $p_A^* = H(\frac{1}{2}\Pi_A + f) < H(\frac{1}{2}\Pi_B + f) = p_B^*$, which is a contradiction. Therefore, we must have $p_A^*, p_B^* > 0$ if $f \leq \underline{q}$. If $f > \underline{k}$, then $p_U^*, p_A^*, p_B^* > 0$ directly from the equilibrium definition of p_A^* and p_B^* and $\underline{k} < \frac{1}{2}$.

Second, I want to show that $p_U^* \leq p_A^*$, with strict inequality if $p_A^* < 1$. This follows directly from the equilibrium definition of p_U^* and p_A^*: $p_U^* = H((\alpha - \frac{1}{2})\Pi_A = f) \leq H(\frac{1}{2}\Pi_A + f) = p_A^*$, and by $\alpha > \frac{1}{2}$, this holds with strict inequality if $p_A^* < 1$.

Third, I want to show that $p_A^* \leq p_B^*$, with strict inequality if $f > \underline{k}$ and $p_A^* < 1$. To do so, we need to consider two cases. First, consider $q^* > 0$. Suppose for a contradiction that $p_A^* > p_B^* \geq 0$. Then $\phi_A > \phi_B$ and $\Pi_A < \Pi_B$. But then $p_A^* = H(\frac{1}{2}\Pi_A + f) \leq H(\frac{1}{2}\Pi_B + f) = p_B^*$, which is a contradiction. Next, consider $q^* = 0$. By $f > \underline{k}$, we have $p_U^* > 0$.Then $\phi_A = p_U^* > 0 = \phi_B$ and $\Pi_A < \Pi_B$. This directly implies that $p_A^* = H(\frac{1}{2}\Pi_A + f) \leq H(\frac{1}{2}\Pi_B + f) = p_B^*$.

If $f > \underline{k}$ and $p_A^* < 1$, then $0 < p_U^* < p_A^* < p_B^*$ directly from the equilibrium definition of the voting probabilities and $\underline{k} < \frac{1}{2}$ and $(\alpha - \frac{1}{2}) < \frac{1}{2}$.

(ii) Let $f \geq \overline{k}$. It follows directly that $p_U^* = p_A^* = p_B^* = H(\overline{k}) = 1$.

□

Proof of Proposition 1.15.

Let $\alpha > \frac{1}{2}$. Recall from Remark 3 that under Compulsory Voting with $f \geq \overline{k}$ we have $p_A^* = p_B^* = p_U^* = 1$, such that $\phi_A(\mathbf{1}, q^*) = \alpha q^* + 1 - q^*$ and $\phi_B(\mathbf{1}, q^*) = (1-\alpha)q^*$. Then $\phi_A(\mathbf{1}, 0) = 1$ and $\phi_B(\mathbf{1}, 0) = 0$. Thus, $\Pi_A(\mathbf{1}, 0) = \Pi_B(\mathbf{1}, 0) = 0$, which in turn implies $\Phi(\mathbf{1}, 0) = 0 \leq \underline{c}$. Therefore, $q^* = 0$ is an equilibrium.

Note that we can apply lemma 2, because $\frac{\partial\phi_A}{\partial q^*} = \alpha - 1 < 0$ and $\frac{\partial\phi_B}{\partial q^*} = 1 - \alpha > 0$. Therefore, $\Phi(\mathbf{1}, q(c))$ is strictly increasing in c on the interval $(\underline{c}, \overline{c})$. It follows that the equilibrium is not necessarily unique.

□

Proof of Proposition 1.16.

Let $\alpha > \frac{1}{2}$ and $\underline{k} > \alpha - \frac{1}{2}$. I want to show that if Compulsory Voting with a high abstention fine $f \geq \overline{k}$ leads to $q^{*C} = 0$, it strictly reduces expected social welfare compared to Voluntary Voting. Let q^{*V} denote the equilibrium probability of acquiring information under Voluntary Voting, and c^{*V} the corresponding equilibrium information costs threshold. Note that under Voluntary Voting, $p_U^{*V} = H\left(\left(\alpha - \frac{1}{2}\right)\Pi_A\right) \leq H(\underline{k}) = 0$ because $\underline{k} > \alpha - \frac{1}{2}$. Also recall that because $\underline{k} < \frac{1}{2}$, we have $p_A^{*V}, p_B^{*V} > 0$. Now, we need to distinguish two cases: $q^{*V} > 0$ and $q^{*V} = 0$.

(i) Suppose $q^{*V} > 0$. Then $c^{*V} > \underline{c}$, which implies $c^{*V} \leq \Phi(\mathbf{p}^{*V}, q^{*V})$ where

$$\Phi(\mathbf{p}^{*V}, q^{*V}) = \alpha\left[\left(\frac{1}{2}\Pi_A(\mathbf{p}^{*V}, q^{*V}) - k_A^*\right)p_A^* + \int_{\underline{k}}^{k_A^*} H(y)dy\right] + (1-\alpha)\left[\left(\frac{1}{2}\Pi_B(\mathbf{p}^{*V}, q^{*V}) - k_B^*\right)p_B^* + \int_{\underline{k}}^{k_B^*} H(y)dy\right]$$

Using this,

$$\begin{aligned}
U(\mathbf{1}, 0) - U(\mathbf{p}^{*V}, q^{*V}) &= \alpha - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k - [\alpha Pr(A \text{ wins}|f=0) + (1-\alpha)Pr(B \text{ wins}|f=0)] \\
&\quad - q^{*V}\Phi(\mathbf{p}^{*V}, q^{*V}) + \int_{\underline{c}}^{c^{*V}} cg(c)\mathrm{d}c \\
&= \alpha - \int_{\underline{k}}^{\overline{k}} kh(k)\mathrm{d}k - [\alpha Pr(A \text{ wins}|f=0) + (1-\alpha)Pr(B \text{ wins}|f=0)] \\
&\quad - q^{*V}\Phi(\mathbf{p}^{*V}, q^{*V}) + c^{*V}q^{*V} - \int_{\underline{c}}^{c^{*V}} G(c)\mathrm{d}c \\
&< \alpha - \overline{k} + \int_{\underline{k}}^{\overline{k}} H(k)\mathrm{d}k - [\alpha Pr(A \text{ wins}|f=0) + (1-\alpha)Pr(B \text{ wins}|f=0)] \\
&< \alpha - \underline{k} - [\alpha Pr(A \text{ wins}|f=0) + (1-\alpha)Pr(B \text{ wins}|f=0)]
\end{aligned}$$

where I use integration by parts and the fact that $H(k) \leq 1$ for all k. To sign the expression in the last line, note that $Pr(A \text{ wins}|f = 0) \geq \frac{1}{2}$. Because $Pr(B \text{ wins}|f = 0) = 1 - Pr(A \text{ wins}|f = 0)$ and $\alpha > \frac{1}{2}$, $\alpha Pr(A \text{ wins}|f = 0) + (1-\alpha)Pr(B \text{ wins}|f = 0) = \alpha\left(2Pr(A \text{ wins}|f = 0) - 1\right) + 1 - Pr(A \text{ wins}|f = 0) > \frac{1}{2}$. Therefore, and because $\underline{k} > \alpha - \frac{1}{2}$, we have $U(\mathbf{1}, 0) < U(\mathbf{p}^{*V}, q^{*V})$ if $q^{*V} > 0$.

(ii) Suppose $q^{*V} = 0$. Then

$$\begin{aligned}
U(\mathbf{1}, 0) - U(\mathbf{p}^{*V}, q^{*V}) &= \alpha - \int_{\underline{k}}^{\overline{k}} k h(k) \mathrm{d}k - [\alpha Pr(A \text{ wins}|f=0) + (1-\alpha) Pr(B \text{ wins}|f=0)] \\
&= \alpha - \overline{k} + \int_{\underline{k}}^{\overline{k}} H(k) \mathrm{d}k - [\alpha Pr(A \text{ wins}|f=0) + (1-\alpha) Pr(B \text{ wins}|f=0)] \\
&< \alpha - \underline{k} - [\alpha Pr(A \text{ wins}|f=0) + (1-\alpha) Pr(B \text{ wins}|f=0)]
\end{aligned}$$

which is strictly negative by the same argument as above. Therefore we have $U(\mathbf{1}, 0) < U(\mathbf{p}^{*V}, q^{*V})$ if $q^{*V} = 0$ as well.

All in all, from $U(\mathbf{1}, q^{*C}) < U(\mathbf{p}^{*V}, q^{*V})$ follows directly that expected social welfare is strictly lower under Compulsory Voting with $q^{*C} = 0$ than under Voluntary Voting.

$\square$

Chapter 2

Selective Exposure Reduces Voluntary Contributions

Experimental Evidence from the German Internet Panel

With Federico Innocenti.

2.1 Introduction

With an abundance of information available, individuals have to select which sources of information are worthy of attention. Because misleading or false information spreads easily on the Internet and especially on social media (Lazer et al., 2018), individuals do not necessarily process correct information. Instead, they might expose themselves to information that confirms their own beliefs or aligns with their preferences. Although the existence of selective exposure is well established in the empirical literature (Del Vicario et al., 2016), little is known about how selective exposure impacts decision-making.

The collective consequences of selective exposure depend on how the acquired information affects an individual's actions: If the information affects only an individual's private actions and outcomes, her selective exposure can only affect her own well-being. If the individual however engages in *collective* action, the information can affect the collective outcome of all individuals involved and social welfare. An important area of collective action where information plays a critical role is the provision of public goods. The exact returns of investing in a public good are often uncertain, which can lead to the under-provision of the public good (Levati et al., 2009). At first sight, providing more information about the returns of a public good could reduce uncertainty and mitigate the problem of under-provision. If however different information sources have opposite claims about the returns of the public good, individuals can strategically select the source which supports their selfish interests, and use the information to justify lower contributions. In this case, information provision can backfire and, contrary to expectations, further reduce investments in 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. On the other side, environmental activism - for instance by Fridays for Future - has a positive impact (Baiardi and Morana, 2020). Second, social distancing, testing, 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 address the question how strategic information acquisition affects the level and efficiency of voluntary contributions to public goods, and thus social welfare. 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 homogenous but 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 the marginal returns 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 decisions based on their prior beliefs. In the *info* treatment, participants have the opportunity to acquire one unit of costless information about the marginal returns of the public good from two unreliable sources with opposing biases: The high-biased source is more likely to report high marginal returns but sometimes reveals low marginal returns, while the low-biased source is more likely to report low marginal returns but sometimes reveals high marginal returns. 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. In this case, an individual is indifferent towards information as long as it is costless. Instead, if social preferences play a role, information might matter. On the one hand, the direction of optimal information acquisition might depend on prior beliefs (Che and Mierendorff, 2019). On the other hand, participants might strategically avoid information that compels them to be more generous (Dana et al., 2007), and strategically seek information that justifies less generous behaviour (Spiekermann and Weiss, 2016).

We conduct our experiment on the German Internet Panel (GIP). The GIP 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 mainly political topics. Embedding our experiment in the GIP allows us to complement the results from our experiment with available GIP data – in particular with the participants' willingness to contribute to environmental protection and to 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, the majority (65%) selects the low-biased source. We find no statistically significant differences in the information acquisition decisions between different prior beliefs. Selective exposure to the low-biased 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, and the share of participants who free-ride increases. In terms of efficiency, the treatment effect is positive when the public good has low marginal returns, i.e. when it is indeed socially efficient to contribute zero. In that case, social welfare increases by up to 12.4%. However, when the public good has high marginal returns, i.e. when it is socially efficient to contribute, the effect of the *info* treatment on efficiency is negative. In that case, social welfare decreases by up to 5.3%.

Furthermore, we find that social preferences affect information acquisition. First, participants who care about efficiency are more likely to acquire information than participants with other motives. Second, among participants who acquire information, selfish participants are more likely to acquire information from the high-biased source than those with efficiency concerns.[1]

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 from the high-biased

[1]We could interpret this behaviour in the sense of a confirmation bias. An individual seeks information confirming that her preferred contribution level is socially desirable. Thus, a selfish individual seeks information revealing that the marginal returns are low with certainty, whereas a socially-oriented individual seeks information revealing that the marginal returns are high with certainty.

source display a lower willingness to contribute to environmental protection than those who acquire information from the low-biased source.

Finally, we rationalize the results from our experiment in a theoretical model which allows for social preferences and self-image concerns. We find that selfish individuals have an incentive to choose the high-biased source because it might reveal with certainty that the marginal returns of the public good are low, and thus allows them to reduce their contributions without suffering a loss in terms of their self-image.

2.2 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 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 subjective beliefs to interpret these normative obligations, they can strategically acquire information to manipulate their beliefs to reduce the subjective 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* informed 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.

2.3 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

$$\pi_i = e - g_i + \omega \sum_{j=1}^{4} g_j \tag{2.1}$$

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, which send one of the two possible signals *high* or *low*. For this information revelation process, we follow Che and Mierendorff (2019). The high-biased source, is biased towards sending the signal that the MPCR is high: If the true MCPR is ω_h, the high-biased source always sends the signal $S_H = high$. If however the true MPCR is ω_l, the high-biased source sends the signal $S_H = low$ only with probability λ. With probability $1-\lambda$, it also sends the signal $S_H = high$. Analogously, the low-biased source is biased towards sending the signal that the MPCR is low: If the true MCPR is ω_l, the low-biased source always sends the signal $S_L = low$. If however the true MPCR is ω_h, the low-biased source sends the signal $S_L = high$ only with probability λ. With probability $1-\lambda$, it also sends the signal $S_L = low$. 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 information from the high-biased source and receives the signal $S_H = low$ (i.e. breakthrough news), she updates her belief to $\mu'_H = Pr(\omega = \omega_h | S_H = low) = 0$. If she receives the signal $S_H = high$, she updates her belief to

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

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 information from the low-biased source and receives the signal $S_L = high$ (i.e. breakthrough news), she updates her belief to $\mu'_L = Pr(\omega =$

$\omega_h | S_L = high) = 1$. If she receives the signal $S_L = low$, she updates her belief to

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

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.

2.3.1 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.[2] 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 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 attitudes towards environmental protection from several other waves of the GIP.[3] 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.[4] The MCS data are publicly available in the GIP data archive at the GESIS-Leibniz Institute for the Social Sciences as well.

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

[3] 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 2.D.

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

2.3.2 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.[5] Moreover, we adapted the instructions to be understandable for members of the general population, 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.[6] 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.[7] 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 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 S_L, or if the MPCR allocated to the participant is low and she acquires the signal S_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

[5]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.

[6]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.

[7]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.

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 euros.

Our questionnaire contained the following parts.[8] 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 high-biased source, and two envelopes were silver, corresponding to the low-biased source. We carefully explained the interpretation of the envelopes. In particular, we told participants that it was possible to infer the true type of the group project only from one of the four envelopes. 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.[9] At the contribution stage, those in the *info* treatment received the information about the content of the envelope and the correct Bayesian posterior.[10] 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 options, we follow the literature which finds that most participants in public good games

[8] 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 2.E.

[9] 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.

[10] 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.

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.

2.4 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.

2.4.1 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 S_L from the low-biased source.[11].

[11] Among the participants who acquired signal S_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 S_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 S_H is 3.83 euros, which however is not significantly different from the average willingness to accept to acquire signal S_L of 3.32 euros (Wilcoxon rank sum test, $p = 0.11$). For both signal S_H and signal S_L, the willingness to pay is significantly different from the willingness to accept (Wilcoxon rank sum test,

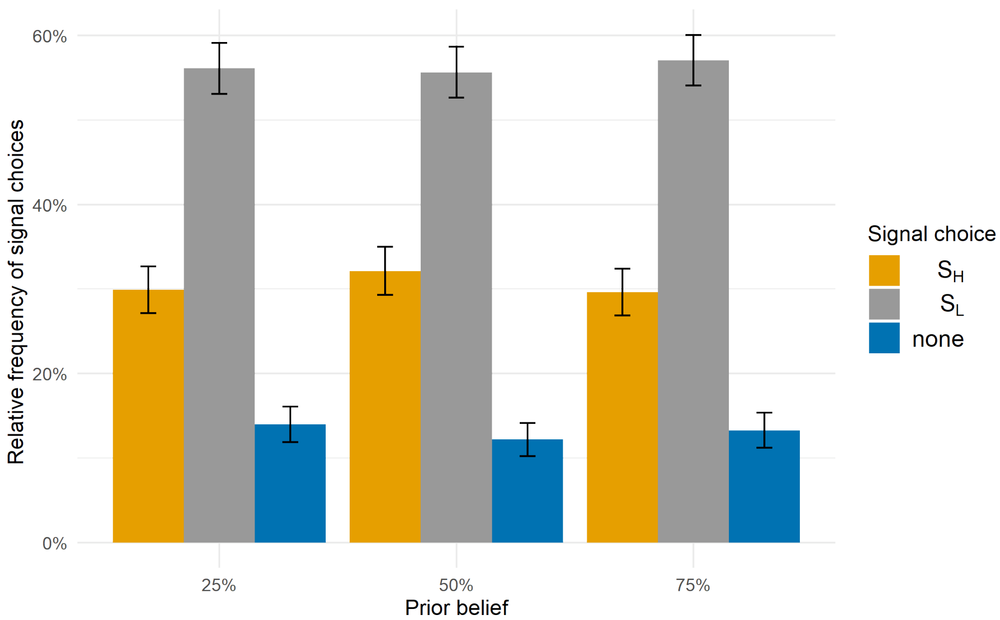


Figure 2.1: Information acquisition choices for the different prior beliefs. Error bars represent 95% confidence intervals.

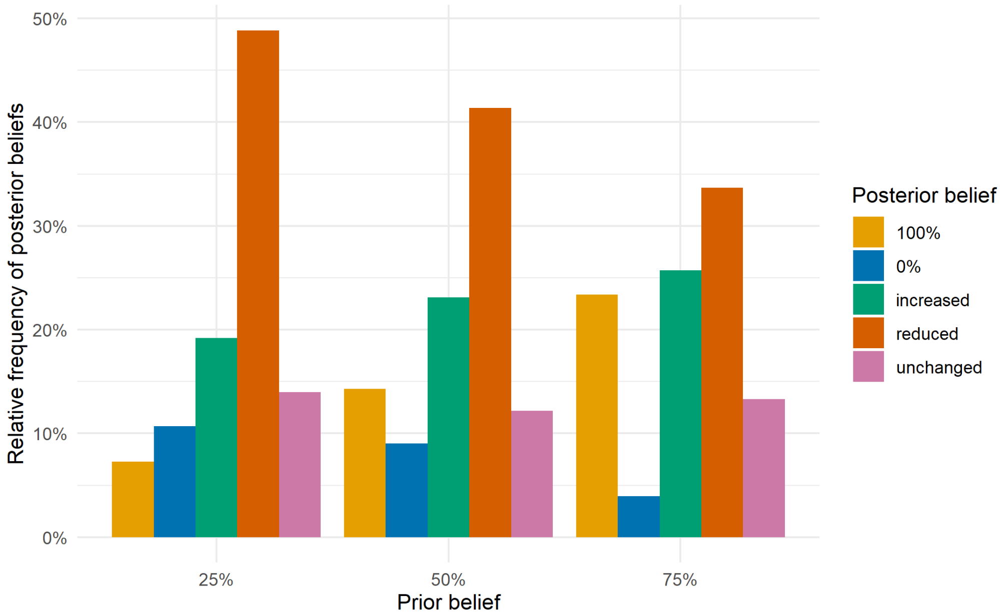


Figure 2.2: Changes in the posterior beliefs in the *info* treatment for each prior belief. An increase in the belief comes from the choice of signal S_H and results in posterior beliefs $\mu'_H \in \{0.4, 0.67, 0.86\}$. A reduction in the belief comes from the choice of signal S_L and results in posterior 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.

$p = 0.0048$ and $p = 0.0021$, respectively). As these questions were not incentivized, they capture only hypothetical willingness to pay. Therefore we will not include them in the further analysis.

A binomial test rejects the Null Hypothesis that participants are equally likely to choose S_H and S_L ($p < 0.0001$).[12] The finding that S_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. Figure 2.1 displays signal choices for the three different prior beliefs. Between prior beliefs, signal choices do not differ significantly.

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 S_L causes the beliefs of most (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 2.2 shows the changes in the posterior beliefs.

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. Figure 2.3 displays average contributions for the three different prior beliefs. The treatment effect is significant for all prior beliefs, but average contributions do not differ significantly between prior beliefs in either treatment.

Figure 2.4 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

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

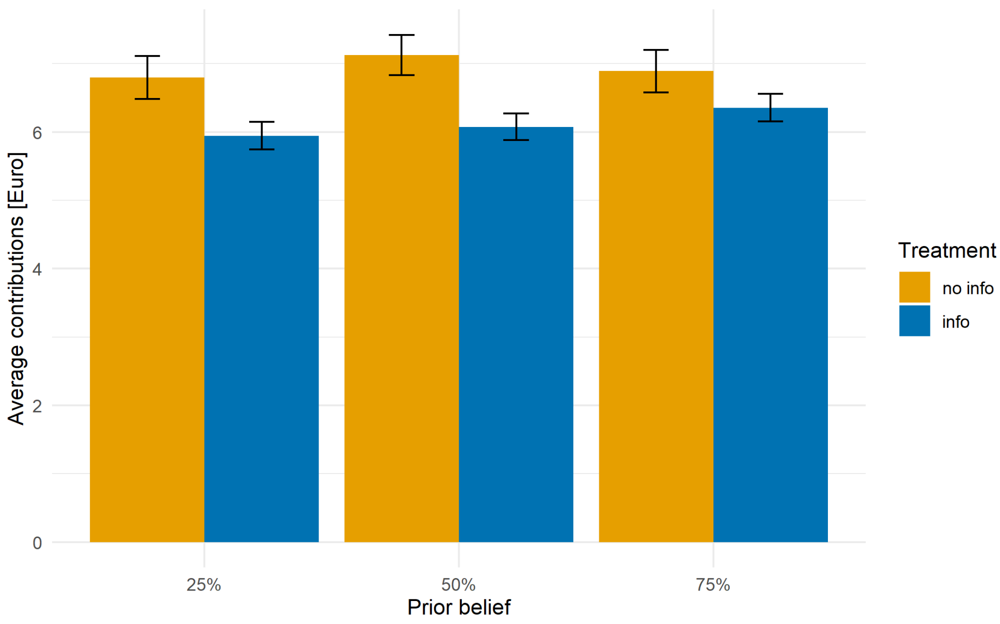


Figure 2.3: Average contributions to the public good in the two treatments, for each prior belief. Error bars represent 95% confidence intervals.

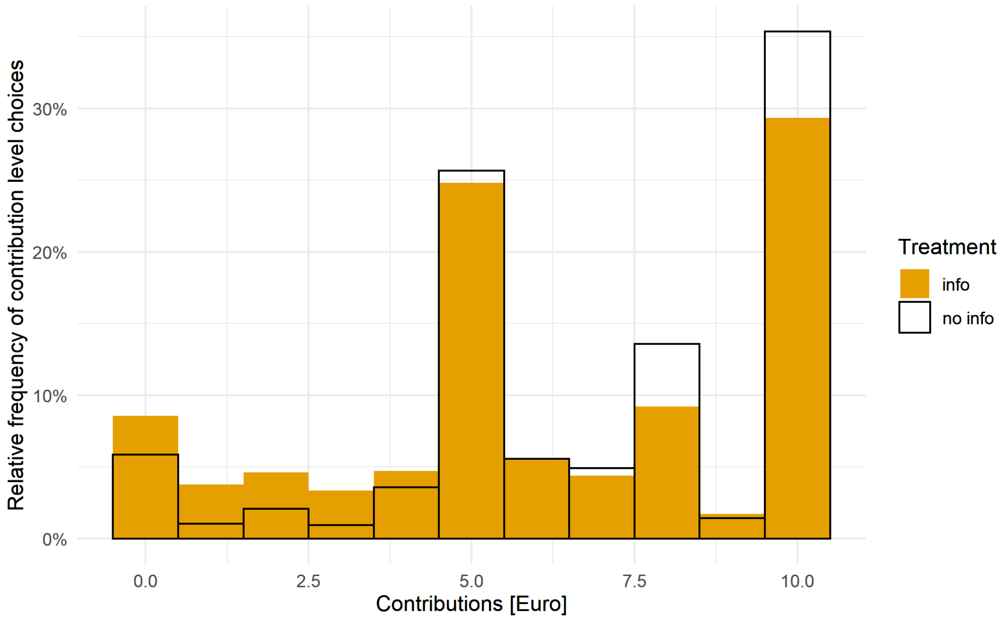


Figure 2.4: The distribution of contributions to the public good in the two treatments.

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

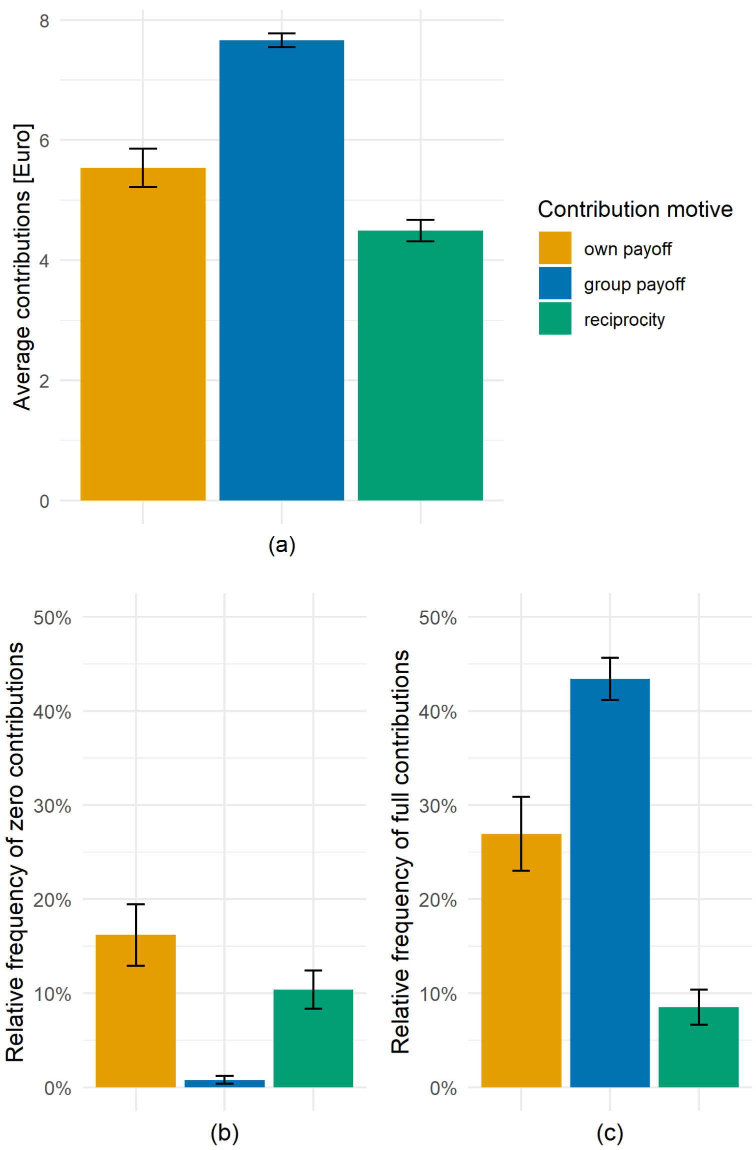


Figure 2.5: Contribution decisions by the three main contribution motives: (a) displays average contributions, (b) displays the relative frequency of zero contributions, (c) displays the relative frequency of full contributions of the whole endowment. “Own payoff” means that the participants indicated 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.

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.[13] Although

[13]Fischbacher et al. (2001) for example find that participants on average contribute about 33% of their

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:[14] 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”.[15] 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.[16] Figure 2.5 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 2.5a). They are also least likely to contribute zero (figure 2.5b) and most likely to contribute the entire endowment (figure 2.5c).

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

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.

[14]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.

[15]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.

[16]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.

nothing. Therefore, define the level of efficiency of a contribution as

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

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 2.6 shows that the treatment effect on efficiency is indeed only positive 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 $\mu = 0.5$.

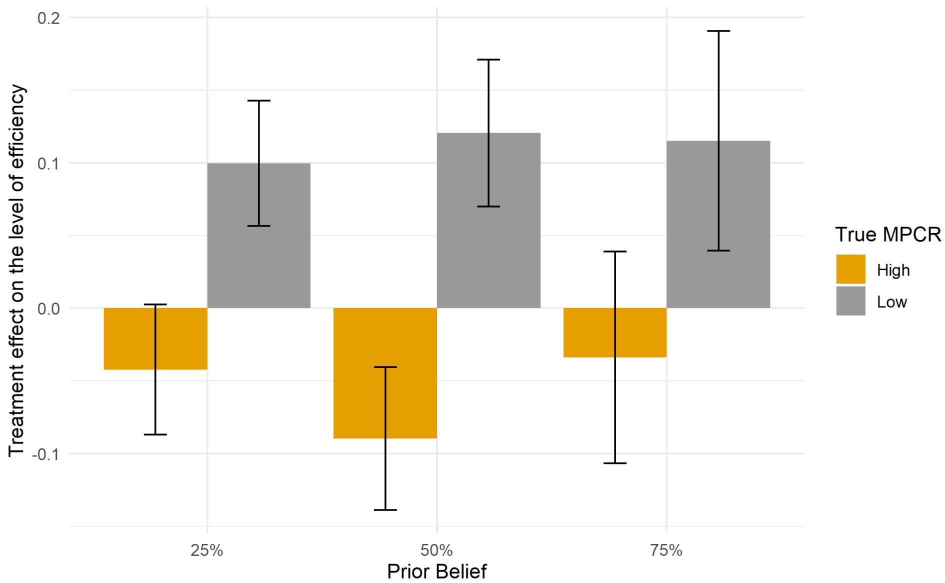


Figure 2.6: The treatment effect on the average level of efficiency is the difference between the average level of efficiency in the *info* treatment and the average level of efficiency in the *no info* treatment. If the true MPCR is high, it is socially efficient to contribute the entire endowment to the public good. If the true MPCR is low, it is socially efficient to contribute nothing. Error bars represent 95% confidence intervals.

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.[17] We then calculated the individual payoffs (equation 2.1) 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% ($\mu = 0.5$).

2.4.2 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.

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 S_H and S_L. Therefore, we estimate two probit regressions that model these two decisions separately.[18]

Table 2.1 presents the probit estimates of the marginal effects of priors and contribution motives on the decision whether to acquire information or not. Table 2.2 presents the effects on the decision whether to signal S_H or signal S_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 S_H. Both effects remain significant at the 1% level when controlling for the comprehension of the experiment.

[17] 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.

[18] An alternative approach is to model the overall decision problem between the three options of acquiring no signal, acquiring S_H, or acquiring S_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 2.15).

Table 2.1: 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.

Table 2.2: Probit model for the decision to acquire signal S_H among those who acquire information.

	Dependent variable:			
	acquired S_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 S_H, and the value 0 if the participant acquired signal S_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.

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 2.B. 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 2.4, 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.[19] Table 2.3 summarizes the three-part model.[20] We estimate a probit regression to model the decision to contribute zero, a truncated normal model for the contribution level on the subsample of participants who contribute $0 < g_i < 10$, and another probit regression to model the decision to contribute the entire endowment.

[19] Alternative models potentially suitable for our type of data include the two-limit Tobit model (appendix table 2.18) 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 2.16 and 2.17) 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 2.A.3.

[20] The full regression tables for all three parts, including the coefficients for the contribution motives and difficulty, are in the appendix section 2.A.1.

Table 2.3: 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 S_H		−0.001			−0.476***			−0.011	
		(0.010)			(0.102)			(0.020)	
acquired signal S_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. *Contributions* is the level of contributions (in euros) for the subset of participants who contributed $0 < g_i < 10$. *Full contribution* is a binary indicator variable. 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. *Motives* captures the difference contribution motives, and *difficulty* captures the perceived difficulty of the entire 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).[21] 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 S_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 S_H are generally less willing to contribute than those in the *no info* treatment.[22]

[21] 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 2.8 – 2.13). 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.

[22] 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 2.33). 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

We also estimate the three-part model again on the two subsamples of those who acquired signal S_H and those who acquired signal S_L separately, using priors and changes in posterior beliefs as explanatory variables (appendix table 2.14). 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.

2.4.3 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 S_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.[23] 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).[24] Higher values of the dependent variable are

table 2.36). In both cases, the sign and significance of the coefficients remain the same.

[23]See appendix 2.D 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.

[24]We additionally report the regression results for every single variable in appendix tables 2.22 – 2.24.

associated with a higher willingness to contribute to environmental protection. Table 2.4 presents the results of the OLS regression, both for the entire sample and for the subsample of those in the *info* treatment.[25]

Table 2.4: OLS regression for the willingness to voluntarily contribute to environmental protection.

	Dependent variable:				
	willingness to contribute to environmental protection				
	(1)	(2)	(3)	(4)	(5)
acquired signal S_H	-0.135^{**}	-0.097	-0.263^{***}	-0.198^{***}	-0.178^{***}
	(0.066)	(0.070)	(0.061)	(0.065)	(0.066)
acquired signal S_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 S_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.

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-

[25]The full table including the coefficients for all control variables is appendix table 2.20.

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 S_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 S_H are significantly less likely to contribute to environmental protection than those who acquired signal S_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 2.29 and 2.30). 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 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.[26] 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.[27] Higher values of the dependent variable are associated with a higher willingness to contribute to COVID-19 containment.

Table 2.5 presents the results of the OLS regression.[28] 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 S_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 S_H and those who did not acquire information are less likely to contribute to COVID-19 containment than those who acquired signal S_L, but the coefficients are not

[26] See appendix 2.D 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.

[27] We additionally report the regression results for every single variable in appendix tables 2.25 – 2.28.

[28] The full table including the coefficients for all control variables is appendix table 2.21.

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.

Table 2.5: OLS regression for the willingness to voluntarily contribute to COVID-19 containment.

	Dependent variable:				
	willingness to contribute to COVID-19 containment				
	(1)	(2)	(3)	(4)	(5)
acquired signal S_H	0.149	0.080	−0.058	−0.061	−0.051
	(0.107)	(0.115)	(0.093)	(0.100)	(0.101)
acquired signal S_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 S_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.

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 high-biased source, while more socially oriented individuals with a higher willingness to contribute are selecting the low-biased source.

2.5 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 acquire signal S_L from the low-biased source 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 social preferences – 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.

Contribution Stage

Consider the Voluntary Contribution Mechanism described in section 2.3. 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.[29] 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 assume the following functional forms:

$$u(g, \hat{g}, \omega) = e - (1-\omega)g + (n-1)\omega\hat{g}$$

$$v(g, \hat{g}, \omega) = (n-1)[e + [(n-1)\omega - 1]\hat{g} + \omega g]$$

$$l(g, g^*) = -\left[g - g^*(\mu)\right]^2$$

We abstract from strategic considerations and therefore treat $\hat{g}$ as exogenous. For a given belief μ, the expected utility of an individual is given by

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

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

$$\frac{\partial \mathbb{E}[U(g, \hat{g}, \mu)]}{\partial g} = -\left[1 - (\omega_l + \mu(\omega_h - \omega_l))\right] + \alpha(n-1)\left(\omega_l + \mu(\omega_h - \omega_l)\right) - \gamma\left[g - g^*(\mu)\right] \tag{2.2}$$

The optimal contribution is a function of beliefs μ:

$$g(\mu) = \min\left\{\max\left\{g^*(\mu) + \frac{1}{\gamma}\left[(1 + \alpha(n-1))\left(\omega_l + \mu(\omega_h - \omega_l)\right) - 1\right], 0\right\}, 10\right\} \tag{2.3}$$

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 $0 \leq \underline{g} < \bar{g} \leq e$, and

[29] A different model specification where v represents the desire to match the individual contribution with the efficient contribution produces similar results.

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

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.

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 high-biased source and μ'_L the updated belief after using the low-biased source. If the individual uses the high-biased source, and receives the signal $S_H = low$ (i.e. breakthrough news), she updates her belief to $\mu'_H = Pr(\omega = \omega_h | S_H = low) = 0$. If she receives the signal $S_H = high$, she updates her belief to

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

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

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

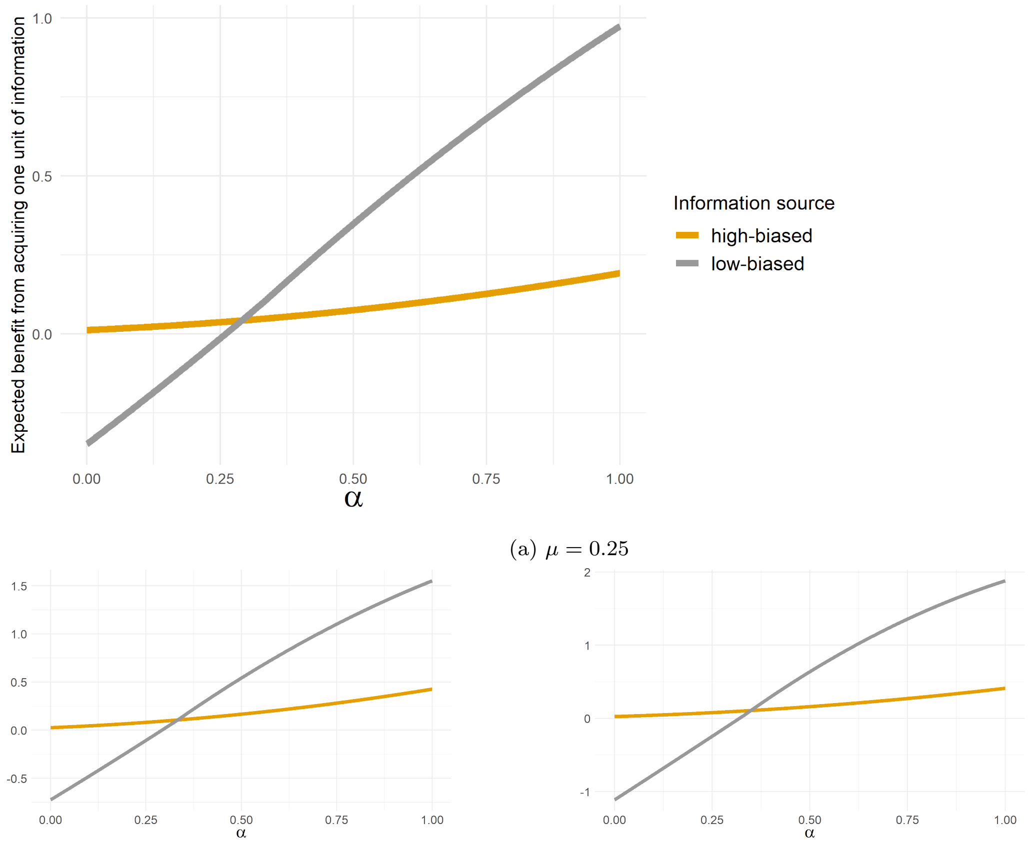
Analogously, when she uses the low-biased source and receives the signal $S_L = high$ (i.e. breakthrough news), she updates her belief to $\mu'_L = Pr(\omega = \omega_h | S_L = high) = 1$. If she receives the signal $S_L = low$, she updates her belief to

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

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

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

Then, compared to not acquiring further information, the expected gain from acquiring one unit of information from the high-biased source is given by $\phi_H \equiv \mathbb{E}_{S_H}[U(\mu'_H)] - U(\mu)$ and the expected gain from acquiring one unit of information from the low-biased source is given by $\phi_L \equiv \mathbb{E}_{S_L}[U(\mu'_L)] - U(\mu)$. The comparison of these two expression allows us to determine which information source an individual wants to acquire a signal from.



(a) $\mu = 0.25$

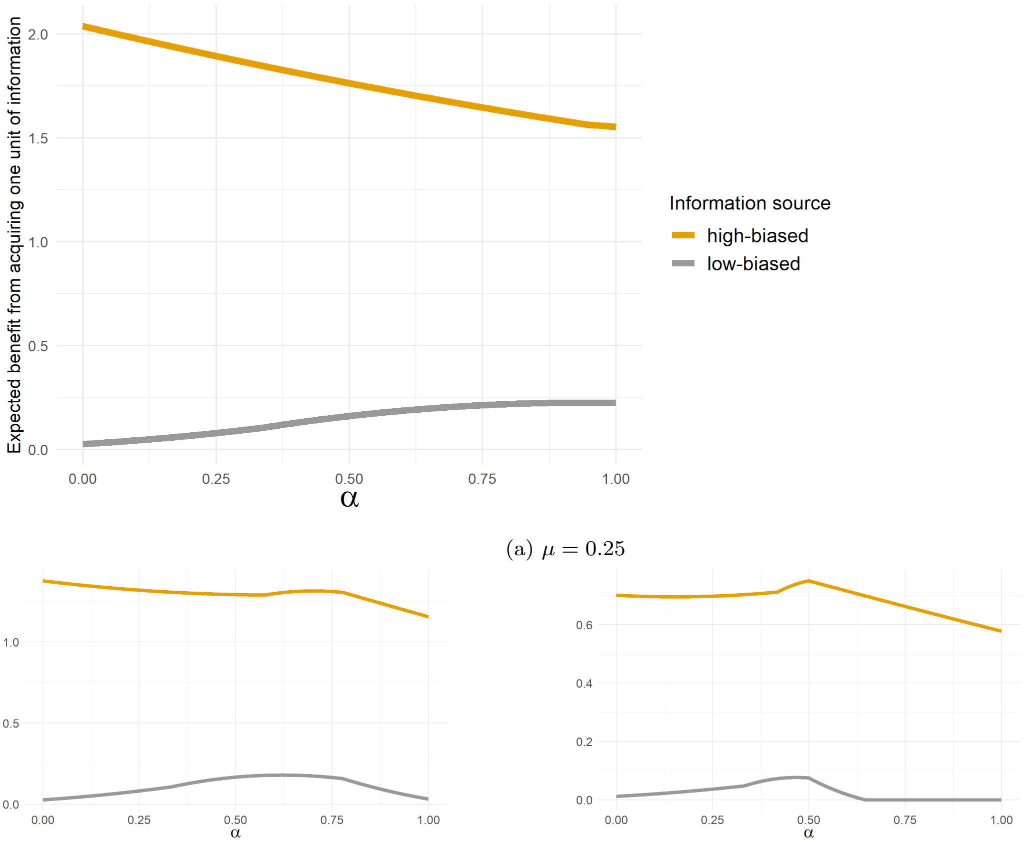
(b) $\mu = 0.5$

(c) $\mu = 0.75$

Figure 2.7: Net expected benefit from acquiring one unit of information from either source for type L and parameters $\gamma = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$.

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 low-biased source or to the high-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.



(a) $\mu = 0.25$

(b) $\mu = 0.5$

(c) $\mu = 0.75$

Figure 2.8: Net expected benefit from acquiring one unit of information from either source for type H and parameters $\gamma = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$.

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.[30] Figures 2.7 and 2.8

[30]When $\gamma \to \infty$, the individual is interested only in matching the reference point g^*. In that case, her expected utility is zero independently of her beliefs, and hence information is useless. Thus, our model rationalizes the finding that those participants who care most about reciprocity (which can be interpreted as the desire to match the reference point) are less likely to acquire information than

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.[31]

The figures illustrate two insights: On the one hand, an individual of type L will acquire information from the low-biased source if her social preferences α are sufficiently large. Figure 2.7 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 high-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 low-biased source. On the other hand, an individual of type H will always acquire information from the high-biased source: Figure 2.8 shows that for the H-type, the expected gains from the high-biased source always exceed the expected gains from the low-biased source.

2.6 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 acquire information from the low-biased source, causing posterior beliefs to decline. Thus, contributions decline and free-riding increases compared to the *no info* treatment. Moreover, we find that social preferences drive information acquisition decisions: Selfish participants are less likely to acquire information, and if they do so, they are more likely to choose the high-biased source than those with social preferences. The high-biased source might reveal with certainty that the marginal returns are low, thereby justifying low contributions. In contrast to that, socially-oriented participants are more likely to acquire information from the low-biased source, which might reveal that the marginal returns are high, thereby justifying high contributions.

The fact that selfish participants avoid information that compels them to behave more generously - and instead strategically seek information that justifies selfish behavior - has

participants with other contribution motives.

[31]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 2.9 for the L-type and in appendix figure 2.10 for the H-type.

already 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 a dictator game is always equal to the endowment and hence unaffected by the participants' actions. Instead, social welfare in a public good game depends directly on participants' actions. We find two channels through which strategic information acquisition reduces social welfare when it is socially efficient to contribute to the public good: First, because the information sources provide noisy information, and because the majority of participants selects the low-biased source, posterior beliefs decline on average, inducing lower contributions even from socially-concerned individuals. Second, selfish individuals are more likely to choose the high-biased source, which allows them to reduce their contributions without suffering losses in terms of their self-image.

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 contributions to the public good 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 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 leads to lower contributions and harms social welfare when it is efficient to provide a public good. 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. 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 scepticism towards science.

Note

This chapter 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, 2020c,d, 2021c,d,e). A study description can be found in Blom et al. (2015). Moreover, this chapter 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).

Appendix to Chapter 2

2.A Additional Tables

First, we provide the full regression tables that correspond to the shortened versions in section 2.4.2. Tables 2.6 and 2.7 report the marginal effects of the probit regressions for the information stage. Tables 2.8, 2.10 and 2.12 report the coefficients for the three-part model where the signal choice is the main explanatory variable, including a specification with interaction effects. Tables 2.9, 2.11 and 2.13 report the coefficients for the three-part model where the posterior belief is the main explanatory variable, including a specification with interaction effects. Table 2.14 shows the three-part model estimated separately on the subsets of those who acquired signal S_H and those who acquired signal S_L.

Then we present alternative model specifications. Table 2.15 reports the results of a multinomial logistic regression for the information acquisition decision. Table 2.16 and table 2.17 form a two-part hurdle model for the contribution decision. The probit regression in table 2.16 models the participation decision, i.e. the decision whether to contribute zero or a positive amount. The censored regression in table 2.17 models the amount decision among those who decide to contribute, i.e. those with $0 < g_i < 10$. Table 2.18 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 2.A.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 2.4.3. Tables 2.20 and 2.21 are the full tables corresponding to the shortened versions in section 2.4.3. Tables 2.22 – 2.28 present the regression results for the single variables employed in our main specifications separately. Tables 2.29 and 2.30 present the regression results for alternative specifications, in which further variables that capture willingness to contribute to environmental protection are added.

2.A.1 Regression Tables: Experimental Results

Table 2.6: 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 2.7: Probit model for the decision to acquire signal S_H among those who acquire information.

	Dependent variable:			
	acquired signal S_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 2.8: 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 S_H		−0.024	−0.011	0.034
		(0.091)	(0.104)	(0.183)
acquired signal S_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 S_H				0.057
				(0.248)
prior = 0.75 * acquired signal S_H				−0.226
				(0.261)
prior = 0.25 * acquired signal S_L				0.070
				(0.224)
prior = 0.75 * acquired signal S_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 2.9: 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 2.10: 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 S_H		−0.083	−0.034	−0.065
		(0.058)	(0.062)	(0.105)
acquired signal S_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 S_H				0.025
				(0.151)
prior = 0.75 * acquired signal S_H				0.065
				(0.151)
prior = 0.25 * acquired signal S_L				0.174
				(0.131)
prior = 0.75 * acquired signal S_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 2.11: 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 2.12: 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 S_H		−0.477***	−0.476***	−0.497***
		(0.108)	(0.102)	(0.166)
acquired signal S_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 S_H				−0.009
				(0.249)
prior = 0.75 * acquired signal S_H				0.062
				(0.241)
prior = 0.25 * acquired signal S_L				0.120
				(0.209)
prior = 0.75 * acquired signal S_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 2.13: 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 2.14: Separate three-Part Models for those who acquired signal S_H or signal S_L.

	acquired signal S_H			acquired signal S_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 S_H. Columns 4 – 6 present the three part model for the subset of those participants who acquired signal S_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 S_H was acquired (columns 1-3), and "reduced posterior" omitted when signal S_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.

2.A.2 Alternative Models

Table 2.15: Alternative model: Multinomial logit model for the information acquisition decision.

	Dependent variable:							
	signal S_H	none	signal S_H	none	signal S_H	none	signal S_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 S_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 2.16: 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 S_H		−0.003	−0.001		
		(0.010)	(0.010)		
acquired signal S_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 2.17: 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 S_H		−0.594***	−0.433**		
		(0.185)	(0.170)		
acquired signal S_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 2.18: 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 S_H		−0.552**	−0.420**		
		(0.223)	(0.202)		
acquired signal S_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.

2.A.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 2.19 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 2.19 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 2.19: 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.

2.A.4 Regression Tables: Additional Results

Table 2.20: 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 S_H	-0.135^{**}	-0.097	-0.263^{***}	-0.198^{***}	-0.178^{***}
	(0.066)	(0.070)	(0.061)	(0.065)	(0.066)
acquired signal S_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 S_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 2.21: 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 S_H	0.149	0.080	−0.058	−0.061	−0.051
	(0.107)	(0.115)	(0.093)	(0.100)	(0.101)
acquired signal S_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 S_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 2.22: OLS regression for the support for a carbon tax.

	Dependent variable:				
	support for carbon tax				
	(1)	(2)	(3)	(4)	(5)
acquired signal S_H	−0.085	−0.024	−0.162***	−0.090	−0.065
	(0.068)	(0.073)	(0.062)	(0.066)	(0.068)
acquired signal S_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 S_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 2.23: OLS regression for lifestyle changes to protect the climate.

	Dependent variable:				
	lifestyle changes				
	(1)	(2)	(3)	(4)	(5)
acquired signal S_H	-0.102^{*}	-0.065	-0.143^{***}	-0.091^{*}	-0.107^{*}
	(0.057)	(0.062)	(0.051)	(0.055)	(0.057)
acquired signal S_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 S_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 2.24: OLS regression for sustainable activities.

	Dependent variable:				
	sustainable activities				
	(1)	(2)	(3)	(4)	(5)
acquired signal S_H	−0.085	−0.102	−0.223***	−0.212***	−0.178***
	(0.058)	(0.063)	(0.054)	(0.058)	(0.058)
acquired signal S_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 S_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 2.25: 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 S_H	0.003	−0.029	−0.032	−0.014	0.003
	(0.070)	(0.077)	(0.063)	(0.069)	(0.071)
acquired signal S_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 S_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 2.26: 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 S_H	0.059	0.004	−0.071	−0.075	−0.060
	(0.095)	(0.103)	(0.084)	(0.091)	(0.092)
acquired signal S_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 S_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 2.27: 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 S_H	0.081	0.042	0.009	0.002	0.012
	(0.091)	(0.097)	(0.081)	(0.086)	(0.087)
acquired signal S_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 S_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 2.28: 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 S_H	0.079	0.031	−0.057	−0.056	−0.041
	(0.094)	(0.101)	(0.083)	(0.089)	(0.090)
acquired signal S_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 S_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 2.29: 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 S_H	−0.079	−0.042	−0.240***	−0.172**	−0.146*
	(0.080)	(0.086)	(0.074)	(0.080)	(0.081)
acquired signal S_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 S_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 2.30: 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 S_H	−0.058	−0.017	−0.363***	−0.299**	−0.272*
	(0.137)	(0.147)	(0.132)	(0.143)	(0.147)
acquired signal S_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 S_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.

2.B 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 2.31 and 2.32 report the marginal effects of the probit estimations for the information stage. Table 2.33 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 2.34 and 2.35 report the marginal effects of the probit estimations for the information stage. Table 2.36 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 2.37 and 2.38 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 2.31: 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 2.32: Robustness check: Probit Model for the decision to acquire signal S_H among those who acquire information, on the subset of those who did not find the questionnaire difficult.

	Dependent variable:			
	acquired signal S_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 S_H, and the value 0 if the participant acquired signal S_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 2.33: 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 S_H		0.006			−0.536***			−0.028	
		(0.012)			(0.134)			(0.026)	
acquired signal S_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. *Contributions* is the level of contributions for the subset of participants who contributed $0 < g_i < 10$. *Full contribution* is a binary indicator variable . *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 2.34: 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 2.35: Robustness check: Probit Model for the decision to acquire signal S_H among those who acquire information on the subset of those with neither too short nor too long response times.

	Dependent variable:			
	acquired signal S_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 S_H, and the value 0 if the participant acquired signal S_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 2.36: 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 S_H		0.009			−0.422***			−0.026	
		(0.011)			(0.112)			(0.023)	
acquired signal S_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 variabl. *Contributions* is the level of contributions for the subset of participants who contributed $0 < g_i < 10$. *Full contribution* is a binary indicator variable. *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 2.37: 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

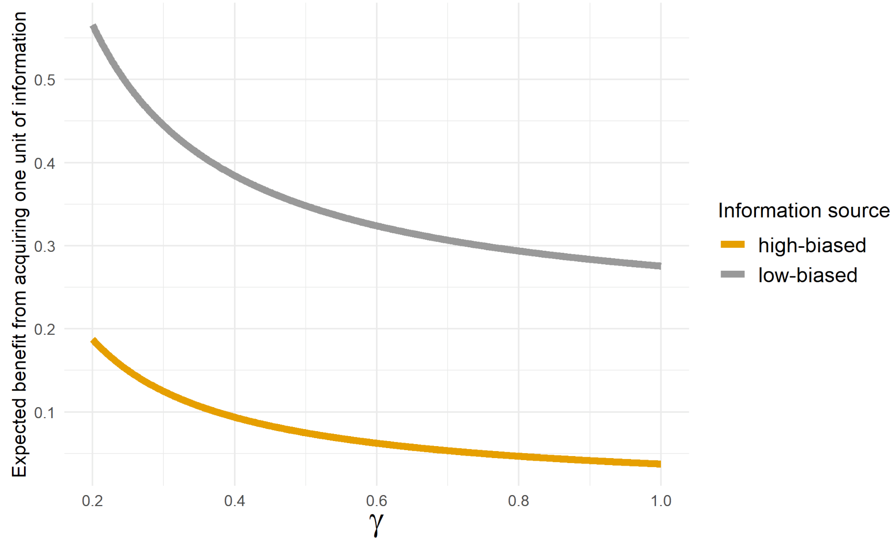
All columns report marginal effects, with robust standard errors in parentheses. The sample is the subsample of those in the *info* treatment, excluding those who did not answer the comprehension question correctly. The dependent variable *acquired information* is a binary indicator variable which takes 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 2.38: Robustness check: Probit Model for the decision to acquire signal S_H among those who acquire information on the subset of those who answered the comprehension question correctly.

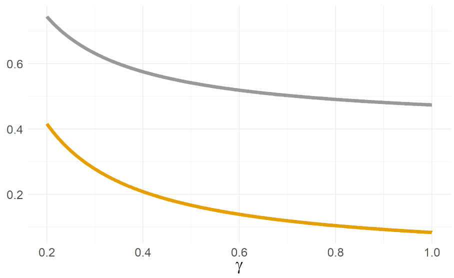
	Dependent variable:		
	acquired signal S_H		
	probit		
	(1)	(2)	(3)
prior = 0.25	−0.018	−0.015	−0.018
	(0.026)	(0.026)	(0.026)
prior = 0.75	−0.030	−0.027	−0.030
	(0.026)	(0.026)	(0.026)
own payoff		0.075**	0.082**
		(0.035)	(0.035)
reciprocity		0.063**	0.068**
		(0.032)	(0.032)
own payoff and group payoff		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 S_H, and the value 0 if the participant acquired signal S_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.

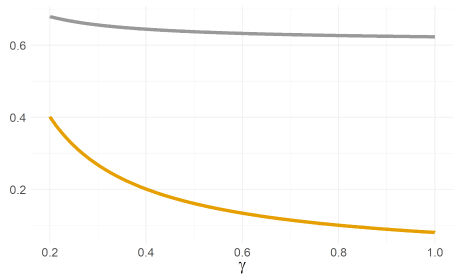
2.C Additional Figures



(a) $\mu = 0.25$

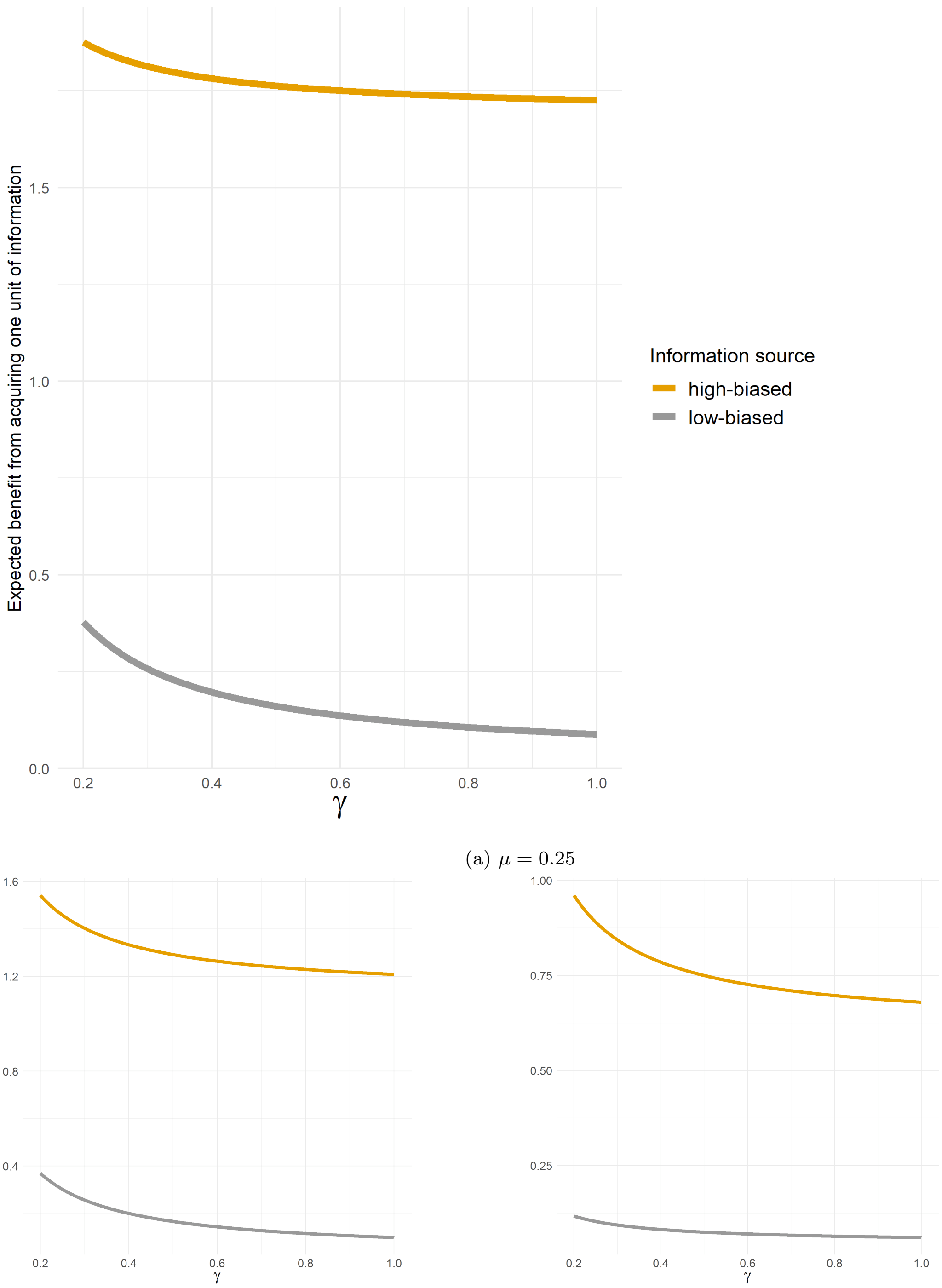


(b) $\mu = 0.5$



(c) $\mu = 0.75$

Figure 2.9: Net expected benefit from acquiring one unit of information from either source for type L and parameters $\alpha = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$.



(a) $\mu = 0.25$

(b) $\mu = 0.5$

(c) $\mu = 0.75$

Figure 2.10: Net expected benefit from acquiring one unit of information from either source for type H and parameters $\alpha = 0.5$ $\hat{g} = 5$, $\underline{g} = 4$ and $\bar{g} = 10$.

2.D Overview of 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 2.39 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 2.39: 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 [32]	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 the test 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.
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	–

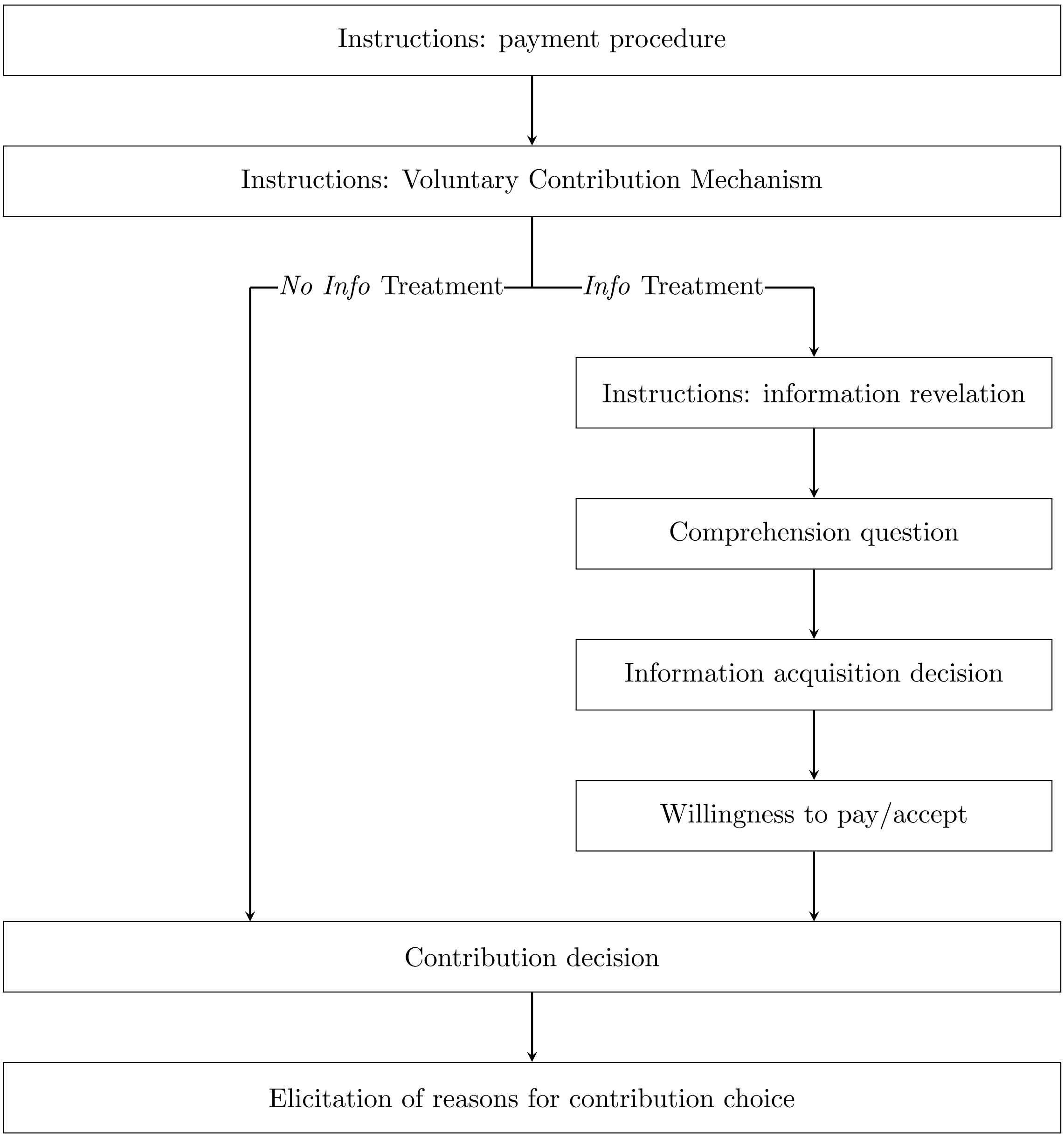
[32] CW refers to the respective week of the Mannheim Corona Study.

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	–

2.E Experimental Instructions

2.E.1 Overview of the Experimental Procedure



2.E.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: ____

2.E.3 Screenshots of the Original Instructions and Questions

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 ›

Figure 2.11: Instructions for the payment procedure.

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 <u>und</u> 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.

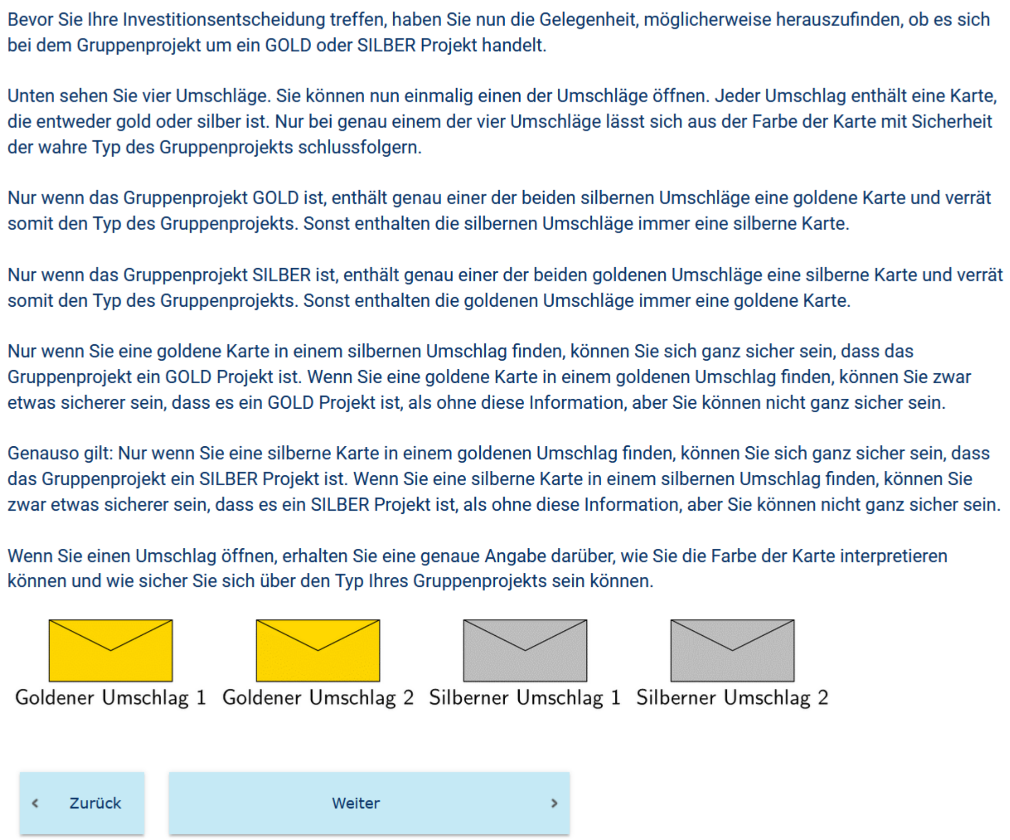
Wenn das Gruppenprojekt GOLD ist, ist der Ertrag für jedes Gruppenmitglied die Hälfte (50%) der Summe aller Investitionen in das Gruppenprojekt. Wenn das Gruppenprojekt SILBER ist, ist der Ertrag für jedes Gruppenmitglied ein Zehntel (10%) der Summe aller Investitionen in das Gruppenprojekt.

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 ›

Figure 2.12: Instructions for the Voluntary Contribution Mechanism. Example for the *info* treatment and a prior of $\mu = 0.75$.



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.

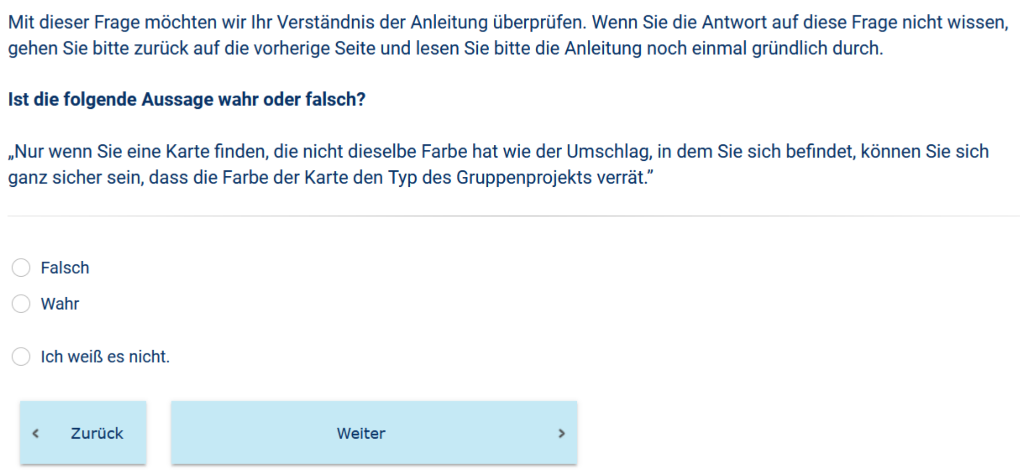
Genauso gilt: Nur wenn Sie eine silberne Karte in einem goldenen Umschlag finden, können Sie sich ganz sicher sein, dass das Gruppenprojekt ein SILBER Projekt ist. Wenn Sie eine silberne Karte in einem silbernen Umschlag finden, können Sie zwar etwas sicherer sein, dass es ein SILBER Projekt ist, als 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 2.13: Instructions for the information revelation process (*info* treatment).



Mit dieser Frage möchten wir Ihr Verständnis der Anleitung überprüfen. Wenn Sie die Antwort auf diese Frage nicht wissen, gehen Sie bitte zurück auf die vorherige Seite und lesen Sie bitte die Anleitung noch einmal gründlich durch.

Ist die folgende Aussage wahr oder falsch?

„Nur wenn Sie eine Karte finden, die nicht dieselbe Farbe hat wie der Umschlag, in dem Sie sich befindet, können Sie sich ganz sicher sein, dass die Farbe der Karte den Typ des Gruppenprojekts verrät."

- Falsch
- Wahr
- Ich weiß es nicht.

‹ Zurück Weiter ›

Figure 2.14: Comprehension question (*info* treatment).

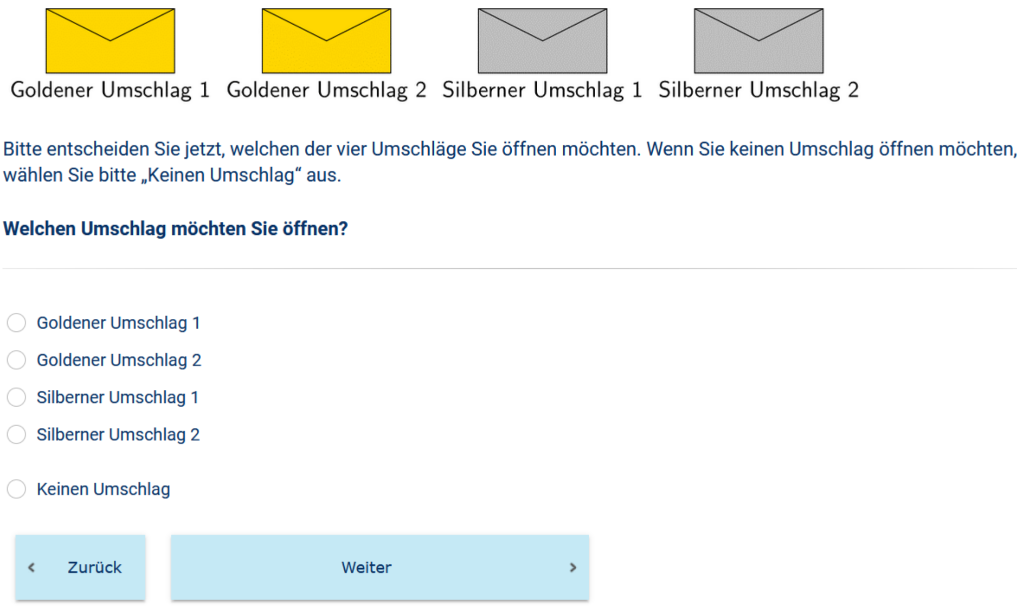


Figure 2.15: Information acquisition decision (*info* treatment).

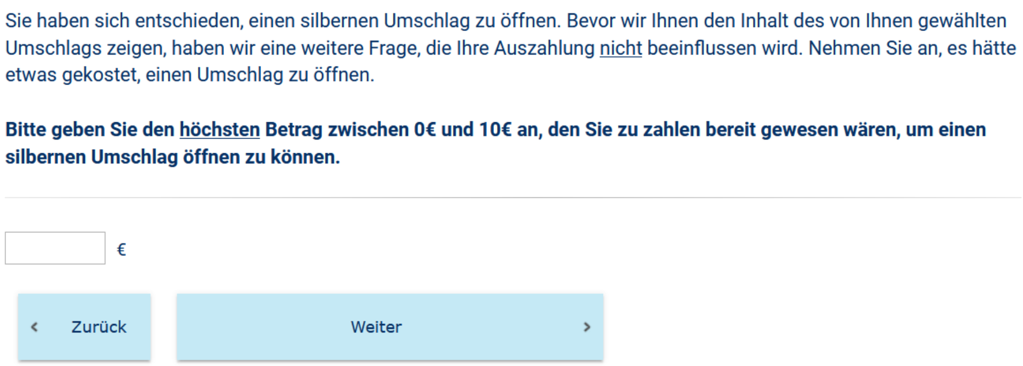


Figure 2.16: If the participant chose to open a silver envelope (*info* treatment): Willingness to pay question.

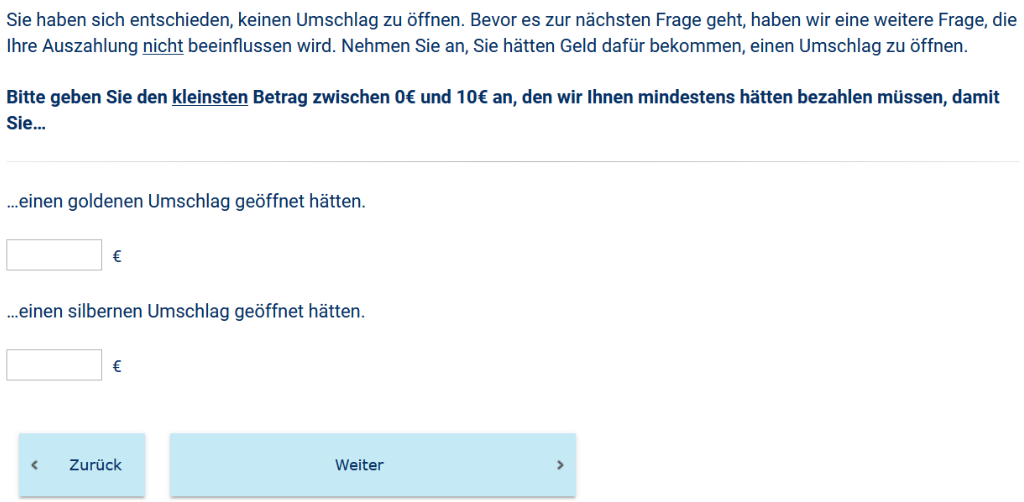


Figure 2.17: If the participant chose not to open an envelope (*info* treatment): Willingness to accept question.

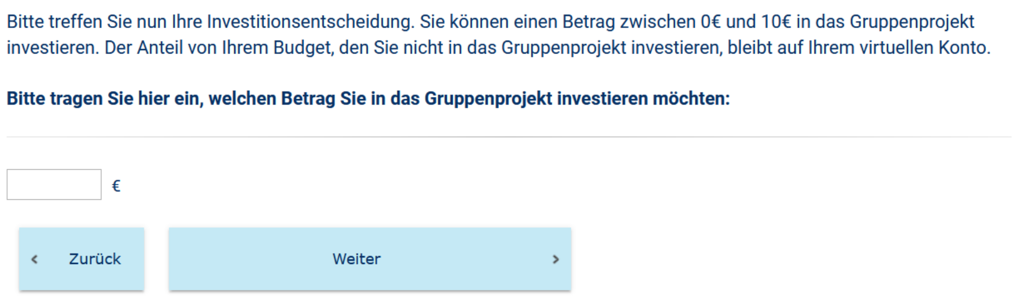


Figure 2.18: Contribution decision (*no info* treatment).

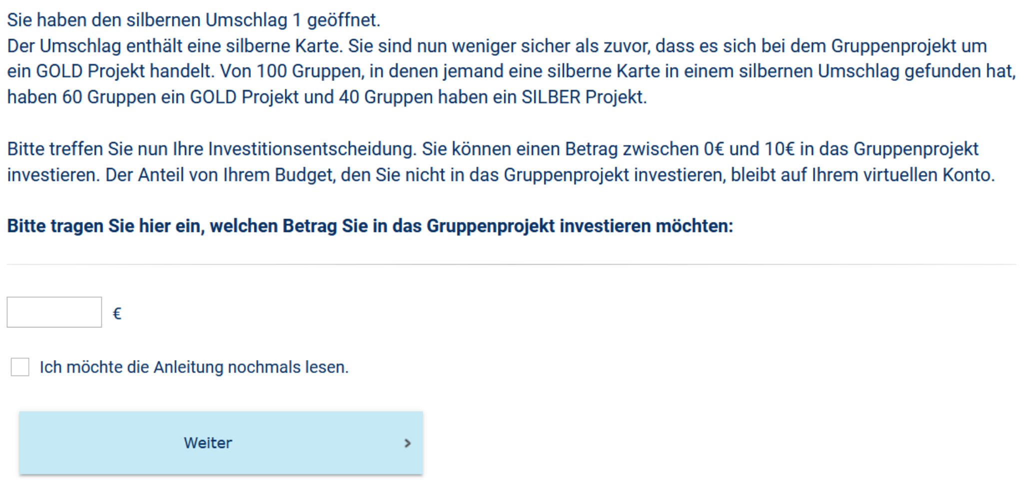


Figure 2.19: If the participant opened a silver envelope and received a silver card: Contribution decision (*info* treatment).

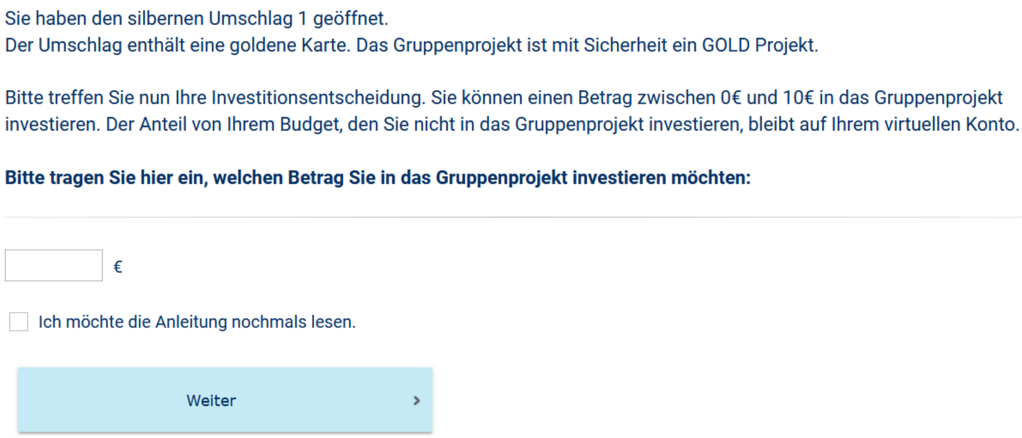


Figure 2.20: If the participant opened a silver envelope and received a gold card: Contribution decision (*info* treatment).

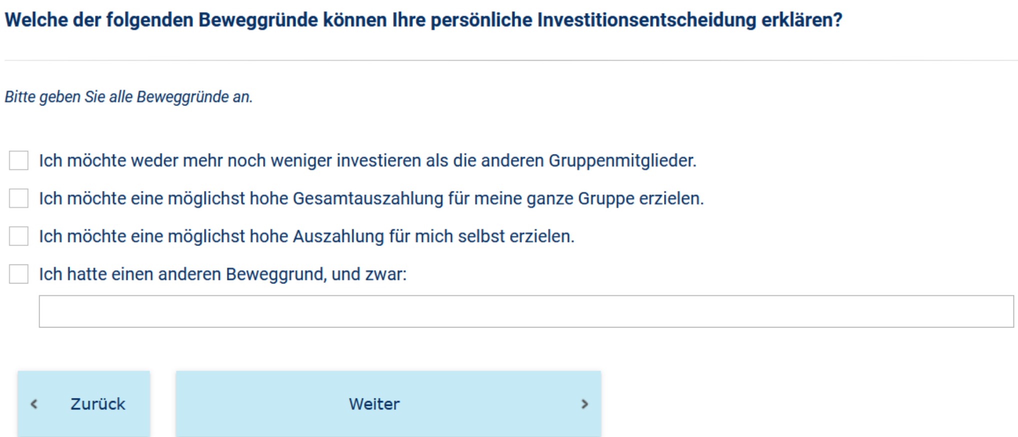


Figure 2.21: Question about the motives for the contribution choice.

Chapter 3

The Value of Choice

Evidence from an Incentivized Survey Experiment

With Hans Peter Grüner.

3.1 Introduction

Do people enjoy making choices? Or do they prefer to have tools at hand that preselect choices for them? A vast range of technologies collects consumer data to facilitate the implementation of automated and personalized preselection mechanisms that surveil, predict, assist, or even replace human choices. Search engines, online news, entertainment media, and online marketplaces use algorithms that present items which are expected to be sparking the user's interest at the top of their search results, make recommendations based on previous preferences, and strategically place advertising catered to the user's profile. One salient example is the recommender system used by Amazon: It prominently places one specific preselected product labelled as "Amazon's choice" on the top of the search results, while still allowing customers to pick from a set of other products instead. More examples of innovative recommender systems include "quantified self" tools which can recommend e.g. personalized workout schedules and sleeping times, or smart home applications which help optimizing energy consumption. In a professional environment, firms can use algorithms which screen candidates in hiring decisions, and courts can use algorithms which predict a defendant's probability to re-offend.

All of these technologies have in common that they preselect alternatives for their users without restricting the overall choice set. Thus, they involve both potential advantages and disadvantages: On the one hand, they can simplify choices and thereby facilitate peoples' lives, but on the other hand, they have the potential to limit the personal freedom of choice.[1] Which of the two effects dominates is the question that we address in this paper. More specifically, we analyze whether, conditional on the outcome of a choice process being a specific alternative, individuals prefer actively choosing this alternative from a set of several alternatives over simply accepting a preselected alternative.

Our experiment is based on the following idea:[2] Consider a set of alternatives X and a partition of X, $P = (X_1, X_2)$ with $X_1 \cup X_2 = X$, $X_1 \cap X_2 = \{\}$, and $\#X_1 < \#X_2$. Thus, because choice set X_1 is smaller, choosing from X_1 is simpler than choosing from X_2. We evaluate choices in two between-subject treatments, in which we vary only the choice environments, but not the set of alternatives: In the one-stage treatment, an individual directly chooses an element in X. In the two-stage treatment, the individual first chooses a choice set X_1 or X_2, already knowing all elements of each set, and then, if necessary, an alternative in her chosen set. The two-stage treatment provides a similar choice environment as the one created by typical recommender systems. Therefore our analysis can be seen as a test of whether the large-scale employment of recommender systems by online media and marketplaces is in line with individuals' preferences.

Our experimental setup enables us to test the following hypothesis: Conditional on a specific realized outcome A, individuals do not care about whether they have actively chosen A from a set of more than one alternative, or whether they simply accepted it when it was the preselected alternative. If this hypothesis is rejected, we can conclude that individuals either have a preference for A being the result of their own active choice, or for accepting a preselected alternative.

In our experiment, we implement the simplest setup possible with three alternatives, such that X_1 is a singleton and X_2 contains two elements. In order to make choices nontrivial, we give the alternatives two scalable dimensions: All alternatives are fair lotteries with two outcomes. This allows us to vary expected payoffs, and thus to estimate a willingness to pay for choice. We develop a structural model for the choice between the three lotteries. In both treatments, the choice of an alternative from a set depends only on the individual's risk aversion. In the two-stage treatment however, the choice between the singleton and the larger set depends also on the individual's value of choice.

[1] The question of whether preselection of alternatives is socially beneficial or not arises also in the context of political reforms. In particular, agenda setting restricts the policy alternatives that are up for election. On the one hand, agenda setting can simplify choices, but on the other hand, the set of political alternatives to choose from might be limited.

[2] Testing for a preference for choice directly is difficult. If we asked "do you prefer to be given A or choosing from the set $\{A, B\}$?", we would not be able to distinguish whether a preference for choosing from the larger choice set comes from a preference for the additional items, of from a preference for choice. Similarly, letting participants chose between being given A or choosing from the set $\{B, C\}$ raises the question of how B and C compare to A. This is why we choose an indirect approach.

We assume that monetary payoffs of the alternative presented as singleton are scaled by a factor that denotes the intensity of individuals' preference for choice. Thus the value of choice is measured in percent of monetary payoffs. We use maximum likelihood methods to estimate the distribution of risk-aversion and the distribution of the value of choice from this structural model.

We conduct our experiment as an incentivized online survey on the German Internet Panel (GIP). The GIP is a long-term study which, since 2012, regularly interviews around 4,000 participants. It covers a multitude of topics, including political views. We make use of these data to explore heterogeneity in the preference for choice: In particular, we correlate the participants' choices in our experiment with their political position on the left-right spectrum and with other variables that measure liberalism and individualism, as well as with their personality traits as measured by the Big Five.

Our experiment yields three main results. First, we find that, on average, participants have a preference for procedures that require them to make fewer choices: In the two-stage treatment, a significantly higher share of participants picks the preselected alternative than in the one-stage treatment. Consistent with this result, the estimation of our structural model reveals that the mean willingness to pay to make an additional choice is negative.

Second, we find substantial subject heterogeneity within our sample: According to the estimates of our structural model, around 41% of the participants have a positive value of choice. Furthermore, the estimated value of choice ranges from -11% to 8% of the monetary payoffs of the lottery presented as singleton.

Third, we show that measurable individual characteristics correlate with the preference for choice. Linking choices to the Big Five personality traits, we find that the preference for the preselected alternative in the two-stage treatment increases in Openness. We also find that there is considerable heterogeneity between two well-defined groups of society: Those participants who report to be leaning politically to the right are more likely to choose the preselected alternative in the two-stage treatment than those leaning towards the left.

3.2 Related Literature

Our paper is related to a recent literature that studies the role of recommender systems on digital trading platforms. This literature (see Budzinski, 2021 for a review) is mainly theoretical and focuses on the one hand on potential benefits of informed recommender systems – in particular on the reduction of transactions costs – and on the other hand on various types of agency costs. The present paper makes two empirical contributions to this literature. First, it tests the practical importance of procedural aspects and related welfare effects that may be associated with recommender systems. Second, it investigates whether prominently placed recommendations to consumers that value choice per se may trigger choices that are biased towards those products that have not been recommended - even when these products are inferior from the consumer's perspective.

On a more general level, this paper is related to the branch of social choice theory that studies preferences over choice sets. This literature emerged from Sen's seminal work on the relevance of freedom of choice for individual well-being (Sen, 2004). Sen distinguishes between two different, but interrelated aspects of freedom: On the one hand, individuals value having different options – the *opportunity aspect* of freedom. On the other hand, individuals value the process of choice itself, concerning both their own decisions as well as the rules operating in society and institutions – which is the *process aspect* of freedom.[3]

Both ideas clearly contrast with traditional rational choice theory, in which preferences over choice sets depend only on the best possible outcome each set permits. In that case, freedom of choice has only an instrumental value in the sense that a larger choice set might permit a better outcome, but no intrinsic value (Sen, 1991; Frey et al., 2004).

The idea that processes matter for choice is captured also by the concept of *procedural utility* (see Frey et al., 2004 for a review).[4] In contrast to outcome utility, procedural utility can arise from individual activities, interactions between people, and in particular from the institutions under which individuals make choices (Frey and Stutzer, 2005; Stutzer, 2020).[5]

This paper is an experimental test of one of the two main assumptions underlying this literature – that individuals care not only about outcomes but also about the choice process that led to a particular outcome.[6] Therefore, our paper relates to two further strands

[3]The emphasis of the process aspect of freedom goes back to Mill (1859). It also lies at the heart of Hayek's theory of a liberal societal order. Hayek (2011) argues that the extent of personal liberty is not determined by the size of the set of actions that an individual can take but by the properties of a "private sphere" in which individuals can make choices without any interference of others.

[4]A psychological corroboration of procedural utility can be found in self-determination theory, which argues that the process through which outcomes are achieved is relevant to the satisfaction of the innate psychological needs of competence, relatedness and autonomy (Deci and Ryan, 2000; Ryan and Deci, 2006).

[5]Empirically, the relevance of procedural utility becomes especially evident in the context of democratic participation: Eligibility to vote increases satisfaction with the outcome of a collective decision (Frey and Stutzer, 2005), and although a single vote is unlikely to affect the outcome, voters exhibit a high willingness to pay to retain the right to vote (Güth and Weck-Hannemann, 1997). Moreover, procedural utility has been shown to play a role in the workplace: Self-employed report higher job satisfaction than employees (Benz and Frey, 2008a,b), and for employees, more involvement in pay procedures is associated with higher levels of satisfaction (Benz and Stutzer, 2002)

[6]For a thorough discussion of *why* individuals may value procedures that require them to make choices, see

in this literature: the theoretical literature on measuring the degree of freedom provided by choice sets, and the experimental literature investigating individuals' preferences for choice.

There are different attempts to formally compare choice sets according to their degree of freedom. First, under uncertain future preferences, utility maximization leads to a preference for flexibility: When an individual is uncertain about her future preferences, she will choose the set of options that contains her preferred options in terms of expected utility and offers most flexibility (Kreps, 1979; Kahn and Lehmann, 1991).[7]

Second, in absence of uncertainty about preferences, various axioms have been proposed for comparison of freedom (Sen, 1991; Bossert et al., 1994; Gravel, 1994; Puppe, 1995, 1996; Nehring and Puppe, 1996; Alcalde-Unzu et al., 2012). When preferences are known, but an individual attaches intrinsic value to freedom, the extent of freedom gained from the specification of the set needs to be weighed against the utility gained from the elements contained in the set. In particular, although a larger choice set always offers more freedom of choice, whether an individual prefers the larger set over a smaller set depends on the value of the alternatives in the set (Sen, 1991; Rosenbaum, 2000). This aspect is particularly relevant to our experiment, because we systematically test how preferences over choice sets depend on the available alternatives by permuting which alternative is excluded from the larger set.

Preferences over choice sets have been investigated in several surveys about hypothetical product choices. A series of experiments from consumer research documents for a large number of different product types that consumers are more likely to choose a brand if it is presented as part of a set rather than alone (Kahn et al., 1987; Kahn and Lehmann, 1991; Glazer et al., 1991).[8] In these studies, participants indicate their hypothetical choice among three brands of the same product type. While the control group chooses directly from the triple, the treatment group is presented with a two-stage choice, where the brands are split into a pair and a single alternative. They then first choose between the pair and

Duus-Otterström, 2011. Note however that distinguishing empirically between the different motivations for valuing choice is beyond the scope of this paper.

[7]Arrow (2006) argues that in the context of constitutional formation, choice sets might be chosen for many individuals. Then, the choice of the choice set has to take into account many, potentially different preferences, while aiming to retain the autonomy of choice for the individuals in the future.

[8]Note that this literature is also related to the literature on choice overload, which shows that consumers are attracted to larger choice sets, but are subsequently less satisfied with their choice (Iyengar and Lepper, 2000; Chernev, 2003, 2006). Although these studies also demonstrate a trade-off between freedom of choice and outcomes, cognitive issues such as confusion play a role when consumers are faced with many options.

the single alternative, and subsequently choose a brand if the pair was chosen. They find that being presented as the single alternative significantly decreased the share of choices for a brand compared to being presented as part of the triple. In a similar experiment, Brenner et al. (1999) find however that when asked which set they preferred, consumers preferred the set containing the single alternative. They argue that grouping increases within-group comparisons, and that when comparing alternatives within a set, the disadvantages of each alternative stand out. Therefore, the single alternative is perceived as better. Drawing on this contradicting evidence, Sood et al. (2004) demonstrate that whether the group has an advantage or a disadvantage in such treatments can crucially depend on the framing of the questions. In our experimental setup, we use an abstract and neutral framing involving lotteries instead of actual consumer products and therefore avoid such biases.

In this literature, the experiment by Bown et al. (2003) is closest to our setup, beause participants choose from a set of three hypothetical casino bets along different choice paths. The authors again compare choices from the triple to choices from a pair and a single alternative. They also establish a preference for choosing from a larger set which can be used to trick individuals into an unattractive offer that is beneficial for the designer of the path of choices.

Further aspects of preference for choice have been studied in this strand of the literature. To test whether choice has an intrinsic value independent of the available alternatives, Leotti and Delgado (2011, 2014) conduct experiments in which participants can choose between receiving an outcome immediately or after a second choice. The monetary outcome of the choice however is determined randomly, such that the expected outcome is the same in both cases. Nevertheless, participants select the path involving a second choice more often, indicating that the act of choosing itself has a value (Leotti and Delgado, 2011).[9] Moreover, reported satisfaction with a hypothetical outcome increases when it is the result of the individual's own choice rather then someone else's choice (Botti et al., 2004; DeCaro et al., 2020) – suggesting that an outcome is perceived differently depending on the process leading to the outcome.[10]

However, none of these surveys are incentivized, such that choices between choice sets do not have actual consequences for the participants. In that case, a preference for choice cannot be distinguished from choosing a larger set for the sake of entertainment only. Our incentivized experiment allows us to estimate an actual monetary value of choice.

[9] The effect vanishes when the outcome involves not only gains but also losses – showing that context matters for the value of choice (Leotti and Delgado, 2014).

[10] However, again, the effect vanishes when the outcome involves losses (DeCaro et al., 2020) or hypothetically disliked alternatives (Botti et al., 2004), although in the latter case participants still prefer making their own choice.

Closest to our analysis is a recent experimental analysis of preferences over choice sets by Le Lec and Tarroux (2020). Like ours, their experiment is incentivized in the sense that subjects' choices affect real outcomes. In order to identify preferences over choice sets, they consider a two stage problem where in the first stage, participants provide a monetary willingness to pay for various choice sets of different size. Knowing that they will be randomly offered one of the choice sets at a random price, they have an incentive to report their true willingness to pay for each choice set in the first stage. Then in the second stage, participants choose an item from the set that they purchased. The authors find that on average participants value a set less than its best component, indicating that subjects have a negative value of having to choose from a set with additional alternatives.[11]

The most notable difference between our experimental approach and the one by Le Lec and Tarroux (2020) concerns the exact type of preference that both setups test for. In their setup participants are exposed to a variety of choice sets, but the choice procedure is a one-stage choice from the randomly chosen set. Participants can only influence the probability of having to choose from a certain choice set by submitting their willingness to pay. In contrast to that, we keep the choice set fixed but expose different participants to different choice environments. In particular, the choice environment is altered exogenously by the experimenters through the preselection of one alternative in the two-stage treatment. Thus the two experiments measure different types of preference for choice: Le Lec and Tarroux measure preferences for autonomously reducing or enlarging the size of a choice set. We however estimate a preference for an exogenous preselection of alternatives as compared to independently choosing between multiple alternatives without interference.

[11] Our estimated average value of not having to make more choices is smaller in absolute value than Le Lec and Tarroux's estimate, and we find that about 41% of participants have a positive value of choice which is more than in Le Lec and Tarroux (25-30%). One potential reason why our results differ is that our experimental design excludes some potentially confounding factors that might increase the value of not having to make more choices: First, Le Lec and Tarroux suggest that individuals might fear making a bad decision in the second stage, and therefore rationally restrict their choice set in the first stage. Because we implement our experiment in an online survey, participants always have the opportunity to use the "back" button to go back to the first stage decision, which should minimize the fear of making mistakes. Second, Le Lec and Tarroux suggest that individuals might use an imperfect heuristic when valuating larger choice sets. Such a cognitive shortcut might be helpful when individual preferences are expected to change in the future, and in order to delay the cognitive costs of ranking all options in the set. This explanation however is plausible only because participants have to make a large number of decisions in Le Lec and Tarroux's experiment. In our experiment however, participants make only one decision between two choice sets, and the decision between alternatives within the set is required directly afterwards, without any delay in between. Third, the goods in the choice sets considered by Le Lec and Tarroux are access to four media websites. Participants might have a willingness to pay for expressing their views about these media that add to the measure of the value of choice. In our experiment, we use an abstract framing in which the goods are lotteries, such that no such expressive choices should play a role.

Thus, our paper can be seen as a test for a preference for making self-determined choices – or in other words a taste for *freedom as independence*.[12]

3.3 Experimental Design

3.3.1 Experimental Treatments

In a between-subjects design, we employ two treatments, in which we vary the choice environment, but keep the set of alternatives to choose from constant.[13] We employ the most simple experimental design possible, using three alternatives A, B, and C. In the *one-stage treatment*, participants directly choose one alternative from the entire choice set $\{A, B, C\}$. In the *two-stage treatment*, participants first choose a choice set. In particular, they can choose between a set that is a singleton and a set that contains the remaining two alternatives. If they choose the latter, they choose an alternative from that set in the second stage.[14] In order to control for potential order effects, we randomize the order in which the alternatives appear in the choice set in both treatments, yielding six experimental groups per treatment.

This treatment design allows us to test the Null Hypothesis which states that people only care about the three alternatives at choice, not the number of steps required to choose a certain alternative. Under the Null Hypothesis, the relative frequency of choice of any alternative presented as singleton in the two-stage treatment is equal to the relative frequency of choice of the respective alternative in the one-stage treatment.[15] If however the Null Hypothesis is rejected, and participants attach a positive value to making a second

[12]In their conclusion, Le Lec and Tarroux conjecture that although "subjects are not willing to enlarge their *own* choice set, this does not necessarily mean that they are willing to let someone else [...] *interfere* with their choice opportunities" (p. 2132). Because our experiment is designed to analyze whether preselection of alternatives make a difference, our results lend themselves to this interpretation of *freedom as independence*.

[13]We pre-registered the experimental design via AsPredicted (`https://aspredicted.org/dt99n.pdf`).

[14]Note that because we implement the experiment in the German Internet Panel, there is a "back" button that allows participants in any stage of the survey to go back to any previous stage. Therefore, subjects might also choose to return to the first stage of our experiment after already having arrived at the second stage. On the one hand, changing one's mind in the second stage might be interpreted as making an additional choice, which could be relevant for the interpretation of our results. On the other hand however, going back and forth between questions does not have any consequences for the final decision, and hence for the outcome of the lottery choice. Therefore, the ability to change one's mind should not affect the value of choice. Although in theory the "back" button might make a difference, an analysis of the timestamps indicating when and for how long a participant visited each question page in the online survey reveals that the "back" button was used by at most one participant at the second stage.

[15]Note that this hypothesis can be tested either by pooling data with different sequences of the alternatives not listed first or by comparing data from the one-and the two stage treatment with the same sequence of all alternatives.

choice (alternative Hypothesis H1a), the relative frequency of choice of the singleton in the two-stage treatment should be lower than the relative frequency of choice of the same alternative in the one-stage treatment. If participants attach a negative value to making a second choice (alternative Hypothesis H1b), the relative frequency of choice of the singleton in the two-stage treatment should be higher than the relative frequency of choice of the respective alternative in the one-stage treatment.

In order to make choices between the alternatives non-trivial, we give the alternatives two scalable dimensions. Participants choose between three lotteries with different expected returns and different variances. We use a choice task similar to the Eckel and Grossman (2002) task in which each lottery has two possible outcomes that occur with equal probability. This lottery choice task has been shown to be easily understandable for participants (Dave et al., 2010). Moreover, the use of lotteries allows us to identify a willingness to pay for the choice amongst more than one alternative.

Table 3.1 shows the three increasingly risky lotteries in the baseline choice set. A risk-neutral participant prefers lottery C, as it yields the highest expected payoff. A risk-seeking participant will prefer lottery C as well, as it is the most risky alternative. A risk averse participant however will be willing to sacrifice expected payoff in order to reduce risk. Therefore, individuals with an intermediate level of risk-aversion will prefer lottery B, while individuals with a high level of risk-aversion will prefer lottery A.

Table 3.1: Baseline choice set

Lottery	L	H	Expected payoff	Standard deviation
A	9	11	10	1
B	7	14	10.5	3.5
C	5	17	11	6

Because we expected participants to be more likely to select the alternative presented as a singleton in the two-stage treatment than in the one-stage treatment, we included an additional treatment to exclude an alternative explanation: the *group attractiveness effect*. This effect has so far only been studied in Psychology, in particular concerning the physical attractiveness or likability of groups of people. It says that when asked to judge the attractiveness of a group of people, participants "find the group more attractive than the average of its members" (van Osch et al., 2015). In our experimental setup, presenting two items as a group might cause a similar effect: During the first choice in the two-stage treatment, i.e. the choice between the two sets $\{A\}$ or $\{B, C\}$, the presentation of $\{B, C\}$ as a group might prevent participants from carefully considering the two individual alternatives the set contains. They might see only the most positive attributes of the two alternatives and match them to form a new, more attractive lottery in their minds. Specifically, they might only consider the highest available low outcome L and the highest available high outcome H. Then, the new, imaginary lottery becomes more attractive then those in the group. If this imagined lottery is preferred over A, it might cause them to choose the set $\{B, C\}$ – although the imagined lottery is not actually available. To test for such a group attractiveness effect, we construct another choice set by adding exactly this more attractive lottery to the baseline choice set.

Because the additional treatment reduces the number of participants available for each treatment, we only test the group attractiveness effect for the case where C is presented as a singleton and $\{A, B\}$ as a group in the two-stage treatment. Specifically, we construct the additional lottery D from the highest available payoff of event L and the highest available payoff of event H of the lotteries A and B. Table 3.2 shows the additional choice set. Note that in this choice set, alternative D dominates alternatives A and B. Therefore, participants should choose only between C and D.

Table 3.2: Additional choice set to test for group attractiveness effects

lottery	L	H	Expected payoff	Standard deviation
A	9	11	10	1
B	7	14	10.5	3.5
C	5	17	11	6
D	9	14	11.5	2.5

If in the baseline choice set $\{A, B, C\}$, the difference in choices between the one-stage treatment and the two-stage treatment is *only* driven by the group attractiveness effect, we should observe no such difference anymore with the additional choice set $\{A, B, C, D\}$, because the more attractive alternative D is available in both treatments. If however the share of choices of C is still lower in the two-stage treatment than in the one-stage treatment, the result cannot be attributed to the group attractiveness effect.

To test for potential order effects in the larger choice set in the two-stage treatment, we use three permutations of the alternatives A, B and D, resulting in 3 additional experimental groups.

3.3.2 Implementation of the Experiment in the German Internet Panel

The German Internet Panel (GIP) is a long-term online panel collecting survey data on political attitudes and preferences, individual behavior, as well as socio-demographic variables. As the central infrastructure project of the Collaborative Research Center (SFB) 884 "Political Economy of Reforms" at the University of Mannheim, the GIP was established in 2012, and has since then been fielded on a bimonthly basis. The GIP relies on a random probability sample of the general population of Germany aged 16 to 75.[16] With additional participants having been recruited in 2014 and 2018, it now offers a pool of over 6,000 panelists, and around 4,000 take part in each wave. All panelists are invited to the survey on the first day of every other month, and have the entire month to complete it. The questionnaire takes around 20 to 25 minutes and completing it is rewarded with a conditional incentive of 4 euros. Participation is further incentivized with a yearly bonus payment of 10 euros if all surveys in that year were completed, or of 5 euros if all but one were completed. The GIP data are publicly available in the GIP data archive at the GESIS-Leibniz Institute for the Social Sciences.

We implemented our experiment as part of the questionnaire of GIP wave 57, which was fielded in January 2022. To simplify the setup for the participants, we framed the lotteries as the toss of a fair coin. We showed them a picture of three coins depicting the respective outcome for heads and tails.[17] To incentivize participants, we randomly drew 750 participants to whom we paid the randomly determined outcome of their selected lottery. This fact and our expected number of participants (around 4,000) were communicated in the instructions (see Appendix 2.E). On average, the participants selected for payment received 10.49 euros.[18]

3.4 Results

In total, 4,079 participants took part in GIP wave 57. Some of them did not complete the survey or skipped our experiment, resulting in an effective sample size of 3,984 participants

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

[17]See appendix 2.E for screen shots of the original instructions as well as English translations.

[18]As a comparison, the German hourly minimum wage was 9.82 euros at the time when the experiment was fielded.

(population: average age 53 years, 48% female, 35% have an academic education). We now present the insights from our experiment in terms of descriptive statistics, and then the results from a regression analysis in which we investigate potential heterogeneity in the treatment effect concerning the participants' individual characteristics and their political attitudes.

3.4.1 Descriptive Results

Overall, 24% of the participants choose the alternative presented first in the one-stage treatment, while 38% choose the alternative presented as singleton in the two-stage treatment.[19] The difference is statistically significant ($p < 0.0001$, two-proportions z-test)[20], such that our Null Hypothesis is rejected in favor of alternative Hypothesis H1b, revealing that on average participants attach a negative value to making a second choice.

Table 3.3 shows the relative frequencies of choices in the baseline choice set $\{A, B, C\}$, depending on which alternative was presented first.[21] In the one-stage treatment, independent of the order of alternatives, a relative majority of participants chooses alternative A, i.e. the least risky lottery, indicating that the participants are relatively risk-averse.

Table 3.3: Relative frequencies of choices in the baseline choice set

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C
One-stage	A	0.42	0.30	0.27
	B	0.50	0.20	0.30
	C	0.49	0.27	0.25
Two-stage	A	0.50	0.24	0.26
	B	0.35	0.40	0.24
	C	0.43	0.20	0.37

[19] The relative frequencies of first alternative choices are significantly different from 1/3 in the one-stage treatment ($p < 0.0001$, binomial test), and from 1/2 in the two-stage treatment ($p < 0.0001$, binomial test), which would correspond to random choice between the presented options.

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

[21] The relative frequencies of choices for all permutations of the three alternatives can be found in appendix table 3.10. We only distinguish between which alternative was presented first here because the relative frequencies of first alternative choices differ only slightly when comparing the permutations of the remaining two elements in the choice sets: The difference is only significantly different from zero between the two permutations $\{B, A, C\}$ and $\{B, C, A\}$ in the one-stage treatment ($p = 0.083$ two-proportions z-test). When A or C are presented first, the difference between the two permutations of the respective choice sets is not significantly different from zero.

Therefore, the shares of first alternative choices differ depending on which alternative was presented first: In particular, in both treatments, when the least risky alternative A is presented first, the relative frequency of first alternative choices is significantly higher than when any of the other alternatives is presented first (figure 3.1).

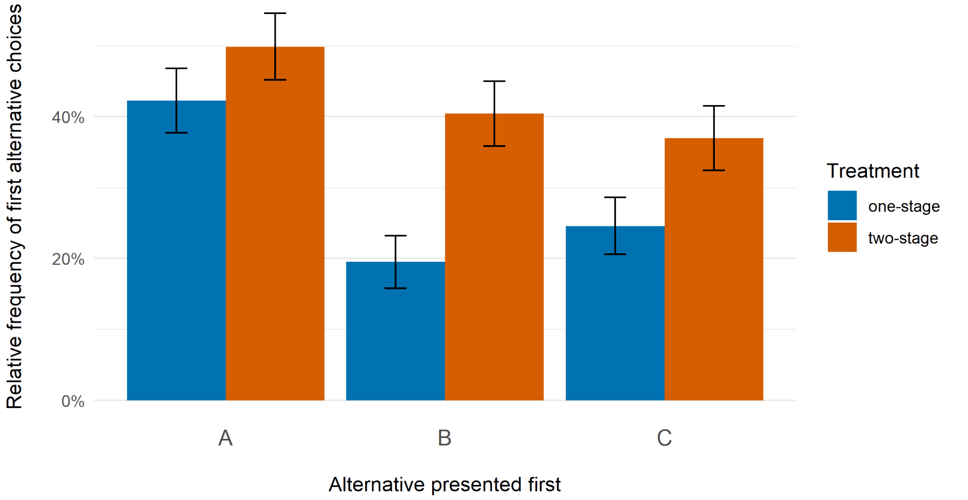


Figure 3.1: Share of choices of the alternative which was presented first in the one-stage treatment, and as singleton in the two-stage treatment. Error bars represent 95% confidence intervals.

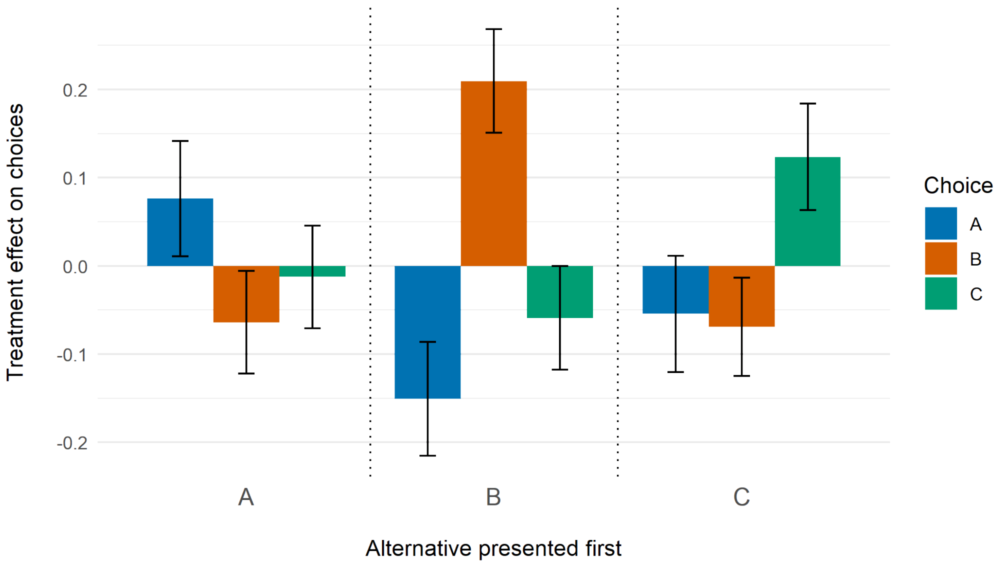


Figure 3.2: Effect of the two-stage treatment on the relative frequency of choices of each alternative, compared to the one-stage treatment. The sample contains only the experimental groups with the baseline choice set $\{A, B, C\}$. Error bars represent 95% confidence intervals.

Moreover, independent of the order of alternatives, the share of first alternative choices increases significantly in the two-stage treatment, compared to the one-stage treatment. The size of the treatment effect however differs slightly depending on which alternative was presented first: In particular, the treatment effect when B is presented first is significantly higher than the treatment effect when A is presented first (figure 3.2).

Because the treatment effect on first alternative choices is positive, we can conclude that there are some participants who choose the alternative presented as singleton in the two-stage treatment, but who would have chosen a different alternative in the one-stage treatment. Which type of participant's choices are affected by the treatment depends on which alternative was presented as the first. Figure 3.2 shows that when A or C are presented first, the share of B-choices decreases significantly in the two-stage treatment, while the other choices do not change significantly. When B is presented first, only the share of A-choices decreases significantly. Thus, only those participants who would have chosen the less risky alternatives A or B in the one-stage treatment are willing to trade-off expected utility from their lottery choice against their utility from making a more simple choice in the two-stage treatment. Those participants who would have chosen the most risky alternative C in the one-stage treatment however are less willing to change their choice in the two-stage treatment.

Table 3.4 shows the relative frequencies of choices for each alternative in the additional choice set $\{A, B, C, D\}$, where C was always presented first.[22] In the one-stage treatment, a relative majority of participants chooses alternative D, which is less risky and has a higher expected payoff than alternative C. Although in this choice set, alternative A and B are dominated by alternative D, some participants still choose these alternatives. In particular, a significant share chooses A, which cannot be explained by rational choice theory.

Recall that we included this additional choice set to test for a potential group attractiveness effect, which would have been an alternative explanation for a negative treatment effect on first alternative choices. However, the treatment effect on first alternative choices is clearly positive in both the baseline choice set as well as in the additional choice set.

[22] The relative frequencies of choices for all permutations of the four alternatives can be found in appendix table 3.11. Again, the relative frequencies of C-choices differ slightly when comparing the permutations of the remaining three elements in the choice sets: The difference is significantly different from zero when comparing the permutation $\{C, A, B, D\}$ to the permutation $\{C, A, D, B\}$ ($p = 0.005$, two-proportions z-test) and to $\{C, D, A, B\}$ ($p = 0.017$, two-proportions z-test) in the two-stage treatment. When comparing $\{C, A, D, B\}$ to $\{C, D, A, B\}$ the difference in the share of C-choices between the permutations is not significantly different from zero.

Table 3.4: Relative frequencies of choices in the additional choice set with four alternatives

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C	Choice of D
One-stage	C	0.30	0.09	0.15	0.47
Two-stage	C	0.16	0.08	0.29	0.46

To ensure that the observed treatment effect indeed captures a preference for choice, and not a preference for completing the questionnaire quickly by avoiding the second stage of the two-stage treatment, we analyze the response times contained in the GIP paradata.[23] If participants in the two-stage treatment chose the preselected alternative only to reduce time spent on the questionnaire, the observed treatment effects on first alternative choices should become smaller once we remove participants who exhibit a preference for quickly completing the experiment from the sample. Therefore, we repeat our analysis on the subsample of those participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment.[24] The treatment effect in this subsample is similar to the effect observed in the overall sample: 23% of the participants choose the alternative presented first in the one-stage treatment, and 36% choose the alternative presented as singleton in the two-stage treatment, where the difference is statistically significant ($p < 0.0001$, two-proportions z-test). The treatment effects on the relative frequencies of choices for each alternative are of similar magnitude in this subsample compared to the overall sample as well (appendix tables 3.12 and 3.13).

3.4.2 Regression Analysis

To investigate whether participants who differ in terms of individual attitudes also differ in terms of their preference for choice, we exploit several questions from previous GIP waves.[25] First, we are interested in whether political preferences are correlated with preferences for choice. To do so, we use participants' self-reported placement on the left-right spectrum. This analysis is motivated by the observation that parties on the political

[23]The median response time required to complete our experiment is 1 minute and 3 seconds for the participants in the one-stage treatment, and 1 minute and 14 seconds for the participants in the two-stage treatment, where a median time of 12 seconds is required for the second stage.

[24]The 25th percentile response time is 38 seconds in the one-stage treatment, and 40 seconds in the first stage of the two-stage treatment. Note that dropping all participants who answer our questions relatively quickly, we remove those who generally do not make an effort in the lottery choice task. The set of those participants who want to reduce their time spent on the questionnaire by avoiding the second stage in the two-stage treatment are a subset of those generally not making an effort.

[25]Appendix table 3.14 gives an overview of how we construct our variable from the GIP questions.

right emphasize personal and in particular entrepreneurial freedom and self-responsibility more than those on the left, leading to the conjecture that those on the right might be less inclined to personally accept a preselected alternative. However, on the other hand, one may conjecture that those on the right believe more in formal authority (see e.g. Altemeyer, 1988 on the concept of right-wing authoritarianism) and thus might be more willing to also personally accept a preselected alternative.

Second, we use those variables from the GIP that most closely capture any underlying preferences for making autonomous decisions in life. The GIP contains a range of questions asking participants about their motivation in their job, including whether it is important to them to (i) realize their own ideas, and (ii) to work independently. Additionally, we use a question that asks about support for the statement "the most important political decisions should be made by the people, not politicians".

Third, we explore heterogeneity in terms of personality traits. In particular, the GIP contains the 10-item Big Five Inventory (BFI-10), which is well-established as a reliable and valid assessment of the five core personality traits Extraversion, Neuroticism, Openness, Conscientiousness, and Agreeableness (Rammstedt, 2007; Rammstedt and John, 2007).

As dependent variable in all regressions we use an indicator variable capturing whether the participant chose the lottery presented first (in the one-stage treatment) or as singleton (in the two-stage treatment). We estimate several specifications: The baseline specification includes only an indicator variable for the treatment and the variable for the individual attitude as well as their interaction, which is the effect of interest. We then add the order of lotteries capturing which alternative was presented first, and, in a third specification, we control for the usual sociodemographic variables, i.e. gender, age, income, and education.

Preferences for Choice and Political Preferences

To analyze political preferences, we classify participants on the left-right spectrum into those positioned strictly to the right of the median participant's position, and those positioned to the left of or on the median. Table 3.5 presents the regression results. The effect of interest is captured by the coefficient on the interaction between *two-stage treatment* and *right-wing*, and it is positive and significant.[26] We can conclude that in the two-stage treatment, those who are leaning towards the right are more likely to choose the alternative presented as singleton than those who are leaning towards the left. This conclusion continues to hold when including the order effect induced by presenting different

[26] We also estimate a Probit model, which can be found in appendix table 3.17. The sign and significance of the coefficients of interest remain unchanged.

alternatives first as well as the usual set of controls.[27]

As a robustness check to ensure that the observed effects are not driven by a preference for completing the questionnaire quickly, we repeat the regression analysis on the subsample of those participants with response times above the 25th percentile of response times in the one-stage treatment or the first stage of the two-stage treatment respectively (appendix tables 3.18 and 3.19). In all specifications the coefficients on the interactions between *two-stage treatment* and *right-wing* remain positive and significant, and they are larger in magnitude than in the regressions for the overall sample.

Table 3.5: Lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.116***	0.046	0.062
	(0.018)	(0.038)	(0.040)
Right-wing	−0.025	−0.033	−0.027
	(0.025)	(0.024)	(0.026)
Two-stage treatment * right-wing	0.072*	0.076**	0.069*
	(0.039)	(0.038)	(0.040)
Constant	0.252***	0.442***	0.391***
	(0.012)	(0.026)	(0.045)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,266	3,266	2,897
R^2	0.021	0.064	0.069
Adjusted R^2	0.020	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". The additional control variables include gender, age, income, and education.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

The results are clearly at odds with our (first) conjecture that those leaning to the right tend to emphasize self-determination in their own lives. Instead, they are consistent with the view that those leaning to the right are more willing to accept authority – in this case the authority of the designers of the experiment.

[27] The full table including the coefficients for the effects of different first alternatives and all controls can be found in appendix table 3.15. The OLS regression results for all permutations of the alternatives within the choice set can be found in appendix table 3.16.

Table 3.6: Lottery choice and job motivation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.121^{***}	0.037	0.060
	(0.031)	(0.044)	(0.049)
Independence	−0.036	-0.041^{*}	−0.030
	(0.022)	(0.022)	(0.024)
Own ideas	0.029	0.024	0.023
	(0.023)	(0.022)	(0.024)
Two-stage treatment * independence	0.041	0.043	0.038
	(0.033)	(0.032)	(0.036)
Two-stage treatment * own ideas	−0.023	−0.022	−0.029
	(0.034)	(0.033)	(0.037)
Constant	0.250^{***}	0.455^{***}	0.408^{***}
	(0.021)	(0.031)	(0.048)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,638	3,638	2,920
R^2	0.021	0.063	0.069
Adjusted R^2	0.019	0.060	0.064

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Independence* is a binary indicator variable for the importance of working independently. *Own ideas* is a binary indicator variable for the importance of realizing own ideas. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". The additional control variables include gender, age, income, and education.
Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Preferences for Choice and Decision Making in Life

To investigate individual preferences decision making in life, we separately look at the questions about autonomous decision-making in the job, and about the wish for direct political participation.

First, concerning the work life, we create two variables which capture whether the participant finds it very important to (i) realize own ideas and (ii) work independently, or not. Table 3.6 presents the regression results.[28] The effects of interest are captured

[28]The full table including the coefficients on all controls can be found in appendix table 3.20 .

by the coefficient on the interactions between *two-stage treatment* and the individual characteristics. However, these coefficients are small and not statistically significant at any conventional level, suggesting that the treatment effect is not different between those who have a preference for autonomous decision-making in the job and those who do not.

Second, concerning political decision-making, we again classify participants into those who want the most important political decisions to be made by the people instead of politicians, and those who do not. Table 3.7 presents the regression results.[29] The effect of interest is again captured by the coefficient on the interaction term, but it is small and not statistically significant at any conventional level, suggesting that the treatment effect is not different between those who have a preference for direct political decision-making and those who do not.

Table 3.7: Lottery choice and political decision making

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.123^{***}	0.046	0.050
	(0.019)	(0.037)	(0.041)
People's decisions	−0.022	−0.023	−0.031
	(0.020)	(0.020)	(0.022)
Two-stage treatment * people's decisions	0.040	0.041	0.053
	(0.031)	(0.030)	(0.034)
Constant	0.252^{***}	0.445^{***}	0.412^{***}
	(0.013)	(0.026)	(0.045)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,721	3,721	2,990
R^2	0.023	0.063	0.070
Adjusted R^2	0.022	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *People's decisions* is a binary indicator variable for whether the participant wants important decisions to be made by the people instead of politicians. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". The additional control variables include gender, age, income, and education.
Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

[29]The full table including the coefficients on all controls can be found in appendix table 3.21.

Preferences for Choice and Big-Five Personality Traits

Beyond our pre-registered analysis of the correlation of preferences for choice with political preferences and personal attitudes towards decision-making, the GIP data allow us to explore heterogeneity in terms of the Big Five personality traits: Extraversion, Neuroticism, Openness, Conscientiousness, and Agreeableness. Table 3.8 presents the regression results.[30] We find that, in the one-stage treatment, higher levels of Openness are associated with a slightly lower probability of choosing the first lottery. In the two-stage treatment however, higher levels of Openness are associated with a higher probability of choosing the first lottery. This conclusion continues to hold when including the order effect induced by presenting different alternatives first and the usual set of controls. The other personality traits do not display any significant effects on first alternative choices. High levels of openness are generally related to creativity, curiosity, and a desire for breaking up routines (John et al., 2008). Thus, a potential interpretation of the regression results is that, more open-minded participants might be more likely to choose the preselected alternative because it is a welcome change compared to having to make their own decisions.

As a robustness check, we again repeat the regression analysis on the subsample of those participants with response times above the 25th percentile of response times in the one-stage treatment or the first stage of the two-stage treatment respectively (appendix tables 3.24 and 3.25). In all specifications sign and significance of the coefficients of interest remain unchanged. The effect of Openness in the two-stage treatment is even larger in magnitude than in the regressions for the overall sample.

Because high Openness has been shown to increase the probability of voting left-wing (see Gerber et al., 2011 for a review of the relationship between the Big Five personality traits and political attitudes), we also estimate a specification which includes both the classification into left- and right-wing and the Big Five as explanatory variables (appendix table 3.26). We find that both those leaning towards the right and those more open-minded are more likely to choose the first lottery.

[30]The full table including the coefficients on all controls can be found in appendix table 3.22. We also estimate a Probit regression (appendix table 3.23). The sign and significance of the coefficients of interest remain unchanged.

Table 3.8: Lottery choice and Big Five personality traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	−0.009	−0.087	0.002
	(0.121)	(0.122)	(0.139)
Extraversion	−0.004	−0.003	0.003
	(0.011)	(0.011)	(0.012)
Agreeableness	−0.002	−0.005	−0.006
	(0.013)	(0.013)	(0.014)
Conscientiousness	−0.002	−0.003	0.011
	(0.014)	(0.013)	(0.016)
Neuroticism	−0.005	−0.004	−0.019
	(0.012)	(0.011)	(0.013)
Openness	-0.022^{*}	-0.020^{*}	−0.016
	(0.011)	(0.011)	(0.012)
Two-stage treatment * Extraversion	−0.001	−0.0004	−0.007
	(0.017)	(0.017)	(0.019)
Two-stage treatment * Agreeableness	−0.010	−0.002	−0.005
	(0.020)	(0.020)	(0.022)
Two-stage treatment * Conscientiousness	0.023	0.023	0.002
	(0.020)	(0.020)	(0.023)
Two-stage treatment * Neuroticism	−0.025	−0.027	−0.010
	(0.018)	(0.017)	(0.019)
Two-stage treatment * Openness	0.049^{***}	0.046^{***}	0.040^{**}
	(0.016)	(0.016)	(0.018)
Constant	0.357^{***}	0.545^{***}	0.478^{***}
	(0.081)	(0.082)	(0.096)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,888	3,888	3,065
R^2	0.027	0.065	0.070
Adjusted R^2	0.024	0.061	0.064

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being “A presented first”. The additional control variables include gender, age, income, and education.
Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

3.5 A Structural Model

Consider a structural choice model with individual risk aversion and an individual willingness to pay for choice, both parameterized. Assume that individuals care about monetary payoffs x and choice sets S.

When choosing an alternative from a choice set with $\#S \geq 2$, the individual cares only about the monetary payoff x of the alternatives. The utility from the outcome x is given by a constant relative risk aversion (CRRA) utility function

$$u(x) = \begin{cases} \frac{x^{1-r}}{1-r} \text{ if } r \neq 1 \\ \ln(x) \text{ if } r = 1 \end{cases} \tag{3.1}$$

with r being the coefficient of relative risk aversion. If $r = 0$ the individual is risk-neutral, if $r > 0$ the individual is risk-averse, and if $r < 0$ the individual is risk-seeking. We assume that r is distributed normally with mean μ_r and variance σ_r^2.

However, when choosing between two choice sets, the relative size of the choice sets plays a role. More specifically, assume that the utility of an outcome x of a lottery that is presented as the singleton is

$$U(x, v) = u((1-v)x) \tag{3.2}$$

where $v < 1$ expresses the extent to which an individual is willing to pay for choosing from the larger set with $\#S = 2$. It can be interpreted as the percentage change in valuation of all outcomes of a lottery when it is the singleton compared to when it is part of a larger choice set. Thus $1 - v > 0$ becomes a scaling factor of the payoff x of an alternative in the smaller choice set. When $1 - v < 1$, the payoffs from a lottery are valuated lower when it is the singleton compared to when it is part of a larger choice set, while when $1 - v > 1$, they are valuated higher.

Because $v \in (-\infty, 1)$ we assume that $1 - v$ follows a log-normal distribution with parameters μ_v and σ_v.[31] The mean and variance of $1 - v$ are given by

$$\mathbb{E}[1-v] = \exp\left(\mu_v + \frac{1}{2}\sigma_v^2\right)$$

[31] We pre-registered a model with a normally distributed value of choice. Note that because $1 - v$ is log-normally distributed, $\log(1 - v)$ is normally distributed. It is possible to alternatively model the value of choice by an additive parameter d in the utility function, such that $U(x, d) = u(x) + d$ and $d \sim N(\mu_d, \sigma_d)$. Then however the value of choice is measured in utility units, not in monetary units, which makes the interpretation of the value of choice more difficult. The main result, i.e. that the mean value of choice μ_d is negative, however remains the same in this model specification.

and

$$\mathrm{Var}[1-v] = \exp\left(2\mu_v + \sigma_v^2\right)\left(\exp(\sigma_v^2) - 1\right)$$

and hence the standard deviation of $1 - v$ is

$$\mathrm{sd}[1-v] = \exp\left(\mu_v + \frac{1}{2}\sigma_v^2\right)\sqrt{\exp(\sigma_v^2) - 1}.$$

We assume that r and v are stochastically independent.

In the following analysis, we will focus on the baseline choice set containing the three increasingly risky lotteries $\{A, B, C\}$, with a sample size of $n = 2,661$.[32]

3.5.1 Estimating Risk Aversion

First consider the one-stage treatment, where participants do not choose between choice sets, but only between alternatives in the entire set. In that case, risk aversion alone matters for the decision between the three lotteries A, B and C.

Consider the constant relative risk aversion utility function $u(x)$ as defined in 3.1. Then, participants derive expected utility

$$EU(L, H) = \frac{1}{2}(u(L) + u(H)) \tag{3.3}$$

from a fair lottery $X = (L, H)$.

For each binary choice between two lotteries, we calculate the value of r for which the lotteries yield the same expected utility. Let $\tilde{r}_{AB}$ denote the threshold risk aversion coefficient at which an individual is exactly indifferent between lotteries A and B, and let $\tilde{r}_{BC}$ denote the threshold risk aversion coefficient at which an individual is exactly indifferent between lotteries B and C. For the baseline choice set, the thresholds are given by $\tilde{r}_{AB} = 0.91$ and $\tilde{r}_{BC} = 0.43$. Thus, in the one-stage treatment, an individual i with $r_i > \tilde{r}_{AB}$ chooses A, an individual with $\tilde{r}_{BC} < r_i < \tilde{r}_{AB}$ chooses B, and an individual with $r_i < \tilde{r}_{BC}$ chooses C. Let $y_i \in \{A, B, C\}$ denote the lottery choice of individual i. Then, the probabilities of choosing each alternative in the one-stage treatment are given by

$$P(y_i = A) = P(r_i > \tilde{r}_{AB}) = \Phi\left(\frac{\mu_r - \tilde{r}_{AB}}{\sigma_r}\right)$$

[32] Recall that in the additional choice set containing four alternatives $\{A, B, C, D\}$, a considerable share of participants chose alternative A or B, although these are strictly dominated by alternative D. These choices cannot be explained by expected utility theory, such that we exclude this choice set from the further analysis.

$$P(y_i = B) = P(\tilde{r}_{BC} < r_i < \tilde{r}_{AB}) = \Phi\left(\frac{\tilde{r}_{AB} - \mu_r}{\sigma_r}\right) - \Phi\left(\frac{\tilde{r}_{BC} - \mu_r}{\sigma_r}\right)$$

$$P(y_i = C) = P(r_i < \tilde{r}_{BC}) = \Phi\left(\frac{\tilde{r}_{BC} - \mu_r}{\sigma_r}\right)$$

where Φ denotes the cumulative distribution function (CDF) of the standard normal distribution.

The likelihood of an individual observation y_i given the parameters μ_r and σ_r is, in the one-stage treatment

$$\ell_{1i}(\mu_r, \sigma_r) = P(y_i = A)^{\mathbb{1}\{yi=A\}} P(y_i = B)^{\mathbb{1}\{yi=B\}} P(y_i = C)^{\mathbb{1}\{yi=C\}}$$

where $\mathbb{1}\{\cdot\}$ denotes an indicator function for the choice of individual i.

Hence, the sample log-likelihood function for the one-stage treatment is

$$L_1(\mu_r, \sigma_r) = \sum_{i=1}^{n_1} \log\left(\ell_{i1}(\mu_r, \sigma_r)\right)$$

where n_1 denotes the sample size in the one-stage treatment. Maximizing $L_1(\mu_r, \sigma_r)$ with respect to μ_r and σ_r allows us to estimate the distribution of risk aversion in the one-stage treatment.

3.5.2 Estimating the Value of Choice

In the two-stage treatment, an individual's lottery choice is affected by both her risk aversion and her value of choice. Therefore, the choice probabilities differ depending on which alternative is presented as the singleton. Consider first the case where A is presented as the singleton and $\{B, C\}$ is the choice set to choose from in the second step. The optimal choice can be derived using a backward induction logic. In the second step, only risk aversion matters for the choice between B and C, i.e. an individual i with a risk aversion coefficient r_i chooses B over C if $r_i > \tilde{r}_{BC}$ and C otherwise. Then in the first step, when the individual chooses between the singleton and the set with $\#S = 2$, her expected utility from the singleton is affected by her value of choice v_i. Hence if $r_i > \tilde{r}_{BC}$, the individual chooses A if $EU(A, v_i, r_i) > EU(B, r_i)$ and B otherwise. Similarly, $r_i < \tilde{r}_{BC}$, the individual chooses A if $EU(A, v_i, r_i) > EU(C, r_i)$ and C otherwise.

To derive the thresholds of the scaling factor $1 - v$ for which individual i chooses the singleton A, consider first the case where $r_i > \tilde{r}_{BC}$ and assume $r_i \neq 1$. Then the individual chooses A if and only if

$$\frac{1}{2}\left[\frac{((1-v_i)L_A)^{1-r_i}}{1-r_i} + \frac{((1-v_i)H_A)^{1-r_i}}{1-r_i}\right] > \frac{1}{2}\left[\frac{L_B^{1-r_i}}{1-r_i} + \frac{H_B^{1-r_i}}{1-r_i}\right]$$

$$\Leftrightarrow 1 - v_i > \left(\frac{L_B^{1-r_i} + H_B^{1-r_i}}{L_A^{1-r_i} + H_A^{1-r_i}}\right)^{\frac{1}{1-r_i}}$$

Note that if $r_i = 1$, the individual chooses A if and only if

$$\frac{1}{2}\left[\ln((1-v_i)L_A) + \ln((1-v_i)H_A)\right] > \frac{1}{2}\left[\ln(L_B) + \ln(H_B)\right]$$

$$\Leftrightarrow 1 - v_i > \sqrt{\frac{L_B H_B}{L_A H_A}}$$

Hence an individual with $r_i > \tilde{r}_{BC}$ chooses alternative A if and only if $1 - v_i > \nabla_{AB}(r_i)$ where

$$\nabla_{AB}(r_i) = \begin{cases} \left(\frac{L_B^{1-r_i}+H_B^{1-r_i}}{L_A^{1-r_i}+H_A^{1-r_i}}\right)^{\frac{1}{1-r_i}} & \text{if } r_i \neq 1 \\ \sqrt{\frac{L_B H_B}{L_A H_A}} & \text{if } r_i = 1 \end{cases}$$

Analogously, an individual with $r_i < \tilde{r}_{BC} < 1$ chooses alternative A if and only if $1 - v_i > \nabla_{AC}(r_i)$ where

$$\nabla_{AC}(r_i) = \left(\frac{L_C^{1-r_i} + H_C^{1-r_i}}{L_A^{1-r_i} + H_A^{1-r_i}}\right)^{\frac{1}{1-r_i}}.$$

Then, the probability of choosing A in the two-stage treatment when A is presented as the singleton is

$$\begin{aligned} P_A(y_i = A) &= P(r_i > \tilde{r}_{BC} \cap 1 - v_i > \nabla_{AB}(r)) + P(r_i < \tilde{r}_{BC} \cap 1 - v_i > \nabla_{AC}(r)) \\ &= \int_{\tilde{r}_{BC}}^{\infty}\int_{\nabla_{AB}(r)}^{\infty} f_{V,R}(v,r)\mathrm{d}v\mathrm{d}r + \int_{-\infty}^{\tilde{r}_{BC}}\int_{\nabla_{AC}(r)}^{\infty} f_{V,R}(v,r)\mathrm{d}v\mathrm{d}r \\ &= \int_{\tilde{r}_{BC}}^{\infty}\int_{\nabla_{AB}(r)}^{\infty} f_V(v)\mathrm{d}v f_R(r)\mathrm{d}r + \int_{-\infty}^{\tilde{r}_{BC}}\int_{\nabla_{AC}(r)}^{\infty} f_V(v)\mathrm{d}v f_R(r)\mathrm{d}r \\ &= \int_{\tilde{r}_{BC}}^{\infty} \left[1 - F_V(\nabla_{AB}(r))\right] f_R(r)\mathrm{d}r + \int_{-\infty}^{\tilde{r}_{BC}} \left[1 - F_V(\nabla_{AC}(r))\right] f_R(r)\mathrm{d}r \end{aligned}$$

where $F_V(\cdot)$ denotes the CDF of $1-v$, $f_V(\cdot)$ denotes the corresponding density function of

$1-v$, $f_R(\cdot)$ denotes the density function of r, and $f_{V,R}$ denotes the joint density function of v and r. Note that the third line follows from the assumption that v and r are independent.

Similarly, the probability of choosing B in the two-stage treatment when A is presented as the singleton is

$$\begin{aligned} P_A(y_i = B) &= P(r_i > \tilde{r}_{BC} \cap 1 - v_i < \nabla_{AB}(r_i)) \\ &= \int_{\tilde{r}_{BC}}^{\infty} \int_{0}^{\nabla_{AB}(r)} f_{V,R}(v,r)\mathrm{d}v\mathrm{d}r \\ &= \int_{\tilde{r}_{BC}}^{\infty} F_V\left(\nabla_{AB}(r)\right) f_R(r)\mathrm{d}r \end{aligned}$$

and the probability of choosing C in the two-stage treatment when A is presented as the singleton

$$\begin{aligned} P_A(y_i = C) &= P(r_i < \tilde{r}_{BC} \cap 1 - v_i < \nabla_{AC}(r)) \\ &= \int_{-\infty}^{\tilde{r}_{BC}} \int_{0}^{\nabla_{AC}(r)} f_{V,R}(v,r)\mathrm{d}v\mathrm{d}r \\ &= \int_{-\infty}^{\tilde{r}_{BC}} F_V\left(\nabla_{AC}(r)\right) f_R(r)\mathrm{d}r. \end{aligned}$$

Then, the likelihood of an individual observation y_i in the two-stage treatment with A as singleton is given by

$$\ell_{2Ai}(\mu_r, \sigma_r, \mu_v, \sigma_v) = P_A(y_i = A)^{\mathbb{1}\{yi=A\}} P_A(y_i = B)^{\mathbb{1}\{yi=B\}} P_A(y_i = C)^{\mathbb{1}\{yi=C\}}$$

where again $\mathbb{1}\{\cdot\}$ denotes an indicator function for the choice of individual i.

For the other two treatments, where B and C are presented as the singleton, the choice probabilities are calculated in an analogous manner, yielding the likelihood functions $\ell_{2Bi}(\mu_r, \sigma_r, \mu_v, \sigma_v)$ and $\ell_{2Ci}(\mu_r, \sigma_r, \mu_v, \sigma_v)$.

Let $t_i \in \{A, B, C\}$ denote the experimental group allocation of individual i in terms of which alternative is presented to i as singleton. Then, the sample log-likelihood function for the two-stage treatment is

$$\begin{aligned} L_2(\mu_r, \sigma_r, \mu_v, \sigma_v) = \sum_{i=1}^{n_2} &\left[1\{t_i = A\} \log\left(\ell_{2Ai}(\mu_r, \sigma_r, \mu_v, \sigma_v)\right) \right. \\ &+ 1\{t_i = B\} \log\left(\ell_{2Bi}(\mu_r, \sigma_r, \mu_v, \sigma_v)\right) \\ &\left. + 1\{t_i = C\} \log\left(\ell_{2Ci}(\mu_r, \sigma_r, \mu_v, \sigma_v)\right) \right]. \end{aligned}$$

where n_2 denotes the sample size in the two-stage treatment, and where for each i, the log-likelihood function differs according to which treatment i received.

To estimate all parameters of interest, μ_r, σ_r, μ_v and σ_v, we follow a two-step procedure. First, on the subsample with the one-stage treatment, we estimate the parameters of the distribution of risk aversion, $\hat{\mu}_r$ and $\hat{\sigma}_r$, that maximize the sample log-Likelihood $L_1(\mu_r, \sigma_r)$. Under the assumption that the distribution of risk aversion remains the same between the two treatments, we can then use these estimates to estimate the distribution of the value of choice on the subsample of the two-stage treatment. More specifically, we keep $\hat{\mu}_r$ and $\hat{\sigma}_r$ fixed and then maximize the sample log-likelihood function $L_2(\hat{\mu}_r, \hat{\sigma}_r, \mu_v, \sigma_v)$ with respect to μ_v and σ_v. Another possibility is to estimate all four parameters jointly by maximizing the overall log-likelihood function of the entire sample. This procedure is computationally more demanding, and the estimated parameters of the distribution of the value of choice are more volatile with respect to the initial guess. Nevertheless, the estimation yields similar results (appendix tables 3.28 and 3.31).

All algorithms suited to maximize our log-likelihood function require an initial guess, which, if multiple local maxima exist, can strongly affect which maximum the algorithm converges to. To reduce the dependence on the initial guess, we proceed as follows: We repeat the estimation for 100 randomly drawn initial guesses, and then select the estimation results which yield the highest value of the log-likelihood function. Moreover, we validate the estimates by ensuring that different maximization algorithms obtain the same results.

Another approach that does not rely on the assumption that the distribution of risk aversion remains the same between the two treatments is to estimate the parameters μ_r, σ_r, μ_v and σ_v jointly for the subsample of the two-stage treatment only. The estimates for μ_r and σ_r from the one-stage treatment are used only as initial guesses for the estimation on the two-stage sample. The success of this estimation procedure depends even more on the initial guess, but after reducing this dependence by again repeating the estimation for 100 randomly drawn initial guesses, it nevertheless yields similar estimates (appendix tables 3.29 and 3.31).

Note that we have to impose non-negativity constraints on σ_r and σ_v for the maximum likelihood estimation. Therefore, these constrained parameters do not necessarily satisfy asymptotic normality, such that inference based on the asymptotic standard errors obtained from the constrained maximization can be incorrect (Barnett and Seck, 2008). A potential solution is to estimate standard errors by bootstrap instead. However, the bootstrap requires to repeat the maximum likelihood estimation for $1,200$ bootstrap replications. As the maximum likelihood estimation critically depends on the choice of the initial value, several randomly chosen initial guesses are required to make sure that the algorithm converges to the global maximum. Therefore, the bootstrap procedure becomes computationally extremely demanding. We use the bootstrap only as a robustness check for the main results, and otherwise report the asymptotic standard errors obtained from the constrained maximization. We find that the estimated bootstrap standard errors are similar in magnitude. Details on the bootstrap procedure and the estimated bootstrap statistics are explained in appendix section 3.A.3.

3.5.3 Results

Table 3.9 presents the maximum likelihood estimation results.[33] The estimated mean $\hat{\mu}_r$ of the distribution of the risk aversion coefficient r implies that the average participant has an intermediate level of risk-aversion. Because $\tilde{r}_{BC} < \hat{\mu}_r < \tilde{r}_{AB}$, the average participant favors alternative B. From the estimated standard deviation we can derive the 95% confidence interval of r, which is $CI_r^{0.95} = [-0.540, 2.252]$. Hence our sample contains participants who are strongly risk-averse but also risk-seeking participants.

Table 3.9: Results of the structural model estimation for $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$.

Parameter	Estimate	Standard error	p-value
μ_r	0.856	0.024	< 0.001
σ_r	0.712	0.034	< 0.001
μ_v	0.010	0.002	< 0.001
σ_v	0.048	0.010	< 0.001

From the estimated parameters $\hat{\mu}_v$ and $\hat{\sigma}_v$ of the distribution of the scaling factor $1-v$, we can derive further properties of the distribution of $1-v$. The estimated mean $\mathbb{E}[1-v] = 1.012$ indicates that the estimated value of choice v is negative, as expected from the positive treatment effect on first alternative choices. The average individual valuates the outcomes of a lottery 1.2% higher when this lottery is the singleton compared to when it is part of a larger choice set.[34] The estimated standard deviation is $sd[1-v] = 0.049$ and the

[33]The bootstrap simulation results can be found in appendix table 3.27.

[34]Given that the outcomes of the lotteries in our experiment are in the ballpark of 10 euros, the average willingness to pay for not having to choose is around 10 cents. As the median response time for the second stage in the two-stage treatment is 12 seconds, interpreting this value as a measure of opportunity costs would correspond to an hourly net wage of 30 euros, which is not unusual but nevertheless quite

estimated 95% confidence interval of $1 - v$ is $CI^{0.95}_{1-v} = [0.920, 1.111]$. This indicates that participants with a positive value of choice valuate the outcomes of a lottery up to 8% lower when this lottery is the singleton compared to when it is part of a larger choice set, while participants with a negative value of choice valuate them up to 11% higher. Moreover, we estimate $P(1 - v < 1) = 0.411$, indicating that around 41% of the participants have a positive value of choice.

As a robustness check, we repeat the estimation on the subsample of participants with response times equal to or above the 25th percentile. The estimated mean of the scaling factor $1-v$ is slightly lower in this subsample, and the variance is slightly higher (appendix tables 3.30 and 3.31). In this subsample, around 43% are estimated to have a positive value of choice.[35] Thus, all in all, our results indicate that – hidden behind the average treatment effect – there is considerable heterogeneity in terms of the value of choice within our sample.

3.6 Conclusion

In this paper, we investigate whether people enjoy making choices. On the one hand, recommendations might benefit consumers who do not care about making choices themselves. On the other hand, if consumers value choice per se, then even well founded recommendations that are supposedly in the consumer's best interest may trigger opposition, and lead to inferior choices and thus to welfare losses.

The evidence from our experiment yields three main insights. First, a larger share of participants picks the first alternative in the two-stage treatment than in the one-stage treatment, indicating that the majority of participants has a preference for not making

high. We thus conclude that, on average, participants must perceive their choice as costly for additional and different reasons.

[35] Overall, our results indicate that the estimation is robust to restricting the sample to other subsets, as long as the size of the subsamples is sufficiently large. To investigate whether the distribution of the value of choice differs between right-wing and center-left participants, we also ran two estimations on these two subsamples. Restricting the sample to those who are strictly to the right of the median participant's position ($n_{\text{right}} = 500$) however yields unreliable estimation results. In particular, while the estimated mean of $1 - v$ is the same in the right-wing subsample as in the overall sample, the estimated variance of $1 - v$ is very close to zero. The distribution of the left-wing subsample however is very similar to the distribution on the overall sample. Therefore, the combination of the estimated distributions of the two subsamples is hardly compatible with the estimated distribution of the overall sample. We further studied the effect of sample size by randomly creating a subsample of size 500 and repeating the estimation on this subsample as well as on the remaining sample. In this case again the estimated mean remains the same in both samples, but the estimated variance of $1 - v$ is again smaller in the small sample than in the large sample. This exercise indicates that sample size matters for the reliability our estimates.

active choices: They are more likely to choose a particular course of action if that choice requires less steps in their decision making process. Consistent with that, the estimation of our structural model yields a negative mean value of choice. This result indicates that algorithms based on paternalistic or assisted choices can make many individuals better off. It can also explain the widespread use of such technologies in practice.

Second, we find that hidden behind the average treatment effect, there is substantial subject heterogeneity. According to the estimates of our structural model, around 41% of the participants have a positive value of choice, and the value of choice ranges from −11% to 8% of the monetary payoffs of the lottery presented as singleton. This heterogeneity indicates that there is not one choice structure that fits all preferences. On the one hand, consumers with a positive value of choice are better off when they are presented a full range of alternatives and hence suffer substantial welfare losses from a binding preselection of alternatives. On the other hand, those with a negative value of choice benefit from the preselection. Thus, even conditional on the individually preferred alternative being the recommended one, the impact of the choice structure on consumers' decicisons critically depends on their preferences for choice. This result stresses the importance of consumer heterogeneity for those who design recommender systems, and raises the question of whether one can tailor the choice structure to choice preferences.

Our third finding is that measurable individual characteristics correlate with the preference for choice. Such variables are often available to firms or institutions and might be used to adapt the choice structure in order to cater to individuals' preferences – thus opening a path to increase the efficiency of recommender systems beyond the current level.

Moreover, the availability of consumer data allows firms to personalize the recommended alternative in order to match the individual's preferences. Future research might investigate how personalizing the preselected alternative impacts the treatment effect. In our experiment, we randomize which alternative is presented as the singleton. Because participants already exhibit a negative value of choice when the preselected alternative is randomized, the natural conjecture is that the preference for not choosing will increase when the preselected alternative is personalized.

Note

This chapter uses data from the waves 42, 46, 55 and 57 of the German Internet Panel (GIP; DOIs: 10.4232/1.13465, 10.4232/1.13679, 10.4232/1.13874; Blom et al., 2020b, 2021b, 2022).[36] A study description can be found in Blom et al. (2015). The GIP is funded by the German Research Foundation (DFG) as part of the Collaborative Research Center 884 (SFB 884; Project Number 139943784; Project Z1).

[36]Note that GIP wave 57 was not yet published at the time of writing this dissertation. Wave 57 can be found in the GESIS data archive as soon as it is published.

Appendix to Chapter 3

3.A Additional Results

3.A.1 Descriptive Results

Table 3.10: Relative frequencies of choices in the baseline choice set, for all permutations of the three alternatives

Treatment	Permutation	Choice of A	Choice of B	Choice of C
One-stage	$\{A, B, C\}$	0.41	0.35	0.23
	$\{A, C, B\}$	0.43	0.25	0.32
	$\{B, A, C\}$	0.48	0.23	0.29
	$\{B, C, A\}$	0.52	0.16	0.32
	$\{C, A, B\}$	0.55	0.21	0.24
	$\{C, B, A\}$	0.42	0.32	0.26
Two-stage	$\{A\}$ vs $\{B, C\}$	0.50	0.24	0.26
	$\{A\}$ vs $\{C, B\}$	0.50	0.24	0.26
	$\{B\}$ vs $\{A, C\}$	0.37	0.41	0.22
	$\{B\}$ vs $\{C, A\}$	0.33	0.40	0.27
	$\{C\}$ vs $\{A, B\}$	0.46	0.20	0.33
	$\{C\}$ vs $\{B, A\}$	0.40	0.19	0.40

Table 3.11: Relative frequencies of choices in the additional choice set, for all permutations of the four alternatives

Treatment	Permutation	Choice of A	Choice of B	Choice of C	Choice of D
One-stage	$\{C, A, B, D\}$	0.25	0.13	0.13	0.49
	$\{C, A, D, B\}$	0.32	0.05	0.15	0.48
	$\{C, D, A, B\}$	0.31	0.08	0.16	0.45
Two-stage	$\{C\}$ vs $\{A, B, D\}$	0.18	0.11	0.21	0.49
	$\{C\}$ vs $\{A, D, B\}$	0.14	0.08	0.34	0.45
	$\{C\}$ vs $\{D, A, B\}$	0.18	0.06	0.32	0.44

Table 3.12: Robustness check: Relative frequencies of choices in the baseline choice set, for the subsample with response times equal to or above the 25th percentile

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C
One-stage	A	0.39	0.32	0.29
	B	0.50	0.19	0.31
	C	0.48	0.25	0.26
Two-stage	A	0.50	0.26	0.24
	B	0.36	0.39	0.25
	C	0.44	0.20	0.36

Table 3.13: Robustness check: Relative frequencies of choices in the additional choice set with four alternatives, for the subsample with response times equal to or above the 25th percentile

Treatment	Alternative presented first	Choice of A	Choice of B	Choice of C	Choice of D
One-stage	C	0.26	0.08	0.13	0.52
Two-stage	C	0.16	0.08	0.26	0.50

3.A.2 Regression Analysis

Table 3.14: Overview of the variables used in the regression analysis and how they are constructed from the GIP questions

Variable	GIP wave	Description
Age	57	denotes the mid point (in years) of the 14 age categories
Agreeableness	13, 37	average score of the two items on agreeableness from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of agreeableness
Choosing the first alternative	57	binary indicator variable which takes the value 1 if participant chose the alternative presented first
Conscientiousness	13, 37	average score of the two items on conscientiousness from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of conscientiousness
Extraversion	13, 37	average score of the two items on extraversion from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of extraversion
Female	57	binary indicator variable which takes the value 1 if the participant reported to be female
First alternative	57	categorical variable, indicates which alternative was presented first (one-stage treatment) or as singleton (two-stage treatment), with “A first” as the omitted reference category
Group	57	categorical variable for the assignment to the permutation of the three alternatives, with “ABC” as the omitted reference category
High income	55	binary indicator variable which takes the value 1 if the participant’s household income is above the median (i.e. above 3500 Euro)
High-school education	57	binary indicator variable which takes the value 1 if the participant completed the high-school diploma (Abitur)
Neuroticism	13, 37	average score of the two items on neuroticism from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of neuroticism
Ideas	42	binary indicator variable which takes the value 1 if the participant’s level of agreement with the statement “it is important to me to realize my own ideas” is equal to or above the median participant’s level
Independence	42	binary indicator variable which takes the value 1 if the participant’s level of agreement with the statement “it is important to me to work independently” is equal to or above the median participant’s level

Openness	13, 37	average score of the two items on openness from the BFI-10 (where the negatively coded item is re-coded before averaging), ranges from 1 to 5, where higher values mean higher levels of openness
People's decisions	46	binary indicator variable which takes the value 1 if the participant's level of agreement with the statement "the most important political decisions should be made by the people, not by politicians" is above the median participant's level
Right-wing	55	binary indicator variable which takes the value 1 if, on a scale from 1 (left) to 11 (right), the participant reported to be strictly further on the right than the median participant's position (which is 6)
Two-stage treatment	57	binary indicator variable which takes the value 1 if the participant was assigned to the two-stage treatment

Table 3.15: Full Table: OLS regression for lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.116***	0.046	0.062
	(0.018)	(0.038)	(0.040)
Right-wing	−0.025	−0.033	−0.027
	(0.025)	(0.024)	(0.026)
B first		−0.241***	−0.254***
		(0.033)	(0.034)
C first		−0.178***	−0.176***
		(0.035)	(0.037)
C first (additional)		−0.286***	−0.283***
		(0.030)	(0.031)
Female			−0.022
			(0.017)
Age			0.001*
			(0.001)
High-school education			0.014
			(0.018)
High income			−0.006
			(0.017)
Two-stage treatment * right-wing	0.072*	0.076**	0.069*
	(0.039)	(0.038)	(0.040)
Two-stage treatment * B first		0.147***	0.132**
		(0.049)	(0.052)
Two-stage treatment * C first		0.057	0.040
		(0.050)	(0.053)
Two-stage treatment * C first (additional)		0.071	0.047
		(0.044)	(0.047)
Constant	0.252***	0.442***	0.391***
	(0.012)	(0.026)	(0.045)
Observations	3,266	3,266	2,897
R^2	0.021	0.064	0.069
Adjusted R^2	0.020	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.16: Robustness check: OLS regression for lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.116***	0.068	0.098*
	(0.018)	(0.053)	(0.055)
Right-wing	−0.025	−0.033	−0.025
	(0.025)	(0.024)	(0.026)
Group ACB		0.010	0.042
		(0.052)	(0.054)
Group BAC		−0.183***	−0.181***
		(0.049)	(0.051)
Group BCA		−0.286***	−0.280***
		(0.044)	(0.046)
Group CAB		−0.179***	−0.155***
		(0.049)	(0.052)
Group CBA		−0.166***	−0.153***
		(0.050)	(0.052)
Group CABD		−0.292***	−0.265***
		(0.045)	(0.047)
Group CADB		−0.278***	−0.244***
		(0.046)	(0.049)
Group CDAB		−0.272***	−0.274***
		(0.045)	(0.046)
Female			−0.022
			(0.017)
Age			0.001
			(0.001)
High-school education			0.014
			(0.018)
High income			−0.007
			(0.017)
Two-stage treatment * right-wing	0.072*	0.078**	0.069*
	(0.039)	(0.038)	(0.040)
Two-stage treatment * group ACB		−0.045	−0.071
		(0.074)	(0.077)
Two-stage treatment * group BAC		0.046	0.021
		(0.071)	(0.075)
Two-stage treatment * group BCA		0.201***	0.168**
		(0.069)	(0.072)
Two-stage treatment * group CAB		−0.0003	−0.039
		(0.071)	(0.075)
Two-stage treatment * group CBA		0.067	0.046
		(0.072)	(0.076)
Two-stage treatment * group CABD		−0.005	−0.047

		(0.066)	(0.069)
Two-stage treatment * group CADB		0.086	0.015
		(0.068)	(0.072)
Two-stage treatment * group CDAB		0.066	0.065
		(0.067)	(0.070)
Constant	0.252***	0.437***	0.370***
	(0.012)	(0.037)	(0.052)
Observations	3,266	3,266	2,897
R^2	0.021	0.068	0.074
Adjusted R^2	0.020	0.063	0.067

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *Group* is a categorical variable for the permutation of the alternatives in the choice set. The omitted reference category is "group ABC". Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.17: Robustness check: Probit regression for lottery choice and political orientation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.331***	0.106	0.150
	(0.052)	(0.097)	(0.103)
Right-wing	−0.079	−0.113	−0.090
	(0.082)	(0.084)	(0.091)
B first		−0.702***	−0.758***
		(0.100)	(0.108)
C first		−0.491***	−0.487***
		(0.098)	(0.104)
C first (additional)		−0.878***	−0.882***
		(0.093)	(0.099)
Female			−0.071
			(0.051)
Age			0.003*
			(0.002)
High-school education			0.045
			(0.054)
High income			−0.017
			(0.052)
Two-stage treatment * right-wing	0.201*	0.227**	0.205*
	(0.112)	(0.114)	(0.122)
Two-stage treatment * B first		0.463***	0.447***
		(0.137)	(0.148)
Two-stage treatment * C first		0.182	0.140
		(0.136)	(0.144)
Two-stage treatment * C first (additional)		0.310**	0.252*
		(0.127)	(0.136)
Constant	−0.668***	−0.139**	−0.300**
	(0.038)	(0.069)	(0.129)
Observations	3,266	3,266	2,897
Log Likelihood	−1,993.034	−1,920.856	−1,679.567
AIC	3,994.068	3,861.713	3,387.134

Note: Probit regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.18: Robustness check: OLS regression for lottery choice and political orientation on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.112***	0.086**	0.115**
	(0.020)	(0.043)	(0.046)
Right-wing	−0.017	−0.017	−0.021
	(0.028)	(0.028)	(0.030)
B first		−0.200***	−0.203***
		(0.038)	(0.039)
C first		−0.108***	−0.103**
		(0.041)	(0.043)
C first (additional)		−0.253***	−0.242***
		(0.033)	(0.035)
Female			−0.018
			(0.019)
Age			0.001
			(0.001)
High-school education			−0.007
			(0.020)
High income			0.013
			(0.019)
Two-stage treatment * right-wing	0.087**	0.082*	0.091**
	(0.044)	(0.043)	(0.046)
Two-stage treatment * B first		0.114**	0.080
		(0.057)	(0.060)
Two-stage treatment * C first		−0.024	−0.058
		(0.059)	(0.062)
Two-stage treatment * C first (additional)		0.021	−0.020
		(0.050)	(0.052)
Constant	0.237***	0.392***	0.344***
	(0.014)	(0.030)	(0.050)
Observations	2,498	2,498	2,231
R^2	0.023	0.064	0.070
Adjusted R^2	0.021	0.061	0.064

Note: OLS regression, robust standard errors in parentheses. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.19: Robustness check: Probit regression for lottery choice and political orientation on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.328***	0.212*	0.288**
	(0.060)	(0.112)	(0.119)
Right-wing	−0.057	−0.059	−0.071
	(0.095)	(0.098)	(0.106)
B first		−0.600***	−0.624***
		(0.117)	(0.126)
C first		−0.298***	−0.287**
		(0.114)	(0.121)
C first (additional)		−0.816***	−0.798***
		(0.106)	(0.112)
Female			−0.060
			(0.059)
Age			0.003
			(0.002)
High-school education			−0.024
			(0.062)
High income			0.044
			(0.060)
Two-stage treatment * right-wing	0.240*	0.233*	0.258*
	(0.129)	(0.131)	(0.141)
Two-stage treatment * B first		0.383**	0.310*
		(0.159)	(0.171)
Two-stage treatment * C first		−0.040	−0.130
		(0.158)	(0.168)
Two-stage treatment * C first (additional)		0.192	0.086
		(0.147)	(0.156)
Constant	−0.715***	−0.271***	−0.430***
	(0.044)	(0.079)	(0.150)
Observations	2,498	2,498	2,231
Log Likelihood	−1,495.805	−1,441.530	−1,268.998
AIC	2,999.609	2,903.061	2,565.996

Note: Probit regression, robust standard errors in parentheses. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.20: Full table: OLS regression for lottery choice and job motivation

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.121***	0.037	0.060
	(0.031)	(0.044)	(0.049)
Independence	−0.036	−0.041*	−0.030
	(0.022)	(0.022)	(0.024)
Own ideas	0.029	0.024	0.023
	(0.023)	(0.022)	(0.024)
B first		−0.256***	−0.261***
		(0.032)	(0.035)
C first		−0.199***	−0.191***
		(0.033)	(0.037)
C first (additional)		−0.293***	−0.299***
		(0.029)	(0.032)
Female			−0.011
			(0.017)
Age			0.001
			(0.001)
High-school education			0.011
			(0.018)
High income			−0.010
			(0.017)
Two-stage treatment * independence	0.041	0.043	0.038
	(0.033)	(0.032)	(0.036)
Two-stage treatment * own ideas	−0.023	−0.022	−0.029
	(0.034)	(0.033)	(0.037)
Two-stage treatment * B first		0.161***	0.140***
		(0.047)	(0.053)
Two-stage treatment * C first		0.069	0.040
		(0.048)	(0.054)
Two-stage treatment * C first (additional)		0.090**	0.061
		(0.042)	(0.047)
Constant	0.250***	0.455***	0.408***
	(0.021)	(0.031)	(0.048)
Observations	3,638	3,638	2,920
R^2	0.021	0.063	0.069
Adjusted R^2	0.019	0.060	0.064

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Independence* is a binary indicator variable for the importance of working independently. *Own ideas* is a binary indicator variable for the importance of realizing own ideas. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which *C* was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.21: Full table: OLS regression for lottery choice and political decision making

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.123***	0.046	0.050
	(0.019)	(0.037)	(0.041)
People's decisions	−0.022	−0.023	−0.031
	(0.020)	(0.020)	(0.022)
B first		−0.248***	−0.256***
		(0.031)	(0.034)
C first		−0.191***	−0.189***
		(0.032)	(0.036)
C first (additional)		−0.287***	−0.291***
		(0.028)	(0.031)
Female			−0.016
			(0.017)
Age			0.001
			(0.001)
High-school education			0.016
			(0.018)
High income			−0.010
			(0.017)
Two-stage treatment * people's decisions	0.040	0.041	0.053
	(0.031)	(0.030)	(0.034)
Two-stage treatment * B first		0.154***	0.149***
		(0.046)	(0.052)
Two-stage treatment * C first		0.060	0.046
		(0.047)	(0.053)
Two-stage treatment * C first (additional)		0.086**	0.066
		(0.042)	(0.046)
Constant	0.252***	0.445***	0.412***
	(0.013)	(0.026)	(0.045)
Observations	3,721	3,721	2,990
R^2	0.023	0.063	0.070
Adjusted R^2	0.022	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *People's decisions* is a binary indicator variable for whether the participant wants important decisions to be made by the people instead of politicians. *First alternative* captures which alternative was presented first, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.22: Full table: OLS regression for lottery choice and Big Five Personality Traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	−0.009	−0.087	0.002
	(0.121)	(0.122)	(0.139)
Extraversion	−0.004	−0.003	0.003
	(0.011)	(0.011)	(0.012)
Agreeableness	−0.002	−0.005	−0.006
	(0.013)	(0.013)	(0.014)
Conscientiousness	−0.002	−0.003	0.011
	(0.014)	(0.013)	(0.016)
Neuroticism	−0.005	−0.004	−0.019
	(0.012)	(0.011)	(0.013)
Openness	-0.022^{*}	-0.020^{*}	−0.016
	(0.011)	(0.011)	(0.012)
B first		-0.232^{***}	-0.247^{***}
		(0.030)	(0.034)
C first		-0.177^{***}	-0.171^{***}
		(0.032)	(0.036)
C first (additional)		-0.275^{***}	-0.282^{***}
		(0.028)	(0.030)
Female			−0.028
			(0.017)
Age			0.001
			(0.001)
High-school education			0.015
			(0.018)
High income			−0.006
			(0.017)
Two-stage treatment * Extraversion	−0.001	−0.0004	−0.007
	(0.017)	(0.017)	(0.019)
Two-stage treatment * Agreeableness	−0.010	−0.002	−0.005
	(0.020)	(0.020)	(0.022)
Two-stage treatment * Conscientiousness	0.023	0.023	0.002
	(0.020)	(0.020)	(0.023)
Two-stage treatment * Neuroticism	−0.025	−0.027	−0.010
	(0.018)	(0.017)	(0.019)
Two-stage treatment * Openness	0.049^{***}	0.046^{***}	0.040^{**}
	(0.016)	(0.016)	(0.018)
Two-stage treatment * B first		0.142^{***}	0.140^{***}
		(0.046)	(0.051)
Two-stage treatment * C first		0.052	0.025
		(0.046)	(0.052)
Two-stage treatment * C first (additional)		0.076^{*}	0.057

		(0.041)	(0.045)
Constant	0.357***	0.545***	0.478***
	(0.081)	(0.082)	(0.096)
Observations	3,888	3,888	3,065
R^2	0.027	0.065	0.070

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which *C* was always presented first.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.23: Probit regression for lottery choice and Big Five personality traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	−0.065	−0.335	−0.058
	(0.352)	(0.367)	(0.421)
Extraversion	−0.013	−0.011	0.010
	(0.036)	(0.037)	(0.042)
Agreeableness	−0.004	−0.016	−0.020
	(0.042)	(0.043)	(0.049)
Conscientiousness	−0.008	−0.009	0.040
	(0.044)	(0.045)	(0.053)
Neuroticism	−0.015	−0.014	−0.062
	(0.037)	(0.039)	(0.044)
Openness	−0.069**	−0.069*	−0.057
	(0.035)	(0.035)	(0.041)
B first		−0.681***	−0.733***
		(0.093)	(0.105)
C first		−0.494***	−0.472***
		(0.090)	(0.102)
C first (additional)		−0.850***	−0.878***
		(0.086)	(0.096)
Female			−0.087
			(0.053)
Age			0.003
			(0.002)
High-school education			0.048
			(0.054)
High income			−0.017
			(0.051)
Two-stage treatment * Extraversion	0.0001	0.003	−0.020
	(0.049)	(0.050)	(0.057)
Two-stage treatment * Agreeableness	−0.025	−0.004	−0.011
	(0.058)	(0.059)	(0.068)
Two-stage treatment * Conscientiousness	0.064	0.064	−0.002
	(0.060)	(0.061)	(0.070)
Two-stage treatment * Neuroticism	−0.064	−0.069	−0.019
	(0.051)	(0.052)	(0.059)
Two-stage treatment * Openness	0.142***	0.140***	0.122**
	(0.048)	(0.048)	(0.055)
Two-stage treatment * B first		0.451***	0.459***
		(0.127)	(0.144)
Two-stage treatment * C first		0.173	0.097
		(0.125)	(0.141)
Two-stage treatment * C first (additional)		0.325***	0.281**

		(0.117)	(0.132)
Constant	−0.331	0.212	−0.025
	(0.259)	(0.273)	(0.324)
Observations	3,888	3,888	3,065
Log Likelihood	−2,358.123	−2,280.746	−1,782.807
AIC	4,740.245	4,597.493	3,609.613

Note: Probit regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which *C* was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.24: Robustness check: OLS regression for lottery choice and Big Five personality traits on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	-0.229	-0.248^{*}	-0.163
	(0.140)	(0.141)	(0.159)
Extraversion	-0.023^{*}	-0.019	-0.012
	(0.013)	(0.013)	(0.014)
Agreeableness	-0.015	-0.017	-0.021
	(0.015)	(0.015)	(0.017)
Conscientiousness	0.006	0.002	0.007
	(0.016)	(0.016)	(0.018)
Neuroticism	-0.002	-0.001	-0.020
	(0.013)	(0.013)	(0.015)
Openness	-0.035^{***}	-0.032^{**}	-0.023
	(0.013)	(0.012)	(0.014)
B first		-0.197^{***}	-0.205^{***}
		(0.035)	(0.039)
C first		-0.123^{***}	-0.109^{***}
		(0.037)	(0.042)
C first (additional)		-0.252^{***}	-0.251^{***}
		(0.031)	(0.034)
Female			-0.024
			(0.020)
Age			0.001
			(0.001)
High-school education			-0.007
			(0.020)
High income			0.011
			(0.019)
Two-stage treatment * Extraversion	0.020	0.020	0.007
	(0.020)	(0.019)	(0.021)
Two-stage treatment * Agreeableness	0.001	0.008	0.017
	(0.023)	(0.023)	(0.026)
Two-stage treatment * Conscientiousness	0.024	0.025	0.008
	(0.024)	(0.023)	(0.026)
Two-stage treatment * Neuroticism	-0.013	-0.016	0.001
	(0.020)	(0.020)	(0.022)
Two-stage treatment * Openness	0.069^{***}	0.063^{***}	0.052^{**}
	(0.019)	(0.018)	(0.021)
Two-stage treatment * B first		0.092^{*}	0.084
		(0.053)	(0.059)
Two-stage treatment * C first		-0.011	-0.065
		(0.054)	(0.060)

Two-stage treatment * C first (additional)		0.024	−0.011
		(0.046)	(0.051)
Constant	0.454***	0.608***	0.577***
	(0.096)	(0.097)	(0.115)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	2,937	2,937	2,350
R^2	0.029	0.068	0.073
Adjusted R^2	0.025	0.062	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.25: Robustness check: Probit regression for lottery choice and Big Five personality traits on the subsample with response times equal to or above the 25th percentile

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	-0.726^{*}	-0.866^{**}	-0.633
	(0.418)	(0.436)	(0.498)
Extraversion	-0.076^{*}	-0.068	-0.040
	(0.042)	(0.044)	(0.050)
Agreeableness	-0.048	-0.056	-0.073
	(0.051)	(0.052)	(0.060)
Conscientiousness	0.020	0.008	0.028
	(0.052)	(0.055)	(0.062)
Neuroticism	-0.008	-0.004	-0.070
	(0.044)	(0.046)	(0.053)
Openness	-0.114^{***}	-0.109^{***}	-0.080
	(0.042)	(0.042)	(0.049)
B first		-0.594^{***}	-0.627^{***}
		(0.109)	(0.123)
C first		-0.344^{***}	-0.303^{**}
		(0.105)	(0.119)
C first (additional)		-0.817^{***}	-0.824^{***}
		(0.099)	(0.110)
Female			-0.076
			(0.061)
Age			0.003
			(0.002)
High-school education			-0.021
			(0.062)
High income			0.038
			(0.059)
Two-stage treatment * Extraversion	0.070	0.070	0.029
	(0.058)	(0.059)	(0.067)
Two-stage treatment * Agreeableness	0.011	0.033	0.065
	(0.069)	(0.071)	(0.081)
Two-stage treatment * Conscientiousness	0.061	0.067	0.013
	(0.071)	(0.073)	(0.082)
Two-stage treatment * Neuroticism	-0.032	-0.042	0.016
	(0.060)	(0.061)	(0.068)
Two-stage treatment * Openness	0.205^{***}	0.197^{***}	0.163^{**}
	(0.056)	(0.057)	(0.065)
Two-stage treatment * B first		0.326^{**}	0.318^{*}
		(0.149)	(0.168)
Two-stage treatment * C first		-0.002	-0.148
		(0.146)	(0.165)

Two-stage treatment * C first (additional)		0.204	0.114
		(0.136)	(0.152)
Constant	−0.005	0.465	0.349
	(0.315)	(0.331)	(0.397)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	2,937	2,937	2,350
Log Likelihood	−1,744.528	−1,684.156	−1,338.890
AIC	3,513.056	3,404.312	2,721.781

Note: Probit regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. The regression is estimated on the subsample of participants with response times equal to or above the 25th percentile of the one-stage treatment or the first stage of the two-stage treatment. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. AIC is the Akaike information criterion.
Significance levels: *p<0.1; **p<0.05; ***p<0.01

Table 3.26: OLS regression for lottery choice, political attitude, and Big Five personality traits

	Dependent variable:		
	Choosing the first lottery		
	(1)	(2)	(3)
Two-stage treatment	0.027	−0.077	−0.071
	(0.136)	(0.138)	(0.145)
Right-wing	−0.032	-0.041^{*}	−0.039
	(0.026)	(0.025)	(0.027)
Extraversion	0.001	0.004	0.006
	(0.013)	(0.012)	(0.013)
Agreeableness	−0.008	−0.011	−0.017
	(0.015)	(0.014)	(0.015)
Conscientiousness	0.004	0.003	0.009
	(0.015)	(0.015)	(0.016)
Neuroticism	−0.012	−0.013	-0.027^{**}
	(0.013)	(0.013)	(0.014)
Openness	−0.017	−0.019	−0.014
	(0.013)	(0.012)	(0.013)
B first		-0.248^{***}	-0.260^{***}
		(0.033)	(0.035)
C first		-0.179^{***}	-0.175^{***}
		(0.036)	(0.037)
C first (additional)		-0.287^{***}	-0.281^{***}
		(0.030)	(0.032)
Female			-0.039^{**}
			(0.018)
Age			0.001
			(0.001)
High-school education			0.015
			(0.018)
High income			−0.005
			(0.017)
Two-stage treatment *Right-wing	0.081^{**}	0.087^{**}	0.082^{**}
	(0.040)	(0.039)	(0.041)
Two-stage treatment * Extraversion	−0.007	−0.010	−0.007
	(0.019)	(0.018)	(0.019)
Two-stage treatment * Agreeableness	−0.012	−0.005	0.005
	(0.022)	(0.022)	(0.023)
Two-stage treatment * Conscientiousness	0.023	0.022	0.010
	(0.023)	(0.023)	(0.024)
Two-stage treatment * Neuroticism	−0.023	−0.021	−0.010
	(0.020)	(0.019)	(0.020)
Two-stage treatment * Openness	0.037^{**}	0.039^{**}	0.036^{*}
	(0.019)	(0.018)	(0.019)
Two-stage treatment * B first		0.158^{***}	0.144^{***}

		(0.050)	(0.053)
Two-stage treatment * C first		0.064	0.045
		(0.051)	(0.054)
Two-stage treatment * C first (additional)		0.082*	0.057
		(0.045)	(0.047)
Constant	0.355***	0.561***	0.540***
	(0.092)	(0.092)	(0.101)
First alternative	No	Yes	Yes
Controls	No	No	Yes
Observations	3,197	3,197	2,832
R^2	0.025	0.067	0.073
Adjusted R^2	0.021	0.061	0.065

Note: OLS regression, robust standard errors in parentheses. The dependent variable is a binary indicator variable which takes the value 1 if the participant chose the alternative presented first. *Right-wing* is a binary indicator variable for the participant's political position on the left-right spectrum. All personality traits range from 1 to 5, where higher values mean that the participant exhibits a higher level of this personality trait. *First alternative* captures which alternative was presented first and its interaction with the treatment variable, with the omitted reference category being "A presented first". "C first (additional)" denotes the additional choice set with four alternatives in which C was always presented first. Significance levels: *p<0.1; **p<0.05; ***p<0.01

3.A.3 Estimation of the Structural Model

Bootstrap

For the maximum likelihood estimation, we have to impose two inequality constraints on the parameters σ_r and σ_v, which naturally cannot be negative. In that case, although the point estimates of the parameters can be estimated correctly, inference based on the asymptotic standard errors obtained from the constrained maximization can be incorrect (Barnett and Seck, 2008). Therefore, we estimate standard errors by bootstrap. The bootstrap method allows for consistent estimation of the standard errors when asymptotic inference is unreliable, by approximating the distribution of the parameters of interest through Monte Carlo simulation. In particular, we randomly draw with replacement from our sample to create $B = 1,200$ bootstrap samples of the same size n as the original sample. Then we obtain the maximum likelihood estimates of the four parameters for each of the B bootstrap samples. To make sure that the maximum likelihood estimates are reliable, we use 10 randomly drawn initial guesses within each bootstrap replication.[37] We use the estimated bootstrap parameters to construct a bias-corrected estimator, the bootstrap standard errors, and confidence intervals. In particular, let θ denote any parameter of interest, and θ^* its maximum likelihood estimate obtained for the original sample. Let $\{\hat{\theta}_1, ..., \hat{\theta}_B\}$ denote the estimates from the B bootstrap replications. Moreover, let $\overline{\theta}$ denote the arithmetic mean of the B bootstrap estimates. Then, the estimated bootstrap bias-corrected estimator is

$$\tilde{\theta} = 2\theta^* - \overline{\theta}.$$

The bootstrap standard error of the maximum likelihood estimate θ^* is

$$\hat{s}(\theta^*) = \sqrt{\frac{1}{B}\sum_{b=1}^{B}\left(\hat{\theta}_b - \overline{\theta}\right)^2}.$$

Let $\hat{q}(\alpha)$ denote the α-th sample quantile of the statistics $\hat{\theta}-\theta^*$. Then a bootstrap $(1-\alpha)\%$ confidence interval is

$$\hat{C} = \left[\theta^* + \hat{q}\left(\frac{\alpha}{2}\right), \theta^* + \hat{q}\left(1 - \frac{\alpha}{2}\right)\right].$$

[37] Note that especially the estimation of μ_v and σ_v critically depends on the initial guess. Because conducting 12,000 maximum likelihood estimations is computationally already very demanding, we cannot increase the number of initial guesses further. The bootstrap distributions of μ_v and σ_v both exhibit some outliers, indicating that in some cases, the algorithm does not converge to the global maximum. Therefore, the results below should be taken with caution.

Note however that $\hat{C}$ might work poorly when the bootstrap estimates $\hat{\theta}$ are not symmetrically distributed around θ^*, i.e. when the sampling distribution is biased. For further details on the bootstrap procedure and the simulation estimates, see Hansen (2002).

Table 3.27 presents the bootstrap simulation results. We conduct Kolmogorov-Smirnov tests for normality of the bootstrap distribution of each parameter. Although limiting normality is impossible for the constrained σ_r and σ_v parameters, where the non-negativity constraints truncate the limiting distribution, the validity of using asymptotic standard errors might be strengthened if the Kolmogorov-Smirnov tests fail to reject normality (Barnett and Seck, 2008). We find that normality of μ_r, σ_r, and μ_v cannot be rejected ($p = 0.719$, $p = 0.508$, and $p = 0.310$ respectively). For σ_v however normality is rejected ($p = 0.001$). Moreover, the bootstrap results are in line with the previous results based on aymptotic theory: The bootstrap standard errors are similar in magnitude to the asymptotic standard errors, and the bootstrap 95% confidence intervals indicate that μ_v or σ_v are significantly different from zero.

Table 3.27: Estimation results and bootstrap statistics for $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1-v) \sim$ Lognormal(μ_v, σ_v)

Parameter	Maximum likelihood estimate	Bootstrap bias-corrected estimate	Bootstrap standard error	Bootstrap 95% confidence interval
μ_r	0.856	0.892	0.015	[0.793, 0.851]
σ_r	0.712	0.741	0.023	[0.641, 0.729]
μ_v	0.011	0.011	0.002	[0.006, 0.015]
σ_v	0.048	0.053	0.010	[0.026, 0.066]

Robustness Checks

Table 3.28: Joint estimation of all four parameters of $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1-v) \sim$ Lognormal(μ_v, σ_v)

Parameter	Estimate	Standard error	p-value
μ_r	0.863	0.0163	< 0.001
σ_r	0.690	0.024	< 0.001
μ_v	0.011	0.002	< 0.001
σ_v	0.048	0.010	< 0.001

Table 3.29: Separate estimation of $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$ for the one-stage treatment ($n_1 = 1,336$) and the two-stage treatment ($n_2 = 1,325$)

Subsample	Parameter	Estimate	Standard error	p-value
One-stage	μ_r	0.856	0.024	< 0.001
	σ_r	0.712	0.034	< 0.001
Two-stage	μ_r	0.844	0.059	< 0.001
	σ_r	0.878	0.217	< 0.001
	μ_v	0.012	0.004	< 0.001
	σ_v	0.080	0.049	0.094

Table 3.30: Maximum likelihood estimates of $r \sim \mathcal{N}(\mu_r, \sigma_r)$ and $(1 - v) \sim \text{Lognormal}(\mu_v, \sigma_v)$ on the subsample of participants with response times equal to or above the 25th percentile ($n_{25} = 2,015$)

Parameter	Estimate	Standard error	p-value
μ_r	0.830	0.026	< 0.001
σ_r	0.694	0.0377	< 0.001
μ_v	0.009	0.003	< 0.001
σ_v	0.051	0.012	< 0.001

Table 3.31: Properties of the estimated distribution of $1 - v$ for the robustness checks I (joint estimation of all four parameters), II (separate estimation for the one-stage and the two-stage treatment), and III (estimation on the subsample of participants with response times equal to or above the 25th percentile)

Estimation	Mean $\mathbb{E}[1 - v]$	Standard deviation sd$[1 - v]$	95% Confidence interval	$P(1 - v < 1)$
I	1.012	0.051	[0.915 , 1.117]	0.414
II	1.015	0.082	[0.865, 1.184]	0.441
III	1.010	0.051	[0.913, 1.114]	0.430

3.B Experimental Instructions

3.B.1 English Translation of the Instructions and Questions

Instructions

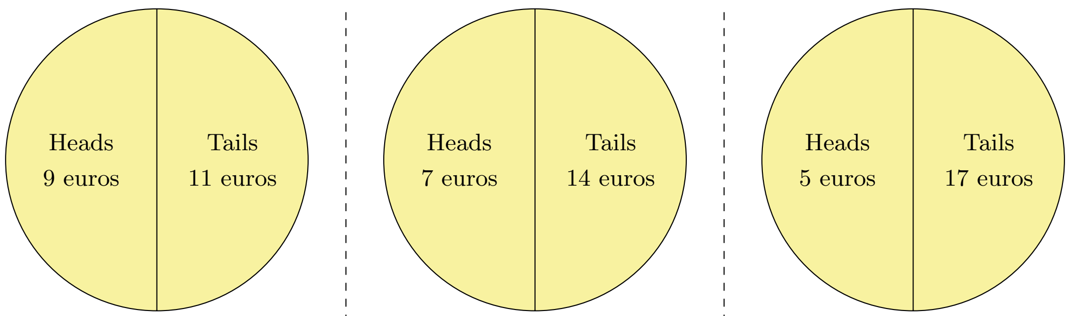
In the following we want to give you the opportunity to win money in a lottery. You will be offered different lotteries to choose from. All you have to do is to choose a lottery. Your potential payoff depends on your own decisions and on chance.

The amounts of money at stake are real. Among those who participate in this study, we will randomly draw 750 people and pay the respective outcomes of the lotteries to the drawn people. All other people will not receive money. Nobody can be drawn more than once. We estimate that approximately 4,000 people will participate in this study. We will notify those who were drawn by April 2022 and transfer the amount to their study account.

One-stage treatment

Below you see the three lotteries to choose from. You can choose exactly one of the three lotteries.

Each lottery is composed of the toss of a fair coin. Therefore each lottery has two possible outcomes – heads or tails. The probability to get heads or tails is equally high for each coin. When the coin shows tails, you will always receive a higher payoff than when the coin shows heads. The lotteries are only different in how high the payoff is for heads or tails respectively.



Lottery A | **Lottery B** | **Lottery C**

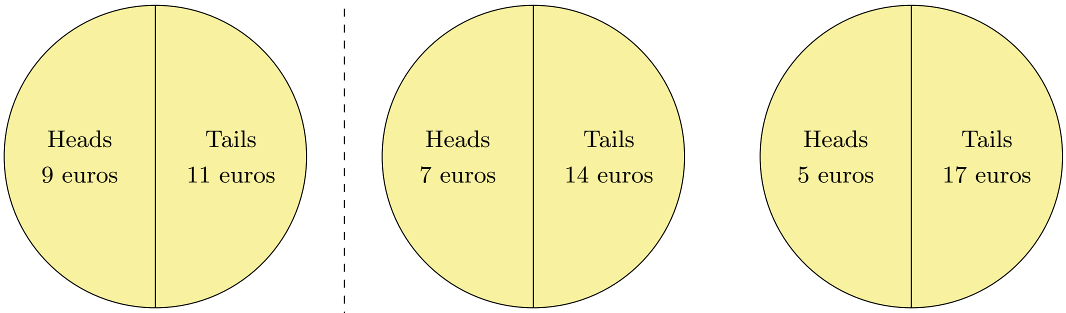
Please choose a lottery now.

- ◯ Lottery A
- ◯ Lottery B
- ◯ Lottery C

Two-stage treatment: Stage 1

Below you see the three lotteries to choose from. You can choose exactly one of the three lotteries. You can choose now whether you immediately take lottery A, or whether you want to make the choice between lottery B and lottery C in the next step.

Each lottery is composed of the toss of a fair coin. Therefore each lottery has two possible outcomes – heads or tails. The probability to get heads or tails is equally high for each coin. When the coin shows tails, you will always receive a higher payoff than when the coin shows heads. The lotteries are only different in how high the payoff is for heads or tails respectively.

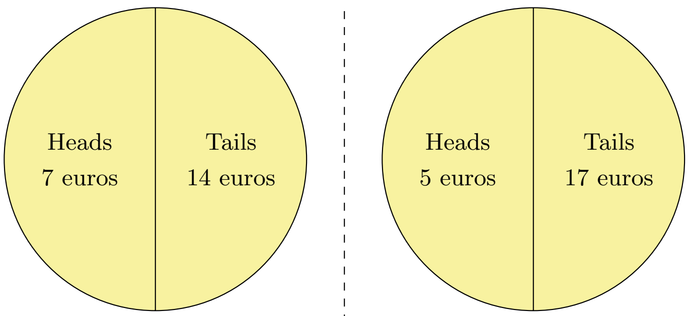


Lottery A **Lottery B** **Lottery C**

Please choose now whether you immediately take lottery A, or whether you want to make the choice between lottery B and lottery C in the next step.

- ◯ I want lottery A immediately.
- ◯ I want to make the choice between lottery B and lottery C in the next step.

Two-stage treatment: Stage 2

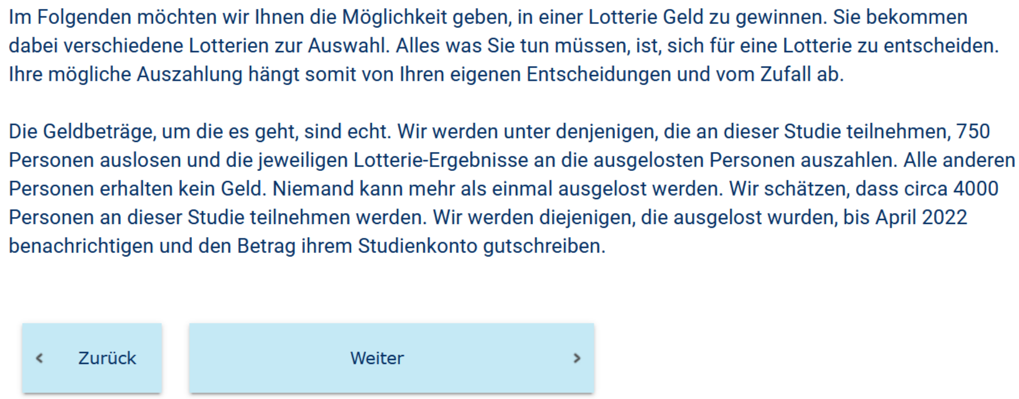


Lottery B **Lottery C**

Please choose a lottery now.

- ◯ Lottery B
- ◯ Lottery C

3.B.2 Screenshots of the Original Instructions and Questions



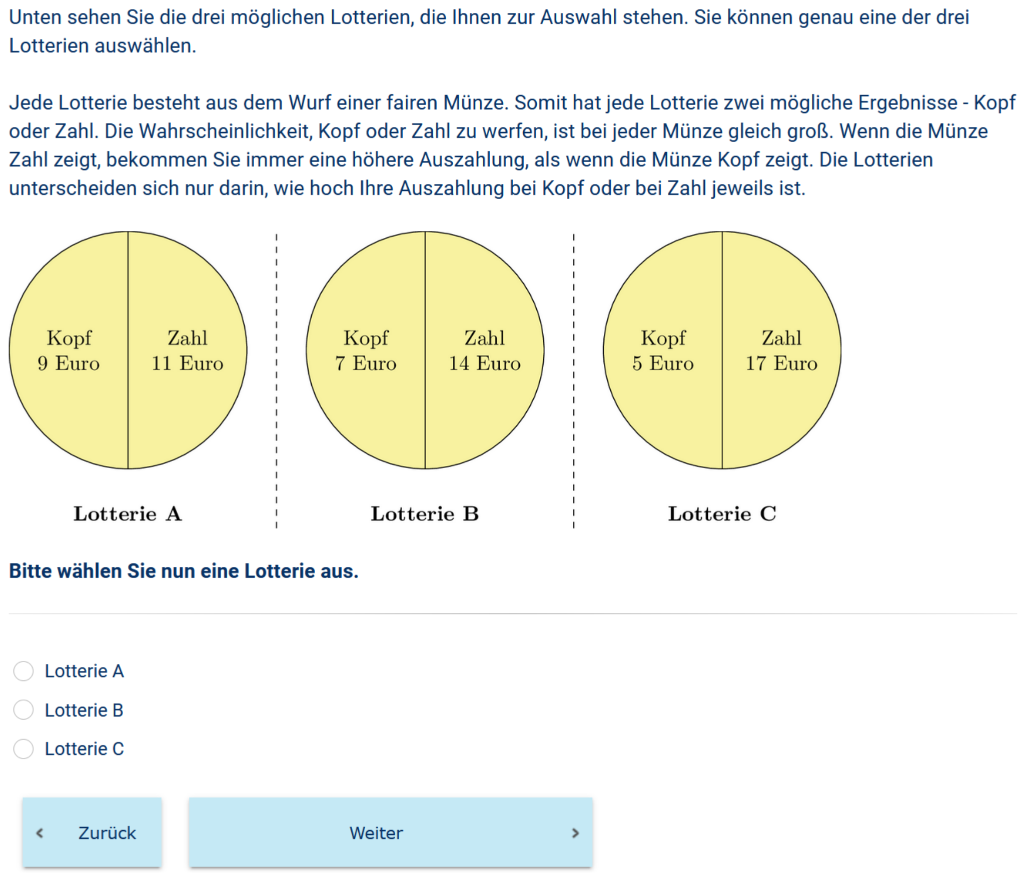
Im Folgenden möchten wir Ihnen die Möglichkeit geben, in einer Lotterie Geld zu gewinnen. Sie bekommen dabei verschiedene Lotterien zur Auswahl. Alles was Sie tun müssen, ist, sich für eine Lotterie zu entscheiden. Ihre mögliche Auszahlung hängt somit von Ihren eigenen Entscheidungen und vom Zufall ab.

Die Geldbeträge, um die es geht, sind echt. Wir werden unter denjenigen, die an dieser Studie teilnehmen, 750 Personen auslosen und die jeweiligen Lotterie-Ergebnisse an die ausgelosten Personen auszahlen. Alle anderen Personen erhalten kein Geld. Niemand kann mehr als einmal ausgelost werden. Wir schätzen, dass circa 4000 Personen an dieser Studie teilnehmen werden. Wir werden diejenigen, die ausgelost wurden, bis April 2022 benachrichtigen und den Betrag ihrem Studienkonto gutschreiben.

‹ Zurück

Weiter ›

Figure 3.3: Instructions



Unten sehen Sie die drei möglichen Lotterien, die Ihnen zur Auswahl stehen. Sie können genau eine der drei Lotterien auswählen.

Jede Lotterie besteht aus dem Wurf einer fairen Münze. Somit hat jede Lotterie zwei mögliche Ergebnisse - Kopf oder Zahl. Die Wahrscheinlichkeit, Kopf oder Zahl zu werfen, ist bei jeder Münze gleich groß. Wenn die Münze Zahl zeigt, bekommen Sie immer eine höhere Auszahlung, als wenn die Münze Kopf zeigt. Die Lotterien unterscheiden sich nur darin, wie hoch Ihre Auszahlung bei Kopf oder bei Zahl jeweils ist.

Bitte wählen Sie nun eine Lotterie aus.

- Lotterie A
- Lotterie B
- Lotterie C

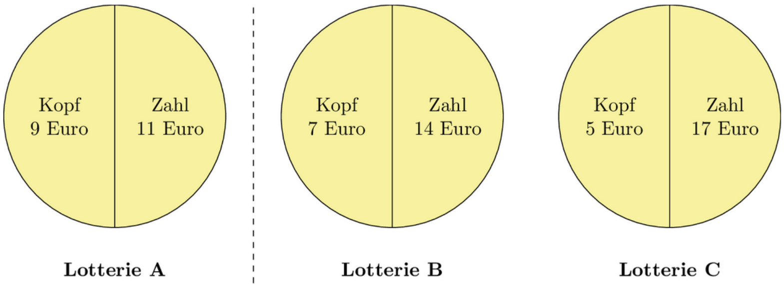
‹ Zurück

Weiter ›

Figure 3.4: One-stage treatment

Unten sehen Sie die drei möglichen Lotterien, die Ihnen zur Auswahl stehen. Sie können genau eine der drei Lotterien auswählen. Sie können nun wählen, ob Sie sofort Lotterie A nehmen, oder ob Sie im nächsten Schritt die Wahl zwischen Lotterie B und Lotterie C treffen möchten.

Jede Lotterie besteht aus dem Wurf einer fairen Münze. Somit hat jede Lotterie zwei mögliche Ergebnisse - Kopf oder Zahl. Die Wahrscheinlichkeit, Kopf oder Zahl zu werfen, ist bei jeder Münze gleich groß. Wenn die Münze Zahl zeigt, bekommen Sie immer eine höhere Auszahlung, als wenn die Münze Kopf zeigt. Die Lotterien unterscheiden sich nur darin, wie hoch Ihre Auszahlung bei Kopf oder bei Zahl jeweils ist.

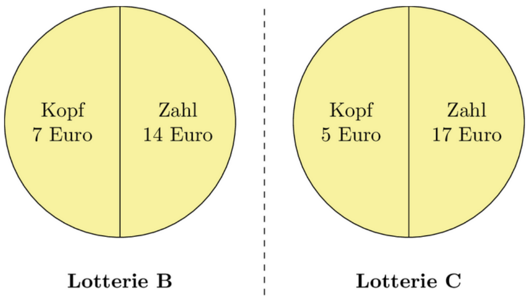


Bitte wählen Sie nun, ob Sie sofort Lotterie A nehmen, oder ob Sie im nächsten Schritt die Wahl zwischen Lotterie B und Lotterie C treffen möchten.

- Ich möchte sofort Lotterie A.
- Ich möchte im nächsten Schritt die Wahl zwischen Lotterie B und Lotterie C treffen.

‹ Zurück | Weiter ›

Figure 3.5: Two-stage treatment: Stage 1



Bitte wählen Sie nun eine Lotterie aus.

- Lotterie B
- Lotterie C

‹ Zurück | Weiter ›

Figure 3.6: Two-stage treatment: Stage 2

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