The Choice of Ideology and Everyday Decisions

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1 Introduction

All human beings seek to understand and actively shape their environment, make consistent decisions, and live a meaningful life (e.g., Baumeister, 1991). In doing so, they are constantly confronted with complexity - such as ambiguous information, unpredictable circumstances, unstable socioeconomic and political conditions, threatening, and uncontrollable events, such as terroristic attacks, natural catastrophes, or a pandemic - amidst which they have to make choices that are consistent with their needs, preferences, and values. In order to understand or even reduce complexity and make decisions, individuals need information. However, information can be ambiguous, unreliable, incomplete, or false. Individuals are confronted with a vast amount of information every day that they have to process, understand, and verify. But how do we know what is true and reliable, and what is false and can lead to bad decisions?

Theories of human information-processing systems usually focus on the selective-attention or memory storage capabilities, that is, how we focus on one stimuli while ignoring others, and how this stimuli is processed and stored (Broadbent, 1958; Newell & Simon, 1972; Simon, 1979; Cowan, 1988). Others are particularly interested in the operations of the sensory systems, that is, how our senses provide the brain information about our environment, how the brain interprets this information, aligning it with the information and events already processed and stored in the memory, and how the data is then transformed into perceptual experiences (Lindsay & Norman, 2013). Cognitive psychologists investigate the role of consciousness in information-processing (Velmans, 1991), while social scientists study the strategies individuals use (e.g., stereotypes, heuristics) to process and evaluate information in a fast and cost-efficient way (Bodenhausen & Lichtenstein, 1987; Gigerenzer et al., 2011).

The latter, in particular, aim to explain how human beings make decisions when information is incomplete and unreliable, time is limited and the future unpredictable. These constraints have given rise to the analysis of different modes of information processing, such as the systematic and heuristic approach (see also the Elaboration Likelihood Model by Petty & Cacioppo, 1986) (Chaiken, 1980; 1987). The systematic processing implies the consideration and evaluation of all available information, and the formation of a judgement based on these elaborations. In a heuristic mode, people only consider a few information cues and base their judgement or decision on these cues (or sometimes even just on one cue). Such cues can be the source of a message, such as a family member, or the length of the message (Todorov et al., 2002). This means that individuals use simple decision rules, such as "Scientists can be trusted in regard to vaccines" to arrive at a conclusion, instead of processing all relevant information they can find in regard to vaccines on their own. Heuristics are hence cost-efficient tools that help individuals to reduce complexity and make decisions, without having to process information in an in-depth manner.

Another "tool" that helps individuals to process and evaluate information to reduce complexity and make decisions are ideologies. Although it may appear that ideologies, or in general belief systems, serve as some sort of heuristic, we regard ideologies in a more holistic approach. Ideologies[1] provide a mental framework, which is not only capable of helping individuals to cope with uncertain states of the world and incomplete information to make decisions (see Khalil, 2011), but it also consists of "social representations that define the social identity of a group" (Van Dijk, 2006, p.116). From an economic perspective, belief systems can be understood as "implicit, non-formal institutions" (Khalil, 2011, p.642), which help individuals to cope with imperfect and limited information, that, from a cognitive perspective, generate coherence in life. At the most basic level, coherence, emerges when reliable patterns exist in the environment that help individuals to understand and evaluate incoming stimuli (such as information). Coherence, or meaning, connects ideas, things, and information in a predictable and consistent way and can be thus defined as a collective, organized network of

[1] In the literature we find various kinds of beliefs according to their different functions, such as Bayesian beliefs or motivated beliefs (Zimmerman, 2002; Pronin, Lin, & Ross, 2002; Bénabou, 2015). However, we refrain here from an extended discussion about such kinds of beliefs and focus on our own understanding of belief systems.

(reliable, and relatively stable) patterns (Baumeister, 1991; MacKenzie & Baumeister, 2014). Ideologies provide such mental meaning-making systems - a predictable, reliable, and relatively stable mental representation of reality that helps individuals to reduce complexity, understand their environment, integrate their own self into this environment (own social role), and make decisions. However, individuals are not passive receivers of beliefs or ideas they are exposed to but are rather attracted to belief systems that resonate with their own psychological needs, values and preferences.

Therefore, in this paper we suggest an approach which is based on interdisciplinary reading and thinking that combines results and concepts from social psychology, political science and economic choice. We discuss the fundamental human condition of imperfect information which defines a role for belief systems and ideologies, the way how individuals find their particular ideology, and how ideologies affect our everyday decision making.

For this purpose we develop the following strand of reasoning: individuals live under conditions of imperfect information, unpredictability, and uncertainty about their environment, amidst which they have to make everyday decisions. To reduce this complexity and understand their social environment, and their own social role in it, individuals search for guidance in information-processing. Ideologies and their mental meaning-making systems offer such guidance as it helps individuals to evaluate incoming stimuli, understand social reality, identify with a certain (ideological) group, and address life's problems. Ideologies also provide interpretations of how the world is and how it should be, by making assumptions and generating narratives about the human existence, social order, historical events, potential threats, and future ideals. "To the extent that different ideologies represent socially shared but competing philosophies of life and how it should be lived (and how society should be governed), it stands to reason that different ideologies should both elicit and express at least somewhat different social, cognitive, and motivational styles or tendencies on the part of their adherents" (Jost et al., 2009, p. 309). This means that individuals do not adopt an ideology randomly but choose the belief system that tend to best resonate with their underlying need system. While Jost (2009) emphasizes this idea in social psychology, Gries et.al. (2020) further extend it and develop a formal model. In this approach it is argued that individuals chose and follow those ideologies that "best" match their underlying needs and preferences.

In the current paper we depart from this fundamental idea and focus (i) on the process of finding and adopting this ideology, and (ii) on applying the ideologies for everyday decisions. Thus, in section 2 we give an answer to the first question: How can an individual know which ideology best matches their needs and preferences. We suggest a sequential procedure of Bayesian information search and learning about ideologies to find out how they appeal to that individual. The starting point for this learning process is the individual's social environment, e.g. family. From their education and social relations they get a first idea about a potential match with various ideologies, such that there is a prior idea of a goodness of match. However, more information can improve the choice, so individuals need to collect more (costly) information in order to determine their true match with an ideology. As we assume that information is collected sequentially these steps of information acquisition may be conducted over a longer time period in life. The more information individuals collect, the better they are able to determine the expected ideological match. At some point the search process terminates as marginal benefits from information become lower than marginal information costs. Furthermore, individuals do not necessarily choose one ideology and completely adhere to all its rules and norms but they rather select a mixture of ideologies and apply the rules of that ideology that are appropriate in a particular situation (Kay & Eibach, 2012). This implies that some individuals may adopt a balanced combination of a multitude of ideologies, while others are attracted to only a few ideologies or even one particular ideology. Once a choice has been made, the individual will rely on the ideologies, which generates a coherent mental representation of reality, to process information and make consistent decisions (through the lens of this ideological reality).[2]

[2]However, if the chosen ideologies repeatedly fail to provide "good service" (in terms of bad decisional outcomes, inaccurate representation of reality [due to changed circumstances] or lack of coherence), individuals re-evaluate or even reject it and search for a

This leads to the second question which is answered in section 3. How do ideologies - once chosen - determine everyday decision making? We have argued that ideologies are a mean of reducing complexity to make "good" decisions at low costs. Thus, ideologies and their rules are an element in standard decision making. Following the rules, norms, and values imposed by a particular ideology not only helps individuals to make consistent decisions and understand the social environment, but it also generates meaningful and reliable patterns of social reality. Thus, we include ideological rules in a formal model in which ideologies guide everyday (economic) decision-making. The rule guides the individual to make decisions consistent with their psychological needs. We explain, for example, why individuals who adopt ecological beliefs are willing to approve higher costs for organic products.

2 Choice of an ideology

In this section we introduce a theoretical model to expound how individuals search for ideologies that resonate with their underlying need structure. We assume that individuals are aware of their psychological and physiological (consumption) needs. They search for viable means to reconcile psychological needs and consumption preferences. Belief systems that are present in the cultural environment offer readily available mental meaning-making systems that serve psychological needs. Individuals are able to enhance their subjective utility if they find belief systems that allow to match their psychological needs and if they can serve their consumption preferences. Hence, we include both, the match value M_K, that indicates the extent of a match between the individual's needs and a particular ideology K, and the level of consumption C in individual's utility function U. As the method of deriving this match value has been elaborated in Gries et al. (2020) we can directly focus on the choice process. For the sake of simplification, we reduce the formal analysis to two available belief systems which we denote by ideology A and ideology B. We assume that the utility is generated by the match

new ideology.

values of ideology A or B and consumption C,

$$U = U(M_A, M_B, C).$$

That is, unlike in Gries et al. (2020) the individual cannot pick an ideology from a list, get to know the match value and obtain the corresponding final utility but they rather engage a sequential process of search, learning and adopting the ideology. To reveal which ideologies match their needs, the individuals search for information about particular ideologies and process this information by using Bayesian updating. As search for information involves costs an optimal choice that includes a given budget and consumption will normally allocate a limited amount of resources to information search. Thus, the costly search for information implies that individual's information set remains incomplete. This means that after an optimal search process the individual adopts those ideologies which best match to their needs and preferences, even if the state of information is incomplete or even low. Modelling this process with an optimal decision as result is the purpose of the next section.

2.1 Information search and Bayesian updating

In this section we describe the process of information acquisition in terms of Bayesian updating, which yields a conditional expected match value for each considered belief system and the corresponding uncertainties for these match values. For an individual the real match value M_K between the ideology K and the individual's needs is unknown. It can be revealed by collecting information. This means, that individuals receive subjective signals about a potential match. Information is imperfect and the signals can vary at each step of the information acquisition. Therefore, we model the match value M_K as a stochastic variable with mean μ_K and variance σ_K^2. While these parameters are unknown, individuals can collect information and apply Bayesian updating to reveal the expected match values conditional on the received information.

Before individuals start to search for information about a particular ideology, they have to form a prior belief about the corresponding match value, i.e., how well the particular ideology can address one's needs. We assume that individuals' prior beliefs about each match value M_K before receiving any information are normally distributed, i.e.,

$$M_K \sim \mathcal{N}(\mu_{K,0}, \sigma^2_{K,0}),$$

where $\mu_{K,0}$ is the initial guess of the expected match value and $\sigma^2_{K,0}$ represents the initial belief of uncertainty. Thus, individuals search for information about belief systems that they run across in their environment. They must have an initial idea about their subjective ideological match[3].

The individual's initial information set about a belief system K is $I_{K,0} = \{\mu_{K,0}, \sigma^2_{K,0}\}$. However, they are able to collect information and update these initial beliefs sequentially. We denote by t_{Info} the number of search steps an individual makes to acquire information. Here we assume that each search step reveals information about all considered belief systems. In each search period, individuals receive a noisy signal $m_{K,t_{Info}}$ about each potential match value. This signal is defined as

$$m_{K,t_{Info}} = M_K + \varepsilon_{K,t_{Info}} \text{ with } \varepsilon_{K,t_{Info}} \sim \mathcal{N}(0, \eta^2_K),$$

where η^2_K is the variance of the noise, which means that it is a measure of the signal's precision. Thus, the signal reveals the real match value M_K with some error $\varepsilon_{K,t_{Info}}$. The lower the variance η^2_K, the more precise is the signal. While this is the ideal case, modelling the signal in general opens up another interesting discussion. In reality, we know that receiving and reading signals is subject to the sender and the receiver. Thus, the signals can be distorted by both senders and receivers. Especially with the increasing use of social media we can observe that false news are more likely to be spread than the truth (Vosoughi et al., 2018). This can be included

[3]This reflects people's preference for belief consonance (Golman et al., 2016). Individuals tend to adopt those ideologies that other persons of their social environment, or the group which they feel to belong to, have chosen. Thus, they can form an initial belief about the ideological match based on the experience in their social environment. For a young person family and friends may play a major role for this prior belief.

in our model, e.g. with a large signal variance η_K^2 as fake news indicate different match values than the truth. In this case more search steps are necessary to reveal the true match. However, this raises costs and when the budget is exhausted, search is stopped while the choice of ideologies may be influenced by fake news. We can even think of additional noisy signals that are send by a propaganda apparatus that may even lead to a shift in the perceived mean.

However, we start with the introduced ideal case and return to the formal model. The distribution corresponds to the likelihood function of the Bayesian formula. We choose a normal distribution as prior and signal because it is a conjugate distribution which implies that the posterior is also normally distributed. Therefore, we can use the obtained posterior normal distribution as a new prior in a next Bayesian updating process. The posterior distribution is given by

$$M_K | I_{i,1} \sim \mathcal{N}(\mu_{K,1}, \sigma_{K,1}^2)$$

with

$$\mu_{K,1} = \frac{\sigma_{K,0}^2}{\sigma_{K,0}^2 + \eta_K^2} m_{K,0} + \frac{\eta_K^2}{\sigma_{K,0}^2 + \eta_K^2} \mu_{K,0} \text{ and } \sigma_{K,1}^2 = \left(\frac{1}{\sigma_{K,0}^2} + \frac{1}{\eta_K^2} \right)^{-1}.$$

The posterior expected value $\mu_{K,1}$ is a weighted sum of the prior and the signal. A more precise signal (low variance η_K^2) leads to a higher weight of $m_{K,0}$ which means that the received information $m_{K,0}$ has a greater impact on the updated expected value $\mu_{K,1}$ than the prior belief $\mu_{K,0}$. If the prior beliefs are strong (low variance $\sigma_{K,0}^2$) the signal $m_{K,0}$ has a low impact on the updated expected match value. Thus, strong believers are less sensitive to new information than people who are very uncertain about their prior beliefs (high $\sigma_{K,0}^2$)[4].

[4] For example, if there is a leader who promotes his ideology in a way that intensively addresses the individuals emotions, then the individual's prior belief about this ideology may be very strong (low $\sigma_{K,0}^2$) and new information has a low impact. The interpersonal relation to the leader also plays a role when people stick to their ideology and are less sensitive to (or reject) new information.

Thus, this first step of information search and updating has not only improved the individuals idea of the expected match value $\mu_{K,1}$ for each ideology; moreover, from $\sigma^2_{K,1}$ we see that uncertainty decreases after obtaining the signal.

This updating procedure can be repeated if an individual makes several attempts to collect information. If t_{Info} is this number of received signals which is equal to the number of search or time steps then

$$M_K | I_{K,t_{Info}} \sim \mathcal{N}(\mu_{K,t_{Info}}, \sigma^2_{K,t_{Info}})$$

with

$$\mu_{K,t_{Info}} = \frac{\sigma^2_{K,0}}{t_{Info}\sigma^2_{K,0} + \eta^2_K} \sum_{s=0}^{t_{Info}-1} m_{K,s} + \frac{\eta^2_K}{t_{Info}\sigma^2_{K,0} + \eta^2_K} \mu_{K,0} \text{ and} \tag{1}$$

$$\sigma^2_{K,t_{Info}} = \left(\frac{1}{\sigma^2_{K,0}} + t_{Info} \frac{1}{\eta^2_K} \right)^{-1} = \frac{\sigma^2_{K,0}\eta^2_K}{t_{Info}\sigma^2_{K,0} + \eta^2_K}, \text{ with } \frac{\partial \sigma^2_{K,t_{Info}}}{\partial \eta^2_K} > 0. \tag{2}$$

These two equations illustrate the updating process. The conditional expected match value depends on the information, which is represented by the sum of signals, and on the number of time steps t_{Info} to collect this information.

Each new piece of information brings the individual closer to the true match values M_K of each belief system K. We can see this from equation (1) if we look at the difference of the updated expected match values in one step of information acquisition,

$$\mu_{K,t_{Info}+1} - \mu_{K,t_{Info}} = \frac{\sigma^2_{K,0}}{(t_{Info}+1)\sigma^2_{K,0} + \eta^2_K} (m_{K,t_{Info}} - \mu_{K,t_{Info}}). \tag{3}$$

The adjustment of the conditional expected match value can go in either direction, depending on the sign of $(m_{K,t_{Info}} - \mu_{K,t_{Info}})$. If the new signal $m_{K,t_{Info}}$ is greater than the current expected match $\mu_{K,t_{Info}}$, the expected match value is increased; else, it is decreased. To what extent it is increased or decreased depends on the factor $\frac{\sigma^2_{K,0}}{(t_{Info}+1)\sigma^2_{K,0}+\eta^2_K}$ which is decreasing with time t_{Info}. Thus, the more information is already available (the greater t_{Info}), the smaller is the adjustment of the expected match value in the updating process.

Furthermore, each search step reduces uncertainty, which we can derive from equation (2) if we look at the difference of the variance in one step,

$$\sigma^2_{K,t_{Info}+1} - \sigma^2_{K,t_{Info}} = -\frac{\sigma^2_{K,0}}{(t_{Info}+1)\sigma^2_{K,0}+\eta^2_K}\sigma^2_{K,t_{Info}} < 0,$$

which is also decreasing when more information is already available. Therefore, the more information has been already accumulated about a particular ideology, the less additional information will reduce uncertainty.We have a decreasing marginal effect of information on uncertainty.

Further, in section 2.3 and 2.4 we will include this Bayesian learning process in the optimization procedure. In preparation for this next step, and for the sake of simplicity, we switch to a setting with a continuous time information acquisition. In the above analysis we have determined the difference in conditional expected match values and in the corresponding variance in one discrete time step. If we assume that such a time step is arbitrarily small we can view $\mu_{K,t_{Info}}$ and $\sigma^2_{K,t_{Info}}$ as continuous differentiable functions in t_{Info} with

$$\begin{aligned} \frac{\partial \mu_{K,t_{Info}}}{\partial t_{Info}} &= \frac{\sigma^2_{K,0}}{t_{Info}\sigma^2_{K,0}+\eta^2_K}(m_{K,t_{Info}} - \mu_{K,t_{Info}}) \text{ and} \\ \frac{\partial \sigma^2_{K,t_{Info}}}{\partial t_{Info}} &= -\frac{\sigma^2_{K,0}}{t_{Info}\sigma^2_{K,0}+\eta^2_K}\sigma^2_{K,t_{Info}} < 0. \end{aligned}$$

With this assumption of continuity and differentiability we can apply a standard expected utility optimization approach in section 2.3 and proof the existence of an optimal solution.

2.2 Defining the optimization problem

We know from the discussion above that individuals strive to find an ideology that best matches their underlying psychological needs, and that different ideologies express different social, cognitive, and motivational styles. However, individuals may have a variety of needs that appear at first contradictive, which cannot be satisfied by only one particular belief system. This means that individuals can be drawn to different ideologies, and hence adopt a mixture of various belief systems to serve their underlying need structure. Practically, they adopt certain beliefs and narratives of belief system A to serve some of their needs, but also agree with the beliefs and values of belief system B, because they address particular needs. Therefore, an belief systems can be mixed and an individual fraction α (respectively $1-\alpha$) of each belief system can be chosen, so that

$$U = U\left(\alpha M_A, (1-\alpha)M_B, C\right) \text{ with } \alpha \in [0,1].$$

In the following sections we will introduce optimization strategies that include the determination of the optimal extent α given the current set of information. Thus, new information may cause a variation in commitment to particular belief systems. Note that the extreme cases $\alpha = 0$ and $\alpha = 1$ are possible if the individual fully adopts only one belief system. Someone who is very passionate about ideology A chooses α close to 1. To set up the decision problem in the most simple way we consider two interrelated constraints, a budget constraint and a time constraint.

Consumption is defined as the amount c of consumption goods and the duration of consumption time t_C,

$$C = ct_C.$$

Income y is generated by the given time allocated to work, which is the working time t_L, and the hourly wage rate w, so that $y = t_L w$. All income is spend on consumption at the given price p of the consumption good. Thus, the income budget constraint is

$$t_L w = y = pc.$$

Rearranging we obtain $c = t_L \frac{w}{p}$ and consequently, consumption is equal to

$$C = t_L \frac{w}{p} t_C. \tag{4}$$

Furthermore, individuals have a time budget that they can split into time for information search t_{Info}, time for consumption t_C and time for working t_L. The disposable time T is already reduced by a institutionally given amount of time for labor t_L. Thus, the time constraint for the disposable time is

$$T = t_{Info} + t_C. \tag{5}$$

The objective is to maximize utility given the income budget constraint. In order to consider uncertainty we assume an exponential utility function which implies constant absolute risk aversion (CARA),

$$U = 1 - \exp\left(-R\left(\alpha M_A + (1-\alpha)M_B + C\right)\right).$$

The parameter $R > 0$ is the coefficient of risk aversion. The match values M_K are stochastic variables with expected values μ_K and variance σ_K^2 for belief system $K \in \{A, B\}$. Therefore, exponential expected utility for two belief systems and consumption is

$$\mathbb{E}[U] = 1 - \exp\Big(-R\Big(\alpha\mu_A - \alpha^2\frac{1}{2}R\sigma_A^2 + (1-\alpha)\mu_B - (1-\alpha)^2\frac{1}{2}R\sigma_B^2 + C\Big)\Big).$$

However, consumers do not know the true expected match values or variances. They only know the conditional distribution of the match values given the information set $I_{K,t_{Info}}$. Thus, after t_{Info} search steps the individual can determine the conditional expected utility

$$\mathbb{E}[U|I_{t_{Info}}] = 1 - \exp\Big(- R\Big(\alpha\mu_{A,t_{Info}} - \alpha^2\frac{1}{2}R\sigma^2_{A,t_{Info}} + (1-\alpha)\mu_{B,t_{Info}} - (1-\alpha)^2\frac{1}{2}R\sigma^2_{B,t_{Info}} + C\Big)\Big),$$

where $I_{t_{Info}} = I_{A,t_{Info}} \cup I_{B,t_{Info}}$ is the accumulated information set for both belief systems A and B. We can see that for a risk averse consumer ($R > 0$) expected utility increases if the match values increase or if the variances, or uncertainties, decrease. We observe that $\mathbb{E}[U|I_{t_{Info}}]$ maximized if the reduced objective function

$$\mathbb{E}[u|I_{t_{Info}}] = \alpha\mu_{A,t_{Info}} - \frac{\alpha^2}{2}R\sigma^2_{A,t_{Info}} + (1-\alpha)\mu_{B,t_{Info}} - \frac{(1-\alpha)^2}{2}R\sigma^2_{B,t_{Info}} + C$$

is maximized[5]. Therefore, we work with this simpler conditional expected utility function in the following analysis. Before we come to our maximization problem we want to make some standard assumptions about marginal utility. We assume that consumers are risk averse with risk aversion parameter R which is sufficiently high, such that we obtain the standard positive marginal expected utility with respect to search steps t_{Info}, as well as decreasing marginal expected utility,

$$\frac{\partial\mathbb{E}[u|I_{t_{Info}}]}{\partial t_{Info}} > 0, \qquad \frac{\partial^2\mathbb{E}[u|I_{t_{Info}}]}{\partial t^2_{Info}} < 0.$$

This is ensured by the following assumption

$$R > \max_{\alpha, t_{Info}}\left(2\frac{\frac{-\alpha\sigma^2_{A,0}d_A}{v_A} - \frac{(1-\alpha)\sigma^2_{B,0}d_B}{v_B}}{\frac{\alpha^2\sigma^2_{A,0}\sigma^2_{A,t_{Info}}}{v_A} + \frac{(1-\alpha)^2\sigma^2_{B,0}\sigma^2_{B,t_{Info}}}{v_B}}, \; 2\frac{\frac{-\alpha\sigma^4_{A,0}d_A}{(v_A)^2} - \frac{(1-\alpha)\sigma^4_{B,0}d_B}{(v_B)^2}}{\frac{\alpha^2\sigma^4_{A,0}\sigma^2_{A,t_{Info}}}{(v_A)^2} + \frac{(1-\alpha)^2\sigma^4_{B,0}\sigma^2_{B,t_{Info}}}{(v_B)^2}}, 0\right). \tag{A1}$$

[5]The function $f: \mathbb{R} \to \mathbb{R}, f(x) = 1 - \exp(-x)$ is monotonically increasing in x. Therefore, it is sufficient to maximize the function in the exponent of our exponential function.

A proof is found in appendix A.1.

This assumption implies that additional search steps, and hence additional information about a certain ideology, always increase the part of the expected conditional utility that is generated by a match. In other words, the more information an individual has about an ideology, the better he or she can reveal how well this ideology can address his or her needs, and hence improve his utility. Risk aversion is assumed to be large enough, so that it compensates possible decreases in utility by low signals. A large parameter R implies that the reduction in uncertainty is dominating. In other words, the most important effect of information is the reduction in uncertainty. With information certainty about the real match value increases and this reduces the uncertainty of making a wrong decision.

Furthermore, if we include the time constraint (5) in (4) we see that consumption is reduced with every search step which represents the search costs. Marginal costs are constantly equal to $t_L \frac{w}{p}$. This brings us to a standard optimization problem which is analyzed in the next subsection.

2.3 Existence of optimal solution

In the previous subsection an information search process using Bayesian updating has been introduced. Since acquiring information is costly, the question is, at which point should the information search stop? Can we find an optimal number of information search steps? In this first step we show in a general analytical way that there exists a solution for this problem. While for many questions this is sufficient, the disadvantage is that we can not determine a general unique explicit solution. For an approximation of an explicit solution however, we need to look a the particular time path of the stochastic signals. Therefore, in section 2.4 we introduce a second procedure that allows to find the optimal number of search steps, in a truely sequential search process.

However, we begin with the existence of a solution for our optimization problem. Plugging in the time constraint (5) in the consumption (4) we obtain

$$C = t_L \frac{w}{p}(T - t_{Info}).$$

Consequently, the maximization problem is

$$\begin{aligned} \max_{\alpha, t_{Info}} \alpha\mu_{A,t_{Info}} - \alpha^2 \frac{1}{2} R\sigma^2_{A,t_{Info}} + (1-\alpha)\mu_{B,t_{Info}} \\ - (1-\alpha)^2 \frac{1}{2} R\sigma^2_{B,t_{Info}} + t_L \frac{w}{p}(T - t_{Info}). \end{aligned} \tag{UM}$$

Furthermore, assuming that searching time t_{Info} and fraction α are low substitutes so that[6]

$$u_{\alpha\alpha} u_{t_{Info} t_{Info}} > u^2_{t_{info}\alpha}, \tag{A2}$$

we can state the following proposition.

Proposition. *Let assumptions* (A1) *and* (A2) *hold. The maximization problem* (UM) *has a solution* (α^*, t^*_{Info}).
Consequently, the belief systems that are chosen with the incomplete information set $I_{t^*_{Info}}$ *yield optimal expected conditional utility.*

Note that we find such a solution for many sequences of the stochastic time path of the signal that fulfills conditions (A1) and (A2). This means that (α^*, t^*_{Info}) relates to one particular sequence. If there is another sequence that satisfies the conditions we find another solution $(\tilde{\alpha}^*, \tilde{t}^*_{Info})$. The history of that random sequence matters; another history another outcome.

However, with this proposition we have formally derived that there exists an optimal search time and an optimal allocation of the considered ideologies. Individuals acquire costly information about various ideologies that are available in the socio-cultural environment. At a certain point they realize that the marginal benefit of more information becomes equal to marginal costs of acquiring them. At that point they stop their search and choose the belief system that best matches their needs. Further, as α^* is between zero and one, the ideological choice can be either a corner solu-

[6] The reason for this assumption is found in appendix A.2.

tion ($\alpha^* = 0, \alpha^* = 1$) which means that only belief system A or B is fully adopted; or an inner solution which means that the individual is attracted by belief system A to the extent α^* and attracted by belief system B to the extent $1 - \alpha^*$. In the latter case the individual adopts an ideological mix consisting of beliefs and narratives from both ideologies A and B.

2.4 Sequential search optimization

While we now know that there exists a solution for the individual's search for an ideology, sometimes it is also interesting to explicitly determine the particular solution that relates to a particular sequence of signals. Therefore, we describe the information search process in a sequential way in the following section. Furthermore, we illustrate this process with a numerical example.

Sequential choice procedure Remember, adopting an ideology requires a longer search and trial period. For example, the search for orientation among young adults can be described by a longer process of searching and experimenting. Trial and experimenting in our model means that after the conduction of a couple of search steps the individual has adopted a belief system K at the extent α and while new information is received α may be adjusted. Thus, trial does not mean fully adopting an ideology and fully dismissing it, but the extent of adoption can be changed. It is indeed a chronological sequence of experiential steps until the match with an own ideological view, which can emerge from a mixture of several belief systems, crystallizes. Consequently, we go back to Bayesian updating as sequential course. The individual starts with some prior beliefs about the potential matches of various belief systems and collects information to update their beliefs in a Bayesian manner. However, this kind of information acquisition is costly and reduces consumption and respective utilities. Therefore, individuals have to decide first if they should start the Bayesian updating process at all, and second when to stop.

Before the Bayesian updating process can be started individuals form a prior belief about the match value $\mu_{K,0}$ for each belief system K with prior variance $\sigma^2_{K,0}$. Again, this indicates how certain the individual is about their prior belief. First of all, the individuals have to determine the allocation of belief systems that gives maximum expected utility from these prior beliefs. That is, given the prior belief, they determine the optimal mixture of ideologies before information is collected. This means that they have to solve the prior maximization problem

$$\max_{\alpha} \mathbb{E}[u|I_0] = \alpha\mu_{A,0} - \alpha^2\frac{1}{2}R\sigma^2_{A,0} + (1-\alpha)\mu_{B,0} - (1-\alpha)^2\frac{1}{2}R\sigma^2_{B,0} + t_L\frac{w}{p}T$$

which gives an optimal α_0^* as result and we denote the optimal expected conditional utility by $E_{\alpha_0^*}[u|I_0]$. Thus, without search the allocation of belief systems that is determined by α_0^* is the optimal choice. This result can be used as a reference point for the decision about the start of the updating process. Note that we have $C = t_L\frac{w}{p}T$ as there has been no time spent for information acquisition, but all time could be used for consumption.

Next, consumers have to decide whether they should start the search or not by comparing the prior expected conditional utility to the anticipated expected conditional utility of the first search step. For the description of sequential search we have to return to discrete time steps. How can this expected conditional utility be anticipated? First, individuals know that search increases utility as it reduces uncertainty, but they do not know the magnitude of this reduction without conducting the first search step. Second, consumers cannot predict the first signal, however acquiring the first piece of information includes search costs. Thus, they have to anticipate the net utility gain of this first search step and only start search if this gain is positive.

In order to anticipate the reduction in uncertainty the individual needs to know the precision of the information signal indicated by the variance of the signals' noise η^2_K. However, with no experiences with information signals this is unknown for the first search step. Therefore, they have to make an initial guess $\tilde{\eta}^2_K$ for η^2_K for each belief system K. This guess $\tilde{\eta}^2_K$ depends on the subjective perception of the individual and represents a guess of the usefulness and also accuracy of a first piece of information. Furthermore, $\tilde{\eta}_K^2$ shows how confident the consumer is about processing the information. One expects that highly educated individuals anticipate a low $\tilde{\eta}_K^2$ as they believe that they are able to better collect and understand information. With the use of this guess $\tilde{\eta}_K^2$ the anticipated variance for the first search step can be determined as

$$\sigma_{K,ant}^2 := \frac{\sigma_{K,0}^2 \tilde{\eta}_K^2}{\sigma_{K,0}^2 + \tilde{\eta}_K^2}.$$

The second unknown variable for a search step is the signal. The best guess for the first signal is their prior belief $\mu_{K,0}$. Without more information the prior belief is already the best guess, so the individual cannot expect something different without new information. This implies that there is no update for the expected match value for this first search decision.

With these guesses about the first signal and its variance the anticipated expected conditional utility for the first search step can be found solving the maximization problem

$$\max_{\alpha} \mathbb{E}[u|I_{0,ant}] =$$
$$\alpha\mu_{A,0} - \alpha^2 \frac{1}{2} R\sigma_{A,ant}^2 + (1-\alpha)\mu_{B,0} - (1-\alpha)^2 \frac{1}{2} R\sigma_{B,ant}^2 + t_L \frac{w}{p}(T-1),$$

which gives $\alpha_{1,ant}^*$ as result and we denote the optimal anticipated expected utility by $\mathbb{E}_{\alpha_{1,ant}^*}[u|I_{0,ant}]$. This time we have $C = t_L \frac{w}{p}(T-1)$ as one time step has been used for information acquisition.

Now the individual can make a decision. If they anticipate a positive net gain in utility,

$$\mathbb{E}_{\alpha_{1,ant}^*}[u|I_{0,ant}] > \mathbb{E}_{\alpha_0^*}[u|I_0],$$

then the information search process starts. However, as decision depends on the subjectively anticipated value $\tilde{\eta}_K^2$, it is possible that the individual does not start the sequential search. Subjectively they do not anticipate a positive net gain in utility, even if the true signals had indicated such a gain. The choice of $\tilde{\eta}_K$ can prevent search and the individual does not collect any information. They never get to know if utility could have been increased with new information.

Now we have to consider further search steps. After each search step consumers have to decide whether they should continue searching for more information or whether their information set already yields optimal utility. Again, they need to anticipate the expected gain in utility from further search. However, with the experience of the first search step they learn how precise the signal is and we assume that their subjective estimate is equal to the true precision of the signal η_K^2. An example may illustrates this point. Once an individual starts collecting information they observe that the signal is rather diffuse, vague, ambiguous, or just gives adumbrations. So we assume that this observation is correct and thus the signal in not precise and respectively η_K^2 is large. In contrast, the information signal may be very clear, consistent, focused and brought to the point. This would be indicated by a small η_K^2. With this assumption we describe the ideal case in which the perceived signal represents the true message from the ideology. However, as already mentioned above in a world of fake news and disinformation we can imagine how a perceived reality via the signal can deviate from the true reality. But this kind of discussion must be left for future research.

Thus, effects on uncertainty as result of the next and all subsequent search steps can be determined $\sigma^2_{K,t_{Info}} = \frac{\sigma^2_{K,0}\eta^2_K}{t_{Info}\sigma^2_{K,0}+\eta^2_K}$ (see also (2)). However, individuals still do not know the signal of the following search step and they also cannot know the expected match value or utility resulting from another step. They again have to anticipate the signal for a further search step. The best guess for this signal $m_{K,t_{Info}}$ is the current expected match value $\mu_{K,t_{Info}}$, which implies that there is no systematic update with respect to the anticipated signal.[7] Therefore, individuals have to solve the following maximization problem for anticipated utility in the next, the $t_{Info} + 1$

[7] This can be seen from equation (3).

period,

$$\max_{\alpha} u^{ant}_{t_{Info}+1} := \alpha\mu_{A,t_{Info}} - \alpha^2\frac{1}{2}R\sigma^2_{A,t_{Info}+1} + (1-\alpha)\mu_{B,t_{Info}} - (1-\alpha)^2\frac{1}{2}R\sigma^2_{B,t_{Info}+1} + t_L\frac{w}{p}(T - t_{Info} - 1)$$

which results in maximum anticipated expected utility $u^{ant,*}_{t_{Info}+1}$. This can be used to make a decision comparing it to the current maximum utility $\mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}]$. If

$$u^{ant,*}_{t_{Info}+1} > \mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}]$$

information search is continued as a positive net gain in utility is anticipated. Search is stopped if either the latest step did not increase expected utility,

$$\mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}] \leq \mathbb{E}_{\alpha^*_{t_{Info}-1}}[u|I_{t_{Info}-1}],$$

or if no further gain in expected utility is anticipated,

$$u^{ant,*}_{t_{Info}+1} \leq \mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}].$$

Then the optimal number of sequential search steps is reached. In appendix A.3 we compare this result to the analytical result of the optimization (UM). We find that differences in the optimal search steps from these two strategies are small. Thus, we conclude that this sequential description is indeed an approximation for the general optimization process.

Numerical examples As we cannot find a general solution for the sequential search problem we analyze some numerical examples of the information search process in discrete time and illustrate the sequential decision path on the surface of expected conditional utility. From these examples we see that the sequential decision process depends on the specific sequence of received stochastic signals.

Suppose that an individual considers two ideologies that - without further information - seem very similar. Therefore, the individual has very close prior beliefs, namely $\mu_{A,0} = 5, \mu_{B,0} = 5.2, \sigma^2_{A,0} = 0.6$ and $\sigma^2_{B,0} = 0.8$. We study examples for two different scenarios that could arise from this starting point.

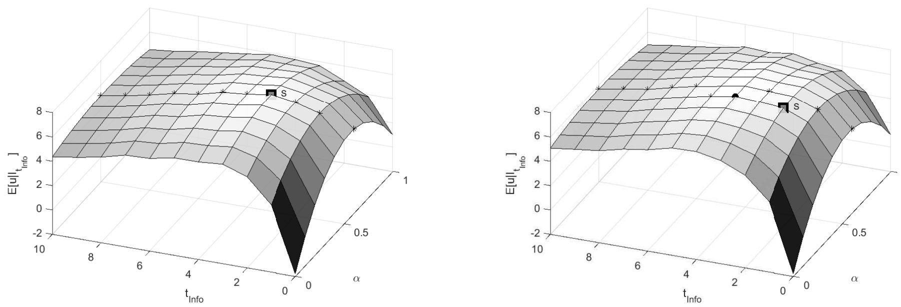
In the *first scenario* both ideologies have the same true match value. Thus, the information search process should reveal that a balanced combination of both ideologies is optimal ($\alpha = 0.5$). Further, in this scenario we want to illustrate that even if the search process starts with rather close prior beliefs and the true match values are identical, different sequences of stochastic signals already generate variations in the number of optimally conducted search steps as well as variations in α. True sequential search does not lead to identical solutions.

In the *second scenario* one ideology has a greater true match value than the other ideology. In this scenario we want to illustrate that - even if the true match value for A is less than for $B$the individual may still combine the two ideologies. The optimal but still limited information set cannot yet fully reveal this difference. In this case the information search process reveals step by step which ideology may turn out to be the better one. Due to search costs the process stops at an optimal number of steps. As we still do not have full information when this search process stops we may get the result that a combination of both belief systems is optimal instead of only choosing the one with the true highest expected match value.

The **first scenario** is discussed with the help of figure 1 where we see the expected conditional utility $\mathbb{E}[u|I_{t_{Info}}]$ for *two different sequences of signals* depending on t_{Info} and α. All parameters remain equal, but due to the different sequences of stochastic signals we obtain slightly different results, which we denote by case 1(a) and 1(b). We choose the risk aversion parameter R sufficiently high, so that assumption (A1) is true for every example sequence of signals. For every time step $t_{Info} = 0, 1, \ldots, T$ we solve the maximization problem for $\mathbb{E}[u|I_{t_{Info}}]$ to find the optimal choice of α. In figure 1 the corresponding maximal utility is depicted as asterisk for every step. The number of sequential search steps that can be found using the description in section 2.4 is indicated as the black square "S" (sequential). We choose $\tilde{\eta}_A = \tilde{\eta}_B = 0.1$ for our examples. Furthermore, the maximal utility over all search steps $\mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}]$ (which represents the general solution of (UM)) is depicted as the black dot if it is not equal to the number of sequential steps. With these two markers we can distinguish between the optimal search steps from sequential search and t^*_{Info} from the general optimization problem (UM) (in discrete time).

In detail, in this first scenario both true expected match values are equal to 6. Thus, search reveals that a balanced combination of both belief systems is the best choice which implies that α^* is close to 0.5. However, we can see in figure 1 that the difference in stochastic sequence leads to different outcomes. In case 1(a) (first sequence of signals) in figure 1 the optimal number of sequential search steps is 3 with $\alpha^* = 0.5$ and expected utility is $\mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}] = 7.61$. We also see that after the first step the optimal choice for α^* is 0.5 and this does not change with further steps. The individual continues to search as the reduction in uncertainty increases expected conditional utility.

In case 1(b) (second sequence of signals) in figure 1 the optimal number of sequential search steps is only 2 with $\alpha^* = 0.4$ and expected utility is $\mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}] = 7.70$. The value for α is not as stable as in case 1(a). This means that the first signals suggest that belief system B has a slightly higher match value than belief system A. More search steps than in case 1(a) would be necessary until α is 0.5. However, search is stopped early as search costs prevent further steps. With less steps the individual saves costs and expected utility is slightly greater than in case 1(a). As intended, the example illustrates, that different sequences of stochastic signals already generate different final outcomes.

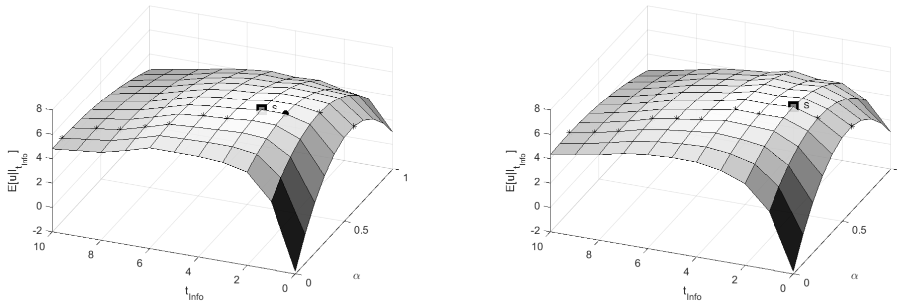


(a) **(b)**

Figure 1: Two outcomes for $\mathbb{E}[u|I_{t_{Info}}]$ with $\mu_{A,0} = 5, \mu_{B,0} = 5.2, \sigma^2_{A,0} = 0.6, \sigma^2_{B,0} = 0.8, \eta^2_A = 1, \eta^2_B = 1, \mu_A = 6, \mu_B = 6, w = 2, p = 4, t_L = 5, T = 10$ and $\tilde{\eta}_A = \tilde{\eta}_B = 0.1$.

For the **second scenario** we only change the true expected match value of belief system A to 4 instead of 6 (B remains with a true match value 6). All other parameters remain equal to the ones in the first scenario. In this second scenario the information search process should reveal that the choice of believe system B is the better one which means that search should end with a value for α close to 0. In figure 2 this can be observed in both cases 2(a) and 2(b) of the example. However, as search is costly maximal utility is reached after only a few search steps. Thus the search process has not yet fully revealed that B is the true better belief system, such that a combination of both belief systems is recommended as optimal. In figure 2 we see that in case 2(a) the number of sequential search steps is 3 with $\alpha^* = 0.4$ and expected utility is $\mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}] = 6.99$. In case 2(b) the number of sequential steps is 2 with $\alpha^* = 0.5$ and expected utility is $\mathbb{E}_{\alpha^*_{t_{Info}}}[u|I_{t_{Info}}] = 6.72$. In both cases more search steps would be necessary until α would approach 0, as theoretically correct solution under perfect information.

What we learn from this example is that search costs lead to a limited set of information. We can have different outcomes even if we choose the same parameters, but without search costs the information search process would eventually reveal which ideology is the better one. The outcomes depend on the specific values of the stochastic signals that are received. Thus, we can further conclude that a higher variance in signals leads to more different outcomes.



(a) (b)

Figure 2: Two outcomes for $\mathbb{E}[u|I_{t_{Info}}]$ with $\mu_{A,0} = 5, \mu_{B,0} = 5.2, \sigma^2_{A,0} = 0.6, \sigma^2_{B,0} = 0.8, \eta^2_A = 1, \eta^2_B = 1, \mu_A = 4, \mu_B = 6, R = 30, \mu_B = 6, w = 2, p = 4, t_L = 1, T = 10$ and $\tilde{\eta}_A = \tilde{\eta}_B = 0.1$.

3 Belief system co-determines decisions

In section 2 we discussed extensively how individuals search for ideologies and figure out which mixture of ideologies matches their underlying need structure. Once a choice has been made, the individual is willing to adhere to the norms, rules, and values of the chosen ideologies, because they generate consistency, certainty and meaning in life. Ideologies, and their mental meaning-making systems help individuals to process incoming stimuli (through the lens of the ideology), understand reality and make decisions, which are consistent with their needs and preferences. So, in this section, we are eager to explain how ideologies help individuals to make "best" everyday decisions once they are adopted. The rules, narratives, norms, and values of a particular ideology imply low information costs and facilliate the individual's understanding and evaluation of information. Furthermore, they free the individual from evaluating the appropriateness of own behavior, the social acceptance of own norms and values, and from coordination and communication problems. Instead, they provide a basis for communication and behavior, for perception, understanding, and evaluation.

Since individuals choose ideologies that resonate with their underlying need structure, adhering to the rules and norms of those ideologies implies consistent behavior. This means, that behaving, perceiving, and making decisions according to chosen ideologies serves individual's needs and increases their utility. These belief-based rules, norms, or values can serve as heuristics and provide a valuable source for information-processing and decision-making. Individuals trust their chosen belief systems, in their accuracy and completeness, and hence rely on them to understand reality and make everyday decisions. Trust plays an important role in belief formation, as individuals do not have resources and the capacity to evaluate all available information but adopt, sometimes even unquestioningly, the propagated beliefs and narratives. Processing information and making choices according to the chosen ideologies, is not only decreasing information and decision costs, but also addressing the psychological needs of the individual: making choices based on the ideological narratives, rules, norms and values generate consistency, increase certainty and order in one's life; perceiving the environment based on the ideological patterns and sharing these perceptions with a social group emphasizes social belonging, identification and approval; but it also generates a sense of self-efficacy and self-esteem, as it increases individual's belief in their capacity to execute behavior and make choices based on their own needs and preferences.

Taking these (subjectively) positive implications of an ideological choice into consideration it becomes clear that individuals are eager to adhere to the rules, norms, and values of the chosen ideologies, and hence make decisions accordingly. So, in the following section, we explain how following these rules and norms in everyday decision-making can enhances individual's subjective utility. This can be illustrated by a standard rational choice model.

3.1 Utilities, rules and consumption decisions

Formally, we assume that each individual has a set of n mental needs that they try to reconcile. However, each person has a different desire for the extent that a certain need has to be served. In addition, we assume that a belief system K addresses each of these need components i ($i = 1, \ldots, n$) at the extent B_{K_i} and we denote by B_K the set of these index numbers for the need components of ideology K,

$$B_K = \{B_{K_1}, B_{K_2}, \ldots, B_{K_n}\}.$$

Suppose R is the set of all behavioral rules, norms or evaluations which could be part of an arbitrary ideology. The leaders of an ideology K can use one index number or a combination of index numbers from B_K to form a rule $r \in R$. Thus, each rule results from a subset of B_K of need-reconciling services that are provided by the corresponding ideology. We denote by $\mathcal{P}(B_K)$ the power set of B_K, which is the set of all subsets of B_K. Then we define the relation

$$\begin{aligned}\mathcal{R}_K = \{(f, r) \in \mathcal{P}(B_K) \times R : f &\text{ is the set of index numbers} \\ &\text{of those needs that build rule } r\}.\end{aligned}$$

Note that it is possible that a certain combination of index numbers, which is represented by a set $f \in \mathcal{P}(B_K)$, implies several rules $r \in R$.

Let $R_K \subseteq R$ be the set of rules r with $(f, r) \in \mathcal{R}_K$. Thus, R_K is the set of rules that ideology K obeys. After adopting a belief system K individuals are principally willing and inclined to follow such rules and norms $r \in R_K$.[8]

We assume in the following that the individual has to make a (consumption) choice and can decide between two different proceedings. The first proceeding would imply the adherence to the rules of a chosen ideology, while the second proceeding would not align with the ideological rules. Sup-

[8] If individuals adopt a combination of ideologies K where each ideology is chosen at a fraction $\alpha_K \in (0, 1)$ they also choose the corresponding fraction of rules from R_K of the chosen ideologies K.

pose ρ is an index that measures the extent at which activities and choices of the individual are in line with the narratives and rules of the belief system. Thus, ρ is the match of ideological rules with the own activities and this serves the underlying psychological needs. Therefore, ρ enters the everyday utility function.

The rule-inconsistent activities are denoted by a_c and these are proceedings that purely relate to consumption. If $\bar{c}_c$ is a standardized pure consumption unit and total pure consumption activities are represented by a_c, total consumption that purely serves consumption purposes is

$$c_c = \bar{c}_c a_c.$$

Activity a_ρ is another consumption activity. Defining again a standardized amount of this kind of consumption by $\bar{c}_\rho$ the total amount of this kind of consumption is

$$c_\rho = \bar{c}_\rho a_\rho. \tag{6}$$

Activity a_ρ, however, not only serves general consumption, it is also consistent with the rules and narratives of the chosen belief system. This means that activity a_ρ is a consumption proceeding that is consistent with individual's psychological needs and thus contributes one unit to the belief-based utility ρ. Hence, the index value of ρ is directly determined by the number of activities that are consistent with the chosen belief system and the psychological needs

$$\rho = a_\rho. \tag{7}$$

As a result, a_ρ generates a positive externality. This belief-based activity serves both, the consumption needs as well as the psychological needs (because the consumption choice is based on the rules of the chosen ideology, which in turn resonates with the psychological needs of the individual). Thus, is it will not only increase the consumption of kind c_ρ, but it will also address intangible benefits ρ. Combining (6) and (7) describes the fixed relation of consumption that serves both psychological and consumption needs,

$$\rho = \frac{1}{\bar{c}_\rho} c_\rho.$$

As ρ serves the psychological needs by behaving belief-conform ρ will directly enter the utility function. With two kinds of consumption goods that both serve consumption preferences the utility function with standard characteristics can be described by

$$u = u(\rho, c_\rho, c_c).$$

We make the standard assumption of positive and decreasing marginal utility with respect to both activities a_ρ and a_c.

3.2 Constraints and choice problem

As c_ρ and c_c are both different kinds of consumption goods we have two prices for these two goods, p_ρ and p_c. To make the argument clear, we assume that there is no direct way to purchase intangible benefits, like buying a unit of self-esteem or social approval.[9] With a given income $\bar{y}$ the budget constraint is simple:

$$p_c \bar{c}_c a_c + p_\rho \bar{c}_\rho a_\rho - \bar{y} = 0.$$

The complete choice problem is

$$\max_{a_c, a_\rho} u = u(\rho, c_\rho, c_c)$$
$$\text{s.t. } p_c \bar{c}_c a_c + p_\rho \bar{c}_\rho a_\rho - \bar{y} = 0.$$

As we assumed a standard choice problem we can apply the Implicit Functions Theorem and obtain optimal activities

$$a_c^* = a_c^*(p_\rho, \bar{c}_\rho, p_c, \bar{c}_c, \bar{y})$$
$$a_\rho^* = a_\rho^*(p_\rho, \bar{c}_\rho, p_c, \bar{c}_c, \bar{y}),$$

[9] These are simplified assumptions, since we can also think of material goods that can directly serve psychological needs. Buying a luxury product, for example, may indirectly increase one's own self-esteem and may lead to higher social approval.

which lead to optimal demand functions for c_ρ^* and c_c^* and an optimal level of serving the belief system ρ^*.

3.3 Interpretation

While it is a standard procedure to derive the optimal demand functions, it is more interesting to look at the first order condition to understand how the choice is determined. From these conditions we obtain

$$\frac{\frac{\partial u}{\partial \rho} + \frac{\partial u}{\partial c_\rho}\bar{c}_\rho}{\frac{\partial u}{\partial c_c}\bar{c}_c} = \frac{p_\rho}{p_c}. \tag{8}$$

In equation (8) the term $\frac{\frac{\partial u}{\partial \rho} + \frac{\partial u}{\partial c_\rho}\bar{c}_\rho}{\frac{\partial u}{\partial c_c}\bar{c}_c}$ gives the willingness to pay for good c_ρ in terms of goods c_c. If $\bar{c}_\rho$ is comparable with $\bar{c}_c$ in serving the pure consumption preference $\left[\frac{\partial u}{\partial c_\rho} = \frac{\partial u}{\partial c_c}\right]$, condition (8) indicates that we are willing to pay more for c_ρ due to the consumption externality. Buying a belief-conform consumption good not only serves individuals' material needs, but it also serves the mental preferences. Similarly, rewriting (8) gives

$$\frac{\frac{\partial u}{\partial \rho} + \frac{\partial u}{\partial c_\rho}\bar{c}_\rho}{p_\rho} = \frac{\frac{\partial u}{\partial c_c}\bar{c}_c}{p_c}.$$

That is, marginal utility per unit income must be equalized, each \$ must generate the same effect on marginal utility. As consumption c_ρ with activity a_ρ has a positive externality by generating consumption related utilities as well as belief related benefits, the individual would be willing to pay more for the same amount of consumption good purchased.

The following example may illustrate this reasoning. If an individual has adopted a green ideology (or environmentalism) as a guiding belief system, a rule could be to eat organic food as often as possible. The individial serves their underlying needs if they behaves according to this belief-based rule. However, while a standard meal with conventionally produced food is normally less expensive than a comparable organic food, due to the positive consumption externality, the individual is willing to pay more to acquire the belief-based (organic) good. The increased demand for the more expensive vegetarian meal is explained by the increased belief-based utility. Following the rules, attitudes and norms applied by the green ideology not only serves tangible preferences of the individual (buying food to be sated), but it also has psychologically positive implications. Acting according to the adopted ideology, not only serves the individual needs, but it also provides a positive self-image and facilitates coherent decision-making.

3.4 Implications for gaining empirical evidence

Beliefs provide a mental guide to understand and adapt to given environmental settings and to process information in a subjectively coherent way. Relying on certain belief-based ideals, rules, and norms to make decisions about what is right or wrong not only reduces anxiety and self-related uncertainty, but it also provides a sense of security and higher self-esteem (Flannelly & Galek, 2010).

Although this implies that beliefs are a potent cause of action, this internal cognitive mechanism seems to be difficult to observe. The revealed preference approach in economics postulates that individuals' (consumption) preferences can be revealed by observing their purchasing behavior, under different price and income conditions. This means that individuals reveal their preference patterns by their market behaviors (Samuelson, 1948). However, the initiating source of this behavior can be difficult to identify[10].

Recent neuroimaging and lesion studies provide evidence that beliefs are indeed "observable" in terms of neural underpinnings in the human brain. The choice of a particular belief system seems to be associated with individual differences in basic neurocognitive mechanisms (for a review see Cristofori & Grafman, 2017). Such physiological measures are useful to assess implicit responses and infer subjective preferences. In neuroeconomics it is assumed that if two different objects elicit neural activation of equal

[10]Several studies show that individuals make decisions that are not consistent with their preferences and beliefs in order to align with social norms or to be liked by significant others (Akerlof & Kranton, 2010; Sinclair et al, 2005; Sechrist & Stangor, 2001).

intensity, the two objects should be equally preferred. However, observing an increased activation toward one object compared to another, the object that induces a higher neural reaction should be preferred (Brosch & Sander, 2013). These studies find differential neurocognitive effects - after a decision, task, or stimulus - that are possibly linked to the previously adopted belief system.

Further, in our model we showed that belief-based consumption not only serves individuals' consumption needs, but also their psychological demands. We can make the assumption that making choices according to one's own belief system implies greater rewards. We can extend the classical revealed preference approach with observable mental processes. Following the rules and principles of a belief system and making choices accordingly, may reveal the belief-based preferences of the individual (such as buying only vegetarian products reveals the adoption of ecologist beliefs). However, as we cannot provide all at once, these suggestions must be left for further research.

4 Summary and conclusion

In this article we answered two major questions: (1) Why and how do individuals search for ideologies and figure out which ideology or which mixture of ideologies matches them best? and (2) How does the ideology - once chosen - determine everyday decision making?

To answer the first question we argue that human beings are constantly confronted with complexity amidst which they have to make consistent choices. In order to understand or even reduce complexity and make decisions, individuals need information. But also, information can be complex, ambiguous, or false. The information set is never complete and costly to acquire. Ideologies, in this regard, help individuals to process and evaluate information and manage reality into coherent and comprehensible regularities, by representing different philosophies of life. Ideologies substitute and/or complement information. But why are different people attracted to different ideologies and belief systems? We suggest that the choice of an ideology is not random, it is driven, among others, by a set of underlying psychological human needs - like needs to understand and control the environment, feel belonged and approved by social others, make autonomous decisions, feel self-efficacious and have a high self-esteem. Ideologies and their unique mental meaning-making systems provide options to serve these needs, that is, they help individuals to process information, understand the social environment, unpredictable events and circumstances, identify with social others, as well as make consistent decisions. Individuals choose the belief systems that best resonate or are consistent with their underlying need structure. How can individuals find the belief system they are most comfortable with? This question is answered by suggesting a Bayesian learning procedure with costly information. Information allows for a better match and reduces the uncertainty of a bad choice. Decreasing marginal utilities from information search lead to an optimal stopping of information acquisition and an optimal decision about the best matching ideology.

The second question addresses the role of ideologies in everyday decisions. Ideologies are an instrument of reducing complexity to make "good" decisions at low costs. Belief-based rules, narratives and norms represent low-cost substitutes for high information and deliberation costs are thus perceived as important instruments in subjective decision-making. Thus, following the rules, norms, and values imposed by the chosen ideology positively enters utility as their consistency with the chosen ideology indirectly serves the underlying needs. This is also formally modelled. An action like the consumption of a meal not only generates utility by satisfying the pure desire to eat. If the consumption is consistent with the ideological rule it generates an extra utility as the individual behaves consistent with their beliefs.

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A Appendix

A.1 Derivation of Assumption (A1)

We have

$$
\begin{aligned}
&\frac{\partial}{\partial t_{Info}} \mathbb{E}[U|I_{t_{Info}}] \\
=&R \exp\left(-R\left(\alpha\mu_{A,t_{Info}} - \frac{1}{2}R\alpha^2\sigma^2_{A,t_{Info}} + (1-\alpha)\mu_{B,t_{Info}} - \frac{1}{2}R(1-\alpha)^2\sigma^2_{B,t_{Info}} + C\right)\right) \\
&\cdot \frac{\partial}{\partial t_{Info}} \mathbb{E}[u|I_{t_{Info}}]
\end{aligned}
$$

with

$$
\mathbb{E}[u|I_{t_{Info}}] = \alpha\mu_{A,t_{Info}} - \frac{1}{2}R\alpha^2\sigma^2_{A,t_{Info}} + (1-\alpha)\mu_{B,t_{Info}} - \frac{1}{2}R(1-\alpha)^2\sigma^2_{B,t_{Info}} + C.
$$

As we assume that consumers are risk averse ($R > 0$) the sign of $\frac{\partial}{\partial t_{Info}} \mathbb{E}[U|I_{t_{Info}}]$ is equal to the sign of $\frac{\partial}{\partial t_{Info}} \mathbb{E}[u|I_{t_{Info}}]$. Thus, we have a positive marginal expected conditional utility if we assume

$$
\begin{aligned}
\frac{\partial}{\partial t_{Info}} \mathbb{E}[u|I_{t_{Info}}] =& \alpha\frac{\partial \mu_{A,t_{Info}}}{\partial t_{Info}} - \frac{1}{2}R\alpha^2\frac{\partial \sigma^2_{A,t_{Info}}}{\partial t_{Info}} + (1-\alpha)\frac{\partial \mu_{B,t_{Info}}}{\partial t_{Info}} - \frac{1}{2}R(1-\alpha)^2\frac{\partial \sigma^2_{B,t_{Info}}}{\partial t_{Info}} \\
=& \alpha\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0} + \eta^2_A}(m_{A,t_{Info}} - \mu_{A,t_{Info}}) + \frac{1}{2}R\alpha^2\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0} + \eta^2_A}\sigma^2_{A,t_{Info}} \\
&+ (1-\alpha)\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0} + \eta^2_B}(m_{B,t_{Info}} - \mu_{B,t_{Info}}) \\
&+ \frac{1}{2}R(1-\alpha)^2\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0} + \eta^2_B}\sigma^2_{B,t_{Info}} > 0,
\end{aligned}
$$

which is equivalent to

$$R > \frac{-\alpha\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}(m_{A,t_{Info}}-\mu_{A,t_{Info}})-(1-\alpha)\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}(m_{B,t_{Info}}-\mu_{B,t_{Info}})}{\frac{1}{2}\alpha^2\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}\sigma^2_{A,t_{Info}}+\frac{1}{2}(1-\alpha)^2\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}\sigma^2_{B,t_{Info}}}$$

$$= 2\frac{-\alpha\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}(m_{A,t_{Info}}-\mu_{A,t_{Info}})-(1-\alpha)\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}(m_{B,t_{Info}}-\mu_{B,t_{Info}})}{\alpha^2\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}\sigma^2_{A,t_{Info}}+(1-\alpha)^2\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}\sigma^2_{B,t_{Info}}}.$$

Additionally, we want to assume decreasing marginal utility with respect to t_{Info}. In order to find the second partial derivative we calculate

$$\begin{aligned}\frac{\partial^2\mu_{i,t_{Info}}}{\partial t^2_{Info}} =& -\sigma^2_{i,0}\frac{\sigma^2_{i,0}}{(t_{Info}\sigma^2_{i,0}+\eta^2_K)^2}(m_{i,t_{Info}}-\mu_{i,t_{Info}})\\ &-\frac{\sigma^2_{i,0}}{t_{Info}\sigma^2_{i,0}+\eta^2_K}\frac{\sigma^2_{i,0}}{t_{Info}\sigma^2_{i,0}+\eta^2_K}(m_{i,t_{Info}}-\mu_{i,t_{Info}})\\ =& -2\frac{\sigma^4_{i,0}}{(t_{Info}\sigma^2_{i,0}+\eta^2_K)^2}(m_{i,t_{Info}}-\mu_{i,t_{Info}})\end{aligned}$$

and

$$\begin{aligned}\frac{\partial^2\sigma^2_{i,t_{Info}}}{\partial t^2_{Info}} &= \frac{\sigma^4_{i,0}}{(t_{Info}\sigma^2_{i,0}+\eta^2_K)^2}\sigma^2_{i,t_{Info}}+\frac{\sigma^2_{i,0}}{t_{Info}\sigma^2_{i,0}+\eta^2_K}\frac{\sigma^2_{i,0}}{t_{Info}\sigma^2_{i,0}+\eta^2_K}\sigma^2_{i,t_{Info}}\\ &= 2\frac{\sigma^4_{i,0}}{(t_{Info}\sigma^2_{i,0}+\eta^2_K)^2}\sigma^2_{i,t_{Info}} > 0.\end{aligned}$$

Again, we observe that

$$\begin{aligned}
&\frac{\partial^2}{\partial t_{Info}^2}\mathbb{E}[U|I_{t_{Info}}] \\
=&-R^2\exp\left(-R\left(\alpha\mu_{A,t_{Info}}-\frac{1}{2}R\alpha^2\sigma^2_{A,t_{Info}}+(1-\alpha)\mu_{B,t_{Info}}-\frac{1}{2}R(1-\alpha)^2\sigma^2_{B,t_{Info}}+C\right)\right) \\
&\cdot\left(\frac{\partial}{\partial t_{Info}}\mathbb{E}[u|I_{t_{Info}}]\right)^2 \\
&+R\exp\left(-R\left(\alpha\mu_{A,t_{Info}}-\frac{1}{2}R\alpha^2\sigma^2_{A,t_{Info}}+(1-\alpha)\mu_{B,t_{Info}}-\frac{1}{2}R(1-\alpha)^2\sigma^2_{B,t_{Info}}+C\right)\right) \\
&\cdot\frac{\partial^2}{\partial t_{Info}^2}\mathbb{E}[u|I_{t_{Info}}]
\end{aligned}$$

is negative if $\frac{\partial^2}{\partial t_{Info}^2}\mathbb{E}[u|I_{t_{Info}}]<0$. This is equal to

$$\begin{aligned}
\frac{\partial^2}{\partial t_{Info}^2}\mathbb{E}[u|I_{t_{Info}}]=&\alpha\frac{\partial^2\mu_{A,t_{Info}}}{\partial t_{Info}^2}-\frac{1}{2}R\alpha^2\frac{\partial^2\sigma^2_{A,t_{Info}}}{\partial t_{Info}^2}+(1-\alpha)\frac{\partial^2\mu_{B,t_{Info}}}{\partial t_{Info}^2}-\frac{1}{2}R(1-\alpha)^2\frac{\partial^2\sigma^2_{B,t_{Info}}}{\partial t_{Info}^2} \\
=&-2\alpha\frac{\sigma^4_{A,0}}{(t_{Info}\sigma^2_{A,0}+\eta^2_A)^2}(m_{A,t_{Info}}-\mu_{A,t_{Info}})-R\alpha^2\frac{\sigma^4_{A,0}}{(t_{Info}\sigma^2_{A,0}+\eta^2_A)^2}\sigma^2_{A,t_{Info}} \\
&-2(1-\alpha)\frac{\sigma^4_{B,0}}{(t_{Info}\sigma^2_{B,0}+\eta^2_B)^2}(m_{B,t_{Info}}-\mu_{B,t_{Info}}) \\
&-R(1-\alpha)^2\frac{\sigma^4_{B,0}}{(t_{Info}\sigma^2_{B,0}+\eta^2_B)^2}\sigma^2_{B,t_{Info}}<0,
\end{aligned}$$

which is equivalent to

$$R>\frac{-2\alpha\frac{\sigma^4_{A,0}}{(t_{Info}\sigma^2_{A,0}+\eta^2_A)^2}(m_{A,t_{Info}}-\mu_{A,t_{Info}})-2(1-\alpha)\frac{\sigma^4_{B,0}}{(t_{Info}\sigma^2_{B,0}+\eta^2_B)^2}(m_{B,t_{Info}}-\mu_{B,t_{Info}})}{\alpha^2\frac{\sigma^4_{A,0}}{(t_{Info}\sigma^2_{A,0}+\eta^2_A)^2}\sigma^2_{A,t_{Info}}+(1-\alpha)^2\frac{\sigma^4_{B,0}}{(t_{Info}\sigma^2_{B,0}+\eta^2_B)^2}\sigma^2_{B,t_{Info}}}.$$

In summary, we need to assume that R is large enough for every possible value of α and t_{Info}, so that we have to make the assumption

$$R > \max_{\alpha,t_{Info}} \left(2\frac{\frac{-\alpha\sigma^2_{A,0}(m_{A,t_{Info}}-\mu_{A,t_{Info}})}{t_{Info}\sigma^2_{A,0}+\eta^2_A} - \frac{(1-\alpha)\sigma^2_{B,0}(m_{B,t_{Info}}-\mu_{B,t_{Info}})}{t_{Info}\sigma^2_{B,0}+\eta^2_B}}{\frac{\alpha^2\sigma^2_{A,0}\sigma^2_{A,t_{Info}}}{t_{Info}\sigma^2_{A,0}+\eta^2_A} + \frac{(1-\alpha)^2\sigma^2_{B,0}\sigma^2_{B,t_{Info}}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}}, \right.$$
$$\left. 2\frac{\frac{-\alpha\sigma^4_{A,0}(m_{A,t_{Info}}-\mu_{A,t_{Info}})}{(t_{Info}\sigma^2_{A,0}+\eta^2_A)^2} - \frac{(1-\alpha)\sigma^4_{B,0}(m_{B,t_{Info}}-\mu_{B,t_{Info}})}{(t_{Info}\sigma^2_{B,0}+\eta^2_B)^2}}{\frac{\alpha^2\sigma^4_{A,0}\sigma^2_{A,t_{Info}}}{(t_{Info}\sigma^2_{A,0}+\eta^2_A)^2} + \frac{(1-\alpha)^2\sigma^4_{B,0}\sigma^2_{B,t_{Info}}}{(t_{Info}\sigma^2_{B,0}+\eta^2_B)^2}}, 0 \right).$$

Note that the fractions in this expression are both finite for every possible choice of α and t_{Info} as the maximum number of search steps is the time budget T. This implies $\sigma^2_{K,t_{Info}} \geq \frac{\sigma^2_{K,0}\eta^2_K}{T\sigma^2_{K,0}+\eta^2_K} > 0$ for all $t_{Info} \in [0,T]$.

If we define $d_K := m_{K,t_{Info}} - \mu_{K,t_{Info}}$ and $v_K := t_{Info}\sigma^2_{K,0} + \eta^2_K$ we can simplify the expression above and our assumption is

$$R > \max_{\alpha,t_{Info}} \left(2\frac{\frac{-\alpha\sigma^2_{A,0}d_A}{v_A} - \frac{(1-\alpha)\sigma^2_{B,0}d_B}{v_B}}{\frac{\alpha^2\sigma^2_{A,0}\sigma^2_{A,t_{Info}}}{v_A} + \frac{(1-\alpha)^2\sigma^2_{B,0}\sigma^2_{B,t_{Info}}}{v_B}}, \right.$$
$$\left. 2\frac{\frac{-\alpha\sigma^4_{A,0}d_A}{(v_A)^2} - \frac{(1-\alpha)\sigma^4_{B,0}d_B}{(v_B)^2}}{\frac{\alpha^2\sigma^4_{A,0}\sigma^2_{A,t_{Info}}}{(v_A)^2} + \frac{(1-\alpha)^2\sigma^4_{B,0}\sigma^2_{B,t_{Info}}}{(v_B)^2}}, 0 \right). \tag{A1}$$

A.2 Proof of the proposition

For simple notation we define $u_{xy} := \frac{\partial^2}{\partial x \partial y}\mathbb{E}[u|I_{t_{Info}}]$. We can solve (UM) using the first order conditions

$$\begin{aligned}
\frac{\partial u}{\partial \alpha} =& \mu_{A,t_{Info}} - \alpha R\sigma^2_{A,t_{Info}} - \mu_{B,t_{Info}} + (1-\alpha)R\sigma^2_{B,t_{Info}} = 0 \\
\frac{\partial u}{\partial t_{Info}} =& \alpha\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}(m_{A,t_{Info}} - \mu_{A,t_{Info}}) + \alpha^2\frac{1}{2}R\frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}\sigma^2_{A,t_{Info}} \\
&+ (1-\alpha)\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}(m_{B,t_{Info}} - \mu_{B,t_{Info}}) \\
&+ (1-\alpha)^2\frac{1}{2}R\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}\sigma^2_{B,t_{Info}} - t_L\frac{w}{p} = 0.
\end{aligned}$$

This system of first order conditions cannot be solved explicitly. However, we can apply the implicit function theorem. We determine the Jacobian matrix

$$J = \begin{pmatrix} u_{\alpha\alpha} & u_{\alpha t_{Info}} \\ u_{t_{Info}\alpha} & u_{t_{Info}t_{Info}} \end{pmatrix} = \begin{pmatrix} u_{\alpha\alpha} & u_{\alpha t_{Info}} \\ u_{t_{Info}\alpha} & u_{t_{Info}t_{Info}} \end{pmatrix},$$

which has determinant

$$\det(J) = u_{\alpha\alpha}u_{t_{Info}t_{Info}} - u^2_{t_{Info}\alpha}$$

which is positive from assumption (A2). Thus, the implicit function theorem implies that there exists a solution α^* and t^*_{Info} for our maximization problem (UM).

In figure 3 we focus on the optimal search steps in the process of information acquisition. In this graph marginal cost of another search step is fixed at $t_L \frac{w}{p}$. Solving for α in first condition $\left[\alpha = \frac{\frac{\mu_{A,t_{Info}}}{R} - \frac{\mu_{B,t_{Info}}}{R} + \sigma^2_{B,t_{Info}}}{\sigma^2_{A,t_{Info}} + \sigma^2_{B,t_{Info}}}\right]$ and plugging in the second leads to the graphical representation of marginal utility with additional search steps. Marginal utility is a decreasing function in search steps due to the assumption (A.1). However, at each step the values of $\mu_{A,t_{Info}}$, $\mu_{B,t_{Info}}$ are the result of a particular time path of signals up to t_{Info} that fulfills condition (A.1). Thus, with each curve in figure 3 we see an example for one sequential time path of signals. As the property of $U' > 0$ and $U'' < 0$ is ensured by assumption (A.1), a sequential search would move ahead until for the first time the equation $U' = t_L \frac{w}{p}$ holds. With this intersection of marginal utilities and costs in figure 3 we illustrate that a solution exist. However, as there are many of these sequential stochastic time paths, there is more than one solution. This is indicated by the different marginal utility curves $U'(\{m^d_{A,t_{Info}}\}, \{m^d_{B,t_{Info}}\})$ for $d = i, j, k$.

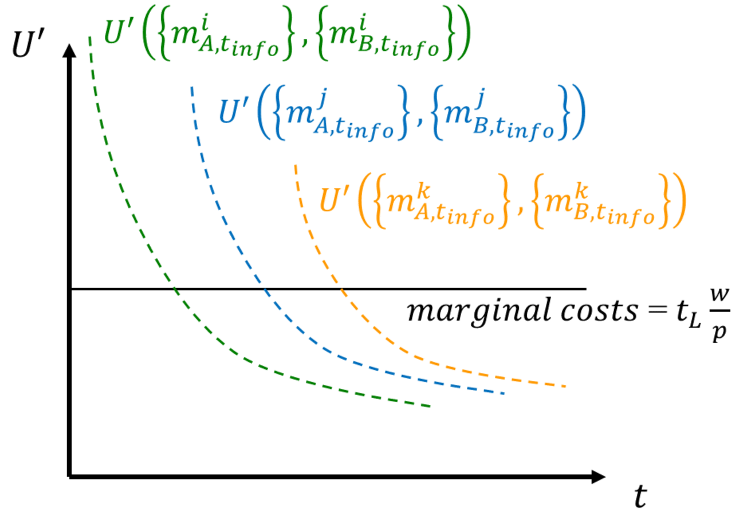

Figure 3: Marginal utilities U' for three different paths i, j, k of stochastic signals, which intersect marginal costs at different times t.

A.3 Comparison between sequential search and the general optimization problem UM

We have already noticed that the start of sequential search depends on the individual perception for the signals' precision which can lead to the result that sequential search is not started, but the optimal number of search steps from the general optimization problem (UM) is $t^*_{Info} > 0$. What else can be different? After each conducted search step t_{Info} individuals choose α as the solution of

$$\frac{\partial \mathbb{E}[u|I_{t_{Info}}]}{\partial \alpha} = \mu_{A,t_{Info}} - \alpha R\sigma^2_{A,t_{Info}} - \mu_{B,t_{Info}} + (1-\alpha)R\sigma^2_{B,t_{Info}} = 0$$

which corresponds to the first order condition of the maximization problem in one variable as well as to one of the first order conditions of the maximization problem (UM). However, (UM) has a second first order condition which is equal to

$$
\begin{aligned}
\frac{\partial \mathbb{E}[u|I_{t_{Info}}]}{\partial t_{Info}} =& \alpha \frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}(m_{A,t_{Info}} - \mu_{A,t_{Info}}) \\
&+ \alpha^2 \frac{1}{2} R \frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}\sigma^2_{A,t_{Info}} \\
&+ (1-\alpha)\frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}(m_{B,t_{Info}} - \mu_{B,t_{Info}}) \\
&+ (1-\alpha)^2 \frac{1}{2} R \frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}\sigma^2_{B,t_{Info}} - t_L \frac{w}{p} = 0.
\end{aligned}
$$

If we assume that the next signal is anticipated as the current expected conditional match value for sequential search this condition becomes

$$
\alpha^2 \frac{1}{2} R \frac{\sigma^2_{A,0}}{t_{Info}\sigma^2_{A,0}+\eta^2_A}\sigma^2_{A,t_{Info}} + (1-\alpha)^2 \frac{1}{2} R \frac{\sigma^2_{B,0}}{t_{Info}\sigma^2_{B,0}+\eta^2_B}\sigma^2_{B,t_{Info}} = t_L \frac{w}{p}
$$

which means that anticipated marginal utility of a further search step only depends on the reduction in uncertainty. As long as this reduction is larger than marginal costs $t_L \frac{w}{p}$ sequential search is continued since this first order condition does not hold (see figure 3).

Note that the sign of $(m_{K,t_{Info}} - \mu_{K,t_{Info}})$, which remains included in the first order condition for optimization problem (UM), can be positive or negative and the choice of R according our assumption ensures that marginal utility is positive. This can cause a difference between the optimal number of search steps from (UM) and sequential search steps in two different ways. On the one hand, it is possible that the following signal brings this second first order condition to hold. Then the optimization problem (UM) stops, but in sequential search one more step is necessary when the anticipated utility gain is positive. Thus, sequential search stops at the next integer, which is only a small mistake caused by our assumption if continuity. More than one additional sequential search step is not possible as sequential search stops if the utility gain from one conducted search step is not positive and this is known after acquiring the next piece of information. On the other hand, it is possible that optimization requires to continue search whereas sequential search is already stopping because the anticipated gain in utility is not positive. In this case the individual does not anticipate an improvement from the signals received. They cannot know that the following signals increase expected utility. This can even lead to a difference in more than one search step compared to optimization (UM). Therefore, the solution for t_{Info} from sequential search is not necessarily equal to the solution t^*_{Info} from the general optimization problem.

We see that the reason for this difference is that solving the optimization problem (UM) requires the knowledge of the signals which implies the knowledge of the factor $(m_{K,t_{Info}} - \mu_{K,t_{Info}})$ for every time t_{Info}. However, the order of the received signals until a certain time t_{Info} does not play a role as we can see from the updating formula (1). In contrast, in sequential search the stopping rule depends on the received signals thus far which means that the order of the signals and their specific stochastic path determine the sequential solution.

Furthermore, the difference in time steps can also imply a difference in the choice of α. Thus, the combination of belief systems that is chosen from sequential search can differ from the combination resulting from (UM). The reason is that uncertainty is higher when less search steps are conducted and utility can be greater with a different combination of belief systems.

In spite of these differences sequential search leads to the same qualitative result as the general optimization problem: we find an optimal stopping rule and an expected utility maximizing number of search steps from the individual's point of view. The sequential search process is more sensitive to the stochastic path of the signals.

A.4 Comparison of numerical examples

We take another look at our first example that is illustrated in figure 1. If we compare the results from sequential search with the overall maximal utility (which corresponds to the general solution of UM) we find differences only in case 1(b). In case 1(a) the number of sequential search steps is equal to the number of optimal steps from the general optimization problem. This implies that also the optimal fraction α^* is equal. Thus, in this case the anticipation for the subsequent expected utility is correct. In case 1(b) sequential search stops after 2 steps, whereas the optimal number from general optimization is 4. This means that after the second step the anticipated gain in utility is not positive, but the specific signals are high enough to increase expected utility. However, individuals cannot know this. They can only elaborate if they expect further increase in utility based on what they know so far. Expected utility after sequential search is 7.70 and expected utility after general optimization is 7.97. Thus, the individual who applies the sequential search process faces a loss in utility. However, the difference is small and from the individual's point of view it is best to stop search early.

In our second example that is shown in figure 2 we see a difference in case 2(a). In case 2(b) sequential search stops at the overall maximal utility again. In case 2(a) the number of optimal steps from general optimization is 2 whereas the sequential number is 3. Thus, the anticipated gain in utility for a third step is positive which implies that sequential search is continued. After conducting the third step the individual knows that this slightly reduces utility from 6.993 to 6.987 and sequential search is stopped as well. However, the loss in utility is small and α^* is equal to the result from the general optimization UM.