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Cognitive Sophistication and Deliberation Times

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Abstract

Behavioral heterogeneity arising from cognitive differences among economic agents plays a fundamental role in the economy. To explain this heterogeneity, models of iterative thinking assume that certain choices indicate higher cognitive effort. That is, choices are used to infer the cognitive process behind the choices themselves. To establish this link choice data is insufficient, thus an individually-measurable correlate of cognitive effort is required. We argue that deliberation times provide this missing link. We present a simple model of heterogeneous cognitive depth, incorporating stylized facts from the psychophysical literature, which makes predictions on the relation between choices, cognitive effort, incentives, and deliberation times. In an experimental test, the predicted relations are readily observed in the data, but only when the features leading to iterative thinking are salient enough. Hence, the predicted relations become a tool to uncover the limits of models of iterative thinking.

JEL Classification: C72 · C91 · D80 · D91.

Keywords: Heterogeneity · Level-k reasoning · Cognitive sophistication · Deliberation times · Depth of reasoning · Cognitive effort.

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1 Introduction

Economic agents form different expectations and react differently even when confronted with the same pieces of information, leading to substantial behavioral heterogeneity, which in turn has long been recognized as a fundamental difficulty for economic theory (e.g., Haltiwanger and Waldman, 1985; Kirman, 1992; Blundell and Stoker, 2005). A key source of heterogeneity is the fact that cognitive capacities differ among individuals, as does the motivation to exert cognitive effort. This observation has given rise to a rich theoretical literature, including level-k models (Stahl, 1993; Nagel, 1995; Stahl and Wilson, 1995; Ho et al., 1998) and models of cognitive hierarchies (Camerer et al., 2004). Such models endow individuals with differing degrees of strategic sophistication or reasoning capabilities, and might hold the key to describe heterogeneity in observed behavior (for a recent survey, see Crawford et al., 2013). In particular, they have proven invaluable to explain behavioral puzzles as overbidding in auctions (Crawford and Iriberri, 2007), overcommunication in sender-receiver games (Cai and Wang, 2006), coordination in market-entry games (Camerer et al., 2004), and why communication sometimes improves coordination and sometimes hampers it (Ellingsen and Östling, 2010). More recently, a small but growing literature in macroeconomics has started to incorporate heterogeneity in cognitive depth and iterative thinking (Angeletos and Lian, 2017), leading to promising insights on the effects of monetary policy (Farhi and Werning, 2017) or low interest rates (García-Schmidt and Woodford, 2018).

Existing models of heterogeneity in cognitive depth, however, face a fundamental problem. So far, there is little direct evidence that heterogeneity in observed choices actually corresponds to differences in depth of reasoning (level of thinking) or cognitive effort. Most of the experimental literature has used observed choices to classify individuals in different cognitive categories. Hence, the observation of a given choice is used to infer the underlying path of reasoning or the thought processes that led to that choice, creating an essentially circular argument. One problem with this approach is that the same choice is always attributed to the same level, although it might very well be the result of completely different decision rules. As a consequence, cognitive effort associated with a choice becomes a non-testable assumption, and the sources of heterogeneity remain in the dark.

To establish that the source of observed behavioral heterogeneity is actually heterogeneity in cognitive effort and capacities, what is needed are individually measurable correlates of cognitive effort beyond choice data. That is, instead of arbitrarily identifying particular choices with particular levels of cognitive depth, one needs to provide a direct measure of effort which allows to independently show that certain choices actually are the result of stronger cognitive effort. We argue that response times, or, more properly in our context, *deliberation times* can be fruitfully used for this purpose.

In the present work, we provide a simple model linking cognitive sophistication to choices and deliberation times, taking into account stylized facts from the psychophysiological literature on response times. The model rests on two key assumptions. The first and more straightforward one is that the total deliberation time of an observed choice is the sum of one-step decision times for a chain of binary hypothetical choices as implicitly postulated in the literature on iterative thinking. That is, if arriving at a choice through iterative thinking requires seven steps, deliberation time is the sum of the decision times associated with the seven corresponding, intermediate decisions. The second assumption is that the time required for each step is a decreasing function of the distance to indifference, as captured by the potential gain of conducting an additional step of reasoning. This assumption is based on a very well-established fact from the literature in psychology and neuroscience, namely that the human ability to discriminate between two stimuli is a function of the difference between the respective stimuli. With increasing difference the mean response time decreases, or in other words, decisions closer to indifference ("harder" decisions) are found to be slower (Dashiell, 1937; Mosteller and Nogee, 1951; Moyer and Landauer, 1967; Krajbich et al., 2014, 2015), while "easier" decisions are faster.

The model provides empirically testable predictions on the measurable effects of cognitive sophistication (or effort), both for choices and deliberation times, and also regarding the effects of economic incentives on both the level of cognitive sophistication, as inferred from choices, and the psychophysiological correlate embodied in deliberation times. We test these predictions in an experiment employing two different games commonly used to study iterative thinking: the beauty contest game (or guessing game; Nagel, 1995), which is the workhorse in that literature, and several variants of the 11-20 money request game, recently introduced by Arad and Rubinstein (2012), in the graphical version of Goeree et al. (2016). These variants all share the same best-reply structure, but the payoff structures are manipulated in order to change the salience of certain features which might encourage iterative thinking. The reason why we use the latter game is that in some of the variants considered in Goeree et al. (2016), reconciling observed behavior with a model of iterative thinking would require inordinately high levels of sophistication, compared to those usually observed in the literature. This provides a natural setting where deliberation times can discriminate whether observed behavior actually corresponds to different levels of cognitive effort.

In the beauty contest game we find longer deliberation times for choices commonly associated with more steps of reasoning, confirming the basic prediction of our model that deliberation time is increasing in cognitive sophistication. That is, the beauty contest game serves as a basic validation of the relationship between cognitive effort and deliberation times. In the 11-20 game, again we show that deliberation times are longer for higher-level choices in situations where the payoff structure makes iterative reasoning salient. However, when iterative thinking is less natural or when a conflict with alternative decision rules (e.g., based on the salience of high payoffs) is likely, this systematic relation between higher-level choices and deliberation times disappears. Rather, in this case we find overall longer deliberation times, suggesting a conflict between competing decision rules. That is, features besides and beyond the best-reply structure matter. More importantly, deliberation times serve as a test of whether iterative-thinking models are appropriate to describe actual play in specific settings.

Our model also relates changes in the incentives to choices and deliberation times. First, it predicts that a player conducts more steps of reasoning if the incentives, as captured by the payoff differences in the underlying game, are systematically increased. However, this does *not* imply that higher incentives necessarily imply longer deliberation times. On the contrary, the second prediction of the model is that deliberation times will be shorter *for a given number of steps* when the incentives are increased, because decisions farther away from indifference require less deliberation. As a consequence, the model can accommodate the observation of higher cognitive depth *and* (simultaneously) shorter deliberation times. Turning to the data, by using implementations of the 11-20 game with different incentive levels, we find a systematic effect of incentives on the depth of reasoning as predicted by the model. In the basic treatment where iterative thinking is salient, we find *both* more higher-level choices and shorter deliberation times when incentives are increased, in line with the prediction that higher incentives should decrease the time required for each single step. More importantly, this demonstrates empirically that higher incentives might reduce deliberation times, even though cognitive effort is increased. This latter finding shows that incorporating the fact that easier decisions are faster into models of cognitive depth is crucial. Otherwise, if decision times per step were assumed to be independent of incentives, higher cognitive depth would go hand-in-hand with longer deliberation times, contradicting the data.

Overall, this paper makes two contributions. First, we are the first to show that heterogeneity in behavior can actually be traced back to heterogeneity in cognitive effort by using direct correlates of the latter rather than exogenously identifying choices with levels of effort. Second, the very same correlates show the limits of models of iterative thinking and heterogeneity in cognitive depth. We show that, depending on the strategic situation, behavioral heterogeneity might be mistaken for heterogeneity in cognitive depth even though there are no actual differences in cognitive effort. Hence, one might be led to draw wrong conclusions if models of iterative thinking are blindly applied without an external way of testing for heterogeneity in cognitive depth. We show that deliberation times can be used as a tool to discriminate among economic problems where behavioral heterogeneity arises mainly from differences in cognitive depth, and hence applying such models is justified, and other problems where extraneous or additional elements are at the source of that heterogeneity, which then require further analysis.

The paper is structured as follows. Section 2 briefly relates our work to the literature. Section 3 introduces the model and derives the predictions. Section 4 describes the experimental design. Sections 5 and 6 present the results of the experiment for the beauty contest and the 11-20 games, respectively. Section 7 presents results on the effect of incentives. Section 8 discusses and summarizes our findings. The Appendix contains a number of additional observations and analyses.

2 Related Literature

There is a small but growing literature employing sources of evidence beyond choice data which suggests that individuals follow step-wise reasoning processes in certain settings. Bhatt and Camerer (2005) and Coricelli and Nagel (2009) show that reasoning in different games, including the beauty contest game, correlates with neural activity in areas of the brain associated with mentalizing (Theory of Mind network), building a notable bridge between social neuroscience and game theory.[1] Brañas-Garza et al. (2012), Carpenter et al. (2013), and Gill and Prowse (2016) relate higher cognitive ability (as measured, e.g., by the Cognitive Reflection Test or the Raven test) with more steps of reasoning in the beauty contest game. Further, Fehr and Huck (2016) find that subjects whose cognitive ability is below a certain threshold lack strategic awareness, that is, they randomly choose numbers from the whole interval. Other works have relied on eye-tracking measurements or click patterns recorded via MouseLab to obtain information on search behavior, which is then used to make inferences regarding level-k reasoning (Costa-Gomes et al., 2001; Crawford and Costa-Gomes, 2006; Polonio et al., 2015). Notably, Lindner and Sutter (2013) found that under time pressure behavior in the 11-20 game was closer to the Nash equilibrium, although the authors recommend caution in interpreting the result. In contrast, Spiliopoulos et al. (2018) find no evidence for Nash equilibrium play. Instead, subjects exhibit a shift to less complex decision rules (requiring less elementary operations to execute) under time pressure in various 3×3 games; this shift is primarily driven by a significant increase in the proportion of level-1 players. In a repeated p-beauty contest Gill and Prowse (2018) show that subjects who think for longer on average win more rounds and choose lower numbers closer to the equilibrium.

Clearly, our work is also related to the growing literature employing response times in economics. Examples include the studies of risky decision making by Wilcox (1993, 1994), the web-based studies of Rubinstein (2007, 2013), and recent studies as Achtziger and Alós-Ferrer (2014) and Alós-Ferrer et al. (2016).[2] To date, however, only a few works in economics have explicitly incorporated response times in models of reasoning. Chabris et al. (2009) study the allocation of time across decision problems. Their model is similar in spirit to ours in that it is motivated by the chronometric "closeness-

[1] Paradigms eliciting iterative thinking, and very specially "thinking about thinking," fall squarely within the domain of social neuroscience. See Alós-Ferrer (2018a) for details.

[2] For a recent discussion of the benefits, challenges, and desiderata of response time analysis in experimental economics see Spiliopoulos and Ortmann (2018).

to-indifference" effect. In particular, they also model response time as a decreasing function of differences in expected utility. However, in contrast to our model they focus on binary intertemporal choices and do not consider iterative reasoning. They report empirical evidence that choices among options whose expected utilities are closer require more time, thus indicating an inverse relationship between response times and utility differences. They argue in favor of the view that decision making is a cognitively costly activity that allocates time according to cost-benefit principles.

Achtziger and Alós-Ferrer (2014) and Alós-Ferrer (2018b) consider a dual-process model of response times in simple, binary decisions where different decision processes interact in order to arrive at a choice. The emphasis of the model, however, is on the effects of conflict and alignment among processes, that is, whether a particular decision process or heuristic supports a more rationalistic one or rather leads the decision maker astray. The predictions of the model help understand when errors, defined as deviations from a normative, rationalistic process, are faster or slower than correct responses.

Alaoui and Penta (2016b) provided a model of iterative thinking where the depth of reasoning is endogenously determined and results from a cost-benefit analysis. Recently, Alaoui and Penta (2016c) have extended this model to incorporate deliberation times, with the key assumption being that each additional step of reasoning increases deliberation times. As in our model, total deliberation time for a given number of steps of reasoning is the sum of the times required to attain the necessary unit of understanding for each step. Hence their model also predicts (for sufficiently similar games) that deliberation time is increasing in the depth of reasoning. They assume that the depth of reasoning is determined by the "value of reasoning" and the "cost of reasoning." The former is linked to the payoff structure of the game, whereas the latter depends on the complexity of the game. The value of reasoning has a maximum-gain representation (Alaoui and Penta, 2016a), that is, it equals the highest possible payoff improvement that an agent could obtain by using the "next step strategy" instead of the current one. The key difference to our model is that we assume that deliberation time of a given step is decreasing in the utility differences. In their model, a higher value of reasoning only affects total deliberation times because it increases the probability of conducting another step, but it does not affect the time required for a given step. Hence, for "equally complex" games their model predicts longer deliberation times for larger incentives, because the time required for a given step is constant.

Finally, our work sheds light on the recent literature exploring the limits of models of iterative thinking, as the experiment of Goeree et al. (2016) mentioned above. It has been pointed out that strategic sophistication, as captured by level-k models, might be heavily dependent on the situation at hand. Hargreaves Heap et al. (2014) suggest that even (allegedly-nonstrategic) level-0 behavior might depend on the strategic structure of the game. In a repeated beauty contest, Gill and Prowse (2018) found that the level of strategic reasoning also depends on the complexity of the situation in the previous round.

Georganas et al. (2015) show that strategic sophistication can be largely persistent within a given class of games but not necessarily across different classes of games. That is, the congruence between level-k models and subjects' actual decision processes may depend on the context. Allred et al. (2016) complement this result showing that the implications of available cognitive resources on strategic behavior are not persistent across classes of games. These difficulties raise the question of whether models of iterative thinking can be actually understood as procedural, that is, as describing how decisions are actually arrived at, or rather as purely descriptive, outcome-based models. Further, if iterative thinking cannot be taken as a persistent mode of behavior (across individuals and across games), it becomes particularly important to identify what triggers its use and in which situations it conflicts with other decision rules. Again, choice data alone is not sufficient to answer these questions.

3 The Model

We model decision making as a process of iterative reasoning as put forward in the literature on iterative thinking (Stahl, 1993; Nagel, 1995; Stahl and Wilson, 1995; Ho et al., 1998). Our model yields testable predictions linking deliberation times to choices and incentives in a specific class of strategic games.

Consider a symmetric, two-player game $\Gamma = (\pi, S)$ with finite strategy space S and payoff function $\pi : S \times S \longrightarrow \mathbb{R}$. Assume that for any $s \in S$ there is a unique best-reply, denoted by $BR(s)$, that is, $BR(s)$ is the unique maximizer of $\pi(\cdot, s)$. The *best-reply structure* of Γ for a starting point $s_0 \in S$ is a sequence $(s^*_k)_{k\in\mathbb{N}}$ such that $s^*_0 = s_0$ and $s^*_k = BR(s^*_{k-1})$. Fix a best-reply structure $(s^*_k)_{k\in\mathbb{N}}$ with starting point s_0. We model a process of iterative thinking as a sequence of binary "choices," where in each step a player evaluates the current strategy s^*_{k-1}, reached after $k-1$ steps of thinking, against strategy s^*_k by comparing $\pi(s^*_{k-1}, s^*_{k-1})$ against $\pi(s^*_k, s^*_{k-1})$. In other words, the player considers the case where his opponent has also conducted $k-1$ steps of thinking, hence uses strategy s^*_{k-1}, and then evaluates the potential gain from conducting an additional step of thinking, that is $\pi(s^*_k, s^*_{k-1}) - \pi(s^*_{k-1}, s^*_{k-1})$. Note that this last evaluation does not necessarily involve conscious calculations, but should rather be understood as a proxy that determines whether to engage in additional deliberation. For example, one way to think about this is that this evaluation happens automatically and that the controlled process of iterative thinking only takes over when the payoff is large enough.[3] In addition, we assume that each step of thinking comes with a cognitive cost. Specifically, the *cognitive cost* associated with the kth step of thinking is given by an arbitrary function $c_i(k)$ with $c_i : \mathbb{N}_+ \longrightarrow \mathbb{R}_+$ assumed only to be weakly increasing ($\mathbb{N}$ denotes the set of

[3]This is, for instance, the approach taken in Benhabib and Bisin (2005), where controlled processes intervene to inhibit automatic reactions only if the potential payoff exceeds a given threshold. Alaoui and Penta (2016b) also follow this approach and argue that it circumvents the infinite-regress problem where thinking about how to determine the value of reasoning is itself costly.

natural numbers including the zero, and $\mathbb{N}_+$ the set of natural numbers without zero). Thus the maximal number of steps of thinking player i is willing (or able) to conduct is given by $T_i = \min\{k \in \mathbb{N} \mid \pi(s^*_{k+1}, s^*_k) - \pi(s^*_k, s^*_k) < c_i(k+1)\}$ if the set is nonempty, and $T_i = \infty$ otherwise.

The depth of reasoning of player i, T_i, depends on both the cognitive cost and the specifics of the payoff structure of the underlying game determining the gain of an additional step of thinking. We now study how systematic changes in the payoff structure affect the depth of reasoning in our model. For brevity, let us denote the potential gain of the kth step of thinking by $u_k = \pi(s^*_k, s^*_{k-1}) - \pi(s^*_{k-1}, s^*_{k-1})$, and notice that $u_k \geq 0$ by construction. Consider two symmetric, two-player games $\Gamma = (\pi, S)$ and $\Gamma' = (\pi', S)$ with the same strategy space S and the same best reply structure $(s^*_k)_{k\in\mathbb{N}}$ with starting point $s_0 \in S$. We say that Γ' has weakly (strictly) *higher incentives* than Γ for step k if $u'_k \geq u_k$ ($u'_k > u_k$) where $u_k = \pi(s^*_k, s^*_{k-1}) - \pi(s^*_{k-1}, s^*_{k-1})$ and $u'_k = \pi'(s^*_k, s^*_{k-1}) - \pi'(s^*_{k-1}, s^*_{k-1})$. Suppose Γ' has weakly higher incentives than Γ for every step k with $k \leq T_i$, that is $u'_k \geq u_k$ for all $k \leq T_i$. Then Γ' induces weakly more steps of reasoning for player i than Γ, since $u'_k \geq u_k \geq c_i(k)$ for all $k \leq T_i$ implies $T'_i \geq T_i$.

Prediction 1. *A player conducting k steps of reasoning weakly increases his depth of reasoning if the incentives for all steps up to k are weakly higher.*

Next, we link this simple model of iterative thinking to deliberation times via two basic assumptions. First, we assume that the deliberation time for conducting k steps of thinking is the sum of the deliberation times required for each step, as in Alaoui and Penta (2016c). Second, we assume that the deliberation time for a given step of thinking is larger the smaller the potential gain for that step, in accordance with well-established chronometric effects (Dashiell, 1937; Moyer and Landauer, 1967; Chabris et al., 2009). Assume player i requires a fixed amount of time, $d_i \in \mathbb{R}_+$, for choosing s^*_0. Then the deliberation time of player i for choosing strategy s^*_k is given by

$$DT_i(s^*_k) = d_i + \sum_{i=1}^{k} f_i(u_i) \text{ with } f_i : \mathbb{R}_+ \longrightarrow \mathbb{R}_{++} \text{ strictly decreasing and positive.}$$

We say that a strategy s requires *more cognitive effort* compared to s', if it is the result of more steps of reasoning, that is $s = s^*_k$ and $s' = s^*_{k'}$ with $k > k'$. In that case, our model implies that $DT_i(s) > DT_i(s')$ if s requires more cognitive effort than s'.

Prediction 2. *For fixed incentives, deliberation time is increasing in cognitive effort.*

This prediction is a straightforward consequence of viewing deliberation times as a sum of binary-choice decision times, hence it is also a prediction of Alaoui and Penta (2016c). The following prediction, however, hinges crucially on our assumption that deliberation times per step are a decreasing function of incentives. Suppose Γ' has strictly higher incentives than Γ for any step $0 < l \leq k$ for some k. Then $DT'_i(s^*_k) = d_i + \sum_{i=1}^{k} f_i(u'_i) < d_i + \sum_{i=1}^{k} f_i(u_i) = DT_i(s^*_k)$ because $f(u'_l) < f(u_l)$ for all $0 < l \leq k$.

Prediction 3. *Deliberation time for a choice corresponding to k steps of thinking is shorter (longer) if the incentives for all steps up to k are increased (decreased).*

For a fixed number of steps of thinking our model predicts shorter deliberation times for higher incentives, because a player requires less time for each step. This, however, does not necessarily imply that one should observe shorter total deliberation times for larger incentives, because under larger incentives subjects potentially conduct more steps of thinking (Prediction 1), which in turn increases overall deliberation time. Thus, in our model larger incentives have a two-fold effect with (weakly) more steps of reasoning on the one hand and shorter deliberation times per step on the other hand.

Last, we remark that it is conceivable that individual differences in cognitive ability affect deliberation times in different ways. In terms of our model, there are two main effects. First, higher cognitive ability could translate into uniformly lower cognitive costs of reasoning, c_i. In that case, players with higher cognitive ability are likely to conduct more steps of reasoning, because $T'_i \geq T_i$ if $c_i(k) \geq c'_i(k)$ for all $0 < k \leq T_i$, which would increase overall deliberation time. Second, higher cognitive ability could also translate into shorter deliberation times per step, which would decrease overall deliberation times. However, that does not mean that deliberation time for players with high cognitive ability will generally be shorter (independently of the number of steps). This is because higher cognitive ability might also result in more steps of reasoning requiring additional deliberation time, so that the overall effect on deliberation times is indeterminate.

4 Experimental Design

We use two games commonly employed to study cognitive sophistication, the classical beauty contest game (Nagel, 1995) and the 11-20 money request game, a more recent alternative that was explicitly designed to study level-k behavior (Arad and Rubinstein, 2012). We ask whether a higher level of reasoning is reflected in higher cognitive effort, or in other words, whether there is a direct link between higher levels of reasoning and deliberation times. We use different versions of the 11-20 game that vary the incentives for iterative thinking leaving the underlying best-reply structure unaffected. This allows us to study how choices and deliberation times react to systematic changes in the payoff structure.

4.1 The Beauty Contest Game

The standard workhorse for the study of cognitive sophistication is the guessing game, or p-beauty contest game (Nagel, 1995). We use a standard, one-shot, discrete beauty contest game with $p = 2/3$. In this game, a population of players has to simultaneously guess an integer number between 0 and 100. The winner is the person whose guess is closest to p times the average of all chosen numbers. The winner receives a fixed prize, which is split equally among all winners in case of a tie. The beauty contest game is a game with usually more than two players. Since we have formulated our model for bilateral interactions, strictly speaking it cannot be directly applied to this situation. However, in the beauty contest game a player's payoff depends only on the average number chosen by all other players and iterative thinking in this game is typically based on beliefs about a representative agent. Our model can be immediately extended to cover this class of games by viewing $\pi(s, s')$ as the payoff of strategy s when a representative agent chooses s', or, equivalently, when average behavior of the opponents corresponds to s'.

In this game it is usually assumed that non-strategic (level-0) players pick a number at random from the uniform distribution over $\{0, \ldots, 100\}$, which yields an expected average of 50. Hence, we assume that the starting point for iterative thinking is given by $s_0^* = 50$. If all players choose s_0^*, then the average of all numbers chosen is 50 and hence the best reply to s_0^* is to choose $s_1^* = 33$, that is the integer closest to 2/3 times 50. Iterating, this defines the best-reply structure of the beauty contest game (s_k^*) where s_k^* is the integer closest to $(2/3)s_{k-1}^*$.[4] This game has two Nash equilibria at 0 and 1.

4.2 The 11-20 Game

The second part of our experiment focuses on variants of the 11-20 money request game, that was introduced by Arad and Rubinstein (2012) as a two-player game specifically well suited to study iterative reasoning. Alaoui and Penta (2016b) used the 11-20 game to test their model of endogenous depth of reasoning. Goeree et al. (2016) introduced a graphical version of the 11-20 game that allows to vary the payoff structure without affecting the underlying best-reply structure of the game. We now describe a generalized version of this graphical 11-20 game. In what follows, we will refer to this game (and variants thereof) simply as "11-20 game."

A_9	A_8	A_7	A_6	A_5	A_4	A_3	A_2	A_1	20
9	8	7	6	5	4	3	2	1	0

Figure 1: Generalized 11-20 game.

[4]This delivers the path $(50, 33, 22, 15, 10, 7, 5, 3, 2, 1, 1, \ldots)$, which is close to that defined by $(2/3)^k 50$. Of course, this is an approximation which ignores the impact of the player on the average, but is accurate unless N is small.

Consider ten boxes horizontally aligned and numbered from 9 (far left) to 0 (far right) as depicted in Figure 1. Each box $b \in \{1, \dots, 9\}$ contains an amount $A_b < 20$ and the rightmost box, $b = 0$, contains the highest amount of $A_0 = 20$. There are two players, $i = 1, 2$, and each has to choose a box $b_i \in \{0, \dots, 9\}$. Each player receives the amount A_{b_i} in the box he chose plus a bonus of R if he chose the box that is exactly one to the left of his opponent's box. That is, payoffs are given by

$$\Pi_i(b_i \mid b_{-i}) = \begin{cases} A_{b_i} & \text{if } b_i \neq b_{-i} + 1 \\ A_{b_i} + R & \text{if } b_i = b_{-i} + 1. \end{cases}$$

A feature of this game is that choosing box 0 is the salient and obvious candidate for a non-strategic level-0 choice, because it awards the highest "sure payoff" of 20 that can be obtained without any strategic considerations. Thus, the rightmost box 0 is a natural anchor serving as a starting point for iterative thinking. If the bonus R is large enough, that is, $R > 20 - \min\{A_b | b = 1, \dots 9\}$, then the best-reply structure for the salient starting point $s_0^* = 0$ is $(s_k^*)_k$ with $s_k^* = k$ for $k = 1, \dots, 9$.[5] In other words, for a sufficiently large bonus the best reply is always to choose the box that is exactly one to the left of your opponent (if there is such a box). In particular, the best-reply path is independent of the specific payoff structure, as long as the conditions mentioned above are fulfilled.

BASE	11	12	13	14	15	16	17	18	19	20
FLAT	17	17	17	17	17	17	17	17	17	20
EXTR	19	18	17	16	15	14	13	12	11	20

Figure 2: Payoff structure for the different variants with low cost.

We use the three versions of the 11-20 game shown in Figure 2.[6] The sure payoffs given by the amounts $A_0, \dots, A_9$ differ across versions, however, they are chosen in such a way that the best-reply structure described above remains unchanged. In the baseline version (BASE) the amounts are increasing from the left box to the rightmost box, containing the highest amount of 20. BASE corresponds to the original version of Arad and Rubinstein (2012) and to the baseline version of Goeree et al. (2016). In BASE

[5] Note that the best reply to an opponent choosing box 9 is to choose box 0, hence for $k > 9$ the best-reply structure cycles repeatedly from 0 to 9. For simplicity, we abstract from this issue and focus only on steps 1-9. Alaoui and Penta (2016b) use a slightly different payoff structure with an additional bonus in case of a tie that breaks this best-reply cycle.

[6] For each of the three versions BASE, FLAT, and EXTR there is a unique mixed strategy Nash equilibrium. For the low cost and low bonus versions those are given by $\left(0, 0, 0, 0, \frac{1}{4}, \frac{1}{4}, \frac{1}{5}, \frac{3}{20}, \frac{1}{10}, \frac{1}{20}\right)$, $\left(0, 0, 0, \frac{1}{10}, \frac{3}{20}, \frac{3}{20}, \frac{3}{20}, \frac{3}{20}, \frac{3}{20}, \frac{3}{20}\right)$, and $\left(0, 0, 0, 0, 0, 0, 0, \frac{3}{20}, \frac{2}{5}, \frac{9}{20}\right)$, respectively.

there is a natural trade-off between the sure payoffs $A_1, \ldots, A_9$ and the bonus, with each incremental step of reasoning being equally costly in terms of sure payoff. We designed the second version in order to remove the trade-off between higher steps of reasoning and sure payoff. This flat-cost version (FLAT) is a modification of BASE where the first iteration results in a cost, but after that all additional steps are identical and come at no further cost in terms of sure payoff. Specifically, all boxes except the rightmost box contain the same amount, which is by some fixed amount lower than the salient amount of 20. Thus, choosing any box except the rightmost gives the same sure payoff and, hence, after the first step any additional step is "costless." FLAT could also be viewed as a modification of Arad and Rubinstein's (2012) costless-iterations version. The extreme version (EXTR) was previously used in Goeree et al. (2016). In this version, all amounts except for the highest one are rearranged to be decreasing from left to right with the second highest amount in the leftmost box. Since the rightmost box still contains the highest amount of 20, this rearrangement does not alter the underlying best-reply structure. However, it crucially affects the cost in terms of sure payoff associated with different levels of reasoning. Choosing box 1 is now disproportionately expensive, and further increments come, in terms of sure payoff, at no cost but instead at a gain. Moreover, this asymmetry potentially opens the door for alternative heuristics, such as choosing the highest amount that still grants the possibility of a bonus, which in this case would imply choosing the leftmost box.

We further varied these three versions of the 11-20 game along two additional dimensions. First, for each treatment there was an additional "high-cost" version, where for BASE and EXTR the amounts $A_1, \ldots, A_9$ range from 2 to 20 in increments of 2 instead of from 11 to 20 in increments of 1, and for FLAT all amounts other than 20 were set to 14 in the high-cost version instead of 17 (see Figure 3). Depending on the treatment, the trade-off between bonus and sure payoff for an additional step of reasoning is decreased or increased under high cost. Second, we varied the incentives to reason by changing the size of the bonus for choosing the box exactly one to the left of the other player's. Specifically, in the additional high-bonus condition, subjects obtained $R = 40$ additional points for the "correct" box, while in the low-bonus condition they only received $R = 20$ additional points.

BASE	2	4	6	8	10	12	14	16	18	20
FLAT	14	14	14	14	14	14	14	14	14	20
EXTR	18	16	14	12	10	8	6	4	2	20

Figure 3: Payoff structure for the different variants with high cost.

4.3 Design and Procedures

A total of 128 subjects (79 female) participated in 4 experimental sessions with 32 subjects each. Participants were recruited from the student population of the University of Cologne using ORSEE (Greiner, 2015), excluding students of psychology, economics, and economics-related fields, as well as experienced subjects who already participated in more than 10 experiments. The experiment was conducted at the Cologne Laboratory for Economic Research (CLER) and was programmed in z-Tree (Fischbacher, 2007).

The experiment consisted of three parts during which subjects could earn points. First, each subject played a series of different versions of the money request game. Each treatment BASE, FLAT, and EXTR was played four times, once for each bonus-cost combination. Second, subjects participated in a single beauty contest game with $p = (2/3)$. In the third part we collected several individual correlates intended to control for cognitive ability, social value orientation, aversion to strategic uncertainty, swiftness, and demographics. There was no feedback during the course of the experiment, that is, subjects did not learn the choices of their opponents nor did they get any information regarding their earnings until the very end of the experiment. All decisions were made independently and at a subject's individual pace. In particular, subjects never had to wait for the decisions of another subject except for the very end of the experiment (when all their decision had already been collected). At that point they had to wait until everybody had completed the experiment so that outcomes and payoffs could be realized.

We now describe each part of the experiment in detail. For the 11-20 games, we randomly assigned the subjects within a session to one of four randomized sequences of the games to control for order effects.[7] Subjects were informed that for every game they would be randomly matched with a new opponent to determine their payoff for that round, hence preserving the one-shot character of the interaction. Each of the three variants BASE, FLAT, and EXTR was played exactly four times, once for each possible combination of cost (low/high) and bonus (low/high).

In the second part, subjects played a single beauty contest game with $p = 2/3$ among all 32 participants in the session. The winner, that is, the subject whose guess was closest to 2/3 times the average of all choices, received 500 points. In case of a tie, the rules specified to split this amount equally among all winners.

In the final part of the experiment, participants answered a series of questions. First, subjects completed an extended 7-item version of the CRT from Toplak et al. (2014), which includes the three classical items from Frederick (2005).[8] Subjects received 5

[7]The exact sequences are provided in the supplementary material (see Online Appendix). Besides our main treatments the sequences contained a further treatment with four additional games discussed in Appendix B.

[8]Subjects also answered the two additional items proposed by Primi et al. (2015), but our results do not change if we use their extended CRT version or a combination of both instead. Other studies (Cappelen et al., 2013; Gill and Prowse, 2016) have also used the Raven test as a proxy for cognitive

points for each correct answer. Next, we elicited aversion to strategic uncertainty using the method by Heinemann et al. (2009) with random groups of four. The task involves measuring certainty equivalents, similarly to Holt and Laury's (2002) multiple price list method, for a situation where payoffs depend on the decision of another subject, that is, strategic uncertainty. In ten situations subjects have to choose between different safe amounts (5 to 50 points) and an option in which they earn 50 points if at least two other members of their group have also chosen that option and zero points otherwise. Subjects were randomly allocated into groups of four, and for each group one of the decision situations was randomly selected for payment. Finally, we collected a measure to control for differences in mechanical swiftness (Cappelen et al., 2013). To that end we recorded the time needed to complete four simple demographic questions on gender, age, field of study, and native language. This part was integrated into a larger questionnaire, which also comprised questions regarding subjects' understanding of the tasks, their perception of its complexity, number of university semesters, left- or right-handedness, average amount of money needed per month, and previous attendance of a lecture in game theory.

To determine a subject's earnings in the experiment the payoffs from each part were added up and converted into euros at a rate of 0.25 € for each 10 points (around $0.28 at the time of the experiment). In addition subjects received a show-up fee of 4 € for an average total renumeration of 15.67 €. A session lasted on average 60 minutes including instructions and payment.[9]

5 Results: Beauty Contest

We first analyze behavior and deliberation times in the beauty contest game. The left panel of Figure 4 depicts the distribution of choices in this game. Of the 128 subjects only two subjects chose a Nash Equilibrium strategy, 18 chose a number close to 33 (level-1), 9 chose a number close to 22 (level-2), 8 chose a number close to 15 (level-3), and 7 subjects chose a number corresponding to higher levels. The target numbers in our four sessions were 27, 28, 29 and 32 and the respective winning numbers were 28, 27, 30 and 32. Hence, the best-performing strategy (among the level-k strategies) would have been the level-1 choice of 33. We classify all choices that are at a distance of at most 2 from the level-k strategy as level-k (for $k \geq 1$), and the remainder as level-0.[10] Given this classification, the average of all guesses by level-0 players is 54.98.

ability. Brañas-Garza et al. (2012) used the Raven test and the CRT by Frederick (2005) in a series of six one-shot p-beauty games and found that CRT predicts lower choices (i.e. higher level), while performance in the Raven test did not.

[9] The original instructions were in German. A translation of the instructions into English can be found in the supplementary material (see Online Appendix).

[10] Classification of levels: Level 1 (31-35), Level 2 (20-24), Level 3 (13-17), Level 4 (8-12), Level 5 (7), Level 0 (rest). There were no choices in the range 1-6. Two subjects with very fast choices of 0 were excluded from the analysis. Our results are robust when those choices are included and classified

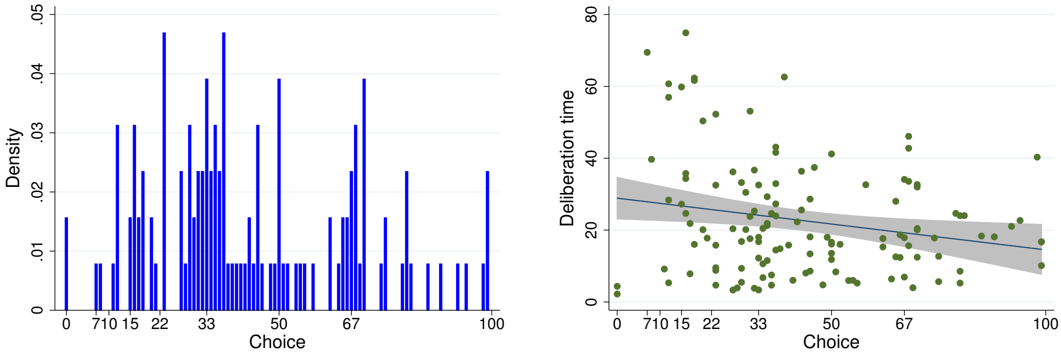

Figure 4: Choices and deliberation times in the beauty contest game.
Notes: Left panel shows histogram of guesses (0-100). Right panel shows a scatter plot of guesses (0-100) vs deliberation time for that guess (in s) and plots the result of a linear regression with 95% confidence interval.

Overall behavior is in line with previous results in the literature, that commonly observe mostly one to three steps of reasoning and a significant amount of unclassified (random) choices, usually thought of as level-0. The right panel of Figure 4 shows a scatter plot of subjects' guesses and the corresponding time taken for that choice. The slope of the regression line suggests a negative correlation between deliberation times and "higher-level" choices. That is, choices corresponding to more steps of reasoning required longer deliberation times.

This observation is consistent with Prediction 2, that is, that deliberation time is increasing in cognitive sophistication. We now test this prediction using a series of three linear regressions with log-transformed deliberation times (log DT) as dependent variable[11] and controls for cognitive ability, individual differences in mechanical swiftness (Cappelen et al., 2013), and gender. The results of those regressions are presented in Table 1. The regressions show a significantly positive effect of higher-level choices on deliberation time. That is, in line with Prediction 2, deliberation time is increasing in the depth of reasoning. This result remains robust when we control for cognitive ability (model 2), measured by the extended CRT, and when we add additional controls.[12] Further, cognitive ability in itself has no effect on deliberation times. Recall that in our model the overall effect of cognitive ability on deliberation time is indeterminate due to two potentially countervailing effects.

Performance in the CRT was previously found to be correlated with level in the beauty contest (Brañas-Garza et al., 2012). Conducting an additional linear regression

as level-0. Further, our results are unchanged for narrower classifications of levels, e.g. where only the level-k strategy ± 1 are classified as level-k.

[11] Deliberation times usually feature a skewed distribution with rare extreme observations, in particular they are not normally distributed. We follow the standard approach in the literature and consider the logarithm of that variable instead, which tends to be normally distributed.

[12] The control variables are defined as follows: CRTExtended (number of correct answers, 0-7), Swiftness (time needed to answer 3 demographic questions, in seconds), and Female (dummy).

Table 1: Linear regressions on log DT for the beauty contest game.

log DT	1	2	3
Level	0.1348**	0.1342**	0.1289**
	(0.0538)	(0.0563)	(0.0561)
CRTExtended		0.0012	−0.0172
		(0.0307)	(0.0321)
Swiftness			−0.3051
			(0.4388)
Female			−0.2440*
			(0.1396)
Constant	2.7865***	2.7823***	3.0965***
	(0.0754)	(0.1328)	(0.2315)
Adjusted R^2	0.0405	0.0327	0.0449
F-test	6.2718**	3.1114**	2.4684**
Observations	126	126	126

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

with level as dependent variable on CRT, we find a significant and positive coefficient for CRT ($N = 126$, $\beta = 0.1483$, $p = 0.0017$). Our results are in line with those previous results in the literature, confirming that subjects with higher cognitive ability tend to make higher-level guesses in the beauty contest game.

6 Results: 11-20 Games

Figure 5 displays the absolute choice frequencies across all instances of the 11-20 game. Choices in BASE closely resemble the behavioral patterns found in Arad and Rubinstein (2012) and Goeree et al. (2016), with most subjects selecting one of the three rightmost boxes corresponding to levels 0 to 3. Behavior in FLAT is similar to that in BASE, with most choices corresponding to not more than three steps of reasoning. Compared to BASE, however, there is a larger fraction of level-0 choices in FLAT, which is consistent with the first step being more costly in terms of sure payoff. In the EXTR variant behavior is comparable to that observed in Goeree et al. (2016), and vastly different from that observed in BASE and FLAT. A large fraction of subjects (between 38% and 62%) chose the rightmost box containing the salient amount of 20, but box 1 and 2 to its left were chosen very rarely compared to BASE and FLAT. Instead, between 25% and 33% of subjects chose one of the two leftmost boxes 8 and 9, which were almost never chosen in the other two variants. Following an iterative-thinking interpretation, these choices correspond (implausibly) to eight or nine steps of reasoning.[13]

[13] When playing against the empirical distribution of choices, the best-performing strategies for BASE, FLAT, and EXTR would correspond to level 2, level 1, and level 1, respectively. Controlling for empirical payoffs does not affect our results.

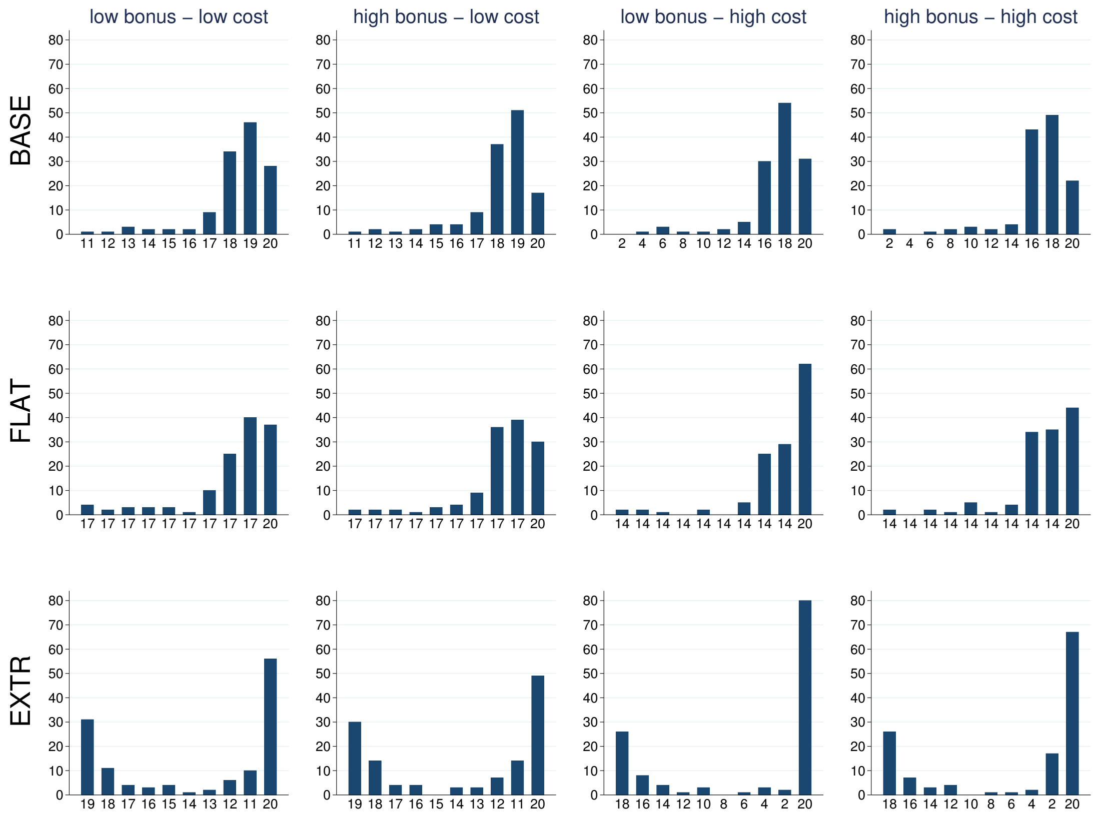

Figure 5: Histograms of choices for each of the 11-20 games.

We now turn to the analysis of deliberation times. For this purpose, we start with bird-eye regressions on the full data set, that is, including all decisions on all variants of the 11-20 game. Table 2 shows GLS random-effects regressions with log DT as the dependent variable including as observations all 12 choices in BASE, FLAT, and EXTR. In all models we control for mechanical swiftness, gender, and the position within the sequence of games (Period).[14]

The regressions confirm that there is a significant and positive relation between deliberation times and depth of reasoning. That is, as predicted, choices associated with more steps of thinking require more deliberation. This relation is unaffected when we include the treatment dummies FLAT and EXTR (model 2), and when we control for cognitive ability as measured by the number of correct answers in the (extended) CRT (model 3). Also, the coefficient of the CRT is significant and positive, that is, subjects scoring higher on the CRT take longer to make their decisions.

[14]Throughout the paper the standard variables for regressions are defined as follows: Level (0-9; a choice of box k is classified as level k); FLAT and EXTR are treatment dummies; CRTExtended (0-7; number of correct answers); Swiftness (time needed to answer 3 demographic questions normalized to $[0, 1]$); Female (dummy); Period (1-16; controls for position in the sequence of games).

Table 2: Random effects panel regressions on log DT for the 11-20 games.

log DT	model 1	model 2	model 3
Level	0.0385***	0.0272***	0.0282***
	(0.0057)	(0.0060)	(0.0060)
FLAT		−0.0309	−0.0308
		(0.0337)	(0.0338)
EXTR		0.1631***	0.1614***
		(0.0351)	(0.0352)
CRTExtended			0.0572***
			(0.0165)
Swiftness	0.2607	0.2626	0.4155*
	(0.2406)	(0.2407)	(0.2335)
Female	0.0943	0.0932	0.1654**
	(0.0744)	(0.0744)	(0.0738)
Period	−0.0884***	−0.0889***	−0.0889***
	(0.0030)	(0.0030)	(0.0030)
Constant	2.5943***	2.5788***	2.2628***
	(0.0928)	(0.0944)	(0.1284)
R^2 (overall)	0.3056	0.3132	0.3417
Wald-Test	1299.4016***	1371.6146***	1385.4388***
Observations	1536	1536	1536

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Beyond this, we observe a significant positive coefficient of EXTR (which is robust to controling for CRT performance), indicating that choices in EXTR generally required longer deliberation times. The average deliberation time in EXTR was 12.6 seconds, whereas the average deliberation time in BASE and FLAT was only 9.9 seconds. Pairwise Wilcoxon signed rank (WSR) tests directly confirm that the average deliberation time in EXTR was significantly higher compared to both BASE ($N = 128$, $z = 4.678$, $p < 0.0001$) and FLAT ($N = 128$, $z = 4.375$, $p < 0.0001$).

In the next step, we consider the three game variants BASE, FLAT, and EXTR separately. To this end, we run separate regressions considering only the four choices taken for each of the variants. Table 3 presents the results of these regressions, which are also illustrated in Figure 6. In those and all following regressions we include controls for cognitive ability, mechanical swiftness, gender, and the position within the sequence of games.

The results confirm our previous findings, showing a positive significant relation between deliberation times and higher-level choices in all three variants of the game. This positive correlation can also be seen in Figure 6, where the solid regression lines have a positive slope for all three variants. There is no effect of cognitive ability on deliberation times in BASE, whereas we find a positive and significant effect in both FLAT and EXTR.

Table 3: Random effects panel regressions of log DT on level.

log DT	BASE	FLAT	EXTR
Level	0.0449**	0.0532***	0.0277***
	(0.0182)	(0.0152)	(0.0079)
CRTExtended	0.0280	0.0628***	0.0848***
	(0.0186)	(0.0186)	(0.0207)
Swiftness	0.5335**	0.4919*	0.2254
	(0.2632)	(0.2617)	(0.2925)
Female	0.1313	0.1883**	0.1926**
	(0.0834)	(0.0830)	(0.0925)
Period	−0.0878***	−0.0934***	−0.0843***
	(0.0049)	(0.0050)	(0.0053)
Constant	2.3286***	2.1742***	2.3157***
	(0.1511)	(0.1497)	(0.1649)
R^2 (overall)	0.3298	0.3621	0.3148
Wald-Test	352.7159***	378.8169***	300.5368***
Observations	512	512	512

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models are restricted to subsamples including only the four decisions in BASE, FLAT or EXTR, respectively.

Table 4: Random effects panel regressions of log DT with controls for the payoff structure.

log DT	BASE	FLAT	EXTR
Level	0.0658***	0.0202	−0.0164
	(0.0210)	(0.0182)	(0.0183)
Rightmost20	0.1634*	−0.2356***	−0.3438***
	(0.0835)	(0.0728)	(0.0991)
LeftmostBox			0.1010
			(0.1201)
Constant	2.2255***	2.3138***	2.6161***
	(0.1605)	(0.1534)	(0.1881)
Controls	Yes	Yes	Yes
R^2 (overall)	0.3294	0.3785	0.3330
Wald-Test	360.2338***	394.5066***	317.7823***
Observations	512	512	512

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models are restricted to subsamples including only the four decisions in BASE, FLAT or EXTR, respectively. Omitted controls are CRTExtended, Swiftness, Female, and Period.

In the next step, we investigate the robustness of the previous conclusion to specific features of the game. First, note that (in all variants) a choice of the rightmost box is appealing because it maximizes the sure payoff (20) and because it minimizes strategic uncertainty, as it yields a guaranteed payoff independently of the choice of the other player. This makes it a salient level-0 strategy. Hence, choices of the rightmost box are

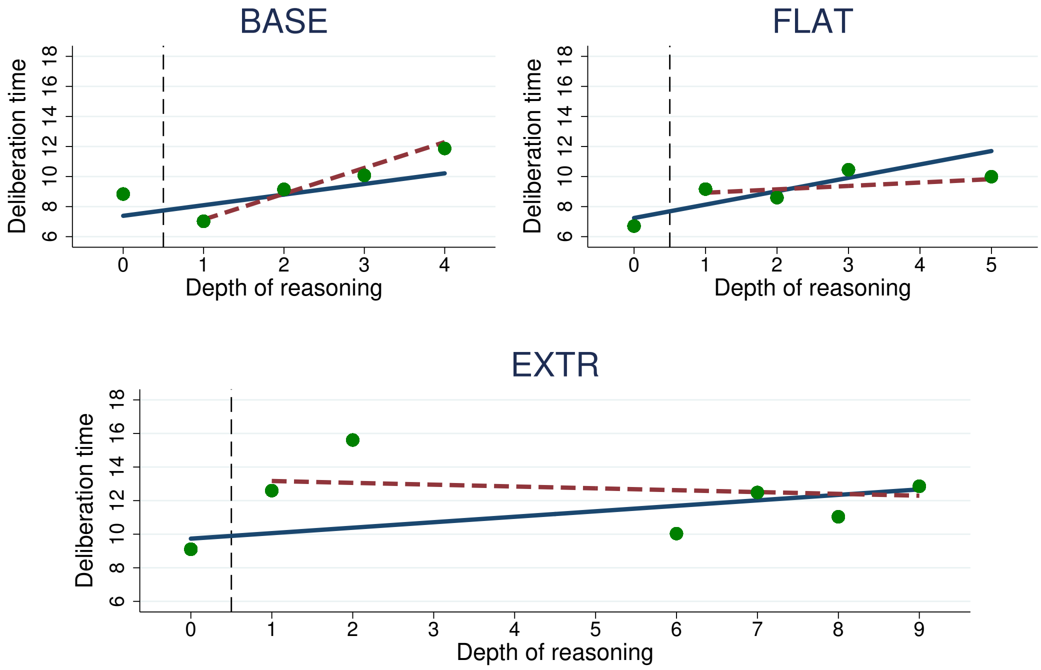

Figure 6: Choices and deliberation times in the 11-20 games.
Notes: Scatter plots of the average deliberation time per level (in s), per 11-20 game variant. The solid (blue) lines shows the result of a linear regression of deliberation times on level. The dashed (red) lines shows the same regression where the choices of the rightmost box were excluded. For illustration purposes, choices with DTs that were more than two SEs away from the mean DT of that level and levels with less than 10 observations are not depicted.

particularly fast, creating a confound. That is, even if there is no relation between the imputed level of cognitive sophistication and deliberation times, if choosing the rightmost box is particularly fast, the regressions might show a non-existing trend. To check for this, we include a dummy indicating those choices, denoted *Rightmost20*. Further, in EXTR a choice of the leftmost box could also be salient because it combines a high sure payoff with a chance of getting the bonus. We thus include another dummy, denoted *LeftmostBox*, into the regression for EXTR. The results of these regressions are shown in Table 4 and illustrated in Figure 6 (dashed lines).

After controlling for choices of the rightmost box, in BASE we still observe a clear positive relation between deliberation time and level. This is illustrated in Figure 6, where the slope of the regression line is still positive even when the level-0 choices are excluded (dashed line). In addition, the dummy itself is not significant. That is, our conclusions for BASE are robust to controlling for imputed level-0 choices.

In game variant FLAT, however, the picture is quite different. Choices of the rightmost box are significantly faster, and this difference actually explains most of the effect of level on deliberation times: level becomes insignificant when adding the dummy *Rightmost20*. This can be seen graphically in Figure 6, where the regression line becomes almost flat when the level-0 choices are excluded (dashed line). Similarly, in game variant EXTR we observe very fast level-0 choices, and no further relation between deliberation times and level. Again, this can be seen graphically in the bottom panel of Figure 6, where the regression line even tends to be downward sloping when the fast level-0 choices are excluded (dashed line).

In summary, we find generally longer deliberation times for higher-level choices, which is in line with Prediction 2, but this can only be seen as a full validation of iterative thinking models for game variant BASE. In this variant, increasing costs make the successive steps associated with iterative thinking particularly salient, and indeed we observe the strongest link between deliberation times and level, which is robust to controlling for choices of the rightmost box containing the salient amount of 20. In contrast, for FLAT and EXTR most of the effect is explained by fast level-0 choices.

In game variant FLAT the comparably large cost associated with the first step of reasoning results in a large fraction of subjects choosing the rightmost box, and these choices are faster. Beyond this observation, there is no evidence of iterative thinking as revealed by response times. However, this observation should not be overemphasized, because in this game variant choices corresponding to more than two steps of reasoning are rare, and this might explain the absence of a relationship for higher-level choices.

This criticism does not affect game variant EXTR, where a large fraction of choices corresponds to nine (imputed) steps of reasoning. In this variant, again level-0 choices are significantly faster, but there is no evidence of a relation between imputed depth of reasoning and deliberation times for higher-level choices. In particular, choices of the leftmost box, while frequent, are not accompanied by longer deliberation times. This result strongly suggests that iterative thinking might be less dominant in EXTR than in BASE although they feature the same best-reply structure. A natural explanation is that even though the best-reply structure would lead to the same steps of iterative thinking, the actual payoffs make other features of the game salient, rendering models of iterative thinking inappropriate for this game variant.

7 Effect of Incentives in the 11-20 Game

In this section we examine the effect of incentives on both choices and deliberation times in the 11-20 game. For this purpose, we make use of the fact that for each 11-20 game variant we also varied the payoff structure along two incentive dimensions, the cost of an additional step and the bonus that could be received.

7.1 Incentives and Choices

A higher bonus increases the value of reasoning for each step, u_k.[15] Hence, according to Prediction 1, if decisions arise from iterative thinking, we would expect the observed level to be weakly higher for a high bonus compared to a low bonus for all treatments. This is indeed the case for BASE and FLAT. In BASE, the average level is 1.7148 for the high bonus versions, larger than the average of 1.5078 for a low bonus (WSR, $N = 128$, $z = 2.915$, $p = 0.0036$). In FLAT, the average level is 1.5820 for the high bonus versions, again larger than the average of 1.4648 for the low bonus versions (WSR, $N = 128$, $z = 2.713$, $p = 0.0067$). However, for EXTR there is no significant difference between the high bonus versions (average level 3.3047) and the low bonus ones (average 3.1248; WSR,$N = 128$, $z = 0.942$, $p = 0.3461$), again casting doubt on whether decisions arise from iterative thinking in this case.

Conversely, higher costs decrease the value of reasoning in all steps for BASE and FLAT, and hence should correspond to weakly lower levels in these variants. In EXTR, however, higher costs sharply lower u_1, but all other values $u_2, \ldots, u_9$ increase (slightly). Hence, the overall effect of higher costs on level in EXTR is indeterminate. We do find lower average levels under high costs compared to low costs for all three variants. The difference is significant for FLAT (high cost, average level 1.2773; low cost, 1.7695; WSR $N = 128$, $z = -4.367$, $p < 0.0001$) and EXTR (high cost, average level 2.8164; low cost, 3.7031; WSR, $N = 128$, $z = -3.145$, $p = 0.0017$), but fails to reach significance for BASE (high cost, average level 1.5000; low cost, 1.7227; WSR, $N = 128$, $z = -1.613$, $p = 0.1068$).

In summary, the changes in the average depth of reasoning resulting from our systematic changes in the payoff structure are in line with Prediction 1. To further examine this conclusion while controlling for individual differences, we turn to a regression analysis. Table 5 shows the results of three random-effects Tobit regressions with level as dependent variable, one for each game variant, using the size of the bonus and the size of the increment (cost) as regressors. In addition, we control for subjects' attitudes towards strategic uncertainty (Heinemann et al., 2009) and previous knowledge of game theory.[16] The regressions confirm that higher costs led to less steps of reasoning in all game variants (significantly negative coefficients for the high cost dummies). Regarding bonus, there is a significant and positive effect of bonus, with more high-level choices for a high bonus, confirming again the observation above. Unsurprisingly, we find no effect of high bonus on level for EXTR. Contrary to the conclusion from the nonparametric test, in FLAT we also find no effect of high bonus on level. In this game variant, however, there is a high concentration of choices on levels 0 and 1 (over 60%), which may explain

[15] There is a strict increase for $k = 1, \ldots, 9$. However, because of the structure of the 11-20 game, the value of u_{10} is unchanged.

[16] The additional control variables are "StratUnc," defined as the number of B choices in the strategic uncertainty task (0-10), and "Gametheory," which is a dummy taking the value 1 if the subject reported having followed a course in game theory.

Table 5: Random effects Tobit regressions of level with controls for bonus and cost

Level	BASE	FLAT	EXTR
HighBonus	0.2811**	0.2829	0.7425
	(0.1295)	(0.1943)	(0.8704)
HighCost	−0.2485*	−0.8270***	−3.0640***
	(0.1292)	(0.1947)	(0.8871)
StratUnc	−0.0186	−0.0864	−0.0330
	(0.0522)	(0.0722)	(0.3257)
Gametheory	0.1071	0.5795	4.2876
	(0.4282)	(0.5932)	(2.6932)
CRTExtended	−0.0474	−0.0968	−0.4359
	(0.0642)	(0.0892)	(0.3992)
Female	−0.3388	−0.7885**	0.6374
	(0.2867)	(0.3966)	(1.8018)
Period	−0.0185	−0.0334	−0.2085**
	(0.0137)	(0.0209)	(0.0954)
Constant	2.0234***	2.7137***	4.2326
	(0.4745)	(0.6579)	(2.9572)
Log likelihood	−892.1128	−897.4692	−803.4438
Wald-Test	13.2723*	30.3227***	21.3988***
Observations	512	512	512

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models are restricted to subsamples including only the four decisions in BASE, FLAT, or EXTR, respectively.

the absence of an effect of bonus on level. Hence, we ran an additional random-effects probit regression (not reported here) on a binary variable that takes the value 1 if level is larger or equal to 1 and 0 otherwise. A positive effect of bonus on this binary variable would indicate that increasing the bonus leads to more choices corresponding to at least one step of reasoning. Indeed, we find a significant positive effect of bonus on this binary variable ($N = 512$, $\beta = 0.4010$, $p = 0.0054$).

7.2 Incentives and Deliberation Times

We now analyze the effect of a change in the incentives on deliberation times. Tables 6, 7, and 8 show the results of a series of random-effects GLS regressions of log DT on level for BASE, FLAT, and EXTR, respectively. The crucial variables are the dummies for the high bonus and high cost conditions, as well as the interactions of level with those. The regressions also control for cognitive ability, swiftness, gender, and period. Additionally, we also control for non-strategic choices by including a dummy for the rightmost box. The reason is that, as shown in Section 6, level-0 choices are significantly faster. Being non-strategic, these choices are unlikely to be affected by changes in incentives.

Table 6: Random effects panel regressions of log DT with bonus and cost for BASE.

log DT	1	2	3	4
HighBonus	-0.1141^{**}	-0.1150^{**}	-0.0275	-0.1151^{**}
	(0.0469)	(0.0462)	(0.0680)	(0.0462)
HighCost	-0.0237	-0.0157	-0.0155	-0.0764
	(0.0465)	(0.0459)	(0.0462)	(0.0664)
Level		0.0659^{***}	0.0932^{***}	0.0510^{**}
		(0.0210)	(0.0265)	(0.0241)
Level × HighBonus			-0.0536^{*}	
			(0.0304)	
Level × HighCost				0.0378
				(0.0299)
Rightmost20	0.0096	0.1413^{*}	0.1538^{*}	0.1504^{*}
	(0.0733)	(0.0837)	(0.0840)	(0.0840)
Constant	2.5073^{***}	2.3071^{***}	2.2551^{***}	2.3205^{***}
	(0.1508)	(0.1644)	(0.1647)	(0.1647)
Controls	Yes	Yes	Yes	Yes
R^2 (overall)	0.3330	0.3353	0.3419	0.3351
WaldTest	350.9656^{***}	370.6264^{***}	369.8558^{***}	372.8499^{***}
Observations	512	512	512	512

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models are restricted to subsamples including only the four decisions in BASE. Omitted controls are CRTExtended, Swiftness, Female, and Period.

The results for bonus and cost are also illustrated in Figure 7. Although the regressions examine the effects of bonus and cost simultaneously for each game type, for expositional clarity we discuss bonus and cost separately in the following two subsections.

7.2.1 Effect of the Bonus

Increasing the bonus has a twofold effect on deliberation times: First, it increases the potential gain from an additional step of reasoning by 20 and thus increases the incentives for the first nine steps. Hence, according to Prediction 3 deliberation times per step should be shorter when the bonus is high. On the other hand, assuming that the cognitive cost is unaffected by a change in the bonus, subjects should conduct more steps of reasoning according to Prediction 1, which should increase overall deliberation time. As a consequence, the aggregate effect on deliberation times is indeterminate. Controlling for the size of the bonus and the interaction of level with bonus allows us to dissect these two explanations.

For the BASE variants (Table 6), we find shorter deliberation times when the bonus is high (model 1). This effect remains when we control for level (model 2), indicating that the direct effect (shorter deliberation times per step) dominates the indirect one (increased deliberation time through increased number of steps). To check whether the increase in deliberation time per level is indeed affected by the bonus, we include the interaction of level with high bonus (model 3). The coefficient for the latter is significantly negative, that is, when the bonus is high subjects require less additional deliberation time per step, confirming Prediction 3. The top-left panel in Figure 7 illustrates this effect: the regression line becomes flatter when the bonus is high.

For the FLAT variants (Table 7), subjects overall deliberate longer in the high bonus condition (model 1). This effect remains when we control for level in model 2. Although, this effect becomes non-significant when we additionally control for the interaction of level with bonus (model 3), we can see in the top-middle panel of Figure 7 that the line for high bonus is shifted upwards. The slopes of the two lines are very similar, and indeed, the interaction is not significant.

Finally, for the EXTR variants (Table 8) we find no evidence that bonus has any systematic effect on deliberation times. This can also be seen from the top-right-hand panel in Figure 7, where both regression lines are flat, even slightly downward sloping.

Summarizing, we find that increasing the bonus decreases deliberation times in BASE (where iterative thinking is most salient), increases deliberation times in FLAT, and has no effect on deliberation times in EXTR (where iterative thinking is not salient at all). The decrease in BASE is a result of shorter deliberation times per step, as predicted by our model, which explains why overall deliberation time decreases although observed levels are higher. We note that this result would be incompatible with any model where the deliberation time per step did not react to incentives.

7.2.2 Effect of the Costs

The predicted effect of an increase in cost depends on the specifics of the underlying payoff structure and hence differs across treatments. In BASE, high cost again has a twofold effect. First, the potential gain for conducting an additional step decreases by 1 for the first nine steps. Hence, according to Prediction 3 we would expect longer deliberation times per step for high cost. However, the decrease in incentives is very small compared to the one resulting from a change in the bonus, and hence this effect is likely to be small as well. On the other hand, because high cost implies smaller payoff differences, subjects potentially conduct less steps of reasoning (again assuming that cognitive costs are unaffected), which in turn should decrease overall deliberation time. Hence, the overall effect is undetermined, and the results for BASE (Table 6) show no effect on deliberation time.

In FLAT, only the potential gain from the first step is lower for high cost, while the remaining steps are unaffected. Hence, we expect longer deliberation times for the first step. Again, the decrease in potential gain for the first step might lead to subjects conducting less steps of reasoning, which in turn might decrease overall deliberation time. The results for this game variant (Table 7) indicate longer deliberation times (model 1)

Table 7: Random effects panel regressions of log DT with bonus and cost for FLAT.

log DT	1	2	3	4
HighBonus	0.1251***	0.1278***	0.0960	0.1258***
	(0.0465)	(0.0465)	(0.0608)	(0.0465)
HighCost	0.1264***	0.1301***	0.1292***	0.0629
	(0.0471)	(0.0470)	(0.0470)	(0.0621)
Level		0.0253	0.0165	0.0093
		(0.0180)	(0.0211)	(0.0203)
Level × HighBonus			0.0207	
			(0.0255)	
Level × HighCost				0.0438*
				(0.0263)
Rightmost20	−0.2924***	−0.2358***	−0.2370***	−0.2168***
	(0.0611)	(0.0730)	(0.0730)	(0.0738)
Constant	2.2525***	2.1722***	2.1851***	2.1810***
	(0.1462)	(0.1573)	(0.1585)	(0.1562)
Controls	Yes	Yes	Yes	Yes
R^2 (overall)	0.3907	0.3918	0.3924	0.3962
WaldTest	419.8691***	423.6446***	424.6026***	426.0934***
Observations	512	512	512	512

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models are restricted to subsamples including only the four decisions in FLAT. Omitted controls are CRTExtended, Swiftness, Female, and Period.

for high costs, although the effect on the depth of reasoning is negative. As in the case of bonus, within our model this can be explained by a change in the time required for each step of reasoning. To test for this change, we additionally control for the interaction of level with high cost (model 4). The coefficient for the latter is significant and positive, as predicted by our model and illustrated by the steeper slope of the solid line in the mid-bottom panel of Figure 7. That is, deliberation times per step are higher for high cost, which explains the overall increase in deliberation time in FLAT.

The payoff structure in EXTR does not allow for a clear-cut prediction for the effect of high cost on deliberation times. The reason is that for high cost, the potential gain for the first step decreases sharply, but the potential gain for all further steps increases slightly. As a consequence, we would expect longer deliberation times for the first step, and shorter deliberation times for all subsequent steps. It is unclear which of these countervailing effects should dominate. The results (Table 8) show significantly positive coefficients for high cost. However, as in the case of bonus we find no effect of level on deliberation times and thus, perhaps not surprisingly, there is also no interaction effect with cost. This can also be seen from the lower right-hand panel in Figure 7. The regression lines are flat, and the line for high cost is shifted upwards. This effect is in

Table 8: Random effects panel regressions of log DT with bonus and cost for EXTR.

log DT	1	2	3	4
HighBonus	0.0247	0.0222	−0.0367	0.0229
	(0.0475)	(0.0477)	(0.0635)	(0.0478)
HighCost	0.1535***	0.1542***	0.1557***	0.1192*
	(0.0482)	(0.0482)	(0.0483)	(0.0642)
Level		−0.0060	−0.0160	−0.0109
		(0.0125)	(0.0144)	(0.0138)
Level × HighBonus			0.0178	
			(0.0126)	
Level × HighCost				0.0106
				(0.0128)
Rightmost20	−0.3208***	−0.3566***	−0.3673***	−0.3522***
	(0.0597)	(0.0958)	(0.0961)	(0.0960)
Constant	2.4673***	2.5075***	2.5451***	2.5246***
	(0.1628)	(0.1833)	(0.1841)	(0.1845)
Controls	Yes	Yes	Yes	Yes
R^2 (overall)	0.3419	0.3415	0.3450	0.3411
WaldTest	334.6085***	334.7270***	336.1415***	335.1723***
Observations	512	512	512	512

Notes: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Models are restricted to subsamples including only the four decisions in EXTR. Omitted controls are CRTExtended, Swiftness, Female, and Period.

contrast to the negative effect of high cost on the depth of reasoning, but unlike for BASE and FLAT this cannot be explained by a change in deliberation times per step.

Summarizing, for the high cost condition we find overall longer deliberation times in FLAT and EXTR, but not in BASE. The increase in FLAT is a result of longer deliberation times per step, confirming Prediction 3. That is, our model can explain why deliberation times in FLAT are increasing for high cost although observed choices correspond to less steps of reasoning. Again, this effect would be incompatible with a model where the time per step is constant.

8 Discussion

In this work, we have introduced a simple model linking cognitive sophistication (as revealed by choices), incentives, and deliberation times, incorporating stylized facts from the psychophysiological literature. We model the total deliberation time of an observed choice as the sum of the deliberation times resulting from a sequence of hypothetical binary decisions that model steps of reasoning. As an immediate consequence we obtain the prediction that exerting higher cognitive effort, that is, conducting more steps of reasoning implies longer deliberation times. They key assumption then builds on the

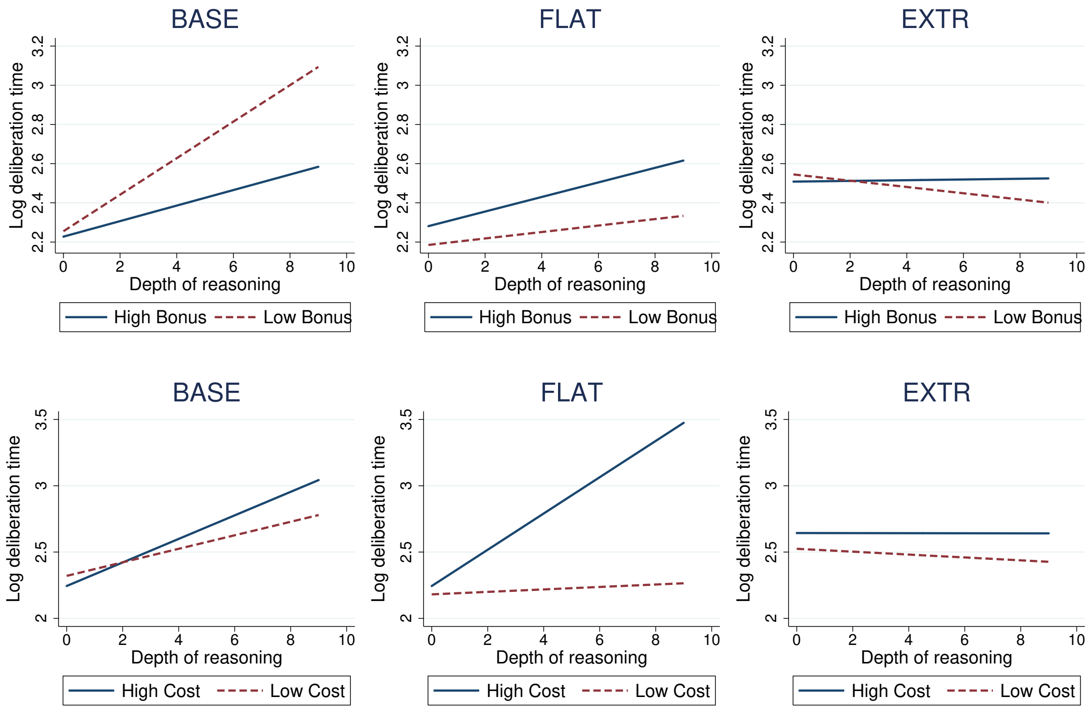

Figure 7: Effect of bonus and cost in the 11-20 games.

Notes: The top panel plots a line with the coefficients obtained from model 3 in Tables 6, 7, and 8 for high bonus (solid blue line) and low bonus (dashed red line), respectively. The bottom panel plots a line with the coefficients obtained from model 4 in Tables 6, 7, and 8 for high cost (solid blue line) and low cost (dashed red line), respectively.

closeness-to-indifference effect, that is, decisions take longer for smaller utility difference between the options. We assume that deliberation time for a given step is a decreasing function of the potential gain (or loss) of that step. This model provides empirically testable predictions regarding the relation of deliberation times, cognitive sophistication as revealed by choices, and incentives.

We then test the predictions of our model using experimental data. In the beauty contest and the original version of the 11-20 money request game, choices attributed to higher steps of reasoning lead to longer deliberation times. In this way, this work is the first to provide direct evidence on the link between heterogeneity in cognitive effort and behavioral heterogeneity. This link is strongest when the payoff structure of the underlying game is such that iterative thinking is salient. However, for games without a salient iterative structure, there is no clear relation between deliberation times and cognitive effort. We conclude that the alleged link between behavioral heterogeneity and cognitive depth is absent in these situations, and applying simple models of iterative thinking is unwarranted. Our work hence also serves as a demonstration that deliberation times can serve as a tool to identify economic problems where features beyond the best-reply structure are crucial determinants of behavioral heterogeneity.

We also show that cognitive depth reacts to monetary incentives. Our model predicts that changes in the incentives that systematically vary the utility difference of a step of reasoning should be reflected in changes in cognitive depth. These effects are found in the data, with the caveat that the link between incentives, cognitive depth, and deliberation times is less than straightforward. In particular, the well-known effects of closeness to indifference imply that higher cognitive effort will be accompanied by shorter deliberation times for a given step of reasoning, resulting in the apparent paradox of higher incentives inducing more steps of reasoning which are implemented in a shorter total deliberation time.

Our results also contribute to a related strand of literature that tries to better understand when iterative thinking describes actual decision processes and what cues trigger it. For example, Ivanov et al. (2009) show that level-k ceases to describe behavior well when the best-reply structure is complex and alternative plausible rules of thumb exist. Chong et al. (2016) show that incorporating a measure of saliency to derive level-0 behavior significantly improves model fit with respect to models where non-strategic agents randomize uniformly. Shapiro et al. (2014) show that the predictive power of the model can vary within a single game when different components of the payoff function are emphasized, with a better fit as the game becomes closer to a standard beauty contest and a worse fit as the pattern of levels of reasoning becomes less salient. This suggests that level-k reasoning is one of many possible decision processes players may employ, and which process ultimately determines the decision can depend on various features of the decision situation. Our results for the different variants of the 11-20 money request game confirm this view.

In conclusion, we provide the missing link between heterogeneity in observed economic choices and imputed differences in cognitive depth and effort. At the same time, our research shows that this link might only be easily observable in situations where an iterative reasoning structure is salient enough. We provide a tool to identify situations where it is warranted to account for heterogeneity in behavior through a direct application of iterative thinking models. This simple expansion of the economist's toolbox is a first step towards a more complete account of the determinants of behavioral heterogeneity.

Appendix A Other Level-0 Specifications in the 11-20 Game

Arad and Rubinstein (2012) argue that choosing 20 in the 11-20 game is a natural anchor for an iterative reasoning process. However, Hargreaves Heap et al. (2014) show that level-0 behavior might depend on the payoff structure of the game. This might be less problematic in our setting because a further appeal of the original 11-20 game, which essentially corresponds to BASE, is that it is fairly robust to the level-0 specification. Specifically, choosing 19 in the original 11-20 game, or box 1 in BASE, is the level-1 strategy for a wide range of level-0 specifications. Still, this robustness depends on the particular payoff structure of the game and hence might be different across the various versions used in our experiment. In this subsection we explore the robustness of BASE, FLAT and EXTR to the level-0 specification.

Let $\sigma_0 = (p_0, \ldots, p_9)$ denote a level-0 specification that assigns probability p_i to box i. Recall that box 0 always contains the salient amount of 20. We want to study the range of σ_0 such that choosing box 1 is still the unique level-1 strategy, that is, $BR(\sigma_0) = \{1\}$. A necessary condition is that $p_0 > \underline{p_0}$, where $\underline{p_0} = (20 - A_1)/R$, which is derived from the condition that the expected payoff of box 1 exceeds that of box 0, i.e. $A_1 + p_0 R > 20$. Table A.1 gives an overview over the values of $\underline{p_0}$ across BASE, FLAT and EXTR for each combination of bonus and cost, and already provides a first intuition: the condition is mild for BASE and FLAT, but not for EXTR.

Table A.1: Lower bounds on p_0

	BASE		FLAT		EXTR	
bonus	low	high	low	high	low	high
low cost	5%	2.5%	15%	7.5%	45%	22.5%
high cost	10%	5%	30%	15%	90%	45%

The condition $p > \underline{p_0}$ is in general not sufficient. It is easy to show that, as long as box 1 contains the second-highest sure amount, that is, $A_1 \geq A_j$ for all $j \neq 0, 1$, and $p_0 > \underline{p_0}$, a sufficient condition is that no box $j \neq 0$ is assigned a probability larger than p_0. This holds in BASE as long as box 0 is most probable under σ_0 (note that this implies $p_0 > 10\%$, hence $p_0 > \underline{p_0}$). Hence, choosing box 1 is the unique level-1 strategy in BASE under fairly weak requirements, in particular even if σ_0 is assumed to be uniform randomization as usually assumed in games without a salient strategy (e.g. the beauty contest game).[17]

For FLAT, the sufficient condition holds if box 0 is most likely under σ_0 and $p_0 > \underline{p_0}$ (similarly to BASE, this latter condition is void for high bonus and low cost). This is a slightly stronger condition, because the lower bounds $\underline{p_0}$ are tighter. In particular, in the extreme case of uniform randomization the level-1 strategy remains to choose box 1 only for high bonus and low cost, while it prescribes to stay with box 0 for the other conditions. Overall, however, the requirement remains mild and amounts to assuming a small degree of salience or box 0.

In Section 6 we assumed that the starting point in the 11-20 game for our model of iterative thinking was to choose the rightmost box containing the salient amount of 20. As just illustrated, the best-reply structure in BASE and FLAT is robust for a wide range of alternative level-0 specifications. Thus, even if, contrary to our level-0

[17] For high cost and low bonus, in the extreme case of uniform randomization choosing box 1 is a best reply, but not a unique one, because it ties with choosing the rightmost box.

assumption, the starting point does not assign probability one to choosing the rightmost box, the best-reply structure and hence our results are unaffected as long as p_0 is not too small.

A different conclusion obtains for variant EXTR. The condition above is not sufficient for this variant because box 1 contains the lowest sure amount, hence the probability assigned to the rightmost box has to exceed the probability of any box j by more than $(A_j - A_1)/R$. This condition together with $p_0 > \underline{p_0}$ is sufficient to make box 1 the unique best response in EXTR. This is a relatively demanding condition, as is the lower bound $p > \underline{p_0}$ in this case. In particular, choosing the leftmost box that grants the second highest sure payoff is the level-1 strategy for a relatively wide range of specifications that include uniform randomization. Hence, the best-reply structure of EXTR is less robust to changes in the level-0 specification, and there is a clear alternative best-reply structure where the leftmost box is the level-1 strategy.

To check for robustness in the case of EXTR we consider an alternative best-reply structure by assuming that the level-0 specification is mixed and the best reply is to choose the leftmost box, which we then classify as the level-1 strategy. The best reply to that is to choose the rightmost box containing the salient amount of 20, now classified as level 2. From there the best-reply structure follows the familiar pattern from right to left. We repeated the complete analysis of EXTR in Sections 6 and 7 for this alternative classification, and found no qualitative difference with the previous analysis.[18] Hence, we conclude that our results, presented in the previous section, cannot be explained by differences in the robustness to the level-0 specification between treatments.

Appendix B A "Social Preference" Variant

The experiment included an additional treatment intended to test for an alternative explanation of the frequent "high-level" choices of the two leftmost boxes in EXTR, as previously observed by Goeree et al. (2016). By choosing the leftmost box in EXTR a subject could obtain the second highest sure amount, while at the same time granting *her opponent* the chance to receive the bonus. If a subject is motivated by some form of other-regarding preferences, choosing the leftmost box might be attractive because it grants somebody else the chance to get a bonus that is relative large in comparison to the subject's own sacrifice in terms of sure payoff. We thus included a treatment, denoted SOCP, which was a variation of FLAT where the *two* rightmost boxes contain both the salient amount of 20. Figure B.1 shows both the low and high cost version of SOCP. Choosing the rightmost box guarantees the highest safe amount of 20, while also, at least theoretically, granting the other player the chance to obtain the bonus by selecting the second, inner box that also contains 20. On the other hand, a purely self-

[18]The alternative regressions are available upon request.

SOCP	17	17	17	17	17	17	17	17	20	20
SOCP	14	14	14	14	14	14	14	14	20	20

Figure B.1: Payoff structure for SOCP in the low (top panel) and high (bottom panel) cost version.

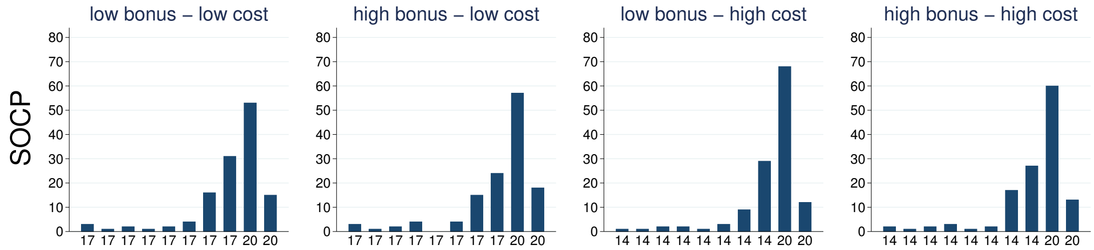

Figure B.2: Frequency distribution of choices in the SOCP variant.

interested individual should not choose the rightmost box, since it is weakly dominated by the inner 20 for all possible beliefs.

As a proxy for prosociality we measured the social value orientation (SVO) of each subject using a computerized version (Crosetto et al., 2012) of the scale developed by Murphy et al. (2011). We used a scaled version of their six primary items in which subjects were asked to choose among different allocations of points between themselves and a randomly selected partner. For the SVO task one of the six items was randomly selected and paid out using a ring matching procedure, that is, each subject received two payments of up to 25 points, one as a sender and one as a receiver. A higher SVO score indicates that a subject is more prosocial.

In SOCP, 36 out of 128 subjects chose the rightmost box at least once. However, we found no difference in SVO scores between subjects choosing the rightmost box at least once and those who never chose it (Mann-Whitney-Wilcoxon test, $N = 128$, $z = -1.068$, $p = 0.2857$), which speaks against the social-preference interpretation. Next, we consider the relative frequency of choosing the rightmost box across all four instances of SOCP per subject. We run a fractional logit regression for this relative frequency with the SVO score as an independent variable. The coefficient of SVO is positive but not significant. Summarizing, we find no evidence that the prosocial motive of granting the opponent the chance to obtain a bonus is a driver of behavior in the 11-20 game.

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Online Appendix: Supplementary Material

Sequence of Games

To control for order effects we counterbalanced the order of the different 11-20 games using the following four randomized sequences. We denote the low cost, low bonus version of BASE, FLAT, EXTR, and SOCP by B, F, E, and S, respectively. Similarly for $X \in \{B, F, E, S\}$ we use the notation $+X$ to indicate high cost, and $X+$ to indicate high bonus, e.g. $+B+$ denotes BASE with high cost and high bonus.

Pseudo-randomized sequences of the 11-20 games used in the experiment.

Sequence 1	B	F	E	S	E+	B+	S+	F+	+F	+S	+B	+E	+S+	+E+	+F+	+B+
Sequence 2	+E	+B	+S	+F	+B+	+F+	+E+	+S+	S	E	F	B	F+	S+	B+	E+
Sequence 3	+F+	+S+	+B+	+E+	B+	F+	E+	S+	+S	+E	+F	+B	E	B	S	F
Sequence 4	S+	E+	F+	B+	F	S	B	E	+E+	+B+	+S+	+F+	+B	+F	+E	+S

Translated Instructions

These are the instructions given to subjects during the experiment. Instructions for each part were presented separately on screen, at the beginning of each part. The original instructions were in German. Text in brackets [...] was not displayed to subjects.

General Instructions

Welcome to this economic experiment. Thank you for supporting our research.

Please note the following rules:

1. From now on until the end of the experiment, you are not allowed to communicate with each other.
2. If you have questions, please raise your hand and one of the instructors will answer your question individually.
3. Please refrain from using any features of the computer that are not part of the experiment.

The experiment consists of five parts and a questionnaire. The experiment involves a series of decisions which will affect your payoff at the end of the experiment. In this experiment you will earn points. At the end of the experiment the points you have earned in each part will be added up and the sum will be exchanged into Euros according to the following exchange rate:

10 **points** = 25 **Eurocents.**

Independently of your decisions, you will receive an additional 4 EUR for your participation in the experiment.

Part 1: [11-20 Games]

In this part you will make a series of 16 decisions. For each decision you will be randomly paired with another participant in the experiment. You will not meet the same participant more than once.

For each decision you will see 10 boxes in line on your screen. Each box contains a certain amount of points.

You have to choose one of the boxes.

Each participant will receive the amount in the box he/she selected. In addition, a participant may get a bonus if the selected box is exactly **one to the left** of the box that the other participant chooses.

The amount of points contained in each box may change from one round to another round. Below you can see an example for such a decision. Note that the amount contained in each box as well as the size of the bonus in the experiment will differ from this example. The size of the bonus and the amount of points contained in each box will be displayed in the following way:

Possible bonus: **30 points**

14	13	12	11	19	18	17	16	15	20

Part 2 [Beauty Contest Game]

In this part you and all other participants in this session will make one decision. You and all other participants each have to choose an integer between 0 and 100.

The participant who chose the number closest to the target number wins. All other participants do not win anything.

To determine the target number, the average of all chosen numbers will be computed and multiplied by 2/3 (in words: two thirds).

Target number= (2/3) * (Average of the numbers chosen by all participants)

The participant who chose the number closest to the target number wins and receives 500 points.

In case there is a tie between two or more participants (because all their numbers are equally close to the target number) the points are split equally among all winners.

Part 3 [Cognitive Reflection Test]

In this part you are asked to answer a series of questions. For each question there is exactly one correct answer.

If you answer the questions correctly, you can earn additional points.

In total you have to answer 9 questions.

For each correct answer you will receive 5 points.

Part 4 [Social Value Orientation]

In this part you have to make a series of decisions about allocating points between you and another randomly selected participant.

Henceforth, we will refer to this randomly selected participant simply as the "other."

In each of the following 6 decisions, you can choose how many points you would like to allocate to yourself and how many points you would like to allocate to the other.

Please select for each decision exactly one of the 9 available allocations.

All amounts are displayed in points.

Please take all decisions seriously, since each of the 6 decisions has the same probability of being selected.

You can receive additional points in case a decision of another participant is selected, where he has allocated points to you.

Part 5 [Strategic Uncertainty]

In this part you have to make 10 decisions for different decision situations. Each situation is independent of the other.

In each situation you can decide between A and B. The amount of points you will earn in this part depends on these decisions.

In this part, you and 3 other randomly selected participants will form a group.

There will be 10 decision situations displayed on your screen in a table. In each of the situations you can choose between option A and option B. At the end of this part, 1 out of the 10 situations will be chosen randomly. Your payment will be according to the situation picked and is determined as follows:

- If you choose option A, you will receive the sure payment given in the second column.
- If you choose option B, your payment will depend on how many members of your group (including yourself) chose B.
  - If 3 or more out of the 4 members of your group chose B, you will receive 50 points.
  - If 2 or less of the 4 members of your group chose B, you will receive 0 points.