# Motivated Information Acquisition[*]

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February 22, 2021

**Abstract**

The literature on motivated reasoning argues that people skew their personal beliefs to feel moral when acting selfishly. We study dynamic information acquisition of decision-makers with a motive to form positive moral self-views and a motive to act selfishly. Theoretically and experimentally, we find that individuals "fish for desirable information": they are more likely to continue (stop) acquiring information, having received mostly information suggesting that acting selfishly is harmful (harmless) to others. Empirically, this tendency is stronger among individuals with above-median cognitive ability. We discuss the resulting welfare effects. We relate our results to the literature on interpersonal Bayesian persuasion.

In this paper, we study empirically and theoretically the information acquisition of a decision-maker for whom information might reconcile two motives that govern her utility. In many situations, decisions are guided both by an egoistic motive—a desire to maximize personal gains—and a moral motive. Growing empirical evidence shows that the moral motive is often belief-based: people want to "feel moral", whether their decisions are actually moral or not

[*]For helpful discussions and comments, the authors are grateful to Thomas Dohmen, Lorenz Götte, Lena Janys, Botond Kőszegi, Sebastian Kube, George Loewenstein, Florian Zimmermann, as well as audience at Bonn Applied Micro Workshop, Workshop on Belief-Dependent Preferences (Copenhagen), Workshop on Behavioral Game Theory (Norwich), Workshop on Contracts and Incentives (Munich) and 10th theem on Social Preferences (Konstanz). Funding by the German Research Foundation (DFG) through CRC TR 224, Project A01 (Chen) and Project B03 (Heese) is gratefully acknowledged.

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(for reviews, see Kunda, 1990; Bénabou and Tirole, 2006; Gino *et al.*, 2016).

This motive to feel moral might compete with the individual's egoistic motive if she believes that maximizing her personal gain is detrimental for others. That is, she cannot behave selfishly while feeling moral. However, the individual is not always certain about whether a self-benefiting choice is harmful to others. Under uncertainty, new information brings the chance of reconciling the egoistic and the moral motive since it may suggest that an egoistic decision is also moral.

Examples are numerous where an egoistic motive might conflict with the motive to feel moral: doctors receive commissions for prescribing certain drugs, but prescribing the commissioned drug might harm the patients' health. A human resource manager may have personal preferences for job candidates of certain ethnicity or gender, but hiring decisions based on her personal taste might harm the company's performance and the job candidates' careers. While it is economical to purchase fast fashion products, doing so might support unethical production.

In these situations, systematic biases in information collection may affect the social outcome of decisions. How doctors gather information about the patients' medical needs may affect the suitability of the prescribed drugs. When a human resource manager's personal taste against minority job candidates sways how she informs herself about the candidates' job-related qualities, the hiring outcome is biased. What information consumers acquire about production conditions of goods may affect the prevalence of unethical production.

This paper makes an empirical and a theoretical contribution. First, we use a laboratory experiment to empirically investigate if there are systematic biases in information collection. The controlled laboratory environments allows to address four challenges facing an empirical investigation of information acquisition. First, to pin down the causal effect of having two potentially conflicting motives on information acquisition, exogenous variation in the motives is required. Second, individuals' often unknown and heterogeneous prior beliefs can act as a confounding factor. Third, the access to information and its interpretation are often heterogeneous, confounding the observed information acquisition behavior. Finally, to analyze dynamic patterns, individuals' information histories must be monitored.

Our experiment addresses these challenges. In the experiment, we induce the moral motive by having the subjects make a binary dictator decision. In the dictator decision, one of the two options reduces the payoff of a receiver, while the other does not. The dictator does not know which option is harmful to the other. We fix the dictator's prior belief about the likelihood of each option being the harmful one. We exogenously vary the existence of an egoistic motive by randomly assigning the dictators into two treatments. In one treatment, one option increases the dictator's own payment, and she knows which option is self-benefiting. Thus, the dictator has an egoistic motive to choose the self-benefiting option. In the other treatment, the dictator's payment is not at stake in the dictator decision. This treatment serves as a baseline. Before making the decision, the dictator can acquire information about which option harms the receiver. Information comes in pieces, is free, and the dictator can stop or continue receiving information at any time. The information has a clear Bayesian interpretation, and we provide the dictators with the Bayesian posterior beliefs after each piece of information. To investigate the dynamics of information acquisition, we record the entire information history of each dictator.

Our main empirical result is that having two motives creates a systematic bias in how people collect information, depending on the previous information received. Each piece of information may be either "good news", indicating that behaving selfishly does not harm the other, or "bad news", indicating the opposite. We find that individuals with an egoistic motive are more likely to *continue* acquiring information after having received mostly bad news; and more likely to *stop* after having received mostly good news. We call this phenomenon "fishing for good news". Furthermore, we find that the tendency to fish for good news is stronger among the dictators with a higher cognitive ability, measured by a Raven's matrices test. This result suggests that this information acquisition behavior is unlikely to be due to limited cognitive abilities.

The paper's second contribution is to formulate a novel model of dynamic information acquisition with an agent whose utility is governed by two competing motives. The model allows for analyzing how an agent's information acquisition behaviour depends dynamically on the observed information histories: information arrives continuously, and at every point of time, the agent can decide to either stop or continue observing the incoming information.

We show that the model consistently explains empirical findings regarding information acquisition in the literature of motivated reasoning: its central prediction is in line with the main empirical result in this paper. It can also explain many other findings, such as those in Dana *et al.* (2007), Feiler (2014), and Grossman (2014). Finally, it may also be applied to contexts with other types of competing motives, which we discuss in the paper's concluding remarks.

In the model, the agent derives utility from her material outcome and from her belief about the likelihood of her choice harming others. Such "belief-based utility" can be interpreted in different ways, and we provide a discussion of the interpretations in Section 1.6. The model brings forward the following intuition why individuals "fish for good news". After bad news indicating that the self-benefiting option harms others, a dictator may be inclined not to choose this option, to avoid a low belief-based utility. Then, more information comes in handy. First, if good news arrived, it may revert her decision, so that she chooses the self-benefiting option instead. Second, even if bad news arrived and she decided to forgo the self-benefit, she would be more certain that doing so actually spares the other from harm. Either way, she is better-off acquiring further information. In contrast, when the dictator has received mostly good news indicating that the self-benefiting option is harmless, she may be inclined to capture the self-benefits. Then, collecting further information bears the risk that the self-benefiting option becomes morally unacceptable, an effect discouraging her from acquiring further information.

Additionally, how does the biased information acquisition driven by an egoistic motive affect the welfare of others? In the model, for some agent types, motivated information acquisition *improves* the welfare of others (Appendix B.2). This counter-intuitive result arises from a moral hazard problem: without the egoistic interest, some agent types acquire only a small amount of information, due to satisficing behavior similar to Simon (1955). Having a self-benefiting option can mitigate this moral hazard problem by causing the agent to choose the non-self-benefiting option only when she is more certain that doing so spares others from harm. This behaviour spurs information acquisition. Our experimental data provide evidence consistent with this prediction (Section 3.2.2).

This paper contributes to the literature of motivated beliefs, leveraging techniques from the literature of strategic information transmission. The literature of motivated beliefs argues that individuals desire to hold certain beliefs and manipulate their beliefs in a self-serving way (for reviews, see Kunda, 1990; Bénabou, 2015). In the domain of prosocial behaviour, the literature shows evidence that individuals want to hold a positive moral self-view (for a review, see Gino *et al.*, 2016).

Emphasizing the individuals' discretion in acquiring information, we reveal the phenomenon that individuals fish for desirable information. This finding contributes to the understanding of the formation of motivated beliefs. Previous studies find that individuals react to *exogenous* information in a self-serving manner (Eil and Rao, 2011; Mobius *et al.*, 2014; Gneezy *et al.*, 2020; Falk and Szech, 2019; Exley and Kessler, 2018), have selective *memories* (Zimmermann, 2020), stay willfully ignorant (Dana *et al.*, 2007; Feiler, 2014; Grossman, 2014; Golman *et al.*, 2017; Serra-Garcia and Szech, 2019), and directly manipulate their beliefs in settings *without information* (Di Tella *et al.*, 2015; Haisley and Weber, 2010). In the psychology literature, Ditto and Lopez (1992) document that individuals require less supportive information to reach their preferred conclusion. They argue that this might be due to individuals' overinterpreting preferred information. In comparison, in our empirical investigation, we focus on individuals' use of information acquisition *itself* as an instrument for motivated beliefs, rather than the fact that information deemed more valid leads to a conclusion faster. We do so by showing the experimental subjects the Bayesian posteriors after each piece of information and hence facilitating Bayesian updating.

In the literature of strategic information transmission, this paper particularly draws on the Bayesian persuasion literature (Kamenica and Gentzkow, 2011), which studies information transmission from one individual to another when the latter does not share the same interests as the former. We show that there is an analogy between the model in this paper and models of interpersonal persuasion (see Section 4.2 for a detailed discussion): a decision-maker who acquires information to align two internal motives faces a similar situation as a person who sends information to another individual to align the other individual's belief (and his subsequent choice) with her own interests. Based on this analogy and drawing on the techniques from Bayesian persuasion, our model provides a framework for analyzing an agent's information preferences over all information structures and enables to study the interaction between the information decision and a subsequent prosocial decision of this agent. We apply this framework to guide our empirical investigation on the dynamics of information acquisition.

This paper also relates to the literature of social preferences. This literature studies what drives the prevalent departures from pure self-interest. Research argues that factors such as warm-glow, fairness concerns, and reciprocity are important driving forces of prosocial behavior (Andreoni, 1990; Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000; Charness and Rabin, 2002). Notably, some theories deviate from outcome-based social preferences and argue that psychological factors can drive prosocial behavior, for example cognitive dissonance (Rabin, 1994; Konow, 2000; Spiekermann and Weiss, 2016), the intention to be fair (Falk and Fischbacher, 2006), a desire to signal one's fairness (Andreoni and Bernheim, 2009), a warm glow from the *perceived* social outcomes of one's decision (Niehaus, 2020), and self-image concerns (Grossman and van der Weele, 2017). Relative to the existing literature, our framework allows for the joint analysis of preferences over general information and prosocial choices.

In our framework, the agent prefers some moral beliefs over others.[1] This aspect drives the bias in information acquisition. Many psychological factors in the previous literature share this feature, e.g. self-image concerns (Grossman and van der Weele, 2017), guilt aversion (Battigalli and Dufwenberg, 2007) or moral constraints as in Rabin (1995). We discuss them in Section 1.6.

We organize the rest of the paper as follows: In Section 1, we present the theoretical results and testable predictions. In Section 2, we detail the experimental design. In Section 3, we provide the empirical analysis of information acquisition. In Section 4, we discuss information cost and also the relation to interpersonal Bayesian persuasion. In Section 5, we conclude and propose ideas for future research.

# 1 Optimal Information Acquisition in Theory

We propose a formal model to analyze an agent's information acquisition in a decision where she has an egoistic motive and a motive to believe that her decision is moral. To highlight the effect of the egoistic motive, we also study

[1] The study of belief-based utility has a long tradition in economics (e.g., Loewenstein, 1987; Geanakoplos *et al.*, 1989; Akerlof and Kranton, 2000; Köszegi, 2006).

the scenario in which the egoistic motive is not present.

After stating the main result, we make three points that are important to understand the interplay between the egoistic and the moral motive. Finally, we connect these three points and lay out the formal proof of the main result.

## 1.1 Model

An agent (she) has to make a decision between two options $x$ and $y$. There is an unknown binary state $\omega \in \{X, Y\} = \Omega$ and the prior belief is that the probability of $X$ is $\Pr(X) \in (0, 1)$. A passive agent, whom we hereafter refer to as *the other* (he), can be affected by the agent's decision between $x$ and $y$. When the agent chooses an option that does not match the state, i.e., $x$ in $Y$ or $y$ in $X$, the option has a negative externality of $-1$ on the other and otherwise not.

**Preferences.** The agent's preferences are governed by two motives, First, if choosing $x$, the agent receives a state-independent *remuneration* $r \geq 0$, while she receives no remuneration if choosing $y$. When $r > 0$, the remuneration constitutes an egoistic motive to choose $x$.[2] The case $r = 0$ serves as the benchmark without egoistic motive. Second, the agent has a moral motive. She dislikes the belief that her decision harms the other. We model this as the agent receiving a non-positive utility $u(a, q)$ when she believes that her choice $a$ is harmless for the other agent with probability $q$. We discuss different interpretations of the belief-based utility in detail in Section 1.6. Note that, when the agent believes that state $X$ holds with probability $p$, she believes that $x$ is harmless with probability $q = p$ and that $y$ is harmless with probability $q' = 1 - p$. Then, when she chooses $a \in \{x, y\}$, her utility is given by

$$U(a, p; r) \quad = \quad \begin{cases} u(a, p) + r & \text{if } \ a = x, \\ u(a, 1 - p) & \text{if } \ a = y. \end{cases} \tag{1}$$

The *belief-based utility* $u$ is weakly increasing in the second argument. We let $u(x, 1) = u(y, 1) = 0$. That is, the dictator feels no disutility if she is certain

[2] The remuneration here is a token standing for not only monetary interests but also any private interest that the agent might have. In the example of a discriminatory human resource manager, the private interest can be the utility of her choosing a candidate of her personally preferred gender.

that her choice does not harm the other. We also call $u$ the *(preference) type* of the agent.

**Information and Strategies.** Before deciding between $x$ and $y$, the agent can acquire information about the state at no cost. Let $\mu(\omega) = 0$ if $\omega = X$ and $\mu(\omega) = 1$ if $\omega = Y$. Time is continuous and at every instant in time the agent can observe an *information process* $(Z_t)_{t\geq 0}$ given by $dZ_t = \mu(\omega)dt + dW_t$ where $(W_t)_{t\geq 0}$ is a standard Brownian motion. The posterior probability that the agent assigns to the state $X$ at the time $t$ is

$$p_t = \Pr(\omega = X|(Z_s)_{s\leq t}).$$

At every point of time, the agent can decide to either stop or continue observing the process $(Z_t)_{t\geq 0}$, depending on the information she has already received. When the agent stops at $t \geq 0$, subsequently the agent chooses an action $a$ that maximizes her payoffs, i.e., $a \in \max_{a\in\{x,y\}} U(a, p_t; r)$ and the game ends. Formally, a strategy of the agent is a real-valued stopping time $\tau$ adapted to the natural filtration generated by the information process.

For technical reasons, we restrict the strategies of the agent and impose the "coarseness condition" that the agent has to stop and take a decision when $p_t \leq \epsilon$ or $p_t \geq 1 - \epsilon$, for some positive, but (arbitrarily) small $\epsilon \approx 0$.[3] First, this is to rule out strategies where the agent observes the information process infinitely with positive probability.

## 1.2 Equilibrium Characterization

**Lemma 1** *There are cutoffs $p_l \leq p_0 \leq p_h$, so that the following constitutes a subgame perfect equilibrium: the agent continues to observe the information process as long as $p_l < p_t < p_h$, and stops whenever $p_t \leq p_l$ or $p_t \geq p_h$.*

The proof is in the Appendix. Lemma 1 shows the existence of an equilibrium. To show the lemma, we leverage an insight from the analysis of Bayesian persuasion (Kamenica and Gentzkow, 2011).

Since there are no cost of observing the information process, any Nash equilibrium must maximize $\mathrm{E}(V(p_\tau))$ with $V(p) = \max_{a\in\{x,y\}} U(a, p; r)$ and

[3]In the experiment, posteriors are rounded to two decimal places, so that e.g beliefs below 0.01% are identified with certainty, essentially implementing $\epsilon = 0.01\%$.

where $p_\tau$ is the stopped belief. This implies that all equilibria are pay-off equivalent.

**Lemma 2** *There is a unique subgame perfect equilibrium in which the agent stops observing the information process whenever he is indifferent between stopping and continuing.*

We prove Lemma 2 in the Appendix and show that the equilibrium in Lemma 2 is given by the belief cutoffs $p_l$ and $p_h$ as follows: let $\bar{V}$ be the smallest concave function with $\bar{V}(p) \geq V(p)$ for all $p \in [\epsilon, 1-\epsilon]$. If $\bar{V}(p_0) = V(p_0)$, then $p_h = p_l$. Otherwise, $I = (p_l, p_h)$ is the largest open interval in $[\epsilon, 1-\epsilon]$ with $\bar{V}(p) > V(p)$ for all $p \in I$.

For the ease of exposition, we focus on the equilibrium in Lemma 2 and simply use $p_l$ and $p_h$ to refer to it. One can show that the main result does not depend on this equilibrium selection.

## 1.3 Main Result: Fishing for Good News

The key difference between the scenarios with and without an egoistic motive is that when there is an egoistic motive ($r > 0$), the agent makes a trade-off between the desire for the remuneration and a desire for accurate beliefs. In this section, we analyze how this trade-off affects the agent's behaviour. Our main result, Theorem 1, concerns the effect on the *intensive margin* of information acquisition, i.e., the agent's decision to continue or stop acquiring information once she has started. In Appendix B.3.1, we discuss the *extensive margin* of information acquisition.

In Theorem 1, we consider all types that plan on acquiring some information and use it in a "responsive" way, i.e., choosing $y$ after information indicating that $y$ is harmless to the other, and $x$ after information indicating that $x$ is harmless to the other.[4] The theorem shows that, when $r > 0$, the agent stops and chooses $y$ only at a more extreme belief in $y$ being harmless, i.e., $1 - p_l(r) \geq 1 - p_l(0)$. Conversely, the agent is willing to stop and choose $x$ at a less extreme belief in $x$ being harmless, i.e., $p_l(r) \leq p_l(0)$.

[4]The theoretical analysis in this section focuses on the trade-off between belief-based utility and the remuneration. It turns out that, when $r > 0$, there are types who choose to acquire some information but choose $x$ regardless of the information they receive. However, such behaviour is not driven by a meaningful trade-off between belief-based utility an remuneration.

**Theorem 1** *Take any preference type $u$ and let $\bar{r} > 0$. If it is strictly optimal in equilibrium to choose $y$ at $p_l(r)$ and $x$ at $p_h(r)$ when $r = \bar{r}$ and also when $r = 0$, then*

$$p_h(\bar{r}) \leq p_h(0), \quad (2)$$
$$1 - p_l(\bar{r}) \geq 1 - p_l(0). \quad (3)$$

Theorem 1 reveals an asymmetry. In intuitive terms, (2) shows that to convince herself to choose the remunerative option $x$, the agent needs less information supporting the innocuousness of $x$ (good news). (3) shows that for choosing the non-remunerative option $y$ the agent needs more information opposing the innocuousness of $x$ (bad news). Taken together, the agent "fishes for good news" to choose the remunerative option.

We elaborate the intuition for such behaviour below in Section 1.4 and lay out the proof of Theorem 1 in Section 1.5.

## 1.4 Intuition for Theorem 1

In Section 1.4.1 to 1.4.3, we highlight three points that are important to understand Theorem 1. In Section 1.4.4, we describe the agent's information acquisition strategy in the scenario without egoistic motive, that is when both options are not remunerative. In Section 1.4.5, we illustrate Theorem 1 with an example.

In each of the subsections 1.4.1 to 1.4.3 , we first discuss the point in intuitive terms, and then state a formal result.

### 1.4.1 The Desired Belief

The first point is that, when one option is remunerative, the agent prefers higher beliefs in the state where this option is harmless. This is because, when believing that the remunerative option is harmless to the other, she can capture the reward without having a bad conscience. In contrast, when she believes that the remunerative option is harmful to the other, she has to trade off between a clear conscience and the remuneration—there is a *moral dilemma*.

Formally, let $r > 0$. Recall that in equilibrium, the agent eventually either stops at $p_h$ or $p_l$, and that at $p_h$ she has a higher belief about the likelihood that $x$ is harmless. Similar to the intuition sketched in the previous paragraph, the following result shows that, in equilibrium, the agent is better off when she stops at the higher belief $p_h$ compared to when she stops at $p_l$. The proof is in the Appendix.

**Lemma 3** *For all $r > 0$, the agent chooses $x$ when stopping at the belief $p_t = p_h$. Further, if the agent weakly prefers to choose $y$ when holding the belief $p_t = p_l$, then, $V(p_l) < V(p_h)$.*

In the next two subsections, we analyze at which beliefs the agent stops. In Section 1.4.2, we analyze at which belief $p_l$ the agent stops and chooses $y$. In Section 1.4.3, we analyze at which belief $p_h$ the agent stops and chooses $x$.

### 1.4.2 Waiting for Good News

In the previous subsection we made the point that the agent prefers to believe that the likelihood of the remunerative option being harmless is high. The second point is: when she believes this likelihood to be low so that she is inclined to choose the non-remunerative option, the agent prefers to continue observing the arriving information. One intuitive reason for this behaviour is that she hopes to receive "good news" so that her belief increases making it optimal to choose the remunerative option. The second reason is that even if no good news arrived, her belief in the innocuousness of the non-remunerative option would increase, and so would her belief-based utility when choosing it. In any case, she is better off continuing. Formally, we show the following result.

**Lemma 4** *For all $r > 0$: if the agent weakly prefers to choose $y$ when holding the belief $p_t = p_l$, then, $p_l = \epsilon \approx 0$.*

**Proof.** At each point of time $t \geq 0$, the equilibrium strategy $\tau^*$, given by $p_l$ and $p_h$, maximizes the continuation payoff $\mathrm{E}(V(p_\tau)|(Z_s)_{s\leq t})$,

$$\begin{aligned} \mathrm{E}(V(p_{\tau^*})|(Z_s)_{s\leq t}) &= \frac{p_h - p_t}{p_h - p_l} V(p_l) + \frac{p_t - p_l}{p_h - p_l} V(p_h) \\ &= u(y, 1 - p_l) + \frac{p_t - p_l}{p_h - p_l} \Big[ V(p_h) - V(p_l) \Big], \qquad (4) \end{aligned}$$

where, for the first equality, we used that $\mathrm{E}(p_{\tau^*}|(Z_s)_{s\leq t}) = p_t$ by Bayes-consistency.[5] For the second equality, we used that the agent chooses $y$ at $p_l$, so that $V(p_l) = u(y, 1-p_l)$. We see that the continuation payoff strictly decreases in $p_l$ since the likelihood of reaching $p_h$, that is $\frac{p_t-p_l}{p_h-p_l}$, decreases in $p_l$ and since the utility $u(y, 1-p_l)$ when reaching the lower belief $p_l$, also decreases in $p_l$. We conclude that, unless the agent is certain that $y$ is harmless, she would like to continue observing the arriving information, thus, $p_l = \epsilon$.[6] ■

### 1.4.3 Good Enough News

The third point is that when she believes that the remunerative option is likely to be harmless, then she decides if to stop and choose this option by trading off her belief-based utility with the remuneration: on the one hand, if she continues, her belief in this option being harmless may increase further, allowing her to have a better conscience when choosing it. However, continuing to acquire information bears the risk of observing information that makes the remunerative option unacceptable, i.e., that leads her to update to a low posterior and to choose the non-remunerative option.

Formally, at each point of time $t \geq 0$, the equilibrium strategy $\tau^*$, given by $p_l$ and $p_h$, maximizes the continuation payoff $\mathrm{E}(V(p_\tau)|(Z_s)_{s\leq t})$. From Lemma 4, we take $p_l \approx 0$, so that $\mathrm{E}(V(p_\tau)|(Z_s)_{s\leq t}) \approx \Pr(p_\tau = p_h|(Z_s)_{s\leq t})V(p_h)$. For expositional purposes only, let $u(x,p)$ be continuously differentiable for $q > p_0$. Using $V(p_h) = u(x, p_h) + r$, the first-order condition with respect to $p_h$ is

$$0 = \Pr(p_\tau = p_h|(Z_s)_{s\leq t})\frac{\partial u(x,p_h)}{\partial p_h} + \frac{\partial \Pr(p_\tau = p_h|(Z_s)_{s\leq t})}{\partial p_h}(u(x,p_h)+r), \quad (5)$$

which shows that the agent makes a trade-off between the marginal increase in belief-based utility from stopping at a higher belief $p_h$ and the marginal decrease in the likelihood of stopping at $p_h$, which comes with the remuneration

[5] Given the strategy $\tau^*$, Bayes-consistency implies $\Pr(p_{\tau^*} = p_h|(Z_s)_{s\leq t}) = \frac{p_t-p_l}{p_h-p_l}$ and $\Pr(p_{\tau^*} = p_l|(Z_s)_{s\leq t}) = \frac{p_h-p_t}{p_h-p_l}$.

[6] Recall the technical restriction that the agent has to stop if $p_t = \epsilon$ where $\epsilon \approx 0$ is arbitrarily small.

$r$. Rewriting (5),[7]

$$0 = \frac{\partial u(x, p_h)}{\partial p_h} p_h - (u(x, p_h) + r). \tag{6}$$

Recalling $u(x, 1) = 0$, one sees from (6) that when the marginal increase in belief-based utility is relatively small for high beliefs $p_t \approx 1$, precisely when $\frac{\partial u(x,1)}{\partial p_h} < r$, the agent is willing to stop and choose $x$ before she is certain that $x$ is harmless. One may say that the agent stops when she has received "good enough news".

### 1.4.4 The Scenario Without Egoistic Motive

Next, we turn to the agent's decision between stopping and continuing acquiring information in the benchmark scenario where both options are *not* remunerative. The agent's utility depends solely on her belief about the likelihood that her action does not harm the other. In this scenario, the agent stops acquiring information only when further certainty no longer increases her utility.

For the agent types $u$ with $u' > 0$, the more certain they are that their decision does not harm the other, the higher their utility would be. For these agent types, it is optimal to acquire as much information as possible. Other agent types have a threshold level of certainty. They are content when believing that it is sufficiently likely that they can spare the other from harm. Any further certainty beyond the threshold does not increase their belief-based utility. At the threshold, such types are indifferent between continuing and stopping, so they may as well stop. This behavior mirrors that of satisficing as in Simon (1955).[8]

Formally, the threshold level of certainty is

$$l(a) = \min \{q : u(a, q) = 0\},$$

which implies that $u(a, q) = 0$ for all $q \geq l$, recalling that $\max_q u(a, q) = 0$ and

[7] Recall that $\Pr(p_{\tau^*} = p_h | (Z_s)_{s \leq t}) = \frac{p_t - p_l}{p_h - p_l} \approx \frac{p_t}{p_h}$, so that $\frac{\partial \Pr(p_\tau = p_h | (Z_s)_{s \leq t})}{\partial p_h} \approx -\frac{p_t}{p_h^2}$. Plugging this into (5) gives $\frac{p_t}{p_h} \frac{\partial u(x,p_h)}{\partial p_h} p_h - \frac{p_t}{p_h^2}(u(x, p_h) + r) = 0$, which simplifies to (6).

[8] We are unaware of a literature where the satisficing behaviour concerns beliefs instead of outcomes.

that $u$ is increasing.[9] The following result formally describes the equilibrium when $r = 0$. It shows that the agent acquires information until she reaches her threshold level of certainty $l(a)$, unless $l(a) > 1 - \epsilon$.[10] Here, it may be the case that the threshold level of certainty is already reached at the prior for one of the options, so that she stops directly.

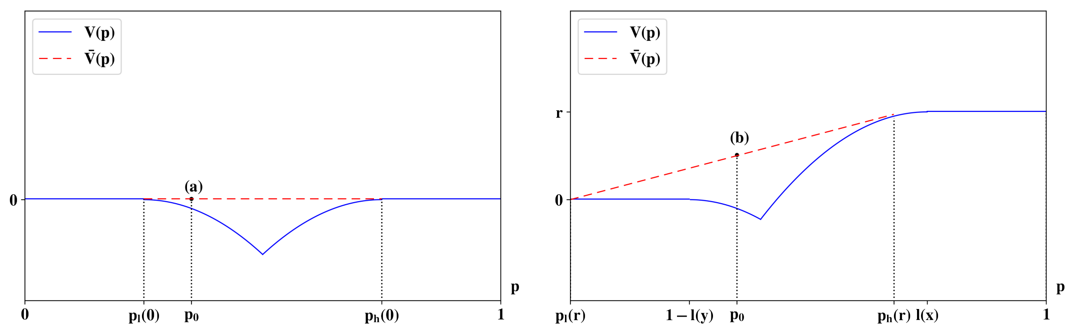
**Lemma 5** *Let $r = 0$. If $\max_{a\in\{x,y\}} l(a) \leq 0.5$ or $p_0 \in (1 - l(y), l(x))^c$, then $p_l = p_0 = p_h$. If $p_0 \in [1 - l(y), l(x)]$, then $p_l = \max\{\epsilon, 1 - l(y)\}$ and $p_h = \min\{l(x), 1 - \epsilon\}$.*

### 1.4.5 Example Illustrating Theorem 1

Figure 1 illustrates the result of Theorem 1 for a type $u$ with threshold level of certainty $l(x) = l(y) = \frac{3}{4}$. In particular, it shows the equilibrium belief cutoffs of this type.

Figure 1: Example

(a) $r = 0$ (b) $r > 0$




The left panel shows the scenario without egoistic motive: the agent acquires information until reaching the threshold level of certainty; the cutoffs are $p_l(0) = 1 - l(y)$ and $p_h(0) = l(x)$. The right panel shows the scenario with egoistic motive: the cutoffs satisfy $p_l(r) \approx 0$ and $p_h(r) < l(x)$. Comparing the cutoffs of both panels, we see that the cutoffs shift when there is an egoistic motive, as the result of Theorem 1 states. The points (a) and (b) highlighted on the dashed lines show the agent's expected payoff $E(V(p_\tau)$ given the prior $p_0$.

[9]The discussion in Section 1.6 explains how the threshold level may be interpreted as a *moral constraint* (Rabin, 1995).

[10]Recall that, for technical reasons, we restrict the agent's strategies, imposing that the agent has to stop at $p_t = \epsilon$ and $p_t = 1 - \epsilon$ for $\epsilon \approx 0$ arbitrarily small.

## 1.5 Proof of Theorem 1

Take any "responsive type" $u$, meaning that it is strictly optimal for the type to choose the option $y$ at the belief $p_l$ and the option $x$ at the belief $p_h$ when $r > 0$ and when $r = 0$. First, recall from Lemma 4 that $p_l(r) = \epsilon$. Hence $p_l(r) \leq p_l(0)$, which shows the second part of Theorem 1, (3).

To show the first part of Theorem 1, (2), first we note that it follows from Lemma 5 that $p_h(0) \in \{1-\epsilon, l(x), p_l(0)\}$. When $p_h(0) = p_l(0)$, the agent is not responsive, so the precondition of the theorem is not fulfilled. It remains to establish that $p_h(r) \leq \min\{1-\epsilon, l(x)\}$. Clearly $p_h(r) \leq 1-\epsilon$ since the agent has to stop at $1-\epsilon$ necessarily. Finally, we show that $p_h(r) \leq l(x)$. Given the definition of $l(x)$ in (7), we know that either $l(x) = 1$ or $\frac{\partial u(x,p)}{\partial p} = 0$ for all $p > l(x)$.[11] If $l(x) = 1$, clearly $p_h(r) \leq l(x)$. For the second case, observe that the derivative of the objective function with respect to $p_h(r)$, which is the left hand side of (6), is strictly negative for any $p > l(x)$ when $r > 0$. This follows since $\frac{\partial u(x,p)}{\partial p} = u(x,p) = 0$ for all $p > l(x)$. Hence, $p_h(r) \leq l(x)$. This finishes the proof of the claim that $p_h(r) \leq \min\{1-\epsilon, l(x)\}$, and thereby the proof of Theorem 1.

## 1.6 Discussion: Belief-Based Utility

This section shows that the belief-based utility in our model can be interpreted in different ways. The key feature of the belief-based utility $u$ is that some beliefs are more desirable than others. Many psychological concepts share this feature: e.g., guilt aversion, self-image concerns or belief-based moral constraints, as we discuss below in detail. We also discuss the related literature.

**Self-Image Concerns.** Bodner and Prelec (2003) propose the notion of "diagnostic utility": an agent's decisions are "diagnostic" about her type. Building on this notion, Grossman and van der Weele (2017) provide a model with self-image concerns in prosocial decisions and a binary information choice. In Appendix B.4, we formulate a variation of the model in Section 1.1 where the belief-based utility $u$ captures self-image concerns and arises in a signalling equilibrium. This model variation follows the existing self-image concern literature in three ways: first, the agent has a continuous prosocial type $\theta \in [0, 1]$

[11] In particular, $l(x) < 1$ implies the continuous differentiability of $u(x,p)$ for $p > l(x)$.

that captures how much she cares about the welfare of the other relative to her own remuneration. Second, she values her prosocial self-image, i.e., her utility depends on her belief about her prosocial type. Third, the final belief together with her action choice are diagnostic about her prosocial type.

We provide sufficient conditions for the existence of a *monotone* equilibrium (Theorem 2 in Appendix B.4): in this equilibrium, the least prosocial types avoid information about their action's consequences altogether. The more prosocial types acquire some information about the state, and the higher their type, the strictly more information they acquire in a Blackwell sense. Hence, agents self-signal high prosociality by stopping at more informative beliefs.

**Moral Constraints.** Rabin (1995) provides a model of moral constraints in which an agent has an exogenous constraint on pursuing her egoistic interest. Specifically, the agent maximizes her self-interest subject to the constraint that her action is not too likely to harm others, captured by a cutoff probability. When the belief-based utility $u(a, q)$ of the model in Section 1.1 takes the following form (7), we may interpret it as capturing such internal moral constraints,[12]

$$u(a,q) = \begin{cases} -w & \text{if } q < l(a), \\ 0 & \text{if } q \geq l(a), \end{cases} \tag{7}$$

where $q$ is the agent's belief about the likelihood that the action is harmless to the other and where $w > r$. The condition $w > r$ ensures that the *moral constraint* $q \geq l(a)$ is binding, meaning that the agent will not choose the self-benefiting option $x$ unless her final belief $q$ satisfies $q \geq l(a)$. The main result Theorem 1 holds for the specification (7).

**Guilt (Aversion).** The belief-based utility $u(a, q)$ from the model in Section 1.1 may capture emotions of guilt. Typically, guilt is formulated as a relative notion in games. That is, the agent's guilt increases in the harm that she inflicts on the receiver, relative to some expectation of the receiver (see e.g., Battigalli and Dufwenberg, 2007). Loosely following the literature,

[12] Rabin (1994) considers the same type of utility function in his analysis.

a guilt formulation of the belief-based utility is[13]

$$u(a,q) = \begin{cases} q - l & \text{if } q < l, \\ 0 & \text{if } q \geq l, \end{cases} \tag{8}$$

where $l \leq 1$ is the "receiver expectation" of not being harmed and $q$ is the agent's belief about the likelihood that the agent's choice $a$ is harmless to the receiver. The main result Theorem 1 holds for the specification (8).

## 1.7 Testable Predictions

In this section, we state two testable predictions that are derived from Theorem 1. These predictions hold whenever a large part of the population is of a "responsive" type. The testable predictions will guide our experimental study on the dynamics of information acquisition presented in Section 2 and 3.

Take an agent whose belief at time $t > 0$ satisfies $p_t < p_0$. Let us compare the belief cutoff $p_l$ of a randomly drawn "responsive" preference type of this agent when $r > 0$, relative to when $r = 0$. Recall that Theorem 1 states that, for all responsive types, $p_l$ is weakly smaller when $r > 0$. Hence, it is more likely that a randomly drawn type has the cutoff $p_l < p_t$ instead of $p_l \geq p_t$. This makes it more likely that a random type continues to acquire information at $t > 0$.

**Model Prediction 1.** Compared to when $r = 0$, when $r > 0$, conditional on having observed information so that $p_t < p_0$, a random agent is more likely to *continue* acquiring further information.

In a similar vein, Theorem 1 implies our second prediction:

**Model Prediction 2.** Compared to when $r = 0$, when $r > 0$, conditional on having observed information so that $p_t > p_0$, a random agent is more likely to *stop* acquiring further information.

Section 2 presents the laboratory experiment.

[13]See e.g., chapter 3.1 in Battigalli and Dufwenberg (forthcoming).

# 2 A Laboratory Experiment With Modified Dictator Games

We conduct a laboratory experiment with modified binary dictator games. All participants have the same initial endowment. Contingent on an unknown state, one of the two options that the dictator has to choose from reduces the payoff of the receiver, while the other option does not reduce the payoff of the receiver. Before deciding, the dictator can acquire information about which option has a negative externality, at no cost.

## 2.1 The Treatment Variations

Our experiment has a $2 \times 2$ design and 4 treatments, as illustrated in Table 1. The treatments vary in two dimensions: The key treatment variation in our experiment is whether one option in the dictator game generates more payoff for the dictator than the other. In the "*Tradeoff*" treatments, one option increases the dictator's payoffs, while the other does not. In the "*Control*" treatments, neither option affects the dictator's payoffs. The comparison between the *Tradeoff* and *Control* pins down the causal effect of having a self-benefiting option on the dictator's information acquisition behavior. We describe the details of this treatment variation below when we present the dictator game.

The second treatment variation concerns the dictator's freedom to acquire no information. It serves two purposes: (i) In the "*NoForce*" treatments, the dictators are *not forced* to acquire any information. These treatments allow us to examine the proportion of dictators who do not acquire any information. However, in these treatments, the dictators who we observe on the intensive margin have self-selected into the information process. (ii) In the "*Force*" treatments, the dictators are *forced* to acquire at least one piece of information before making their decisions in the dictator game. This modification eliminates the confounding effects from potential self-selection into the information process.[14]

[14]We explain in details this (potential) selection effect when we analyze the data in Section 3.

Table 1: Treatments

| | With Self-Reward | No Self-Reward | Shorthand |
|---|---|---|---|
| No Forced Draw | *Tradeoff–NoForce* | *Control–NoForce* | ***NoForce*** |
| One Forced Draw | *Tradeoff–Force* | *Control–Force* | ***Force*** |
| Shorthand | ***Tradeoff*** | ***Control*** | - |

This table presents our four treatments in a two by two design. *Tradeoff* vs. *Control* is our key treatment variation. The dictators in *Tradeoff* can gain additional payment by choosing a particular option in the modified dictator game, while those in *Control* cannot. *Force* vs. *NoForce* differ in that in the former the dictators have to acquire at least one piece of information, while in the latter they can choose to acquire no information.

## 2.2 The Dictator Game

Table 2: Dictator Decision Payment Schemes

(a) *Control* Treatments

| | Good state ($x$ harmless) | Bad state ($y$ harmless) |
|---|---|---|
| $x$ | $(\mathbf{0}, 0)$ | $(\mathbf{0}, -80)$ |
| $y$ | $(0, -80)$ | $(0, 0)$ |

(b) *Tradeoff* Treatments

| | Good state ($x$ harmless) | Bad state ($y$ harmless) |
|---|---|---|
| $x$ | $(+\mathbf{25}, 0)$ | $(+\mathbf{25}, -80)$ |
| $y$ | $(0, -80)$ | $(0, 0)$ |

These tables present the dictator games in the *Control* and *Tradeoff* treatments. The number pairs in the table present (dictator's payment, receiver's payment).

At the beginning of the experiment, all subjects receive 100 experimental points as an endowment. Each experimental point is equivalent to 5 Euro-cents. With this endowment, the subjects play the dictator game. Table 2 presents the payment scheme of the dictator game in the *Tradeoff* and the *Control* treatments respectively. In all treatments, the dictator chooses between two options, $x$ and $y$. There are two states of the world, *"x harmless"* or *"y harmless"*. Depending on the state, either option $x$ or option $y$ reduces a receiver's payment by 80 points, while the respective other option does not affect the receivers' payment. Note that each option harms the receiver in one of the states. This design makes sure that the dictator cannot avoid the risk of harming the receiver without information about the state. In *Control*, the dictator receives no additional points regardless of her choice and the state. In *Tradeoff*, $x$ is self-benefiting for the dictator: she receives 25 additional points when choosing $x$, but no additional points when choosing $y$.

***Good* State vs *Bad* State.** For the ease of exposition, we hereafter refer to state *"x harmless"* as the *"Good state"*, and state *"y harmless"* as the *"Bad state"*. In state $x$ *harmless*, option $x$ increases the dictator's payments without disadvantaging the receiver. Believing that she is in state $x$, the dictator can choose the self-benefiting option $x$ without feeling immoral. In contrast, in state $y$ *harmless*, option $x$ increases the dictator's payment at the cost of a reduction in the receiver's payment. Although this labeling is not meaningful in the *Control* treatments, we will generally refer to *"x harmless"* as the *Good state* and *"y harmless"* as the *Bad state* for consistency.

The dictator starts the experiment without knowing the state that she is in. She only knows that in every twenty dictators, seven are in the *Good state*, and thirteen are in the *Bad state*. That is, the dictator starts the experiment with a prior belief of 35% on that she is in the *Good state* and of 65% on that she is in the *Bad state*. A high prior belief in the *Bad State* strengthens the moral dilemma: choosing the self-benefiting option $x$ without further information most likely harms the receiver.

Before making the decision, the dictator can draw additional information and obtain more accurate beliefs about the state that she is in. We describe the information in the next subsection.

## 2.3 The Noisy Information

We design a noisy information generator for each state, which generates information that is easily interpretable. Specifically, each piece of information is a draw from a computerized box containing 100 balls. In the *Good* state, 60 of the balls are white and 40 are black; in the *Bad* state, 40 balls are white and 60 are black (see Figure 3 in Appendix A.1). The draws are with replacement from the box that matches each dictator's actual state. After each draw, we display the Bayesian posterior belief about the likelihood of each state on the subject's individual computer screen, to reduce the cognitive cost of interpreting the information and to prevent non-Bayesian updating.

**Good News vs. Bad News** For the ease of exposition, we refer to a white ball as a piece of "good news" and a black ball as a piece of "bad news". This is because, in the *Good state*, dictators draw a white ball with a higher probability. Hence, the draw of a white ball leads to an increase in the dictator's belief about the likelihood of the *Good state*, in which the dictator in the *Tradeoff* treatments can choose $x$ and gain the additional payment without reducing the payment of the receiver. Reversely, in the *Bad state*, dictators would draw a black ball with higher probability. A black ball is an evidence for the *Bad* state. In *Control*, we will still refer to a white ball as good news and a black ball as bad news for consistency, although the dictators in *Control* should not have a preference over the two states, hence also not over the color of the balls.

## 2.4 The Experimental Procedure

The experiment consists of three parts: the preparation stage, the main stage, and the supplementary stage.

**The Preparation Stage.** (i) The dictator reads paper-based instructions about the dictator decision and the noisy information. (ii) In these instructions, we also describe Bayes' rule and tell the dictator that later in the experiment, we are going to help them to interpret the information by showing them the Bayesian posterior beliefs after each ball that they draw. (iii) Besides, the instructions specify that each experiment participant starts the experiment with 100 points of an endowment. (iv) We also inform them that option $x$ is harmless for 7 out of 20 of the dictator and $y$ for 13 out of 20. That is, the dictator's prior information is that the Good state has a likelihood of 35% on the *Good* state and that the *Bad* state has a likelihood of 65%.

After reading the instructions, the dictators answer five control questions designed to check their understanding of the instructions. They keep the paper-based instructions for reference throughout the experiment.

**The Main Stage.** In the main stage, (i) the dictators can acquire information about the state that they are individually in; (ii) they choose between $x$ and $y$ in the dictator game.

Specifically, the dictator can acquire a piece of information by clicking a button that makes the computer draw a ball randomly from the box matched to their actual individual state (see Figure 3 in A.1). The draws are with replacement. After each draw, the screen displays the latest ball drawn and the Bayesian posterior beliefs about the *Good state* and the *Bad state* given all the balls drawn so far (rounded to the second decimal, see Figure 4 in Appendix A.1). There are two buttons on the screen: one to draw an additional ball, and the other to stop drawing and proceed to the dictator game. To proceed, the dictator must click on one of the buttons.

In the *NoForce* treatments, the dictator can draw from zero to infinitely many balls. This means she can proceed to the dictator game without drawing any ball, and we do not enforce any maximal number of balls that she can draw. In the *Force* treatments, the dictator must draw at least one ball, and after the first draw, the dictator has full autonomy regarding when to stop drawing just like in *NoForce*. Besides drawing balls, throughout the experiment the dictators have no other way to learn about the true state that they are in. It is common knowledge that the receiver does not learn the information acquired by the dictator.

The draws do not impose any monetary cost on the dictator. The time cost of acquiring information is limited: between draws, there is a mere 0.3 second time lag to allow the ball and the Bayesian posterior belief to appear on the computer screen. It means that a dictator can acquire 100 balls within 30 seconds, which would yield almost certainty.

Having ended the information acquisition, the dictator chooses between $x$ and $y$ in the dictator game in Table 2a (in the *Control* treatments) or Table 2b (in the *Tradeoff* treatments). After that, in the implementation stage, the dictators' choices are implemented and the payments are calculated.

**The Supplementary Stage.** (i) We elicit the dictator's posterior beliefs about the state after the dictator game. The belief elicitation is incentivized.[15] We compare the elicited and the Bayesian posterior beliefs in Appendix A.9. We find that, for a majority of dictators, their elicited posterior beliefs and their Bayesian posterior beliefs coincide, and the deviation is not significantly different between *Tradeoff* and *Control* (two-sided Mann-Whitney-U test, p=0.29). (ii) The subjects take part in the Social Value Orientation (SVO) slider measure, which measures "the magnitude of concern people have for others" and categorizes subjects into altruists, prosocials, individualists, and the competitive type (Murphy *et al.*, 2011). (iii) The subjects answer a questionnaire surveying their socio-demographics, e.g., the gender and age. They also answer a 5-item Raven's progressive matrices test (Raven *et al.*, 1998), which measures cognitive ability. We report the details of the questionnaire and the Raven's test in Appendix A.9.

**Treatment Assignment and Implementation Stage.** We randomize within each laboratory session: (i) the *Tradeoff* and *Control* treatments, (ii) the states: we randomly assign 35% of the laboratory terminals to the *Good state*, and 65% to the *Bad state*. The subjects are then randomly seated and randomly matched in a ring for the dictator game. The subjects are told that their decisions would affect the payment of a random participant in the same experimental session other than themselves. After all the subjects have made their dictator decisions, the experiment moves on to the implementation stage, where we inform the subjects that the dictator game decisions are being implemented and their payments are affected according to another participant's dictator game decision. Each subject plays the dictator game only once.

We conducted the experiment in October and December 2018 at the BonnEconLab (*NoForce* and *Force* treatments respectively). 496 subjects took part (168 in *Tradeoff–NoForce*, 167 in *Control–NoForce*, 82 in *Tradeoff-Force* and 79 in *Control-Force*). Among the subjects, 60% are women, and 93% are students. They are, on average, 24 years old, with the youngest being 16 and the oldest being 69. The subjects are balanced between treatments, concerning gender, student status, and age (see Appendix A.9). We used z-tree (Fischbacher, 2007) to implement the experiment and hroot (Bock *et al.*, 2014) to invite subjects and to record their participation. Instructions and interfaces on the client computers were written in German, as all subjects were native German speakers.

**Payments.** In the experiment, payments are denoted in points. One point equals 0.05 Euro. At the end of the experiment, the details of the points

[15] We incentivize the belief elicitation using the randomized Quadratic Scoring Rule adapted from Drerup *et al.* (2017) and Schlag *et al.* (2013). For the stated belief that the likelihood of the good state is $b$%, we calculate the following value

$$M = \begin{cases} \frac{(b-100)^2}{100} & \text{if} \quad x \text{ is harmless,} \\ \frac{b^2}{100} & \text{if} \quad y \text{ is harmless.} \end{cases} \quad (9)$$

Then, the computer draws a random number $A \sim U[0, 100]$ and the dictator receives 30 points if $A > M$.

and the equivalent payments earned in the experiment are displayed on the individual computer screens. The subjects received payments in cash before leaving the laboratory. The total earnings of a subject were the sum of the following components: an endowment of 5 Euro, an additional 1.25 Euro if the subject was in treatments *Tradeoff* and chose $x$, a 4 Euro reduction if the subject's randomly assigned dictator made a decision that reduces her payments, a random payment of either 1.5 or 0 Euro for revealing their posterior beliefs, a payment ranging from 1 to 2 Euro depending on the subject's decisions in the SVO slider measure, a payment ranging from 0.3 to 2 Euro depending on the decisions in the SVO slider measure of another random subject in the same laboratory session, and a fixed payment of 3 Euro for answering the questionnaire. A laboratory session lasted, on average, 45 minutes, with an average payment of 11.14 Euro.

# 3 Data Analyses

In this section, we present the empirical analyses using data from our experiment. We summarize our data in Appendix A.6 and proceed below with the analyses of the dictators' information acquisition behavior.

## 3.1 Main Finding: Fishing for Good News

The main finding from the experiment is that the dictators in *Tradeoff* behave as if they were "fishing for desirable information": having received predominantly bad news, the dictators in *Tradeoff* are more likely to *continue* acquiring information than those in *Control*; having received predominantly good news, the dictators in *Tradeoff* are more likely to *stop* acquiring information. We provide two analyses showing this behaviour: in Section 3.1.1, we compare the decisions to continue acquiring information after the first draw between *Tradeoff* and *Control*. In Section 3.1.2, we analyze the entire information acquisition histories, leveraging statistical tools from survival analysis.

### 3.1.1 The Effect of the First Piece of Information

To investigate the treatment effect on the dynamics of information acquisition, we first test the treatment effect on the dictators' decision to continue acquiring information after having received one piece of good or bad news respectively. In the experiment, the good or bad nature of the first draw of information is exogenous.[16]

According to whether the first piece of random information they receive is good news or bad news, we separate the dictators into two groups. In each group, we compare between *Tradeoff* and *Control* the dictators' decisions to continue acquiring information right after the first piece of information.

**Finding 1** *After receiving the the first piece of information, (i) if it is good news, significantly less dictators in Tradeoff continue acquiring information than in Control; (ii) if it is bad news, a similar fraction of dictators continue acquiring information in Tradeoff and in Control.*

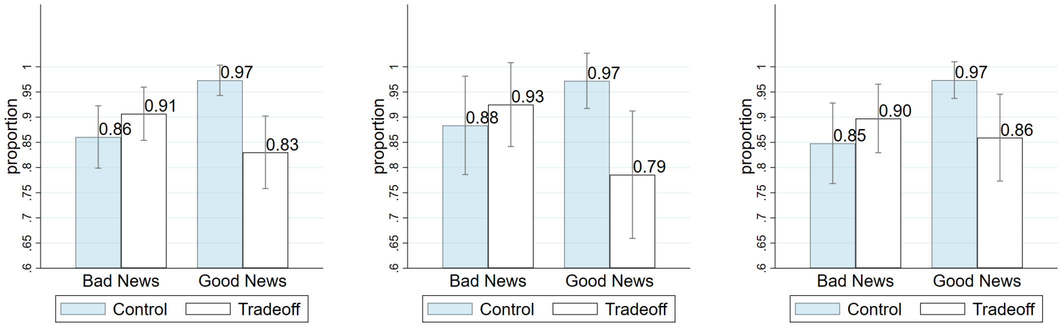
Finding 1 shows that facing a self-benefiting option makes individuals more likely to stop acquiring further information when the previous information indicates the innocuousness of this option. On the opposite, when the previous information suggests that the self-benefiting option harms others, individuals continue acquiring information in a similar way as when no option is self-benefiting. Figure 2 presents the proportions of dictators who continue acquiring information right after the first piece of information. We also find that the difference in the propensity to stop acquiring information after good news and bad news respectively is significantly different between the treatments at the 1% level (probit regression, see table 8 in Appendix A.4).

**Discussion: Self-Selection in *NoForce*.** The dictators in *Force* have to acquire at least one piece of information, while the dictators in *NoForce* do not. The dictators in *NoForce* who do not acquire any information are not included in this analysis. This self-selection out of the information acquisition only happens in *NoForce*. It might explain why Finding 1 is stronger in *Force* than in *NoForce*. In the *NoForce* treatment variation, in *Tradeoff*, 25 out of 26 dictators who do not acquire information choose $x$, while in *Control*, 10 out of 12 dictators who do not acquire information choose $y$. Had these dictators received a further piece of information *supporting* their dictator decisions, i.e., good news in *Tradeoff* and bad news in *Control*, they would also likely stop and take the same decisions, an effect that would strengthen Finding 1.

[16]This is because the composition of the 100 balls in the boxes depends solely on the exogenous state, and the draws are random.

Figure 2: Proportion of Dictators Continuing after the First Draw

(a) Pooled Data (b) *Force* Treatments (c) *NoForce* Treatments




These figures present the proportion of dictators who continue acquiring information after the first draw. ***: $p < 0.01$. Note that in *Control*, the within treatment difference given different first news is due to the asymmetric prior belief of 35% in the *Good* state.

### 3.1.2 The Entire Information Histories

Now we turn to the dictators' entire information acquisition process. Taking *Control* as the baseline, we analyze the dependence of the *Tradeoff* dictators' decision to continue or to stop acquiring information on whether up to that point they have received more good news or more bad news. Our model predicts that having received more good news, dictators in *Tradeoff* are more likely to stop the information acquisition; having received more bad news, dictators in *Tradeoff* are more likely to continue for the information acquisition.

In the framework of a Cox proportional hazard model, we compare the decision to stop acquiring further information between *Tradeoff* and *Control*, given these two types of information histories: the ones with more pieces of good news, and the ones with more pieces of bad news.[17]

In this analysis, the crucial independent variable is whether an information history has more good news or more bad news. Each dictator's information history evolves over time. To be able to include this variable into our analyses, we split each dictator's complete information history at the unit of individual draws.[18] The resulting data set consists of *pseudo-observations* at the person-draw level. For every draw of each dictator, the pseudo-observation records the dictator's information history up to that draw, whether the dicta-

[17]The Cox model has the advantage that the coefficient estimates are easy to interpret. We report a robustness check using the logistic model in Appendix A.3. The results of the logistic model are in line with those of the Cox model.

tor chooses to stop or continue acquiring information directly after that draw, and time-constant characteristics of the dictators such as her identity, treatment assignment, and gender. For each pseudo-observation, we distinguish between information histories with more pieces of good news and histories with more pieces of bad news, using a binary dummy variable.

As for the dependent variable, we are interested in the dictator's *hazard* to stop acquiring information. The Cox proportional hazard model factors the hazard rate to stop acquiring information into a baseline hazard function $h_0(t)$ and covariates $X_t$ that shift the baseline hazard proportionally, as in (10). The baseline hazard function $h_0(t)$ fully captures the time dependency of the hazard.[19]

$$h(t|X_t) = h_0(t) \cdot exp(X_t \cdot b). \tag{10}$$

Our model specification is as follows:

$$h(t|X) = h_0(t) \cdot exp(\beta_1 \text{Tradeoff} + \beta_2 \text{Info} + \beta_{12} \text{Tradeoff} \times \text{Info} + \alpha z_t), \tag{11}$$

where "Tradeoff" is a dummy variable for treatment *Tradeoff*, "Info" is a categorical variable denoting information histories that have more pieces of bad news, good news, or an equal number of bad and good news, with bad news dominance as the baseline, $z_t$ is a control variable that measures the accuracy of the individual belief after each ball drawn.[20] We also control for the differences in cognitive ability (measured by the score in a Raven's matrices test) and prosocial types (categorized by the SVO measure of Murphy *et al.*, 2011) by stratifying the Cox model by these variables (Allison, 2002).[21]

[18]In survival analysis, the method of splitting episodes is often used to obtain time-varying covariates (see Blossfeld *et al.*, 2019, pp 137-152).

[19]Unlike many other regression models, the Cox model naturally includes no constant term, since the baseline hazard function already captures the hazard rate at covariate vector 0 (see for example Cleves *et al.*, 2010).

[20]In the experiment, the prior belief in the Good state is 0.35, a belief smaller than 0.5. Therefore, the posterior belief is more accurate after an information history with $k$ more pieces of bad news than goods news relative to one with $k$ more pieces of good news than bad news. To prevent this difference from being picked up by the Info dummy, we control for information accuracy. For this, we use the (expected) Brier score (Brier, 1950) of the beliefs as a proxy for the accuracy of beliefs: $\text{belief}_{\text{Good}} \times \text{belief}^2_{\text{Bad}} + \text{belief}_{\text{Bad}} \times \text{belief}^2_{\text{Good}}$.

[21]Stratification in the Cox model allows the baseline hazard function $h_0(t)$ to vary with respect to the variables of stratification. As shown in Table 4, after the stratification, our main covariates affect the hazard to stop acquiring information proportionally. That is, the proportional hazard assumption of the Cox model is not violated.

Using this model, we analyze the treatment effect of having a self-benefiting option on the hazard to stop acquiring information when the dictators have received more good news and more bad news respectively.

First, given information histories with more bad news than good news, the between treatment comparison of the stopping hazard can be expressed by the following hazard ratio:

$$\begin{aligned}\text{HR}_{Bad} = \frac{h(t|\text{Bad, Tradeoff } = 1)}{h(t|\text{Bad, Tradeoff} = 0)} &= \frac{exp(\beta_1 \cdot 1 + \beta_2 \cdot 0 + \beta_{12} \cdot 1 \cdot 0 + \alpha z_t)}{exp(\beta_1 \cdot 0 + \beta_2 \cdot 0 + \beta_{12} \cdot 0 \cdot 0 + \alpha z_t)} \\ &= \frac{exp(\beta_1 + \alpha z_t)}{exp(\alpha z_t)} \\ &= exp(\beta_1); \qquad (12)\end{aligned}$$

Recall that in Section 1.7 the model predicts that having received more bad news, the dictators in *Tradeoff* "fish for information". That is, the hazard to stop acquiring information is lower in *Tradeoff* than in *Control* given information histories dominated by bad news, i.e, $\text{HR}_{Bad} < 1$, or equivalently, $\beta_1 < 0$.

Second, the model predicts that having received more good news, dictators in *Tradeoff* have a higher hazard to stop acquiring information than those in *Control*. This comparison is captured by the following hazard ratio:

$$\begin{aligned}\text{HR}_{Good} = \frac{h(t|\text{Good, Tradeoff } = 1)}{h(t|\text{Good, Tradeoff} = 0)} &= \frac{exp(\beta_1 \cdot 1 + \beta_{2,\text{Good}} \cdot 1 + \beta_{12,\text{Good}} \cdot 1 \cdot 1 + \alpha z_t)}{exp(\beta_1 \cdot 0 + \beta_{2,\text{Good}} \cdot 1 + \beta_{12,\text{Good}} \cdot 0 \cdot 1 + \alpha z_t)} \\ &= \frac{exp(\beta_1 + \beta_{2,\text{Good}} + \beta_{12,\text{Good}} + \alpha z_t)}{exp(\beta_{2,\text{Good}} + \alpha z_t)} \\ &= exp(\beta_1 + \beta_{12,\text{Good}}). \qquad (13)\end{aligned}$$

Our model predicts that $\text{HR}_{Good} > 1$. That is, $\beta_1 + \beta_{12,\text{Good}} > 0$.

The coefficient estimates of the Cox model yield Finding 2.

**Finding 2** *(i) Having received more bad news than good news, the dictators are more likely to* ***continue*** *acquiring information in Tradeoff than in Control; (ii) while they are more likely to* ***stop*** *in Tradeoff than in Control, having received more good news than bad news.*

In Table 4 in Appendix A.2, we report the Cox model estimates, with standard errors clustered at the individual level. Column (1) shows that $\beta_1$

is estimated to be $-.29$ ($p = .02$), so that the estimate of $\text{HR}_{Bad} = exp(\beta_1)$ is $exp(-.29) = .75$. This means, given information histories with more bad news, the hazard to stop acquiring information is 25% lower in *Tradeoff* than in *Control*. Column (1) also shows that $\beta_{12,Good}$ is estimated to be .43 ($p = .03$), so that the estimate of $\text{HR}_{Good} = exp(\beta_1 + \beta_{12,Good})$ is $exp(-.29 + .43) = 1.15$. This means, in contrast, given information histories with more good news, the hazard to stop acquiring information is 15% higher in *Tradeoff* than in *Control*. In *Force* and *NoForce*, the results point in the same direction (Table 4).

### 3.1.3 Mechanism

An intuitive explanation of the information acquisition behaviour in Finding 1 and 2 is the following: upon receiving bad news, the dictators in *Tradeoff* may be inclined to choose $y$ and forgo the remuneration that they would receive for choosing $x$. If they continue the inquiry, new information may arrive that reverts their opinion and makes them choose the remunerative option $x$ instead. This possibility encourages them to continue drawing balls. In contrast, when they have received good news and are inclined to behave selfishly, further information may be bad news and revert their current desirable beliefs. This risk discourages them from drawing further information.

This intuition suggests that Finding 1 and 2 are not driven by cognitive limitations. Specifically, the intuition is in line with the model of strategic information acquisition and its predictions in Section 1.1.

**Finding 3** *(i) Having received more bad news than good news, subjects with an above median result in the IQ test are more likely to continue acquiring information in Tradeoff than in Control; (ii) while they are more likely to stop in Tradeoff than in Control, having received more good news than bad news. (iii) Both effects are larger, compared to the average subject.*

In the experiment, when we focus on dictators with a cognitive ability above the median (measured by a Raven's matrices IQ test), we find that the effects in Finding 2 are *larger* than the effects when all dictators are considered.

Specifically, we split the sample at the median of the dictators' cognitive ability and estimate the Cox model as in Finding 2 using the respective data.

We report the details of this analysis in Table 5, Appendix A.2. The estimates of both $\beta_1$ and $\beta_{12,Good}$ are insignificant when the below-median dictators are considered (Column (2), Table 5), while they are significant when the above-median dictators are considered (Column (1), Table 5). We find that having received more bad news, the above-median dictators' hazard to stop acquiring information in *Tradeoff* is 30% lower than that in *Control*.[22] Having received more good news, the hazard to stop acquiring information in *Tradeoff* is 27% higher than that in *Control*.[23] The magnitude of the effects when all the dictators are considered are 25% and 15%.

## 3.2 Additional Results

### 3.2.1 Posterior Beliefs

In this section, we investigate the dictators' final Bayesian posterior beliefs in the likelihood of the remunerative option being harmless. We compare the belief distributions between *Tradeoff* and *Control*. Our analysis is motivated by the main empirical results (Finding 1 and Finding 2) and Theorem 1. First, we compare the posteriors of those who draw more good news; second, we compare the posterior beliefs of those who draw more bad news. The analysis reveals systematic differences.

**Finding 4** *(i) Having drawn more good news than bad news, dictators in Tradeoff stop acquiring information at a lower belief in the Good state than those in Control. (ii) Having drawn more bad news than good news, dictators in Tradeoff stop acquiring information at a higher belief in the Bad state than those in Control.*

Finding 4 shows that having received more good news, dictators in *Tradeoff* stop at a *lower* level of certainty that the remunerative option is harmless to the other, compared to the dictators in *Control* (mean: 0.63 in *Tradeoff* and 0.66 in *Control*). In contrast, when having received more bad news, dictators in *Tradeoff* stop at a *higher* level of certainty that the remunerative option is harmful (mean: 0.16 in *Tradeoff* and 0.17 in *Control*. Both effects are marginally significant (two-sided Mann-Whitney-U test, $p = 0.10$).

[22] $\text{HR}_{Bad} = exp(\beta_1)$ is estimated to be $exp(-.35) = .70$.

[23] $\text{HR}_{Good} = exp(\beta_1 + \beta_{12,Good})$ is estimated to be $exp(-.35 + .59) = 1.27$.

This asymmetry in the certainty levels mirrors the asymmetry in the information acquisition strategy in Finding 2. It is also in line with Theorem 1.

When it comes to the overall posterior beliefs, Bayes' consistency states that the mean posterior beliefs must be equal to the prior belief in both treatments. In accordance with it, we find that the mean posterior beliefs are not significantly different between *Tradeoff* and *Control* (mean: 0.33 in *Tradeoff*, 0.34 in *Control*; student t-test, $p = 0.56$).[24]

### 3.2.2 Receiver Welfare

In *Tradeoff*, option $x$ increases the dictator's payment while option $y$ does not. This treatment causes the dictators to alter their way of acquiring information (Finding 1 and 2). Does this bias in information acquisition make the dictators in *Tradeoff* more often choose the option that reduces the receiver's payment?

Comparing the receiver welfare between *Tradeoff* and *Control* directly confounds two effects. The treatment may affect the dictator's choice between $x$ and $y$ in two ways: first, it may directly affect the dictator's decision given her final belief about which option is harmful (*the decision effect*). Second, it may affect how the dictator acquires information and hence her final belief about which option is harmful. This in turn may affect which option she chooses (*the information effect*). In Appendix B.2, we show that our theory predicts that the decision effect *increases* the likelihood of making harmful decisions when the belief-based utility only depends on the likelihood of harming the other. In contrast, there are agent types for whom the information effect *reduces* the likelihood of making harmful decisions.

Below, we develop an empirical strategy to analyze the decision and the information effect in our experimental data.

**Identification Strategy.** To empirically disentangle the two effects, we construct a *Counterfactual* scenario, in which the dictators acquire information as in *Control*, but decide as in *Tradeoff* given the final posterior beliefs (as illustrated in Table 3). When comparing the receiver welfare in the *Counterfactual* to the *Control* treatment, we isolate the decision effect by keeping

[24]This finding is reconciled with the distributional differences by the observation that in *Tradeoff* slightly more dictators ended up with a posterior belief above the prior, although the difference is insignificant (*Tradeoff*: 30%; *Control*: 29%; Chi-Square, $p = .14$).

fixed the final posterior beliefs; when comparing the receiver welfare in the *Counterfactual* to that in the *Tradeoff* treatment, we isolate the information effect by keeping fixed the decision between $x$ and $y$ given beliefs.

Table 3: Constructing the *Counterfactual* scenario

| | *Control* | *Tradeoff* |
|---|---|---|
| posterior beliefs | $\times$ | |
| decision given belief | | $\times$ |
| compared to the *Counterfactual* | *decision effect* | *information effect* |

**Finding 5** *The decision effect is negative: when controlling for the dictators' beliefs, having a remunerative option makes the dictators more often choose the harmful option.*

First, we compare the *Counterfactual* with the *Control* and find a negative decision effect. In the *Counterfactual*, the proportion of harmed receivers is higher than in the *Control* treatment (38% compared to 27%). Our data show that in both states the dictators in *Tradeoff* are more likely to choose $x$ than dictators in *Control* (Chi-Square, $p = 0.00$).

**Finding 6** *The information effect is positive: when controlling for the dictators' decision given their belief, having a remunerative option changes how dictators acquire information in a way such that the harmful option is chosen less often.*

Second, we compare *Tradeoff* with the *Counterfactual* and find a positive information effect. In *Tradeoff*, the proportion of harmed receivers is lower than in the *Counterfactual* (32% compared to 38%). It shows that had the dictators in *Tradeoff* acquired information the way the dictators in *Control* did, they would have inflicted more harm on the receivers.

Aggregating both effects, the proportion of harmful decisions does not significantly differ between *Tradeoff* and *Control* (32% compared to 27%, Chi-Square $p = 0.17$). It is increased from 27% (*Control*) to 38% (*Counterfactual*) by more selfish decision-making, i.e., the decision effect, and is decreased from 38% (*Counterfactual*) to 32% (*Tradeoff*) by motivated information acquisition, i.e., the information effect.

### 3.2.3 Information Acquisition

**Finding 7** *In the NoForce treatment variation, where the dictators can opt out of information acquisition, 85% dictators in Tradeoff and 93% dictators in Control acquire information before the dictator decision (Chi-Square test,* $p = 0.02$*).*

Finding 7 shows that one option being remunerative has an effect on the extensive margin of information acquisition. Similar observations have been made in settings where dictators can acquire or decline information that reveals the state at once (e.g Dana *et al.*, 2007; Feiler, 2014). In our setting, notably, even when facing a self-benefiting option, as high as 85% dictators decide to acquire information about which option reduces the payoff of the receiver.

In addition, we do *not* find an overall lower propensity to acquire *noisy* information when individuals' selfish interests are involved in the decision:

**Finding 8** *Dictators in Tradeoff and Control draw a similar amount of pieces of information.*

Figure 5 in the Appendix A.7 presents the distribution of the number of information pieces drawn by the dictators. There is no significant difference between *Tradeoff* and *Control* (mean: *Tradeoff*: 10:63, *Control*: 10.15; two-sided Mann-Whitney-U test, $p = 0.98$).

# 4 Discussion

## 4.1 Information Cost

In this paper, we examine how an individual's desire for believing in her good moral conduct affects her way of acquiring relevant information. The focus of our investigation is the tradeoff between an egoistic motive and a morally desirable belief. In emphasizing individuals having preferences over beliefs, our investigation follows the motivated belief literature (Bénabou and Tirole, 2016). In this section, we discuss another factor that may affect information acquisition, information cost.

Information cost might take different forms, e.g., material cost, cognitive cost or time cost of sampling. Methodologically, to avoid our empirical results being confounded by information cost, we are careful to limit the information cost in our experiment. First, the subjects do not pay for the information in any material form. Second, we limit the subjects' cognitive costs of interpreting information by giving them the Bayesian posterior beliefs after each draw of information. Individuals with higher cognitive ability should be less prone to biases caused by cognitive costs (Bénabou and Tirole, 2016). In our experiment, Finding 3, shows that when restricting the analysis to subjects with above-median cognitive ability, our main result (Finding 2) becomes *stronger*, a result showing that our main finding is unlikely driven by cognitive costs. Third, we minimize the time cost of sampling by imposing only a minimum time lag of 0.3 second between draws of information. On average, the dictators in the experiment spend 57 seconds acquiring information.

While our investigation focuses on the trade-off between beliefs and egoistic rewards, the role of cost for information acquisition is an interesting topic studied, for example, in the literature of rational inattention. The interaction between beliefs, rewards and information costs might be an interesting direction for future research.

## 4.2 Bayesian Persuasion

In this section, we discuss the relation of our model in Section 1.1 to the literature on Bayesian persuasion (Kamenica and Gentzkow, 2011). The equilibrium characterization in Section 1.2 (Lemma 1) shows that any equilibrium can be characterized by a Bayes-consistent distribution of stopped beliefs $p_\tau$ with support on two posteriors $p_l \leq p_0 \leq p_h$. This distribution maximizes

$$\mathrm{E}(V(p)) \tag{14}$$

for $V(p) = \max_{a \in \{x,y\}} U(a, p; r)$ across all Bayes-consistent distributions of posterior beliefs.

This formulation of the (dynamic) information acquisition problem of the agent with two competing motives makes the relation to models of interpersonal Bayesian persuasion most apparent. The problem is equivalent to that of a sender who tries to "persuade" a distinct receiver by transmitting information about a pay-off relevant state and where the sender's payoff only depends on the posterior belief $p$ of the receiver and is given by $V(p)$ (compare to Kamenica and Gentzkow, 2011). Hence, on a conceptual level, the problem of using information to align two internal motives, and the problem of transmitting information to another person with the goal to align the person's beliefs and actions with the sender's interest, are analogous.

Applying techniques from Bayesian persuasion to study information transmission involving a receiver with belief-based utility, Schweizer and Szech (2018) theoretically study the optimal revelation of medical information to a receiver with anticipatory utility; Lipnowski and Mathevet (2018) offer a generalized model of information transmission to a receiver with psychological preferences.

# 5 Concluding Remarks

This paper analyzes the information acquisition dynamics in decisions involving a motive to feel moral and a competing egoistic motive. In the theoretical investigation, we employ a model that captures the motive to feel moral by directly allowing beliefs to enter the utility function. The agent derives disutility when she believes that her decision is harmful to others. As a main result, we deduce that, driven by her egoistic motive, the agent "fishes for good news": she is more likely to continue acquiring information after receiving information suggesting negative externalities of a selfish decision ("bad news"). Reversely, after receiving information indicating no harm ("good news"), the agent is more likely to stop. The belief-based utility can be interpreted in many ways —e.g., guilt aversion (Battigalli and Dufwenberg, 2007), moral constraints (Rabin, 1995), or self-image concerns (Bodner and Prelec, 2003; Grossman and van der Weele, 2017)— which all share the feature that certain beliefs are more desirable, a feature pertinent to the result.

For the empirical investigation, we conduct a laboratory experiment. The controlled laboratory environment allows us to exogenously switch on and off the egoistic interest in the decision. Further, it permits to control confounding factors such as the heterogeneity in the prior belief, the interpretation of information, and access to information. In the experiment, we find that having an egoistic motive makes individuals "fish for good news". This effect is more substantial among individuals with above-median cognitive ability, a result suggesting that this effect is unlikely to be due to limited cognitive abilities.

The paper opens up directions of future research. The discussion of self-image concerns in Section 1.6 (and Appendix B.4) provides a novel model of Bayesian persuasion with signaling. In this model, a sender releases information about a utility-relevant state and, in doing so, signals about a distinct and also utility-relevant sender type. We demonstrates how the persuasion problem can be related to a problem of solving an ordinary differential equation, which then allows for a closed-form solution. We believe that this approach may prove fruitful in future research about interpersonal persuasion, for example in models where the receiver infers a pay-off relevant sender type from information sent by the latter about a distinct state.

The key feature of our model is that the decision-maker has two competing motives, one urging her to choose a particular action, and the other urging her to act upon her belief about an unknown state. This feature is present in many economic contexts beyond those covered in this paper. Imagine a food lover presented with a delicious new dish. While she longs for the dish, she also wants to believe that the food is healthy. How would she inquire about the healthiness of the food? Similar trade-offs arise for example in smoking and workout decisions. Applying the model to such situations with two competing *self-regarding* motives provides testable predictions for future empirical analysis. A theoretical work by Carrillo and Mariotti (2000) considers a setup where two self-related motives arise from time inconsistent preferences and show that strategic ignorance may result. Schweizer and Szech (2018) consider a setup with a medical patient whose utility depends both on her future health outcomes and her anticipation. They show that the patient-optimal medical test partially reveals her health condition.

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# Appendix
# (for online publication)

## A Empirical Appendices

### A.1 Experimental Design

Figure 3: The Noisy Information Generators

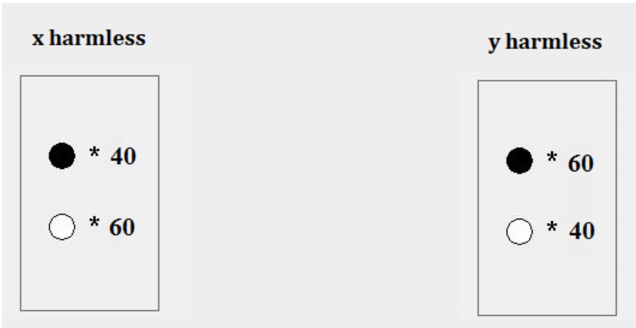
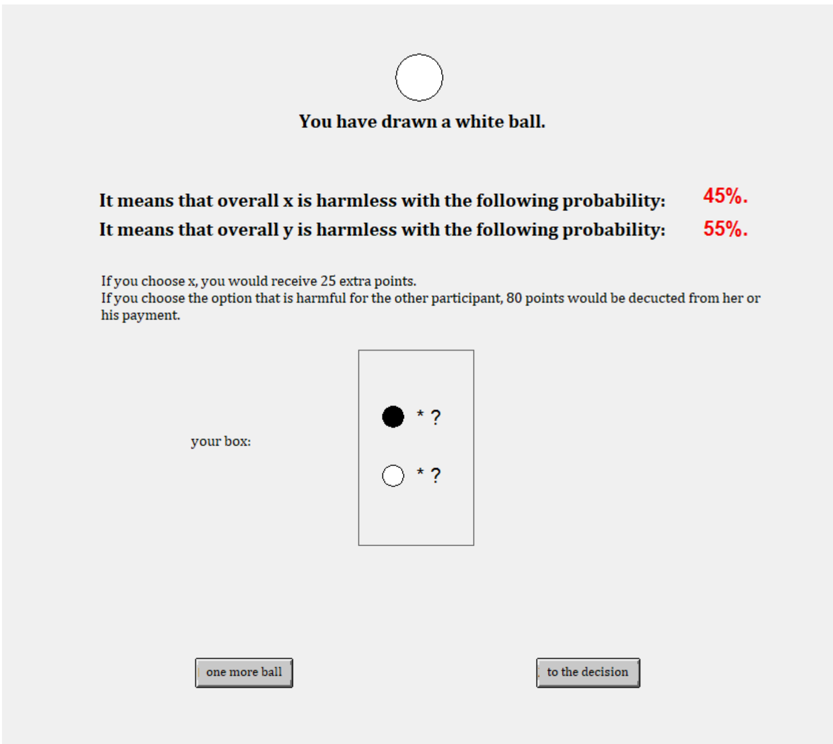



Figure 4: Screenshot of the Information Stage



## A.2 The Cox Model Results

Table 4: The Cox Proportional Hazard Model Results

| Coef. | Covariate | Pooled (1) | (2) | Force (3) | NoForce (4) |
|---|---|---|---|---|---|
| $\hat{\beta}_{\mathbf{1}}$ | treatment *Tradeoff* | -.29** | -.24* | -.38* | -.18 |
| | | (.12) | (.13) | (.21) | (.16) |
| $\hat{\beta}_{\mathbf{12}}$ | Tradeoff × | | | | |
| | Good news dominance | .43** | .41** | .32 | .42* |
| | | (.20) | (.21) | (.39) | (.26) |
| | Balanced | -.35 | -.42 | -.59 | -.34 |
| | | (.38) | (.38) | (.69) | (.47) |
| $\hat{\beta}_2$ | Good news dominance | -.14 | -.23 | -.18 | -.23 |
| | | (.16) | (.18) | (.31) | (.22) |
| | Balanced | -.52** | -.56** | -.48 | -59** |
| | | (.24) | (.23) | (.38) | (.30) |
| *Control Variables*: | | | | | |
| Belief Accuracy | | Yes | Yes | Yes | Yes |
| *Stratified by*: | | | | | |
| Gender, IQ, Prosociality FEs | | Yes | Yes | Yes | Yes |
| Force treatment FE | | No | Yes | – | – |
| Observations (individuals) | | 458 | 458 | 161 | 297 |
| Chi2 p-value | | .00 | .00 | .00 | .00 |
| Violation of PH | | NO | NO | NO | NO |

This table presents the estimated *coefficients* of the Cox model in (11), with standard errors clustered at the individual level. *, **, and *** denote significance at the 10, 5, and 1 percent level. The dependent variable is the hazard to stop acquiring information, and the key coefficients of interests are $\hat{\beta}_1$ and $\hat{\beta}_{12}$. $\exp(\hat{\beta}_1)$ reflects the treatment effect on the dictators' hazard to stop acquiring further information, given information histories dominated by bad news; and $\exp(\hat{\beta}_1 + \hat{\beta}_{12}|\text{Good news dominance})$ reflects the treatment effect on the hazard, given information histories dominated by good news (see the derivation in Equation (13)). The fixed effects are taken into account by stratification, which allows the baseline hazard to differ according to the control variables, i.e., gender, the prosocial types (categorized by the SVO test), and the cognitive ability (categorized by the score in a Raven's matrices test). We also control for the belief accuracy, measured by the Brier score of the beliefs after each draw (see Footnote 20). The reported likelihood Chi-square statistic is calculated by comparing the deviance ($-2\times$ log-likelihood) of each model specification against the model with all covariates dropped. The violation of the proportional hazard assumption of the Cox model (PH) is tested using Schoenfeld residuals. In all four cases and for each covariate, the PH is not violated. Also, there is no global violation. We use the Breslow method to handle ties.

Table 5: The Cox Model Results For Above and Below Median Raven's Scores

| Coef. | Covariate | Above Median (1) | Below Median (2) |
|---|---|---|---|
| $\hat{\beta}_{\mathbf{1}}$ | treatment *Tradeoff* | -.35** | -.17 |
| | | (.16) | (.20) |
| $\hat{\beta}_{\mathbf{12}}$ | Tradeoff × | | |
| | Good news dominance | .59** | .21 |
| | | (.27) | (.30) |
| | Balanced | .32 | -1.02* |
| | | (.54) | (.59) |
| $\hat{\beta}_2$ | Good news dominance | -.10 | -.25 |
| | | (.22) | (.27) |
| | Balanced | -.98** | -.21 |
| | | (.40) | (.32) |
| *Control Variables*: | | | |
| Belief Accuracy | | Yes | Yes |
| *Stratified by*: | | | |
| Gender, IQ, Prosociality FEs | | Yes | Yes |
| Force treatment FE | | No | No |
| Observations (individuals) | | 267 | 191 |
| Chi2 p-value | | .00 | .00 |
| Violation of PH | | NO | NO |

This table presents the Cox model results for the subjects above and below median cognitive ability, measured by the number of correctly answered questions in a Raven's matrices test, pooling data from all treatments. Standard errors are clustered at the individual level. The median number of correct answers to the Raven's test is four out of five in our experiment. In this table, the subjects above the median have given correct answers to four or five questions in Raven's test, and the subjects below the median have correctly answered below four questions in Raven's test. We find that subjects with higher cognitive ability have a higher tendency to "fish for desirable information". For a comprehensive table description, please see that of Table 4.

## A.3 Robustness Check of the Cox Model Estimate: A Logistic Regression

Using the data at the person-draw level, we estimate the following logistic model as a robustness check of the Cox model estimate and find a result similar to Finding 2 from Section 3.1.2.

$$logit\, h(X) = X_t \cdot b + Z \cdot a + (C + T \cdot c), \tag{15}$$

where $h(X)$ is the probability that the dictator stops acquiring information after that draw; $X$ denotes the same covariates of interest as in the Cox model, i.e.,

$$X \cdot b = \beta_1 \text{Tradeoff} + \beta_2 \text{Info} + \beta_{12} \text{Tradeoff} \times \text{Info}. \tag{16}$$

The control valuables in $Z$ include gender, cognitive ability, prosociality and belief accuracy, all measured in the same way as in the Cox model in Section 3.1.2. $T$ is a vector of time dummies, which captures the time dependency of the probability to stop acquiring information.

When interpreting the results, this logistic model can be viewed as a hazard model in which the covariates proportionally affect the *odds* of stopping the information acquisition (Cox, 1975). Formally, consider such a hazard model,

$$\frac{h(t)}{1-h(t)} = \frac{h_0(t)}{1-h_0(t)} \cdot exp(X_t \cdot b + Z \cdot a).$$

Then,

$$\underbrace{log\left(\frac{h(t)}{1-h(t)}\right)}_{logit\, h(X)} = \underbrace{log\left(\frac{h_0(t)}{1-h_0(t)}\right)}_{C+T\cdot c} + X_t \cdot b + Z \cdot a. \tag{17}$$

Unlike in the framework of the Cox model, the coefficients here cannot be interpreted as hazard ratios. Instead, they should be interpreted as odds ratios. Our prediction that the hazard to stop acquiring information is lower in *Tradeoff* when bad news dominates suggests a negative $\beta_1$ in (16). And the prediction that the hazard is higher when good news dominates suggests a positive $\beta_1 + \beta_{12,Good}$. Results reported in Table 6 support these predictions.

Table 6: The Logistic Model Results

| | | Pooling All | | Force | NoForce |
|---|---|---|---|---|---|
| $\hat{\beta}_\mathbf{1}$ | treatment *Tradeoff* | -.25* | -.26* | -.56** | -.18 |
| | | (.15) | (.15) | (.25) | (.18) |
| $\hat{\beta}_\mathbf{12}$ | Tradeoff × | | | | |
| | Good news dominance | .37* | .37* | .71* | .34 |
| | | (.22) | (.22) | (.37) | (.26) |
| | Balanced | -.54 | -.53 | -.62 | -.40 |
| | | (.40) | (.41) | (.73) | (.49) |
| $\hat{\beta}_2$ | Good news dominance | -.21 | -.21 | -.14 | -.26 |
| | | (.18) | (.18) | (.29) | (.24) |
| | Balanced | -.67** | -.68** | -.46 | -78** |
| | | (.28) | (.28) | (.46) | (.35) |
| *Control Variables*: | | | | | |
| Belief Accuracy | | Yes | Yes | Yes | Yes |
| Gender, IQ, Prosociality | | Yes | Yes | Yes | Yes |
| Time Dummies | | Yes | Yes | Yes | Yes |
| Force Treatment Dummy | | No | Yes | – | – |
| Observations (person-draws) | | 4,658 | 4,658 | 1,567 | 2,932 |
| Pseudo R2 | | .07 | .07 | .09 | .07 |

This table presents the estimated *coefficients* of the logistic model, with standard errors clustered at the individual level. *, **, and *** denote significance at the 10, 5, and 1 percent level. The dependent variable is the hazard to stop acquiring information, and the key coefficients of interests are $\hat{\beta}_1$ and $\hat{\beta}_{12}$. $\exp(\hat{\beta}_1)$ reflects the treatment effect on the dictator's odds to stop acquiring further information, given information histories dominated by bad news. And $\exp(\hat{\beta}_1 + \hat{\beta}_{12}|\text{Good news dominance})$ reflects the treatment effect on the odds, given information histories dominated by good news. We control for belief accuracy, gender, the prosocial types (categorized by the SVO test), and the cognitive ability (measured by a Raven's matrices test). The time dependency of the odds is accounted for by including a dummy for each period.

## A.4 The Difference in Difference in Finding 1

We can view the first draw as another treatment dimension, resulting in the following 2 x 2 design:

Table 7: 2 x 2 design with the First Draw

| | With Self-Reward | No Self-Reward |
|---|---|---|
| First Draw Good News | *Tradeoff–First News Good* | *Control–First News Good* |
| First Draw Bad News | *Tradeoff–First News Bad* | *Control–First News Bad* |

Finding 1 shows that depending on whether the first draw of information is good or bad news, a self-reward makes the dictators either more or less likely to stop acquiring information. Now, we compare how the difference in the likelihood to stop after good and bad news differs across *Tradeoff* and *Control*.

To test the difference in the difference, we estimate the following probit regression:

$$probit(continue) = b_1\text{Tradeoff} + b_2\text{Good} + b_{12}\text{Tradeoff} \cdot \text{Good} + c,$$

where Tradeoff is a dummy that takes value 1 if the dictator is in treatment *Tradeoff*, Good is a dummy that takes value 1 if the dictator's first draw is good news. Table 8 presents the regression estimate; $b_{12}$ is significantly negative, showing that the different propensity to continue acquiring information after good and bad news respectively differs significantly between the *Tradeoff* and the *Control* treatments.

Table 8: Probit Regression Estimate

| Coef. | Pooled | Force | NoForce |
|---|---|---|---|
| $b_1$ | .24 | .25 | .24 |
| | (.21) | (.39) | (.26) |
| $b_1$ | .84*** | .72 | .91*** |
| | (.28) | (.50) | (.35) |
| $\mathbf{b_{12}}$ | **-1.21*** ** | **-1.37** ** | **-1.10** ** |
| | **(.36)** | **(.62)** | **(.44)** |
| $c$ | 1.08*** | 1.19*** | 1.03*** |
| | (.14) | (.25) | (.17) |
| N | 458 | 161 | 297 |
| Chi2 p | .00 | .05 | .02 |

## A.5 Receiver Welfare

Table 9: The Effects of Remuneration on Receiver Welfare

(a) The Decision Effect

| | |
|---|---|
| *Counterfactual:* | |
| % harm | 38% |
| (# total dictators) | (246) |
| *Control:* | |
| % harm | 27% |
| (# total dictators) | (246) |
| *The decision effect:* | -11% |

(b) The Information Effect

| | |
|---|---|
| *Tradeoff:* | |
| % harm | 32% |
| (# total dictators) | (250) |
| *Counterfactual:* | |
| % harm | 38% |
| (# total dictators) | (246) |
| *The information effect:* | +6% |

This table presents the decision effect and the information effect of the remuneration in our experiment. The *Counterfactual* is calculated by combining the posterior beliefs from the *Control* and the mapping from beliefs to choices in the dictator game from *Tradeoff*. Comparing the *Conterfactual* to the *Control* (*Tradeoff*), we obtain the decision effect (information effect).

## A.6 Summarizing Statistics

Table 10: Basic Information of Dictators

| | | no. obs. | Good State | female | student | av. age |
|---|---|---|---|---|---|---|
| Force | Tradeoff | 82 | .34 | .45 | .95 | 22 |
| | Control | 79 | .37 | .54 | .95 | 22 |
| | p value | | .73 | .24 | .96 | .50 |
| NoForce | Tradeoff | 168 | .35 | .66 | .93 | 24 |
| | Control | 167 | .35 | .65 | .92 | 24 |
| | p value | | .97 | .79 | .52 | .36 |
| Pooled | Tradeoff | 250 | .35 | .59 | .94 | 24 |
| | Control | 246 | .36 | .61 | .93 | 24 |
| | p value | | .82 | .62 | .56 | .26 |

This table summarizes the basic characteristics of the dictators in each treatment. We compare these characteristics between *Tradeoff* and *Control*. For the state, gender, and student status we report the p-values of the Chi-Square test. For the dictators' age, we report the p-value of the two-sided Mann-Whitney-U test.

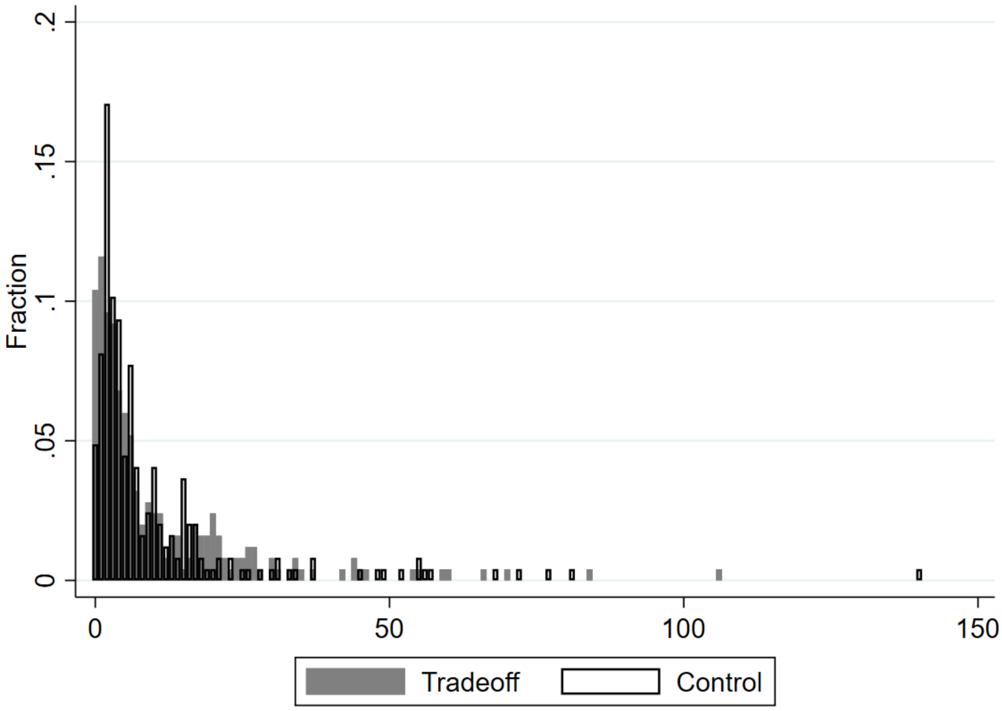
## A.7 Number of Draws and the Posterior Beliefs

Table 11: Information Acquisition Behavior

| | | no. balls (median) | av. belief at decision |
|---|---|---|---|
| Force | Tradeoff | 7.5 | .30 |
| | Control | 4 | .36 |
| | p value | .04 | .04 |
| NoForce | Tradeoff | 5 | .34 |
| | Control | 6 | .33 |
| | p value | .92 | .76 |
| Pooled | Tradeoff | 6 | .33 |
| | Control | 5 | .34 |
| | p value | .24 | .30 |

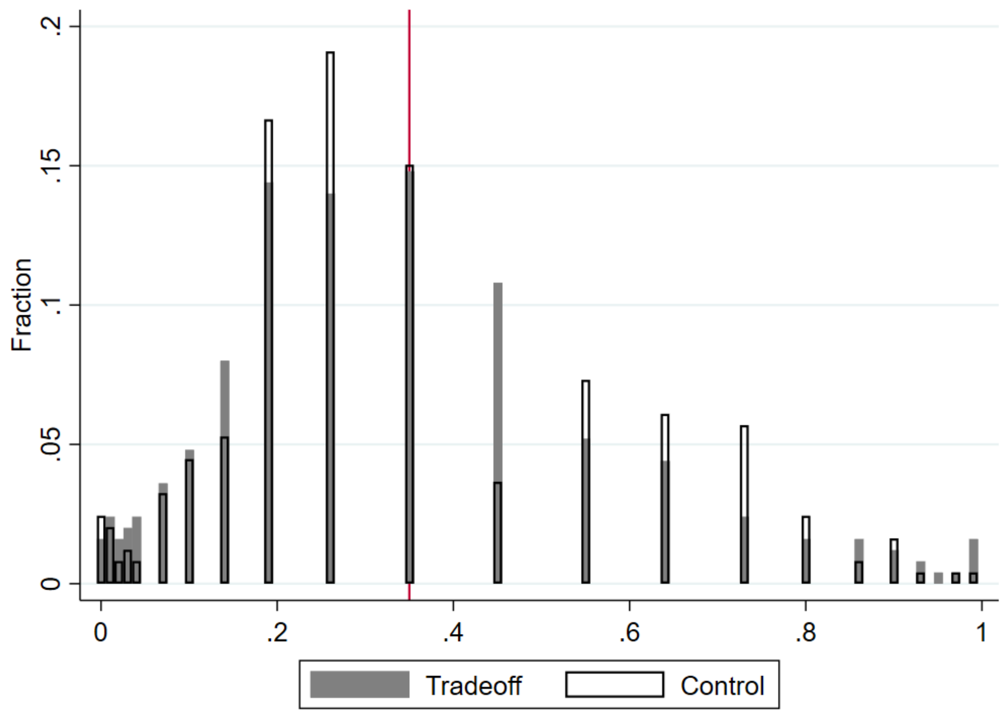
This table presents the statistics of the dictators' information acquisition behavior and the p-values of the two-sided Mann-Whitney-U test comparing between *Tradeoff* and *Control*, respectively. In the *NoForce* treatments, only dictators who draw at least one ball are included.

Figure 5: Histogram of the Number of Balls Drawn




This figure presents the number of balls that the dictators drew in *Tradeoff* and *Control* respectively. The distribution is not significantly different between *Tradeoff* and *Control* (two-sided Mann-Whitney-U test, $p = .98$).

Figure 6: Histogram of the Posterior Beliefs




This figure shows the histogram of the dictators' Bayesian posterior beliefs about the likelihood of the Good State when they end the information stage in *Tradeoff* and *Control*. The red vertical line represents the prior belief.

## A.8 Dictator Game Decision

Table 12: Dictator Game Decisions

| | | Choosing $x$% | | | Harm % |
|---|---|---|---|---|---|
| | | Good | Bad | Overall | |
| Force | Tradeoff | .71 | .43 | .52 | .38 |
| | Control | .62 | .14 | .32 | .23 |
| | p-value | .46 | .00 | .01 | .04 |
| NoForce | Tradeoff | .86 | .39 | .55 | .30 |
| | Control | .51 | .18 | .29 | .29 |
| | p-value | .00 | .00 | .00 | .84 |
| Pooled | Tradeoff | .82 | .40 | .54 | .32 |
| | Control | .55 | .16 | .30 | .27 |
| | p-value | .00 | .00 | .00 | .17 |

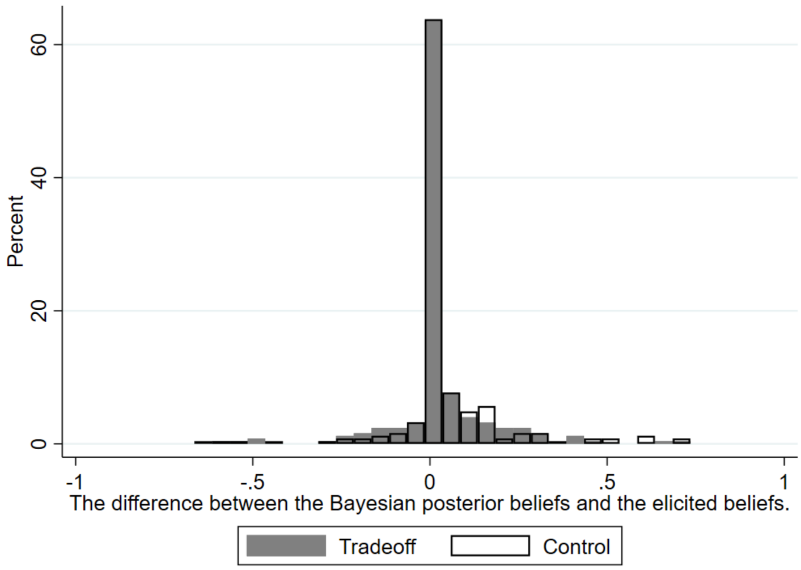
The first three columns of this table present the proportions of dictators who choose $x$ in *Good* and *Bad* state and in each treatments. Recall that in the *Good* state, $x$ does not harm the receiver, while in the *Bad* state it does. The last column presents the percentage of dictators whose decision reduce the receivers' payoffs in the dictator game. The p-values are from the Chi square tests comparing between *Tradeoff* and *Control* respectively.

## A.9 The Supplementary Stage

After the experiment, we elicited the dictators' posterior beliefs on the state and their SVO scores. We also asked them to answer a questionnaire consisting of questions on their sociodemographics (gender, age, etc.). Five items from Raven's progressive matrices intelligence test are also included.

**Elicited Beliefs** In the experiment, we display to the dictators the Bayesian posterior belief on the states (rounded to the second decimal) after each draw of information. After a dictator stops acquiring information, we elicit her belief of option $x$ being harmless, given all the information acquired. The elicitation is incentivized by the randomized Quadratic Scoring Rule adapted from Drerup *et al.* (2017) and Schlag *et al.* (2013).

Figure 7: The Belief Difference




This figure shows the histogram of the difference between the rounded Bayesian posterior belief and the elicited belief that option $x$ is harmless.

In Figure 7, we present the distribution of the difference between the elicited and the rounded Bayesian belief in *Control* and *Tradeoff* respectively. The deviation of the elicited beliefs from the Bayesian beliefs does not significantly differ between *Control* and *Tradeoff* (two-sided Mann-Whitney-U test, $p = .29$). In *Control*, the benchmark treatment, the dictators' elicited beliefs of $x$ being the harmless option are on average 3.30 percentage points higher than the rounded Bayesian beliefs (two-sided Wilcoxon signed rank test, $p = .00$). In *Tradeoff*, the dictators state beliefs that are higher than the rounded Bayesian beliefs by 1.84 percentage on average (two-sided Wilcoxon signed rank test, $p = .00$) .

**Cognitive Abilities** On average, the subjects answered 3.6 out of 5 questions in Raven's matrices test correctly. There is no significant difference between *Control* and *Tradeoff* treatments (Chi-square $p = .12$). When asked a simple question on probability, in both treatments more than 90% of the subjects answer correctly (*Treatment*: 92%, *Control*: 94%; Chi-square test $p = .51$).[25]

**SVO Scores** The average SVO score of all the subjects is 20.49, with no significant difference between *Tradeoff* and *Control* treatments (two-sided Mann-Whitney-U test, $p = .84$). According to Murphy *et al.* (2011), 48% subjects are categorized as "prosocials", 15% "individualists" and 37% "competitive type".

[25] We use the following question to elicit the subjects' understanding of probabilities: Imagine the following 4 bags with 100 fruits in each. One fruit will be randomly taken out. For which bag, the probability of taking a banana is 40%?
A. A bag with 20 bananas.
B. A bag with 40 bananas.
C. A bag with 0 banana.
D. A bag with 100 bananas.
The correct answer is B.

# B Theory Appendices

## B.1 Proofs

### B.1.1 Preliminaries for the Proofs

First, we establish two claims that we will use to prove both Lemma 1 and Lemma 2. For this, recall the definition of the cutoff beliefs $p_l$ and $p_h$ following the statement of Lemma 2.

**Claim 1** *Let $p_t \in [p_l, p_h]$. For any continuation strategy $\tau$,*

$$\mathrm{E}(V(p_\tau)|(Z_s)_{s\leq t}) \leq \bar{V}(p_t) \tag{18}$$

**Proof.** We have

$$\mathrm{E}(V(p_\tau)|(Z_s)_{s\leq t}) \quad \leq \quad \mathrm{E}(\bar{V}(p_\tau)|(Z_s)_{s\leq t}) \leq \bar{V}(\mathrm{E}(p_\tau)|(Z_s)_{s\leq t}) = \bar{V}(p_t),$$

where we used that $V \leq \bar{V}$ for the first inequality and Jensen's inequality for the second inequality. For the final equality, we use that $\mathrm{E}(p_\tau|(Z_s)_{s\leq t}) = p_t$ by Doob's optional stopping theorem.[26] ■

Now, consider the candidate equilibrium strategy $\tau^*$ where the agent continues to observe the information process as long as $p_l < p_t < p_h$, and stops whenever $p_t \leq p_l$ or $p_t \geq p_h$.

**Claim 2** *Let $p_t \in [p_l, p_h]$. The strategy $\tau^*$ satisfies*

$$\mathrm{E}(V(p_{\tau^*})|(Z_s)_{s\leq t}) = \bar{V}(p_t) \tag{19}$$

**Proof.** We consider two cases: if $V(p_0) = \bar{V}(p_0)$, by definition, $p_h = p_l = p_0$ and the agent immediately stops at $t = 0$, i.e., $\Pr(p_{\tau^*} = p_0) = 1$, which directly yields the result in this case. If $V(p_0) < \bar{V}(p_0)$, then, $\bar{V}$ is linear on all open intervals $I' \subseteq [\epsilon, 1-\epsilon]$ satisfying $p_0 \in I'$ and $V(p) < \bar{V}(p)$ for all $p \in I'$, by its minimality. Now, $(p_l, p_h)$ is the largest such interval, which implies that $V$ and $\bar{V}$ must coincide at $p_l$ and $p_h$,[27]

$$V(p_h) = \bar{V}(p_h), \quad \text{and} \quad V(p_l) = \bar{V}(p_l). \tag{20}$$

[26] See e.g., Revuz and Yor (2013).

[27] One checks that this is also true if $(p_l, p_h) = (\epsilon, 1-\epsilon)$ by the minimality of $\bar{V}$.

Finally, for any $p_t \in [p_l, p_h]$,

$$\begin{aligned} \mathrm{E}(V(p_{\tau^*})|(Z_s)_{s\le t}) &= \Pr(p_{\tau^*} = p_h|(Z_s)_{s\le t})V(p_h) + \Pr(p_{\tau^*} = p_l|(Z_s)_{s\le t})V(p_l) \\ &= \Pr(p_{\tau^*} = p_h|(Z_s)_{s\le t})\bar{V}(p_h) + \Pr(p_{\tau^*} = p_l|(Z_s)_{s\le t})\bar{V}(p_l) \\ &= \bar{V}(p_t), \end{aligned}$$

where we used (20) for the equality on the second line. For the equality on the third, we used the earlier observation that $\bar{V}$ is linear on $(p_l, p_h)$ together with Bayes' law. ■

### B.1.2 Proof of Lemma 1

Let $\tau^*$ be the candidate equilibrium strategy where the agent continues to observe the information process as long as $p_l < p_t < p_h$, and stops whenever $p_t \le p_l$ or $p_t \ge p_h$. Claim 1 and Claim 2 together imply that at any point of time, following $\tau^*$ is weakly optimal, hence $\tau^*$ is an equilibrium. This proves Lemma 1.

### B.1.3 Proof of Lemma 2.

Take any equilibrium $\tau^{**}$ in which the agent stops observing the information process whenever he is indifferent between stopping and continuing. It follows from Claim 1 and Claim 2 that, when $p_t \in (p_l, p_h)$, it is strictly optimal for the agent to continue acquiring information: stopping yields $V(p_t)$, which is strictly smaller than $\bar{V}(p_t)$, and there is a continuation strategy which yields $\bar{V}(p_t)$ by Claim 2. When $p_t \in \{p_l, p_h\}$, if the agent would stop acquiring information, his payoff would be $V(p_t) = \bar{V}(p_t)$, given (20). Thus, it follows from Claim 1 that it is weakly optimal to stop acquiring information, so the agent stops under $\tau^{**}$. Finally, we conclude that $\tau^{**}$ is identical to $\tau^*$ (see the proof of Lemma 1 for the definition of the equilibrium $\tau^*$.)

### B.1.4 Proof of Lemma 3

Take the strategy $\tau'$ where the agent never stops observing the information process (unless $p_t \le \epsilon$ or $p_t \ge 1-\epsilon$, and she has to stop). Given $\epsilon \approx 0$, she acquires almost complete information about the state. Note that her expected utility when doing so is $\mathrm{E}(\mathrm{V}(\mathrm{p}_{\tau'})) \approx (1-p_0)V(0) + p_0 V(1) \ge (1-p_0)u(y,1) + p_0(u(x,1)+r)$ since she can almost always choose $y$ in the state when $y$ is harmless and $x$ in the state when $x$ is harmless. Given that $u(x, 1) = 0$ and $u(y, 1) \leq 0$, we have $(1 - p_0)V(0) + p_0V(1) \geq (1 - p_0)u(y, 1) + p_0r > u(y, 1)$. It follows that the equilibrium strategy $\tau^*$ given by the cutoff beliefs $p_l$ and $p_h$ must yield a payoff strictly larger than $u(y, 1)$ as well when $\epsilon$ is sufficiently small, that is $\mathrm{E}(V(p_{\tau^*})) > u(y, 1)$.

First, this implies that the agent does not choose $y$ at $p_h$ when $\epsilon$ is sufficiently small: suppose she does so, then, she will also choose $y$ at $p_l < p_h$ since at $p_l$ she is more certain that $y$ is harmless, ceteris paribus. However, when she always chooses $y$, her payoff is weakly smaller than $u(y, 1)$ since $U(y, p, r) = u(y, 1 - p) \leq u(y, 1)$ for all $p$.

Second, this implies that $V(p_h) > u(y, 1)$ when $\epsilon$ is sufficiently small: suppose that $V(p_h) \leq u(y, 1)$. Then, also $V(p_l) = \max_{a \in \{x,y\}} U(a, p_l, r) \leq u(y, 1)$ since $U(y, p, r) = u(y, 1 - p) \leq u(y, 1)$ for all $p$ and $U(x, p_l, r) \leq U(x, p_h, r) \leq u(y, 1)$. However, $V(p_h) \leq u(y, 1)$ and $V(p_l) \leq u(y, 1)$ together imply $\mathrm{E}(V(p_{\tau^*})) \leq u(y, 1)$, which contradicts with the observation $\mathrm{E}(V(p_{\tau^*})) > u(y, 1)$ when $\epsilon$ is small enough. Given that we assumed that the agent weakly prefers $y$ at $p_l$, we have $V(p_l) = u(y, 1 - p_l) \leq u(y, 1)$. We conclude that $V(p_h) > V(p_l)$ since $V(p_h) > u(y, 1)$.

## B.2 Receiver Welfare

Intuitively, the positive information effect of the empirical Finding 6 may be explained by a moral hazard problem. When $r = 0$, the dictator's payment is not at stake, and the agent might acquire little information. Consequently, she may be ill-informed about the state and sometimes mistakenly chooses the harmful option. Option $x$ being remunerative can mitigate this moral hazard problem: the dictator now wants to be more certain that $y$ is harmless before she chooses it. This means that the dictator might less often mistakenly choose $y$ when the remunerative $x$ is harmless and $y$ is harmful, reducing the propensity of harming the receiver.

To formalize this intuition, let $v(a, \omega)$ denote the utility of the other when the agent chooses $a \in \{x, y\}$ in $\omega \in \{X, Y\}$. For any $p \in (0, 1)$ and $r > 0$, let $a(p, r) = \arg\max_{a \in \{x,y\}} U(a, p, r)$.[28]. For any $r > 0$, let $\tau(r)$ be the equilibrium information acquisition strategy of the agent given by the belief cutoffs $p_l(r)$

[28]When the agent is indifferent between $x$ and $y$, let $a(p, r) = x$. The agent never stops when being indifferent, so that this choice is irrelevant for our analysis.

and $p_h(r)$; see Lemma 2 and thereafter, here we highlight the dependence on $r$. Given this notation,

$$\mathrm{DE} = \mathrm{E}\Big[v(a(p_{\mathcal{T}(0)}, r), \omega)\Big] - \mathrm{E}\Big[v(a(p_{\mathcal{T}(0)}, 0), \omega)\Big]. \tag{21}$$

is the decision effect of the remuneration $r > 0$ on the welfare of the other, and

$$\mathrm{IE} = \mathrm{E}\Big[v(a(p_{\mathcal{T}(r)}, r), \omega)\Big] - \mathrm{E}\Big[v(a(p_{\mathcal{T}(0)}, r), \omega)\Big]. \tag{22}$$

is the information effect. Proposition 1 show that the decision effect is always negative when the belief-based utility only depends on the likelihood of harming the other. It also shows that for some types the information effect is positive and even offsets the decision effect, thereby leading to an overall positive effect on the welfare of the other. These results are consistent with the empirical findings, Finding 5 and Finding 6. The proof is in Section B.2.1 and B.2.2.

**Proposition 1** *Take any $r > 0$.*

1. *For any preference type $u$ with $u(x, -) = u(y, -)$, the decision effect is negative,* $\mathrm{DE} \leq 0$.
2. *There is an open set of types $u$, so that the information effect and the overall effect are positive,* $\mathrm{IE} > 0$ *and* $\mathrm{DE} + \mathrm{IE} > 0$.

### B.2.1 Proof of Proposition 1, first item

Let $p^*(r)$ solve

$$u(x, p) + r = u(y, 1 - p). \tag{23}$$

Let $u(x, p) = u(y, p)$. It is easy to see that $p^*(r) < 0.5$ when $r > 0$ and $p^*(r) = 0.5$ when $r = 0$. Note that the agent's optimal decision between $x$ and $y$ is given by

$$a(p, r) = \begin{cases} x & \text{if } \; p > p^*(r) \\ y & \text{if } \; p < p^*(r). \end{cases} \tag{24}$$

Fix $\bar{r} > 0$. Comparing the scenarios when $r = \bar{r}$ and when $r = 0$, the agent may only take different decisions if her final belief $p_\tau$ is in $[p^*(\bar{r}), 0.5)$. At a final belief $p_\tau \in [p^*(\bar{r}), 0.5)$, the agent chooses $x$ when $r = \bar{r}$ and $y$ when $r = 0$. The receiver is (weakly) better off with the choice $y$ since the likelihood of harming the receiver with $y$ is $p_\tau < 0.5$ and the likelihood of harming the receiver with $x$ is $1 - p_\tau > 0.5$. This shows that, fixing any information acquisition strategy $\tau$, the receiver is better off when the agent decides according to the decision rule $a(-, 0)$ as opposed to the rule $a(-, \bar{r})$.

To prove the second item of Proposition 1, we take the preference types given by

$$u(x, q) = u(y, q) = \begin{cases} 0 \quad \text{for} \quad q \geq l, \\ -\alpha(l - q) \quad \text{for} \quad q < l \end{cases} \tag{25}$$

for some $\frac{1}{2} < l < 1$ satisfying $p_0 \in (1 - l, l)$. We establish a preparatory result.

**Claim 3** *For all $r \geq 0$, it holds $p^*(r) \to \frac{1}{2}$ when $\alpha \to \infty$.*

**Proof.** Note that $\alpha \to \infty$ implies that, for $q < l$, we have $u'(a, q) = \alpha \to \infty$. In particular, for any $\epsilon > 0$ there is $\bar{\alpha}(\epsilon)$ such that for all $\alpha > \bar{\alpha}$ and $p < \frac{1}{2} - \epsilon$, we have $u(x, 1 - p) - u(x, p) > r$. Hence, $u(y, 1 - p) - u(x, p) > r$, using that $u(x, q) = u(y, q)$ for all $q$. Given (23), this implies $p^*(r) \geq \frac{1}{2} - \epsilon$. Further, it follows from (25) and (23) that $p^*(r) \leq \frac{1}{2}$, finishing the proof of the claim. ■

### B.2.2 Proof of Proposition 1, second item

Take a preference type as in (25). Recall the characterization of $p_l(r)$ and $p_h(r)$ after Lemma 1, where we highlight the dependence on $r$ here. Take $\bar{r} > 0$. When $\epsilon \approx 0$,

$$p_l(\bar{r}) = \epsilon, \text{ and} \tag{26}$$
$$p_h(\bar{r}) = l, \tag{27}$$

given (25), and Lemma 5 implies

$$p_l(0) = 1 - l, \text{ and} \tag{28}$$
$$p_h(0) = l \tag{29}$$

for $\epsilon$ sufficiently small. First, it follows from Claim 3 that when $\alpha$ is sufficiently large, both when $r = 0$ and $r = \bar{r}$, the agent strictly prefers $y$ at the belief $p_l(0) = 1 - l < \frac{1}{2}$. In other words, the decision rules $a(-, \bar{r})$ and $a(-, 0)$ both choose $y$ at $p_l(0)$. Given (28) and the assumption that $l > \frac{1}{2}$, we have $p_h(0) > \frac{1}{2}$. Hence, $p_h(0) > p^*(r)$ for all $r \geq 0$. So, the decision rules $a(-, \bar{r})$ and $a(-, 0)$ both choose $x$ at $p_h(0)$. We conclude that the decision effect is zero.

Second, given (26) - (29), it holds $p_h(\bar{r}) = p_h(0)$ and $p_l(\bar{r}) < p_l(0)$ when $\epsilon \approx 0$. So, the agent chooses the option $y$ at a higher belief in the harmfulness of $y$ when $r = \bar{r}$ relative to when $r = 0$. Further, the agent chooses the option $x$ at the same belief. Fixing the decision rule $a(-, 0)$ and varying the information acquisition strategy, we see that the information effect is strictly positive.

Altogether, we have shown for the types as in (25) that the sum of the decision effect and the information effect is strictly positive when $\alpha$ is sufficiently large, DE + IE $> 0$. Clearly, by continuity, this is still true for any type with belief-based utility function $\hat{u}$ "close-by" to the belief-based utility $u$ as in (25).[29]

## B.3 Information Avoidance

In this section, we discuss two additional results of our model and the respective empirical evidence: the avoidance of noisy information and of information revealing the state at once. While our experiment focuses on *noisy* information, our preference model (1) can be used to analyze both the acquisition of noisy information that arrives sequentially, as well as information that reveals the state at once. These additional theoretical results are in line with the empirical findings in this paper (see Section 3.2) and also with the empirical findings by Dana *et al.* (2007) and Feiler (2014), as explained further below.

### B.3.1 Avoidance of Noisy Information

Our model predicts that with or without a remunerative option, some agent types move on to the decision without acquiring any noisy information.

[29] Formally, if we consider the $L_2[0, 1]$-norm on the space of belief-based utility functions, there is an open set $U$ with $u \in U$, so that the sum of the decision effect and the information effect is positive for all $\hat{u} \in U$.

This may be surprising in the scenario where no option is remunerative. In this scenario, indeed, for the types with $u' > 0$ it is optimal to acquire as much information as possible. In particular, these agents will not avoid information completely. However, other agent types have a threshold level of certainty. They are content when believing is sufficiently likely that they can spare the other from harm. Any further certainty beyond the threshold does not increase their belief-based utility. This behavior mirrors that of satisficing as in (Simon, 1955). If, given the prior belief, they are already more certain than the treshold requires that one of the options is harmless, they are indifferent between continuing and stopping, and may as well stop.

When one of the options is remunerative, the incentives to acquire information are different. First, the agent would decide to not acquire noisy information only if she would choose the remunerative option at the prior belief. Otherwise, she would "fish for information" that justifies this choice (compare to Lemma 3 and Theorem 1). Second, when considering to avoid information and to choose the remunerative option immediately or to acquire further information, the agent is aware that further information poses an undesirable risk since it might reverse her decision from the remunerative to the non-remunerative option. When this risk outweighs her utility gain from having more certain beliefs, the agent avoids noisy information completely. The proof is in Section B.3.3.

**Proposition 2** *For any $r = 0$ ($r > 0$) and for any prior $p_0 \in (0, 1)$, there is a set $S_r(p_0)$ of preference types $u$ for which it is (strictly) optimal to avoid information completely.*

**Empirical Findings.** In line with Proposition 2, in the experiment, we find that 15% of the dictators do not acquire any noisy information in the *Tradeoff–NoForce* treatment (Chi-Square $p = 0.00$).[30] Among those, 96% choose the remunerative option $x$ (25/26). Here, theory suggests that these dictators avoid information because they are worried about bad news arriving, indicating that $x$ harms the other.

We find that 7% of the dictators do not acquire any noisy information in the *NoForce–Control* treatment (Chi-Square $p = 0.00$). Among those, only 17% choose the remunerative option $x$ (2/12). Here, theory suggests that

[30] Recall that in Force, it is not feasible to stop immediately.

the dictators who avoid noisy information completely are satisfied with 65% certainty that $y$ is the harmless option.

### B.3.2 Avoidance of Information Revealing the State at Once

Proposition 3 shows that when there is a remunerative option, then, for any prior belief, there are types of dictators who would avoid information that reveals the state all at once. The proof is in Section B.3.4.

**Proposition 3**

1. *Take $r \geq 0$. For any prior $p_0 \in (0, 1)$, there is a set of preference types $u$ that prefer no information over receiving a signal that perfectly reveals the state.*

2. *Take any prior beliefs $p_0' < p_0 \in (0, 1)$. Take a type where $u$ is strictly concave in the second argument. If she prefers no information over receiving a signal that perfectly reveals the state when holding the prior belief $p_0$, she also does so when holding the larger prior belief $p_0$.*

Proposition 3 is consistent with the empirical finding of Dana *et al.* (2007), who, in a dictator environment similar to ours, find that a significant fraction of dictators avoids information that reveals the *ex-ante* unknown state all at once. Feiler (2014) further documents that the fraction of dictators who avoid such perfectly revealing information increases with the dictator's prior belief that a self-benefiting option has no negative externality. The second part of Proposition 3 shows that the model predicts also this finding for a large class of preference types.

### B.3.3 Proof of Proposition 2

Take $r = 0$. For any prior $p_0(0, 1)$, there is an open set of thresholds $l(x) \in (0, 1)$ and $l(y) \in (0, 1)$ such that $p_0 > l(x)$ or $p_0 > 1 - l(y)$. The claim for $r = 0$ follows then from Lemma 5. Take $r > 0$. It follows from the characterization of the belief cutoffs after Lemma 2 that $p_h \leq l(x)$. Hence, if $p_0 > l(x)$, the agent stops acquiring information immediately in the equilibrium given by $p_h$ and $p_l$. More generally, whenever $p_0 > p_h$, the agent stops acquiring information immediately in the equilibrium given by $p_h$ and $p_l$.

### B.3.4 Proof of Proposition 3

The first item of Proposition 3 is a corollary of Proposition 2: it says that a preference type prefers to receive no information over all possible information acquisition strategies, including those given by the belief cutoffs $p_l = \epsilon$ and $p_h = 1 - \epsilon$, which yield information arbitrarily close to a signal that reveals the state perfectly. For example, types with $p_0 > l(x)$ cannot achieve a higher payoff than from stopping directly and choosing $x$ since this strategy yields $V(p_0) = r + u(x, p_0) = r$, given the definition of $l(x)$, (7). The payoff when revealing the state is $p_0 V(1) + (1-p_0)V(0) = p_0 r + (1-p_0) \max(0, r + u(x, 0))$, which is strictly smaller than $r$ if $u(x, 0) < 0$. Hence, these types strictly prefer to receive no information over receiving a signal that reveals the state perfectly.

Now, we prove the second item of Proposition 3. Fix a prior $p_0 \in (0, 1)$. Take any prior belief $p_0' < p_0 \in (0, 1)$. Consider an agent type with $u$ strictly concave in the second argument. Suppose that, given the prior $p_0'$, she prefers to receive no information over receiving a signal that perfectly reveals the state. We show that the agent also prefers to avoid information when the prior is $p_0$. There are two cases. In the first case, $x = \arg\max_{a \in \{x,y\}} U(a, 0; r)$. This implies that the agent strictly prefers $x$ over $y$ at any belief $p \in [0, 1]$. The strict concavity of $u$ implies

$$u(x, p_0) > p_0 u(x, 1) + (1 - p_0) u(x, 0), \tag{30}$$

which is equivalent to

$$V(p_0) > p_0 V(1) + (1 - p_0) V(0), \tag{31}$$

which shows that the agent strictly prefers to avoid information at the prior belief $p_0$. In the second case, $y \in \arg\max_{a \in \{x,y\}} U(a, 0; r)$. Since we assumed that the agent avoids information given the prior belief $p_0'$,

$$V(p_0') \quad > \quad (1 - p_0') V(0) + p_0' V(1) \tag{32}$$

Now, we use that the agent prefers $x$ at $p_h$ given Lemma 3, and that $V(0) =$

$\max_{a\in\{x,y\}} U(a,0;r) = U(y,0;r) = u(y,1) = 0$. Thus, (32) implies

$$r + u(x, p_0') \;\;>\;\; rp_0'. \tag{33}$$

Rearranging,

$$r > -\frac{u(x, p_0')}{1 - p_0'} \tag{34}$$

It follows from the concavity of $u$ that $\frac{-u(x,p)}{1-p} = \frac{u(x,1)-u(x,p)}{1-p}$ is strictly decreasing in $p$. Thus,

$$r > -\frac{u(x, p_0)}{1 - p_0}, \tag{35}$$

or equivalently,

$$r + u(x, p_0) \;\;<\;\; rp_0. \tag{36}$$

Thus, the type also prefers to avoid information when the prior is $p_0$. This finishes the proof of the second item.

## B.4 Self-Image Concerns

### B.4.1 Model Variant and Result

The game is as in Section 1.1: there is an agent who can observe the information process $(Z_t)_{t\geq 0}$ at no cost. The agent can stop at any time, and chooses between $x$ and $y$ subsequently. Relative to Section 1.1, we modify the preferences of the agent. We follow the existing literature on self-image concerns in the prosocial domain in three aspects: first, the agent has a prosocial type $\theta \in [0,1]$ that captures how much she cares about the welfare of the other relative to her own remuneration. Second, she is concerned about her prosocial self-image, i.e., her utility depends on the belief about her prosocial type (e.g., Grossman and van der Weele, 2017). Third, the stopped belief together with the subsequent choice of an action $a$ are "diagnostic" about her own prosocial type (Bodner and Prelec, 2003).

Formally, a type $\theta$ who stops observing the process at $t = \tau$, holding a belief $p = p_\tau$, and who chooses $a \in \{x, y\}$, has the following utility (compare to (1)),

$$U(a,p;\theta,r) = \begin{cases} u(x,p) + rw(\theta) & \text{if } a = x, \\ u(y, 1-p) & \text{if } a = y, \end{cases} \tag{37}$$

where the belief-based utility is

$$u(a,q) = \begin{cases} q + \psi \mathrm{E}(\theta | p_\tau = q, a = x) & \text{if } a = x, \\ q + \psi \mathrm{E}(\theta | p_\tau = 1-q, a = y) & \text{if } a = y. \end{cases} \tag{38}$$

The first term in (38) represents the prosocial concern and the second term represents the dianostic part of the utility, with $\psi > 0$. The function $w$ is continuously differentiable and strictly decreasing in the prosocial type, so that agents with higher prosocial type care less about their own remuneration from choosing the self-benefiting option $x$. A strategy is a mapping $\sigma$ from types to stopping times.

We study the situation with egoistic motive ($r = 1$). The following result provides sufficient conditions for the existence of a perfect Bayesian equilibrium that is *monotone*, meaning that more prosocial types acquire more information about the state in a Blackwell sense.[31]

**Theorem 2** *Let $r = 1$. Take a distribution $F$ of the prosocial types $\theta$ with log-concave density and support $[0,1]$. Let $0 < \psi(\psi + w') < 1$, $w(1) < 1 + \psi < w(0)$, and $p_0 + \psi\mathrm{E}(\theta) + (1-p_0)w(1) > (1+\psi)$. For $\epsilon > 0$ sufficiently small, there exists a monotone perfect Bayesian equilibrium with the following properties.*

1. *There is $k \in (0,1)$ such that all types $\theta < k$ acquire no information and all types $\theta \geq k$ acquire partial information about the state.*

2. *If a type $\theta \geq k$ is more prosocial than another type $\theta'$, i.e., $\theta > \theta'$, then, the type $\theta$ uses a strategy that generates signals that are Blackwell strictly more informative about the state relative to the strategy of $\theta'$.*

The conditions in the statement of Theorem 2 are sufficient, but not necessary. The following proof shows how the conditions ensure that the equilibrium is

[31] There are also pooling equilibria. However, the goal here is to show that there may exist equilibria in which types self-signal about their prosociality by stopping at more or less informative beliefs about the consequences of their action choice on others.

interior (i.e., $k \in (0,1)$), monotone, and that the best response of the types $\theta \geq k$ is pinned down locally by a first-order condition.

### B.4.2 Proof: Candidate Equilibria

**Strategies.** Let $\epsilon > 0$. Take $k \in [0,1]$. We define an associated strategy $\sigma^k$. Take a type $\theta < k$. The type stops observing the information process directly at the prior $p_0$. Take a type $\theta \geq k$. The type uses the belief cutoff $p_l = \epsilon$, that is, she stops observing the information process when $p_t \leq p_l$, and chooses $y$ subsequently. She also stops if $p_t \geq v^k(\theta)$ and chooses $x$ subsequently, where $v^k$ is defined as follows,

$$v^k(\theta) = c_1 e^{\int_k^\theta g^k(z)dz} + \epsilon \tag{39}$$

for $g^k(z) = \psi\left[\psi z - \psi \mathrm{E}(\theta|\theta \geq k) + w(z) - 1 + 2\epsilon\right]^{-1}$ and for a constant $c_1 \geq p_0$, so that $v^k(k) \geq p_0 + \epsilon$ for all $k$. We see that $v^k(\theta)$ solves the following ordinary differential equation (ODE).

$$(v^k)'(\theta) = v^k(\theta)g(\theta). \tag{40}$$

Later, when analyzing the best response, we will show that the ordinary differential equation (40) will turn up as first-order condition of the agent's maximization problem.

**Feasibility.** In the rest of this section, we restrict the domain of $k$ to ensure that $v^k(\theta) \leq 1 - \epsilon$ for all $\theta \geq k$, so that $\sigma^k$ is a feasible strategy.

Recall that $w$ is continuous, and so is $\mathrm{E}(\theta|\theta \geq k)$ in $k \in [0,1]$ since the distribution of $\theta$ has a density and since its support is $[0,1]$. The assumptions $w(1) < 1 + \psi < w(0)$ imply

$$w(1) < 1 + \psi \mathrm{E}(\theta|\theta \geq 1) \tag{41}$$

and

$$w(0) > 1 + \psi \mathrm{E}(\theta|\theta \geq 0). \tag{42}$$

Altogether, the intermediate value theorem implies that there is $\tilde{k} \in (0,1)$

such that

$$w(\tilde{k}) = 1 + \psi \mathrm{E}(\theta|\theta \geq \tilde{k}). \tag{43}$$

Recall that $w$ is strictly decreasing in $\theta$ and note that $\mathrm{E}(\theta|\theta \geq k)$ is strictly increasing in $k$ since the density of $\theta$'s distribution is log-concave (see e.g., Burdett, 1996). Hence,

$$w(\theta) < 1 + \psi \mathrm{E}(\theta|\theta \geq k) \tag{44}$$

for all $k \geq \tilde{k}$ and all $\theta \geq k$.

The following Lemma 6 shows that $g^k > 0$. Further, the lemma shows that $g$ is uniformly bounded above. Using, (40), this implies that for any $c_1 \geq p_0$, there is minimal $k(c_1) \in [\tilde{k}, 1]$ such that $p_0 + \epsilon \leq v^k(\theta) \leq 1 - \epsilon$ for all $k \geq k(c_1)$ and $\theta \geq k$. Hence, $\sigma^k$ is a well-defined strategy for $k \geq k(c_1)$. In the remainder of this proof, let $k \geq k(c_1)$.

**Lemma 6** *Let $w(0) > 1 + \psi$, and $0 < \psi(\psi + w') < 1$. Then, $g^k(\theta) > 0$, $(v^k)'(\theta) > 0$ and $(v^k)''(\theta) > 0$ for all $k, \theta \in [0, 1]$. Further, $g^k(\theta)$ is uniformly bounded.*

**Proof.** Recall (40). Hence, $(v^k)' > 0$ if $g > 0$. Note that $g^k(\theta) > 0$ if

$$\psi\theta + w(\theta) \geq 1 + \psi \mathrm{E}(\theta|\theta \geq k) \tag{45}$$

since $\epsilon > 0$. Now, (45) holds for $\theta = 0$ since $w(0) \geq 1 + \psi$. Further, it holds for $\theta > 0$ since $\psi + w' > 0$ implies $\psi\theta + w(\theta) > 1 + \psi$. Second, note that it follows from (40) that

$$(v^k)'' = (v^k)'g + vg' = (v^k)(g^2 + g') \tag{46}$$

Hence, $(v^k)'' > 0$ if $g^2 + g' > 0$. Let $h = \frac{1}{g}$, i.e., $g = \frac{1}{h}$. Then, $g' = -\frac{h'}{h^2}$. Hence, $g^2 + g' > 0$ if $1 - h' > 0$. By definition, $h' = \psi(\psi + w')$, and, by assumption, $\psi(\psi + w') < 1$. We conclude that $(v^k)'' > 0$. Third, note that the assumption that $h' = \psi(\psi + w') > 0$ implies that $g$ is maximal at $\theta = 0$. This implies $g^k(\theta) \leq \frac{1}{\epsilon + w(0) - 1 - \psi}$ for all $k, \theta \in [0, 1]$. Since also $g > 0$ for all $k, \theta \in [0, 1]$, we conclude that $g$ is uniformly bounded. ■

**Beliefs.** We define a belief system $\mu^k(a,q)$ for $k \geq k(c_1)$. Given $\sigma^k$, the following beliefs are well-defined by Bayes-consistency:

$$\mathrm{E}(\theta|p_\tau = q, a; \sigma^k) \;=\; \begin{cases} (v^k)^{-1}(q) \;\text{ for }\; q \geq v^k(k) \;\text{ and }\; a = x, \\ \mathrm{E}(\theta|\theta \leq k) \quad \text{for} \quad q = p_0 \;\text{ and }\; a = x, \\ \mathrm{E}(\theta|\theta \geq k) \quad \text{for} \quad q = \epsilon \;\text{ and }\; a = y, \end{cases} \tag{47}$$

where we used that $(v^k)' > 0$ from Lemma 6. Let

$$\mu(y,q) = \begin{cases} \frac{q}{1-\epsilon}\mathrm{E}(\theta|\theta \geq k) \;\text{ for }\; q \leq 1-\epsilon, \\ \mathrm{E}(\theta|\theta \geq k) \;\text{ for }\; q \geq 1-\epsilon, \end{cases} \tag{48}$$

and

$$\mu(x,q) = \begin{cases} 0 \;\text{ for }\; q \leq p_0 - \epsilon, \\ \frac{q-(p_0-\epsilon)}{\epsilon}\mathrm{E}(\theta|\theta \leq k)\text{for }\; p_0 - \epsilon \leq q < p_0, \\ \mathrm{E}(\theta|\theta \leq k) \;\text{ for }\; p_0 \leq q < v^k(k), \\ (v^k)^{-1}(q) \;\text{ for }\; v^k(k) \leq q \leq v^k(1), \\ 1 \;\text{ for }\; q > v^k(1). \end{cases} \tag{49}$$

We see that $\mu(a,q)$ is consistent with the beliefs that are implied by $\sigma^k$ through Bayes rule, (47). We see that $\mu(x,q)$ is weakly increasing in $q$ and continuously differentiable at all $q > v^k(k)$. The pairs $(\sigma^k, \mu^k)$ are the candidate equilibria.

### B.4.3 Proof: Best Response to a Candidate Equilibrium

Take $\sigma^k$ and $\mu^k$ and consider the best response. Consider the candidate belief-based utility

$$u(a,q) = q + \psi\mu(a,q). \tag{50}$$

Take any $\theta \geq k$ for which it is not optimal to stop directly at the prior given $\sigma^k$ and $\mu^k$. In the following, we rely on the previous analysis of the model with belief-based utility from Section 1.1 to characterize the best response for $\theta$.

**Claim 4** *There is a best response characterized by belief cutoffs $p_l < p_0$ and*

$p_h > p_0$, *meaning that the agent stops if and only if* $p_t \le p_l$ *or* $p_t \ge p_h$.

Let $V(p) = \max_{a\in\{x,y\}} U(a,p;\theta,r)$. Let $\bar{V}$ be the smallest concave function with $\bar{V}(p) \ge V(p)$ for all $p \in [\epsilon, 1-\epsilon]$. Following the steps of the proofs of Lemma 1 and Lemma 2 in Appendix B.1 verbatim, we show that the results of the two lemmas hold. In particular, the argument from the proof of Lemma 2 shows the claim and that

$$V(p_l) = \bar{V}(p_l), \tag{51}$$

$$V(p_h) = \bar{V}(p_h), \tag{52}$$

compare to (20).

**Claim 5** *It is optimal to choose* $x$ *at* $p_h$.

Compare the statement of the claim to Lemma 3. We note that $u(y,1) \le u(x,1)$ given $\sigma^k$ and $\mu^k$, and normalize the belief-based utility to $\tilde{u}(a,q) = u(a,q) - u(x,1)$. This way, $\tilde{u}(x,1) = 0$ and $\tilde{u}(y,1) \le 0$. Following the steps of the proof of Lemma 3 verbatim, while replacing $u$ by $\tilde{u}$ therein, shows that it is optimal to choose $x$ at $p_h$ and that

$$V(p_h) > V(p_l). \tag{53}$$

**Claim 6** *It is optimal to choose* $y$ *at* $p_l$ *and it holds that* $p_l = \epsilon$ *when* $\epsilon > 0$ *is sufficiently small.*

Compare the statement of the claim to Lemma 4. First, we argue that it is *not* optimal to choose $x$ at $p_l$. This implies that it is also optimal to choose $x$ at any $p \ge p_l$ given the definitions of the payoffs (37) and since the belief utility $q + \mu(x,q)$ is increasing in $q$ and the belief utility $\mu(y,q)$ is decreasing in $q$. Hence, $V(p) = \max_{a\in\{x,y\}} U(a,p;\theta,r) = U(x,p;\theta,r)$ for $p \ge p_l$. Given the definition of $\mu(x,q)$, (49), we note that $\bar{V}(p_0) = V(p_0)$, so that it is optimal for $\theta$ to stop acquiring information directly. This contradicts with the initial assumption. Now, following the lines of the proof of Lemma 4 and using (53) and that $u(y,q)$ is weakly increasing in $q$ for $q > 1 - p_0$, we show that $p_l = \epsilon$, that is Lemma 4 holds.

Together with Claim 4 - 6, the next result, Claim 7 finishes the characterization of the best response when it is not optimal to stop the information process directly.

**Claim 7** *We have* $p_h = v^k(\theta)$.

**Proof.** Take any $\theta \geq k$ for which it is not optimal to stop directly at the prior. Given Claim 4 - 6, it is optimal for $\theta$ to use a strategy with belief cutoffs $p_l = \epsilon$ and $q$ for some $q > p_0$: she stops only if $p_t \leq \epsilon$, after which she chooses $y$, or she stops if $p_t \geq q$, in which case she chooses $x$.

Now, we show that the optimal upper belief cutoff is given by $q = v^k(\theta)$. For this, fix $p_l = \epsilon$, and consider the agent's expected payoff from using the upper cutoff $q \geq p_0$,

$$\frac{q - p_0}{q - \epsilon} u(y, 1 - \epsilon) + \frac{p_0 - \epsilon}{q - \epsilon}\Big[u(x, q) + w(\theta)\Big]. \tag{54}$$

It turns out to be useful for the algebra to subtract $u(y, 1 - \epsilon)$ from the objective function (54). Doing so, and taking the first-order condition with respect to $q$ gives

$$\begin{aligned} & \frac{p_0 - \epsilon}{q - \epsilon} u'(x, q) - \frac{p_0 - \epsilon}{(q - \epsilon)^2}(u(x, q) + w(\theta) - u(y, 1 - \epsilon)) = 0 \\ \Leftrightarrow \quad & u'(x, q)(q - \epsilon) = u(x, q) + w(\theta) - u(y, 1 - \epsilon). \end{aligned} \tag{55}$$

Recalling the definition of $\mu^k$, (49),

$$u(x, q) = q + \psi(v^k)^{-1}(q) \tag{56}$$

for $q \geq v^k(k)$. Combining (55) and (56),

$$q - \epsilon + \psi((v^k)^{-1})'(q)(q - \epsilon) = q + \psi(v^k)^{-1}(q) + w(\theta) - u(y, 1 - \epsilon). \tag{57}$$

Now, we would like to check if $q = v^k(\theta)$ satisfies the first-order condition. For $q = v^k(\theta)$, we have $((v^k)^{-1})'(q) = \frac{1}{(v^k)'(\theta)}$. Rewriting (57),

$$-\epsilon + \psi \frac{v^k(\theta) - \epsilon}{(v^k)'(\theta)} = \psi\theta + w(\theta) - u(y, 1 - \epsilon).$$

Using that $u(y, 1 - \epsilon) = 1 - \epsilon + \psi \mathrm{E}(\theta | \theta \geq k)$,

$$\begin{aligned} & -\epsilon + \psi \frac{v^k(\theta) - \epsilon}{(v^k)'(\theta)} = \psi\theta + w(\theta) - 1 + \epsilon - \psi \mathrm{E}(\theta | \theta \geq k) \\ \Leftrightarrow \quad & (v^k(\theta) - \epsilon) g(\theta) = (v^k)'(\theta) \end{aligned} \tag{58}$$

for $g(z) = \psi\Big[\psi z - \psi\mathrm{E}(\theta|\theta \geq k) + w(z) - 1 + 2\epsilon\Big]^{-1}$. Using the definition (39), one checks that $v^k(\theta)$ satisfies the ordinary differential equation (58), hence the first-order condition (55).

To conclude the proof, we show that the solution to the first-order condition (55) is unique and maximizes (54). For this, we argue that $u''(x,q) < 0$ for $q \geq v^k(k)$.[32] Recall that $u(x,q) = q + (v^k)^{-1}(q)$ for $q \geq v^k(k)$. Recall from Lemma 6 that $(v^k)''(\theta) > 0$, so $v^k$ is strictly convex. Since $v^k$ is strictly increasing in $\theta$ by Lemma 6, this implies that $(v^k)^{-1}(q)$ is strictly concave, hence $u(x,q)$ is strictly concave for $q \geq v^k(k)$. The concavity of $u(x,q)$ implies that

$$u'(x,q)(q-\epsilon) - \Big[u(x,q) - w(\theta) + u(y,1)\Big] \tag{59}$$

is strictly decreasing in $q$ for $q \geq v^k(k)$ when $\epsilon \approx 0$.[33] Thus, using (55), the objective function (54) is strictly concave for $q \geq v^k(k)$. Therefore, $v^k(\theta)$ is the unique solution to (55) and maximizes (54) across all $q \geq v^k(k)$.

Finally, note that we constructed $\mu(x,q)$ and thereby $u(x,q)$ such that (54) is not maximized by any $p_0 \leq q < v^k(k)$. Suppose otherwise. Then, the strategy given by the belief cutoffs $p_l = \epsilon$ and $q$ must maximize $\mathrm{E}(V(p_\tau)$ with $V$ defined as after Claim 4. Note that, given the definitions of $\mu(x,q)$, (49), and $U(a,p;\theta,r)$, (37), the function $V$ is linear on $[p_0, v^k(k))$ and has a jump upwards at $v^k(k)$. This shows that, fixing $p_l = \epsilon$, the expected payoff $\mathrm{E}(V(p_\tau)$ is maximized by either $q = p_0$ or by $q = v^k(k)$ on the interval $[p_0, v^k(k)]$. Our initial assumption that it is not optimal to stop acquiring information directly rules out $q = p_0$. We conclude that $v^k(\theta)$ is the unique global maximizer. ■

### B.4.4 Proof: Equilibrium Construction

We define an auxiliary map $f$ from $c_1$ to a type $f(c_1)$. This map will split the types into those that acquire no information under the best response to $(\sigma^k, \mu^k)$, and those that acquire some information. First, we restrict the domain. Note that for $c_1 \geq p_0$, we have

$$v^k(k) \geq p_0 + \epsilon, \tag{60}$$

[32]For $q = v^k(k)$, $u''(x,q)$ is the right-sided derivative.

[33]To see why, consider the derivative with respect to $q$ for $\epsilon \approx 0$. It is given by $u''(x,q)q + u'(x,q) - u'(x,q) = u''(x,q) < 0$.

given (39). Given Lemma 6, this implies $v^k(1) > p_0$. Take $\delta > 0$. Denote $\bar{c_1} = 1 - \delta - \epsilon$, which implies that, given $c_1 = \bar{c_1}$, we have $v^k(k) = 1 - \delta$. For any $c_1$, take $k = k(c_1)$, meaning that, given $c_1$, it holds

$$v^{k(c_1)}(1) = 1 - \epsilon. \tag{61}$$

The inequalities (60) and (61) together with $(v^k)' > 0$ (see Lemma 6) imply that for all $p_0 \le c_1 \le \bar{c_1}$ and $\theta \ge k(c_1)$, it holds $v^{k(c_1)}(\theta) \in [p_0 + \epsilon, 1 - \epsilon]$. Hence, the strategy $\sigma^{k(c_1)}$ is well-defined when $p_0 \le c_1 \le \bar{c_1}$.

We consider a candidate best response to $(\sigma^{k(c_1)}, \mu^{k(c_1)})$ where the agent stops only if $p_t \le \epsilon$, or if $p_t \ge q$; further, if she stops at $p_t \le \epsilon$, she chooses $y$, and if she stops above $q$, then she chooses $x$ (compare to the results in Section B.4.3.) Given Claim 7, it is sufficient to restrict to candidate strategies with $q \ge p_0 + \epsilon$ since $v^k(\theta) \ge p_0 + \epsilon$, see (60). Another candidate best response is that the agent stops observing the information process directly. Given Lemma 3, she chooses $x$ when stopping directly. Given $\sigma^{k(c_1)}$ and $\mu^{k(c_1)}$, a type $\theta$ prefers to stop observing the information process directly to using the candidate strategy given by the belief cutoffs $\epsilon$ and $q \ge p_0 + \epsilon$ if

$$\begin{aligned} & \frac{q - p_0}{q - \epsilon}\Big[(1-\epsilon) + \psi\mu(y, 1-\epsilon)\Big] + \frac{p_0 - \epsilon}{q - \epsilon}\Big[q + \psi\mu(x, q) + w(\theta)\Big] \\ \le \; & p_0 + \psi \mathrm{E}(\theta | \theta \le k(c_1)) + w(\theta). \end{aligned} \tag{62}$$

Since $w'(\theta) < 0$ and since $q > p_0$, the difference of the left hand side minus the right hand side is strictly increasing in $\theta$. Hence, there exists a unique cutoff $\theta(q) \in [0, 1]$ such that a type $\theta$ prefers to stop directly if $\theta < \theta(q)$ and a type prefers to use $p_l = \epsilon$ and $q$ if $\theta > \theta(q)$. Since $q$ was arbitrary, we obtain a cutoff

$$f(c_1) = \inf\{\theta(q) : q \ge p_0 + \epsilon\} \in [0, 1] \tag{63}$$

such that a type $\theta$ prefers to stop directly over *all* strategies given by belief cutoffs $\epsilon$ and some $q \ge p_0 + \epsilon$ if $\theta < f(c_1)$, and prefers some such strategy given by belief cutoffs $\epsilon$ and $q$ over stopping directly if $\theta > f(c_1)$.

**Construction.** We claim that there is $c_1 \in [p_0, \bar{c_1}]$ such that

$$f(c_1) = k(c_1). \tag{64}$$

For such $c_1$, the characterization of the best response in Section B.4.3 shows that, for all types $\theta < k(c_1)$ it is strictly optimal to acquire no information, and for all types $\theta \geq k(c_1)$ it is optimal to acquire some information and to use the strategy with the belief cutoffs $p_l = \epsilon$ and $p_h = v^{k(c_1)}(\theta)$. Since $\mu^{k(c_1)}$ is a belief system that is consistent with $\sigma^{k(c_1)}$ by definition, this shows that $\mu^{k(c_1)}$ and $\sigma^{k(c_1)}$ constitute a perfect Bayesian equilibrium, and finishes the proof of Theorem 1.

To show (64), it is useful to define by $\phi(c_1)$ the utility difference of the type $\theta = k(c_1)$ from the strategy where she stops directly at the prior and chooses $x$ relative to the strategy where she stops only if $p_t \leq \epsilon$, choosing $y$ thereafter, or if $p_t \geq v^{k(c_1)}(k(c_1))$, choosing $x$ thereafter.

**Step 1** *If $c_1 = p_0$ and $\epsilon > 0$ is sufficiently small, it is not optimal for the type $\theta = k(c_1)$ to stop directly given $\sigma^{k(c_1)}$ and $\mu^{k(c_1)}$ . That is, $\phi(p_0) < 0$.*

**Proof.** Note that by definition of $\mu^k$ ((47)),

$$\mu^{k(c_1)}(x, q) = \begin{cases} \mathrm{E}(\theta|\theta \leq k(c_1)) & \text{for} \quad q = p_0, \\ (v^{k(c_1)})^{-1}(q) & \text{for} \quad q \geq v^{k(c_1)}(k(c_1)). \end{cases} \tag{65}$$

Recall that, for $c_1 = p_0$, we have $v^{k(c_1)}(k(c_1)) = p_0 + \epsilon$, given (39). Therefore, $(v^{k(c_1)})^{-1}(q)$ equals $k(c_1)$ for $q = p_0 + \epsilon$, which is strictly larger than $\mathrm{E}(\theta|\theta \leq k(c_1))$. When $\epsilon \approx 0$, $\theta$ is therefore strictly better off when observing the information process as long as $p_t \in [\epsilon, p_0 + \epsilon]$, choosing $x$ when stopping at $p_t = p_0 + \epsilon$, and choosing $y$ when stopping at $p_t = \epsilon$ than when using the strategy where she stops directly at $p_0$ and choosing $x$. Hence, it is not optimal to stop at the prior directly. ■

**Step 2** *If $c_1 = \bar{c_1}$, and $\epsilon, \delta > 0$ are sufficiently small, it is strictly optimal for the type $\theta = k(c_1)$ to stop directly given $\sigma^{k(c_1)}$ and $\mu^{k(c_1)}$. That is, $\phi(\bar{c_1}) > 0$.*

**Proof.** Recall that $\bar{c_1} = 1 - \delta - \epsilon$. It follows from Claim 5 - Claim 7 that it is either optimal for $\theta = k(c_1)$ to stop directly or to use the strategy given by the belief cutoffs $p_l = \epsilon$ and $p_h = v^{k(c_1)}(k(c_1))$. Let $k = k(c_1)$. Stopping directly is strictly optimal if

$$
\begin{aligned}
& U(x, p_0; \theta, r) > \frac{p_0 - \epsilon}{p_h - \epsilon} U(x, p_h; \theta, r) + \frac{p_h - p_0}{p_h - \epsilon} U(y, \epsilon; \theta, r), \\
\Leftrightarrow \quad & p_0 + \psi \mathrm{E}(\theta | \theta \leq k) + w(\theta) \qquad (66) \\
> \quad & \frac{p_0 - \epsilon}{v^k(k) - \epsilon} \Big[ v^k(k) + \psi k + w(\theta) \Big] + \frac{v^k(k) - p_0}{v^k(k) - \epsilon} \Big[ 1 - \epsilon + \psi \mathrm{E}(\theta | \theta \geq k) \Big].
\end{aligned}
$$

Note that $\delta \approx 0$ and $\epsilon \approx 0$ implies $\bar{c_1} = 1 - \delta - \epsilon \approx 1$, which in turn implies $k(c_1) \approx 1$ by the definition of $k(c_1)$. The equation (66) holds for $\delta > 0$, $\epsilon > 0$, and $k(c_1) - 1$ sufficiently small if

$$
\begin{aligned}
& p_0 + \psi \mathrm{E}(\theta | \theta \leq k(c_1)) + w(1) > p_0(1 + \psi + w(1)) + (1 - p_0)(1 + \psi) \\
\Leftrightarrow \quad & p_0 + \psi \mathrm{E}(\theta | \theta \leq k(c_1)) + (1 - p_0) w(1) > 1 + \psi. \qquad (67)
\end{aligned}
$$

The condition (67) holds because of the assumption $p_0 + \psi \mathrm{E}(\theta) + (1 - p_0) w(1) > 1 + \psi$ of Theorem 2. Finally, since all previous arguments were true for all $\delta > 0$ and $\epsilon > 0$ sufficiently small, we can choose these parameters small enough so that (66) holds. This finishes the proof that $\phi(\bar{c_1}) > 0$. ■

Finally, note that $\phi$ is continuous in $c_1$: this is because it depends on $c_1$ only through $k(c_1)$ and $v^{k(c_1)}(k(c_1))$. However, $k(c_1)$ is continuous in $c_1$ and $v^{k(c_1)}(k(c_1)) = c_1 + \epsilon$ is also continuous in $c_1$. Using Step 1 and Step 2, it follows from the intermediate value theorem, that there is $c_1 \in (p_0, \bar{c_1})$ such that $\phi(c_1) = 0$. This implies $f(c_1) = k(c_1)$ by the definition of $f$ and $\phi$.

# Appendix: Experimental Instructions (for online publication)

## C Original Instructions in German

In this online appendix, we include the original instructions that we used in the experiment. The original instructions are paper-based and in German language. They are similar in all four treatment: *NoForce Tradeoff*, *Force-Tradeoff*, *Force-Control* and *NoForce-Control*. We include the instructions in *NoForce-Tradeoff* in full and point out the deviation from them in the three other treatments respectively. We include the English translation of these instructions in Online Appendix D.

### C.1 Treatment: NoForce-Tradeoff

## Allgemeine Erklärungen

Wir begrüßen Sie zu dieser Studie! Im Rahmen dieser Studie können Sie eine nicht unerhebliche Summe Geld verdienen. Lesen Sie die folgenden Erklärungen daher bitte gründlich durch! Wenn Sie Fragen haben, strecken Sie bitte Ihre Hand aus der Kabine – wir kommen dann zu Ihrem Platz.

**Während der Studie ist es nicht erlaubt, mit den anderen Studienteilnehmern zu sprechen, Mobiltelefone zu benutzen oder andere Programme auf dem Computer zu starten.** Die Nichtbeachtung dieser Regeln führt zum Ausschluss aus der Studie und von allen Zahlungen. Ihr Einkommen aus dieser Studie bekommen Sie am Ende der Studie bar ausbezahlt. Während der Studie sprechen wir nicht von Euro, sondern von Punkten. Ihre gesamte Auszahlung wird also zunächst in Punkten berechnet und dann am Ende in Euro umgerechnet, wobei gilt:

**1 Punkt = 5 Cent**.

**Teilnehmerzuordnung:** Durch eine Zufallsentscheidung hat Ihnen der Computer aus allen Studienteilnehmern in diesem Raum einen anderen Teilnehmer zugeordnet. Im folgenden bezeichnen wir den Ihnen zugeordneten Studienteilnehmer als 'den anderen Teilnehmer'.

Benutzen Sie diesen Teilnehmerbogen gerne als Referenz während der Bearbeitung am Computer. Im Vorlauf zur Bearbeitung der Studie werden wir Sie bitten, einige Kontrollfragen zu bearbeiten.

## Wahrscheinlichkeiten

In diesem Abschnitt möchten wir Sie ein wenig mit mathematischen Wahrscheinlichkeiten vertraut machen.

Stellen Sie sich folgende Situation vor: In einem Raum sitzen 10 Teilnehmer. Jeder Teilnehmer hat eine Box. Die Teilnehmer können keine der Boxen sehen, wissen aber folgendes:

- In jeder Box befinden sich 10 Bälle.
- 5 der 10 Teilnehmer haben eine Box mit 6 weißen Bällen und 4 schwarzen Bälle (Situation A).
- 5 der 10 Teilnehmer haben eine Box mit 4 weiße Bällen und 6 schwarze Bällen (Situation B).

Stellen Sie sich nun folgendes vor: Sie sind einer der Teilnehmer. Die Wahrscheinlichkeit, dass Sie sich in Situation A befinden, ist also 50 %. Ein Computer zieht einen Ball aus Ihrer Box und legt ihn nach dem Ziehen wieder zurück. Wenn Sie die Farbe des gezogenen Balles erfahren, hift dies, besser einzuschätzen in welcher Situation Sie sich befinden.

Frage: Was ist die Wahrscheinlichkeit, dass Sie sich in Situation A befinden, gegeben dass der gezogene Ball weiß ist?

Wahrscheinlichkeiten, welche zusätzliche Information - wie die Farbe des gezogenen Balles - berücksichtigen, werden auf statistisch korrekte Weise nach einem mathematischen Gesetz, dem Satz von Bayes' berechnet. Die Berechnung ist kompliziert, und benötigt mehrere Rechenschritte. **Daher zeigen wir Ihnen die statistisch korrekten Wahrscheinlichkeiten an, wann immer sie entscheidungsrelevant sind.**

Beispiel (Antwort zur Frage):

$$\begin{aligned}
& \text{Wahrscheinlichkeit von Situation A, gegeben, dass der gezogene Ball weiß ist} \\
= \; & \text{W'keit von Situation A} \cdot \left[\frac{\text{W'keit, dass der gezogene Ball in Situation A weiß ist}}{\text{W'keit, dass der gezogene Ball weiß ist}}\right] \\
= \; & 50\% \cdot \frac{60\%}{50\%} \\
= \; & 60\%.
\end{aligned}$$

Die Wahrscheinlichkeit von Situation A, gegeben, dass der gezogene Ball schwarz ist, wird auf ähnliche Weise berechnet. **Bitten bearbeiten Sie nun die erste Kontrollfrage am Computer.**

## Ihre Entscheidungen

Sie erhalten nun 100 Punkte auf ihr Punktekonto. Als Nächstes fällen Sie eine Entscheidung, die Ihre eigene Auszahlungshöhe und die Auszahlungshöhe des anderen Teilnehmers beeinflusst, welcher ebenfalls 100 Punkte auf sein Punktekonto erhalten hat. Die Entscheidungen des anderen Teilnehmers haben jedoch keine Auswirkung auf Ihre Auszahlungshöhe.

Ihre Entscheidung besteht daraus, zwischen zwei Optionen, X und Y, zu wählen.

1. Eine dieser Optionen ist für den anderen Studienteilnehmer 'schädlich' und führt dazu, dass er 80 Punkte weniger ausgezahlt bekommt.

2. Die andere der Optionen hat keine Auswirkung auf den anderen Studienteilnehmer, diese Option ist 'sicher'.

3. Für je 7 von 20 Entscheidern ist die Option X sicher und Option Y schädlich (35 % Wahrscheinlichkeit), und für je 13 von 20 Entscheidern

ist die Option Y sicher und Option X schädlich (65 % Wahrscheinlichkeit). Es wurde vom Computer bereits zufällig ausgewählt, welche Option in Ihrem Fall sicher und welche schädlich ist.

4. Unabhängig davon, ob Option X oder Option Y für den anderen Teilnehmer sicher ist, bekommen Sie selber 25 Punkte mehr ausgezahlt, wenn Sie sich für Option X entscheiden.

## Ihre Information

Bevor Sie sich entscheiden, können Sie zusätzliche Information darüber erhalten, welche der Optionen der Computer für Sie als sicher ausgewählt hat. Wenn Sie die Entscheidung ohne zusätzliche Information treffen möchten, drücken Sie bitte direkt auf 'Entscheidung ohne zusätzliche Information'. Wenn Sie die Entscheidung mit zusätzlicher Information treffen möchten, drücken Sie bitte auf 'Entscheidung mit zusätzlicher Information'

In einer Box befinden sich 100 weiße oder schwarze Bälle. Falls Option X sicher ist, befinden sich in der Box 60 weiße Bälle, und 40 schwarze Bälle. Falls Option Y sicher ist, befinden sich in der Box 40 weiße Bälle, und 60 schwarze Bälle.

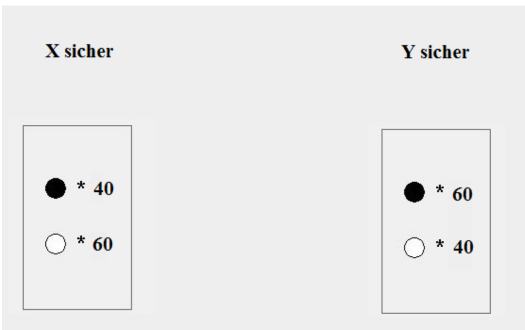



Figure 8: Box mit 40 schwarzen und 60 weißen Bällen (X sicher); Box mit 60 schwarzen und 40 weißen Bällen (Y sicher)

Sie werden die Box nicht gezeigt bekommen, aber sie können den Computer einen Ball zufällig aus der Box ziehen lassen. Dafür klicken Sie auf die Schaltfläche 'Ein weiterer Ball'. Nach Ihrem Klick wird der Ball, den der Computer aus der Box gezogen hat, auf dem Bildschirm eingeblendet. Danach legt der Computer den Ball in die Box zurück, sodass sich wieder 100 Bälle in der Box befinden.

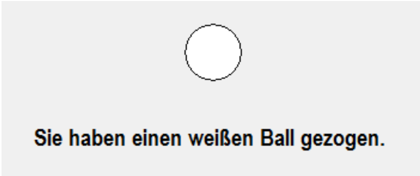



Figure 9: Beispiel: Der vom Computer gezogene Ball ist weiß.

Sie können danach einen weiteren Ball ziehen lassen. Dafür klicken Sie wiederum auf die Schaltfläche ‘Ein weiterer Ball’. Sie können unbegrenzt viele Bälle ziehen lassen. Wenn Sie keine Bälle mehr ziehen lassen möchten, klicken Sie auf die Schaltfläche ‘Zur Entscheidung’.

Erinnern Sie sich, dass mehr weiße Bälle in der Box sind, wenn Option X sicher ist (60 weiße Bälle), als wenn Option Y sicher ist (40 weiße Bälle)? Wenn Sie also sehen, dass ein weißer Ball gezogen wurde, ist dies ein Hinweis darauf, dass Option X sicher ist. Nach jedem Ball wird die statistisch korrekte Wahrscheinlichkeit, dass Option X sicher ist, eingeblendet. Dabei werden alle Bälle, die Sie bereits gezogen haben, berücksichtigt.[34]

Die betroffene Person weiß nicht, ob oder wieviel Sie sich informiert haben. Sie erfahren am Ende der Studie nicht, ob X oder Y die schädliche Aktion ist. Es ist kostenlos für Sie, zusätzliche Information vor Ihrer Entscheidung zwischen X und Y zu erhalten.

## C.2 Treatment: NoForce-Control

...

[34] Für die genaue Berechnung der Wahrscheinlichkeit, dass Option X sicher ist, wird ein mathematisches Gesetz, der Satz von Bayes, benutzt. Die exakte Berechnungsformel, wenn z.B. ein einziger weißer Ball gezogen wurde, ist folgende:

$$\begin{aligned} & \text{Wahrscheinlichkeit, dass Option X sicher ist, gegeben, dass der gezogene Ball weiß ist} \\ = \; & \text{W'keit, dass Option X sicher ist} \\ & \cdot \frac{\text{W'keit, dass der gezogene Ball weiß ist, wenn Option X sicher ist}}{\text{W'keit, dass der gezogene Ball weiß ist}}. \end{aligned}$$

Dies ist die einzige objektiv richtige Berechnungsweise.

# Ihre Entscheidungen

...

Ihre Entscheidung besteht daraus, zwischen zwei Optionen, X und Y, zu wählen.

...

4. Ihre eigene Auszahlungshöhe ist unabhängig davon, ob Sie sich für X oder Y entscheiden. Ihre Auszahlungshöhe ist auch unabhängig davon, ob Option X oder Option Y für den anderen Teilnehmer sicher ist.

...

## C.3 Treatment: Force-Tradeoff

...

# Ihre Information

Bevor Sie sich entscheiden, können Sie zusätzliche Information darüber erhalten, welche der Optionen der Computer für Sie als sicher ausgewählt hat.

...

## C.4 Treatment: Force-Control

...

# Ihre Entscheidungen

...

Ihre Entscheidung besteht daraus, zwischen zwei Optionen, X und Y, zu wählen.

...

4. Ihre eigene Auszahlungshöhe ist unabhängig davon, ob Sie sich für X oder Y entscheiden. Ihre Auszahlungshöhe ist auch unabhängig davon, ob Option X oder Option Y für den anderen Teilnehmer sicher ist.

...

## Ihre Information

Bevor Sie sich entscheiden, können Sie zusätzliche Information darüber erhalten, welche der Optionen der Computer für Sie als sicher ausgewählt hat.

...

# D Instructions English Translation

## D.1 Treatment: NoForce-Tradeoff

## General Explanations

Welcome to the study! In this study, you can earn a good amount of money. Please carefully read the following explanations! Shall you had questions, please stick your hand out of the cubicle—we will come to your seat.
**During the study, it is not allowed to talk with other participant, to use mobile phones, nor to start other programs on the computer.** The violation of these rules will lead to an exclusion form the study and any payment. You will receive your payment of the study at the end of the study in cash. During the study, we do not talk about Euro. Instead we will talk about points. Your total payment will be calculated in points and translated into Euro at the following rate:

**1 Point = 5 Cent**.

**Participant Pairing:** The computer has paired you with another participant who is randomly selected from all the participants in the room. In the following, we refer to the participant whom you are paired with as 'the other participant'.

Please feel free to refer back to this Instruction when you are working on the computer. Before the study starts, we will ask you to answer a couple of contrl questions.

## Probabilities

In this section, we want to familiarize you with mathematical probabilities.

Imagine the following situation: in a room there are 10 participants. Every participant has a box. The participants cannot see the boxes but know the following:

- In each box there are 10 balls.
- 5 of the 10 participants have a box with 10 white balls and 4 black balls (Situation A).
- 5 of the 10 participants have a box with 4 white balls and 6 black balls (Situation B).

Now imagine the following: you are one of the participants. So the probability that you are in Situation A is 50%. A computer draws a ball out of your box and places it back into the box after the draw. When you find out the color of the drawn ball, it helps to better assess what situation you are in.

Question: What is the probability that you are in Situation A, given that the drawn ball is white?

Probabilities, which take additional information into account—such as the color of the drawn ball—are calculated in a statistically correct manner according to a mathematical law, Bayes' theorem. The calculation is complicated and requires several calculation steps. **We therefore show you the statistically correct probabilities whenever they are relevant for your decision.**

Example (Answer to the Question):

$$
\begin{aligned}
& \text{Probability of Situation A, given that the drawn ball is white} \\
= \; & \text{Probability of Situation A} \cdot \left[ \frac{\text{Probability that the drawn ball in situation A is white}}{\text{Probability that the drawn ball is white}} \right] \\
= \; & 50\% \cdot \frac{60\%}{50\%} \\
= \; & 60\%.
\end{aligned}
$$

The probability of Situation A, given that the drawn ball is black, is calculated in a similar way. **Now, please process to the first control question on the computer.**

## Your Decisions

You obtain now 100 points to your points account.

Next you make a decision that affects your own payout amount and the payout amount of the other participant, who also received 100 points on the points account. However, the decisions of the other participant have no impact on your payout amount.
Your decision is to choose between two options, X and Y.

1. One of these options is 'harmful' to the other study participant and leads to 80 points less being paid out to the participant.

2. The other of the options has no effect on the other study participant, this option is 'safe'.

3. For every 7 out of 20 decision-makers, option X is safe and option Y is harmful (35 % probability), and for every 13 out of 20 decision-makers, option Y is safe and option X is harmful (65 % probability ). The computer has already chosen at random which option is safe and which is harmful in your case.

4. Regardless of whether option X or option Y is safe for the other participant, you will receive 25 points more yourself if you choose option X.

## Your Information

Before you make a decision, you can get additional information about which of the options the computer has selected to be safe for you. If you want to make the decision without additional information, please click directly on 'Decision without additional information'. If you want to make the decision with additional information, please click on 'Decision with additional information '.

There are 100 white or black balls in a box. If option X is safe, there are 60 white balls and 40 black balls in the box. If option Y is safe, there are 40 white balls and 60 black balls in the box.

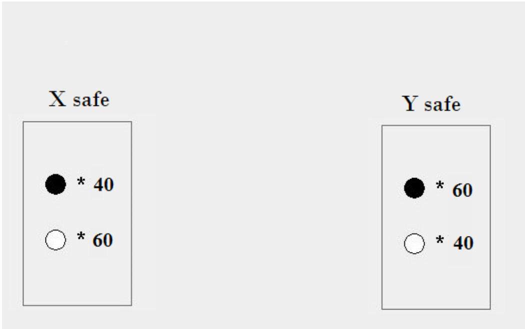



Figure 10: Box with 40 black and 60 white balls (X safe); Box with 60 black and 40 white balls (Y safe)

You won't be shown the box, but you can have the computer draw a ball out of the box at random. To do this, click the button 'Another Ball'. After you click, the ball that the computer drew out of the box will appear on the screen. Then the computer puts the ball back in the box so that there are 100 balls in the box again.

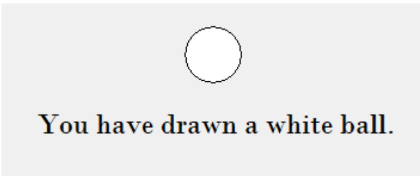



Figure 11: Example: The ball drawn by the computer is white.

You can then let another ball be drawn. To do this, click the 'Another Ball' button again. You can have an unlimited number of balls drawn. If you do not want to have any more balls drawn, click the button 'To the decision' .

Do you remember that there are more white balls in the box when option X is safe (60 white balls) than when option Y is safe (40 white balls)? So if you see that a white ball has been drawn, it is an indication that option X is safe. After each ball, the statistically correct probability that option X is safe is displayed. All balls that you have already drawn are taken into account.[35]

The person affected by your choice does not know whether or how much you have obtained information. You won't find out at the end of the study whether X or Y is the harmful action. It is free of charge for you to obtain additional information before making your decision between X and Y.

### D.2 Treatment: NoForce-Control

# Your Decisions

...
Your decision is to choose between two options, X and Y.

...

4. Your own payout amount is independent of whether you choose X or Y. Your payout amount is also independent of whether option X or option Y is safe for the other participant.

### D.3 Treatment: Force-Tradeoff

...

# Your Information

Before you make a decision, you can get additional information about which of the options the computer has selected to be safe for you.
...

[35] A mathematical law, Bayes' theorem, is used to accurately calculate the probability that option X is safe. The exact calculation formula, if e.g. a single white ball has been drawn, is the following:

$$\begin{aligned} & \text{Prob. that option X is safe conditional on the ball drawn being white} \\ = & \text{ Prob. that option X is safe} \\ & \cdot \frac{\text{Prob. that a white ball is drawn conditional on option X being safe}}{\text{Prob. that a white ball is drawn}}. \end{aligned}$$

This is the only objectively correct calculation method.

### D.4 Treatment: Force-Control

## Your Decisions

...

Your decision is to choose between two options, X and Y.

...

4. Your own payout amount is independent of whether you choose X or Y. Your payout amount is also independent of whether option X or option Y is safe for the other participant.

...

## Your Information

Before you make a decision, you can get additional information about which of the options the computer has selected to be safe for you.

...