Choosing Between and Allocating Time Across Contracts: an Experimental Study*

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Abstract

There are two ways in which people usually engage with contracts—compensation schemes to execute tasks. They can choose between them (contract choice), or allocate time across them (contract time allocation). In this paper, we study how people behave in each of these problems. A standard model suggests that drafting a cost-effective contract that both induces an agent to choose it and allocate time to it presents a significant challenge. However, our experimental results indicate that this tradeoff might be less pronounced than the model predicts due to what we call the attractiveness bias–a tendency for subjects to allocate more time to contracts they find appealing, even when the model suggests they should get relatively little time.

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1 Introduction

Much progress has been made in understanding when a contract's compensation scheme will induce an Agent to behave in a way that is beneficial to a Principal. However, in a world where different contracts compete for the Agent's attention, knowing how the Agent decides what contracts to engage with in the first place is equally important. After all, a contract's effectiveness in inducing a desired behavior is only useful if someone is willing to engage with it, given the other contracts available.

There are two ways in which the Agent can engage with a contract: by choosing from a menu of contracts (*contract choice*) or by allocating time across the contracts in the menu (*contract time allocation*). Examples of contract choice include workers who choose between exclusive contracts, busy contractors who often can only add one new contract to their portfolio and, hence, must choose which contract to include given the contracts they are offered, and CEOs who decide between the different compensation packages that companies offer. Examples of contract time allocation include food delivery workers who split their time between existing food delivery apps, contractors who must split their time between the projects in their portfolio, and employees who must decide how to split their time between tasks they must perform. Whereas contract choice has received some attention in the experimental literature, contract time allocation remains understudied (see the Related Literature section).

In this paper, we design an experiment to study contract choice and, more importantly, time allocation between contracts. In the first part of the experiment, subjects choose one contract from several pairs of contracts. In the second part, they allocate a time budget between the contracts in these pairs. We are particularly interested in how our subjects' behavior in the experiment can inform the design of contracts that perform well in these two problems.

Our contracts pay a lottery that yields either a high or a low prize.[1] The lottery that the Agent receives depends on whether she completes a task by a deadline (which the Agent self-imposes when allocating time). If she does, she will play a lottery in which the probability of getting the high prize is higher than in the lottery she would play if she did not complete the task by the deadline. We interpret the contract's low and high prizes as

[1] Real-world contracts do not typically use randomization; however, randomization in our contracts emulates the uncertainty a person faces in completing a task by a deadline. Therefore, even if she allocates plenty of time to a task, she cannot be sure that she will complete the task by the deadline. However, by allocating more time to a task, she can at least increase the probability of completing the task by the deadline.

hard incentives, i.e., the Agent's payment, and the probabilities of getting the high prize conditional on succeeding and failing the task as *soft* incentives, given they influence the Agent's beliefs about the likelihood of getting the high prize. Importantly, these beliefs are a function of the time allocated to a contract's task. Finally, the difficulty of the task being contracted for is proxied by the success rate of others who attempted the same task under a given deadline in the past. Based on this rate, subjects can form beliefs about how difficult the task is and, hence, how likely they are to succeed in the task by the deadline.

Our experimental design is informed by a standard model of choice and time allocation between contracts that makes sharp predictions about behavior in the experiment given the contracts we use. Therefore, the model's predictions provide a benchmark to interpret the behavior of our subjects. There are two features of our contracts that play a central role in these predictions. The first feature is the expected utility of the lottery that the contract yields if a subject cannot complete the contract's task by the deadline. We call it the contract's *(expected) flat fee*. The second feature is the difference in the expected utility of the lottery the contract yields if a subject completes the task by the deadline and the flat fee. We call this difference the contract's *(expected) bonus*. Our contracts can thus be interpreted as *bonus-based* contracts: they pay a (expected) flat fee plus a (expected) bonus conditional on performance.

Based on these two features, the model offers three lessons about the subjects' behavior in the experiment. First, the flat fee is crucial for the effectiveness of a contract in contract-choice. Second, a contract's bonus is the *only* contractual feature that should matter for contract-time allocation. These two lessons imply a third: a resource-constrained principal faces a trade-off when designing bonus-based contracts. Increasing a contract's flat fee at the expense of its bonus will help to compete for the Agent's choice, but at the expense of making it less competitive in attracting his time. Similarly, increasing the bonus at the expense of the flat fee will help a contract to attract an Agent's time but at the expense of making it less competitive for the Agent's choice.

Our experiment allows us to investigate the validity of these lessons. In the experiment, we present subjects with eight pairs of contracts. In the first part of the experiment, subjects must choose one contract from each pair. They will then have 60 seconds to attempt to complete the chosen contract's task. In the second part of the experiment, they must split 120 seconds across the two contracts in each pair.

We designed these pairs of contracts to achieve three goals. The first goal is to investigate how *ceteris paribus* changes in a contract's parameters affect its performance in contract-choice and contract-time allocation. For instance, how do subjects respond to changes on hard as opposed to soft incentives? The second goal is that the pairs should incorporate the Principal's resource constraint. The third goal is that the model should make sharp predictions about choice and time allocation in the experiment. To achieve these goals, we paired a *baseline* contract with four types of contracts derived from it by modifying either its prizes, probabilities of getting the high prize, or the degree of difficulty of its task, while keeping their expected costs at or below the expected cost of the baseline contract. The four types of contracts are confidence, risk, dominated, and ambiguous contracts.

In confidence contracts, the Agent gets the high prize with a higher probability than in the baseline if she is successful in the task but with a lower probability than in the baseline if she fails it. They are thus a mean-preserving spread in probabilities (relative to the baseline), which makes them more attractive than the baseline for more confident subjects in contract-choice (hence the contracts' name). In risk contracts, the high prize is higher than in the baseline, but the low prize is lower. They are thus a mean-preserving spread in prizes (relative to the baseline). Therefore, the Agent will face a riskier lottery than in the baseline contract, no matter if she solves the task. In dominated contracts, the probability of getting the high prize is smaller than in the baseline, regardless of whether the subject can solve the task. Whereas the choice between the baseline and a dominated contract is obvious, time allocation is trickier (as discussed later). Finally, in ambiguous contracts, the contract only provides partial information about the difficulty of its underlying task.

Our results suggest that a contract's flat fee matters more than the bonus when subjects choose between contracts, corroborating the model's first lesson. However, whereas the model implies that the marginal rate of substitution between the flat fee and the bonus is linear—and, hence, independent of the level of the flat fee—, our results suggest that it is decreasing: lower flat fees require progressively higher bonuses. Given the resource constraint, this implies that subjects shy away from a contract that compensates them poorly if they do not complete the task, even if the contract compensates them generously if they do.

Our results also suggest that subjects allocate more time to contracts with a higher bonus, consistent with the model's second lesson. Surprisingly, however, they also imply that subjects also care about the contract's overall attractiveness when allocating time and, hence, about its flat fee. In fact, our subjects allocate more time, on average, to the contract they chose in a pair, even when this contract has a lower bonus. We call this tendency the “attractiveness bias” because allocating more time to the contract one deems more “attractive” in choice can lead to a sub-optimal time allocation. Subjects’ choices and time allocations between the baseline and one of the dominated contracts provide the clearest evidence for this type of behavior: over 95 percent of subjects choose the baseline over the dominated contract, as the model predicts, but only 11 percent of the subjects allocate more time to the dominated contract, even though it has a higher bonus.

These results imply that the trade-off implied by the model’s third lesson is less pronounced than expected (although it exists). In fact, our results imply that the Principal should not offer contracts with a flat fee that is too low, even if the goal is to attract an Agent’s time. Although decreasing a contract’s flat fee allows the Principal to increase the bonus while satisfying her resource constraint, the more she decreases the flat fee, the less attractive the contract becomes. This hinders its performance in both contract-choice (as expected) and (surprisingly) contract-time allocation due to the attractiveness bias. Therefore, the vital tension for a Principal designing bonus-based contracts subject to a cost constraint is deciding how much to lower the contract’s flat fee to increase its bonus while ensuring that its flat fee is not too low.

Regarding what types of contracts are more likely to succeed in the contract choice and time allocation, we find that confidence contracts fare better on average than the other contracts in both cases. In particular, they fare better than risk contracts, which suggests that manipulating soft incentives, i.e., increasing the spread in beliefs, is more effective than manipulating hard incentives, i.e., increasing the spread in payoffs. In contract-choice, this is due to our subjects being both overconfident and risk-averse. In contract-time allocation, this is due both to their higher bonuses and attractiveness in choice.

Finally, as a byproduct of our design, we test how well the model accounts for our subject’s behavior. Overall, 62 percent of the model’s predictions are correct, so the model fares well on average. However, the model’s average degree of success masks considerable heterogeneity across subjects and predictions. The model’s success in predicting the behavior of individual subjects ranges from 18 to 88 percent (median: 63 percent), whereas its success across predictions ranges from 11 to 96 percent (median: 63 percent). When we split the predictions between choice and time predictions, the model gets 65.5 percent of choice predictions and 59.4 of time predictions correct. Although this might suggest that the model performs equally well in describing subjects’ choices and time allocations, they hide a meaningful difference at the individual level. Only 29 of our 90 subjects adhere to the model’s choice predictions more frequently than its time predictions. This is to be expected, given that some of the model's time predictions would still hold for a broad class of preferences over contracts. In contrast, its choice predictions rely on the preferences we use.

The remainder of the paper is structured as follows. Section 2 discusses the related literature. Section 3 introduces the model we used to design the experiment and make predictions. Section 4 describes our experimental design. In Section 5, we state and discuss our results. Section 6 summarizes the paper's main takeaways.

2 Literature Review

This paper relates to four literature strands: attention/time allocation, choice between contracts, multitasking in contract theory, and non-exclusive contracting in contract theory.

Time/Effort Allocation The classic study of (static) time allocation is Becker (1965), where time is introduced as a scarce input to the household's optimization problem. Closer to what we do, Burmeister-Lamp et al. (2012) examine agents who allocate their time between a wage job (their "day job") and a new (risky) enterprise, which corresponds to the time allocation between the baseline and the risk contracts in our setup. Burmeister-Lamp et al. (2012) find that entrepreneurs' risk attitudes do not reliably predict their actual time allocation, which contradicts their theoretical results. In contrast, our model predicts risk attitudes should not affect time allocations. Other papers compare the effectiveness of different contracts in incentivizing effort provision. Although most of these papers investigate piece-rate contracts (e.g., Gneezy and Rustichini (2000)), some papers study non-linear contracts such as the one we study in this paper. For instance, Fehr et al. (2007) show that exclusive contracts that pay a non-enforceable bonus conditional on performance outperform contract theory's optimal contract in incentivizing effort provision. Although our contracts can be interpreted as paying a flat fee plus a bonus conditional on performance, the bonus is enforceable. Moreover, the critical feature of our contracts is that they are *not* exclusive.

Choice Between Contracts Sinander (2024) proposes a behavioral notion of (relative) overconfidence and axiomatizes what he calls Moral Hazard preferences, i.e., the preferences over contracts of the agent in the canonical Moral Hazard problem. Our preferences over contracts can be interpreted as a particular case of his preferences when exerting effort is costless, and our notion of (relative) over-confidence agrees with his proposed notion of (relative) over-confidence when restricted to the contracts we use. Experimentally, some papers investigate the choice between contracts, but most of the literature (see, for example, Cadsby et al. (2007), Eriksson and Villeval (2008) and Dohmen and Falk (2011)) focuses on the choice between fixed-payment contracts versus contracts that reward the agent conditional on performance. They find that more productive subjects choose contracts that pay conditional on performance over fixed-payment contracts. In contrast, we study the choice between a specific type of performance-based contract.

Multitask Contract Theory Dewatripont et al. (2000) reviews the literature on multitask contract theory, where a principal has to incentivize the agent to execute multiple tasks. The classic paper in this literature is Holmstrom and Milgrom (1991). Analogously to what happens to time allocation in our paper, the agent in this literature allocates effort to different tasks, and, hence, encouraging effort in one task can crowd out the effort on the other task, which is known as *effort substitution*. Whereas this literature studies a single principal designing a contract to incentivize the agent to exert effort on the different tasks, our goal is to design a contract that can attract the agent's time to one task at the expense of the other.

Nonexclusive Contract Theory Several papers examine the implications of non-exclusive contracts in different markets (e.g., Ales and Maziero (2016) and Attar et al. (2011)) and optimal contracting in non-exclusive relationships (e.g., Bisin and Guaitoli (2004) and Attar et al. (2014)). When there are multiple principals, the phenomenon of effort substitution encourages principals to vie for the agent's attention, which can lead to exclusivity, i.e., the agent engages with only one principal's task (see, for example, Martimort (1996), Dixit (1998) and Bernheim and Whinston (1998)). While we have "effort" (i.e., time) substitution in our setup, our model predicts that the agent will allocate time to both projects whenever there are decreasing returns to the time allocated to a task. Consistent with this prediction, most of our subjects allocate time to both tasks.

3 Model and Predictions

This section presents the model we use to predict how subjects choose between and allocate time across two contracts. We then highlight the key factors the model predicts should drive choice and time allocation, introduce the types of contracts we study, and state the model's specific predictions about choice and time allocation in the pairs of contracts we consider.

3.1 Environment

Our contracts specify how an agent will be paid to solve a task by a deadline. Therefore, our contracts are compensation schemes.[2] If the Agent successfully completes the task by the deadline, she receives a high prize H with probability p_S or a low prize L with probability $1 - p_S$, where $L < H$. If she fails the task, she receives H with probability p_F and L with probability $1 - p_F$, where $p_F < p_S$.

Utility of a Contract To evaluate a contract, the Agent must form beliefs about the task's difficulty. Our contracts inform the Agent of the fraction $\alpha \in [0, 1]$ of people who could solve the task by the given deadline. We call such α the *completion rate*, and it proxies the difficulty of a task. Therefore, the vector $(H, L, \alpha, p_S, p_F, t)$ describes a contract $\mathcal{L}$. We denote the set of these contracts by $\mathbb{L}$. Figure 1 graphically represents a contract $\mathcal{L} \in \mathbb{L}$.

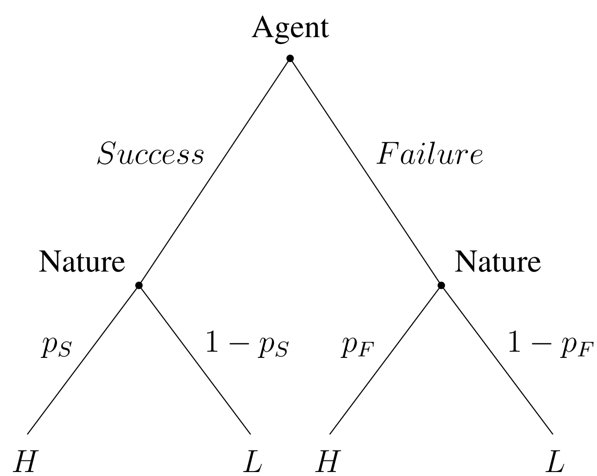

Figure 1: Graphical Representation of a Contract

We assume that the Agent is a (subjective) expected utility maximizer, which, upon learning the difficulty α of the task and the amount of time she has to solve it, updates her beliefs about her probability of solving the task and uses this updated belief to calculate the expected utility of the contract.[3] Formally, the agent evaluates a contract $\mathcal{L} \in \mathbb{L}$ by a utility

[2] In the experiment, the task is solving a maze in a given amount of time.

[3] For each α, this evaluation formula for contracts is a particular case of the preferences of an agent in the canonical moral hazard problem when contracts only have two outputs, time is replaced by effort, and the cost of effort is zero. See Sinander (2024).

function $U : \mathbb{L} \to \mathbb{R}$ defined as

$$U(\mathcal{L}) := \boldsymbol{p}(\alpha, t)\,(p_S u(H) + (1 - p_S)u(L)) + (1 - \boldsymbol{p}(\alpha, t))\,(p_F u(H) + (1 - p_F)u(L))\,, \tag{1}$$

where $u : \mathbb{R} \to \mathbb{R}$ is a strictly increasing (Bernoulli) utility function and $\boldsymbol{p}(\alpha, t)$ is the Agent's belief that she will solve the task in, at most, t units of time given that a fraction α of people have done so.

Choice Between Contracts When choosing between two contracts in a pair, say $\mathcal{L}_1$ and $\mathcal{L}_2$, the Agent maximizes U. Hence, for $i \in \{1, 2\}$, she chooses $\mathcal{L}_i$ from the menu $\{\mathcal{L}_1, \mathcal{L}_2\}$ if and only if $U(\mathcal{L}_i) \geqslant \max\{U(\mathcal{L}_1), U(\mathcal{L}_2)\}$.

Time Allocation Across Contracts When allocating time across two contracts, the Agent allocates a budget of T units of time between the two contracts' underlying tasks to maximize the sum of the contracts' expected utilities.

To state the Agent's optimization problem, let $\mathcal{L}_{t^\star}$ be the contract with the same characteristics as $\mathcal{L}$, except for the deadline, now given by $t^\star$.[4] For each $t \geqslant 0$, define the time-conditional utility function $U(\cdot|t) : \mathbb{L} \to \mathbb{R}$ be $U(\mathcal{L}|t) := U(\mathcal{L}_t)$.

Given two contracts $\mathcal{L}_1$ and $\mathcal{L}_2$, suppose that the Agent allocates t minutes to $\mathcal{L}_1$, and $T - t$ to $\mathcal{L}_2$. She will then engage in the contracts $(\mathcal{L}_1)_t$ and $(\mathcal{L}_2)_{T-t}$, which she evaluates by $U(\mathcal{L}_1|t)$ and $U(\mathcal{L}_2|T - t)$. We assume that the Agent allocates time by solving

$$\max_{t \in [0,T]} \left[U(\mathcal{L}_1|t) + U(\mathcal{L}_2|T - t)\right]. \tag{2}$$

We further assume that, for all $\alpha \in [0, 1]$,

1. $\boldsymbol{p}(\alpha, 0) = 0$;

2. $\boldsymbol{p}(\alpha, \cdot)$ is increasing, concave, and continuously differentiable.[5]

The concavity of $\boldsymbol{p}(\alpha, \cdot)$ means decreasing returns to time allocated to a task.

3.2 Bonus, choice, and time allocation

To derive predictions about choice and time allocation, define, for every $\mathcal{L} \in \mathbb{L}$,

[4] The completion rate α still gives the fraction of people that successfully completed the task when the deadline was t.

[5] If $\boldsymbol{p}$ were linear or convex, the solution of the optimization problem (2) would be to allocate T to the same contract that would receive more time if $\boldsymbol{p}$ was concave.

$$
\begin{aligned}
U_S^{\mathcal{L}} &:= p_S u(H) + (1-p_S)u(L) \\
U_F^{\mathcal{L}} &:= p_F u(H) + (1-p_F)u(L) \\
\Delta_{\mathcal{L}} &:= U_S^{\mathcal{L}} - U_F^{\mathcal{L}} = (p_S - p_F)(u(H) - u(L))
\end{aligned}
.
$$

$U_S^{\mathcal{L}}$ is the expected value of the lottery the Agent gets if she succeeds in solving the task, and $U_F^{\mathcal{L}}$ is the expected value of the lottery the Agent gets if she fails to solve the task. We refer to $U_S^{\mathcal{L}}$ as the contract's *success payoff* and $U_F^{\mathcal{L}}$ as its (expected) *flat fee*. Finally, we say that $\Delta_{\mathcal{L}}$ is the (expected) *bonus* of $\mathcal{L}$. Given the Agent's utility function over contracts, $\Delta_{\mathcal{L}}$ decomposes into $(p_S - p_F)$, the *spread in probabilities*, and $(u(H) - u(L))$, the *spread in prizes*.

As we now show, although a contract's bonus influences both choice and time allocation, the model predicts that the difference in flat fees matters for choice independently of its impact on the bonus. In contrast, it matters for time allocation only through its effect on the bonus. This can create a wedge between choice and time allocation predictions because the model can predict that the Agent should choose one contract over the other but allocate more time to the contract that is not chosen.

Choice Prediction Recall that given two contracts, $\mathcal{L}_1$ and $\mathcal{L}_2$, $\mathcal{L}_1$ should be chosen from $\{\mathcal{L}_1, \mathcal{L}_2\}$ if and only if $U(\mathcal{L}_i) \geqslant \max\{U(\mathcal{L}_1), U(\mathcal{L}_2)\}$. Substituting the evaluation formula (1) in this expression and manipulating, we get that $\mathcal{L}_1$ is chosen from $\{\mathcal{L}_1, \mathcal{L}_2\}$ if and only if

$$
\boldsymbol{p}(\alpha_1, t_1)\Delta_{\mathcal{L}_1} - \boldsymbol{p}(\alpha_2, t_2)\Delta_{\mathcal{L}_2} \geqslant U_F^{\mathcal{L}_2} - U_F^{\mathcal{L}_1}.
$$

Assuming, as is the case for most choices in our experiment, that $\alpha_1 = \alpha_2 = \alpha$ and that $t_1 = t_2 = t$, $\mathcal{L}_1$ is chosen from $\{\mathcal{L}_1, \mathcal{L}_2\}$ if and only if

$$
\boldsymbol{p}(\alpha, t)(\Delta_{\mathcal{L}_1} - \Delta_{\mathcal{L}_2}) + \left(U_F^{\mathcal{L}_1} - U_F^{\mathcal{L}_2}\right) \geqslant 0 \tag{3}
$$

The inequality (3) implies that choice depends on the agent's beliefs and two contractual features: the difference in the contracts' bonuses and their flat fees. Since the marginal utility of increasing the flat fee is 1, whereas the marginal utility of increasing the bonus is $p(\alpha, t)$, we get to the model's first insight:

Lesson 1 *When the Agent chooses between contracts, increasing the flat fee makes a contract more attractive than increasing its bonus.*

Time Prediction Solving 2 implies that the time $t_{\mathcal{L}_1}$ allocated to contract $\mathcal{L}_1$ must satisfy:

$$\frac{\boldsymbol{p}'(\alpha_2, T - t_{\mathcal{L}_1})}{\boldsymbol{p}'(\alpha_1, t_{\mathcal{L}_1})} = \frac{\Delta_{\mathcal{L}_1}}{\Delta_{\mathcal{L}_2}},$$

where $\boldsymbol{p}'(\alpha_i, \cdot)$ is the derivative of $\boldsymbol{p}$ with respect to time. Given our assumption that $\boldsymbol{p}$ is concave, the mapping $t \mapsto \frac{p'(\alpha_2, T-t)}{p'(\alpha_1, t)}$ is non-decreasing. Therefore, $t_{\mathcal{L}_1}$ is a non-decreasing function of the ratio of the bonuses of $\mathcal{L}_1$ and $\mathcal{L}_2$, i.e., the higher $\frac{\Delta_{\mathcal{L}_1}}{\Delta_{\mathcal{L}_2}}$ is, the higher $t_{\mathcal{L}_1}$ will be. In particular, if both tasks are equally difficult (if $\alpha_1 = \alpha_2 = \alpha$), then the contract with a higher bonus will receive more than $\frac{T}{2}$, hence more time than the other contract.

Lesson 2 *In two contracts with the same completion rate, the only contractual feature that matters for attracting time is the size of the bonus.*

The expected cost of a contract $\mathcal{L}$ for a risk-neutral principal is

$$\text{EC}(\mathcal{L}) \coloneqq \alpha(p_S \times H + (1 - p_S) \times L) + (1 - \alpha)(p_F \times H + (1 - p_F) \times L). \tag{4}$$

Assume now that the principal is designing the contract under the constraint that $\text{EC}(\mathcal{L}) \leqslant B$, for some $B > 0$. Note that

$$\text{EC}(\mathcal{L}) = [\alpha(p_S - p_F) + p_F]\,(H - L) + L. \tag{5}$$

This implies that if the constraint is binding and the Principal wishes to increase a contract's bonus, either by increasing $H - L$ or $p_S - p_F$, she must decrease its flat fee, either by decreasing p_F or L, and vice-versa. Therefore, Lessons 1 and 2 now imply:

Lesson 3 *When the Principal is resource-constrained, she faces a trade-off. Designing a contract that is more effective in contract-choice makes it less effective in contract-time allocation, and vice-versa.*

3.3 Contract Types

We now introduce the types of pairs of contracts in the experiment and state the model's choice and time allocation predictions for these types. For an explicit derivation and detailed discussion of these predictions, see Appendix A.

The pairs of contracts in the experiment consist of a *baseline* contract, such as the one in Table 1, paired with eight other contracts derived from the baseline by making controlled changes to its characteristics. We consider four different types of controlled changes, which induce four different types of contracts: confidence (C), risk (R), dominated (D), and ambiguous (A).

Table 1: Characteristics of $\mathcal{L}_B$

Characteristics	Value
High Prize	H_B
Low Prize	L_B
Completion rate	α_B
Probability High Prize — Solve	p_S^B
Probability High Prize — Not Solve	p_F^B

3.3.1 Confidence Contracts

A *confidence* contract $\mathcal{L}_C$ has the same prizes, completion rate, and deadline as $\mathcal{L}_B$, but the probability of getting the high prize if the Agent succeeds in the task is greater than the corresponding probability in $\mathcal{L}_B$, whereas the probability of winning the high prize if the Agent fails in the task is lower than the corresponding probability in $\mathcal{L}_B$.

Formally, $\mathcal{L}_C$ is a confidence contract if $H_C = H_B$, $L_C = L_B$, $\alpha_C = \alpha_B$ and

$$p_F^C < p_F^B < p_S^B < p_S^C \text{ and } p_F^B + p_S^B = p_S^C + p_F^C.$$

Intuitively, a confident agent, that is, one who believes that she is very likely to succeed in the task, will choose this contract over the baseline contract because the probability of getting H if she succeeds in the task is higher than in the baseline. However, given the increase in the spread in probabilities, the model predicts that confidence contracts should always attract more time.

3.3.2 Risk Contracts

A *risk* contract $\mathcal{L}_R$ has the same probabilities, completion rate, and deadline as the baseline contract $\mathcal{L}_B$, but its high prize is greater than the high prize of $\mathcal{L}_B$, whereas its low prize is smaller than the low prize of $\mathcal{L}_B$. Moreover, the average of the high and low prizes in $\mathcal{L}_B$ and $\mathcal{L}_R$ are the same. Formally, $\mathcal{L}_R$ is a risk contract if $p_S^R = p_S^B$, $p_F^R = p_F^B$, $\alpha_R = \alpha_B$, and

$$L_R < L_B < H_B < H_R \text{ and } L_R + H_R = L_B + H_B.$$

Intuitively, risk contracts are appealing to risk-seeking agents. However, as we show in Section 3.4.2), how confident the Agent is (i.e., the value of $\boldsymbol{p}(\alpha, t)$) also influences the choice between a risk contract and the baseline. However, given the increase in the spread in probabilities, the model predicts that risk contracts should always attract more time.

3.3.3 Dominated Contracts

A *dominated* contract $\mathcal{L}_D$ has the same prizes, completion rate, and deadline as $\mathcal{L}_B$, but both probabilities of winning the high prize are lower than those in $\mathcal{L}_B$. Formally, $H_D = H_B$, $L_D = L_B$, $\alpha_D = \alpha_B$, but

$$p_S^D < p_S^B \text{ and } p_F^D < p_F^B.$$

An agent should always choose the baseline contract over a dominated one. Time allocation, however, depends on the ratio of bonuses. Therefore, dominated contracts allow us to test whether the Agent understands the relevance of the bonus when allocating time. In particular, do subjects know that an attractive contract in choice should sometimes receive less time than a more attractive one?

3.3.4 Ambiguous Contracts

An ambiguous contract has the same prizes, probabilities of getting the high prize, and deadline as $\mathcal{L}_B$, but the completion rate is ambiguous because the Agent does not know the exact value of the completion rate. Formally, $H_A = H_B$, $L_A = L_B$, $p_S^A = p_S^B$, $p_F^A = p_F^B$, but, for some $\varepsilon > 0$,

$$\alpha_A \in [\alpha_B - \varepsilon, \alpha_B + \varepsilon].$$

Intuitively, the choice between an ambiguous contract and the baseline depends on the Agent's ambiguity attitude. That is, ambiguity-averse agents should choose the baseline over an ambiguous contract, whereas ambiguity-seeking agents should do the opposite.

3.4 Predictions

We now state the model's choice and time allocation predictions between the types of pairs we use in the experiment.

3.4.1 Confidence Contracts

Prediction 1 (Choice C) *An agent should choose the confidence contract over the baseline one if and only if $\boldsymbol{p}(\alpha, t) \geqslant \alpha$, i.e., if she believes that her probability of solving the task* *is higher than the probability of a randomly selected person in the population solving the task.*[6]

Prediction 2 (Time C) *An agent should allocate more time to a confidence contract than to the baseline one.*

Prediction 3 (Time C_r) *The amount of time allocated to a confidence contract increases as $p_S^C - p_F^C$ increases.*

3.4.2 Risk Contracts

Prediction 4 (Choice R)

1. *If an agent is sufficiently risk-loving, she will choose the risk contract.*
2. *If an agent is sufficiently risk-averse, she will choose the baseline one.*
3. *For intermediate levels of risk aversion, the choice depends on the Agent's confidence. Specifically, given a level of risk aversion, only sufficiently confident subjects will choose the risky contract over the baseline one.*[7]

Prediction 5 (Time R) *An agent should allocate more time to a risk contract than the baseline one.*

Prediction 6 (Time R_r) *The amount of time allocated to the risk contract increases as $H_R - L_R$ increases.*

3.4.3 Dominated Contracts

Prediction 7 (Choice D) *The Agent should always choose the baseline contract over a dominated one.*

Prediction 8 (Time D) *When $p_S^D - p_F^D > p_S^B - p_F^B$, the Agent should allocate more time to $\mathcal{L}_D$. When $p_S^D - p_F^D < p_S^B - p_F^B$, the Agent should allocate more time to $\mathcal{L}_B$.*

Prediction 9 (Time D_r) *The amount of time allocated to a dominated contract increases as $p_S^D - p_F^D$ increases.*

[6] We interpret the condition $\boldsymbol{p}(\alpha, t) \geqslant \alpha$ as saying that the agent is over-confident at completion rate α, where we use over-confidence in the sense of over-placement.

[7] See Appendix A for a derivation of the model's formal prediction.

3.4.4 Ambiguous Contracts

To make predictions about ambiguous contracts, we must make assumptions about how the Agent resolves the uncertainty about α_A. We assume that the Agent reduces ambiguity to risk by taking the completion rate of an ambiguous contract as the convex combination of the endpoints of the interval specified in the ambiguous contract, where the weights she assigns to the endpoints measure her ambiguity attitude. [8]

Prediction 10 (Choice A) *Assuming that $\boldsymbol{p}(\cdot, t)$ is increasing given the deadline t, the Agent should choose the baseline contract over the ambiguous one if and only if she is ambiguity averse.*

Since time predictions about ambiguous contracts require assumptions about the cross-derivative of the belief function with respect to time and the completion rate, we refrain from making time predictions for ambiguous contracts and let the experimental results inform us about subjects' time allocation when facing such contracts.

4 Experimental Design

The experiment consisted of three parts. In Part I, subjects chose a contract from pairs of contracts, where each contract in a pair had a 60-second deadline. In Part II, subjects revisited the same pairs of contracts, but now they had 120 seconds to allocate across the contracts in a pair. In Part III, we elicit those subjects' characteristics required to test the model. At the end of the experiment, subjects had to solve three mazes to determine how much they won. We explain how we selected the three mazes when discussing the subjects' payoffs below.

The task associated with each contract is to solve a maze with a completion rate α.[9] An important aspect of the design is that subjects only saw the mazes associated with the contracts after Parts I, II, and III were completed. Therefore, the contract's completion rate was the only information they had about the difficulty of a maze when choosing and allocating time.

Table 2 displays the contracts we used in the experiment. $\mathcal{L}_B$ acted as the baseline contract. We then generated two contracts for each type of contract described in Section 3.3:

[8] See Appendix A for the formal model the agent uses to resolve the uncertainty about the completion rate.

[9] More precisely, the completion rate was the fraction of a pool of undergraduate students that could solve the maze in, at most, 60 seconds.See Appendix B.1 for details on the procedure to generate and calibrate the mazes.

two confidence contracts ($\mathcal{L}_{C_1}$ and $\mathcal{L}_{C_2}$), two risk contracts ($\mathcal{L}_{R_1}$ and $\mathcal{L}_{R_2}$), two dominated contracts ($\mathcal{L}_{D_1}$ and $\mathcal{L}_{D_2}$), and two ambiguous contracts ($\mathcal{L}_{A_1}$ and $\mathcal{L}_{A_2}$). Therefore, subjects had to choose and allocate time in 8 pairs of contracts composed of $\mathcal{L}_B$ and each one of these eight derived contracts.

A key feature of the contracts in Table 2 is that their expected cost for a risk and ambiguity-neutral principle is, at most, that of the baseline contract. That is, we take the expected cost of the baseline contract as the Principal's resource constraint. Without this constraint, the principal could easily compete against the baseline by offering a contract with higher prizes or higher probabilities of getting the high prize than the baseline.

Contract	$\mathcal{L}_B$	$\mathcal{L}_{C_1}$	$\mathcal{L}_{C_2}$	$\mathcal{L}_{R_1}$	$\mathcal{L}_{R_2}$	$\mathcal{L}_{D_1}$	$\mathcal{L}_{D_2}$	$\mathcal{L}_{A_1}$	$\mathcal{L}_{A_2}$
High Prize	\$8	\$8	\$8	\$10	\$12	\$8	\$8	\$8	\$8
Low Prize	\$4	\$4	\$4	\$2	\$0	\$4	\$4	\$4	\$4
Completion Rate	.5	.5	.5	.5	.5	.5	.5	[.4, .6]	[0,1]
High Prize | Complete	.6	.8	1	.6	.6	.1	.3	.6	.6
High Prize | Not	.4	.2	0	.4	.4	0	0	.4	.4
Expected Value	6	6	6	6	6	4.4	4.6	6	6

Table 2: List of Contracts in the Experiment

4.1 Part I: Choosing Between Contracts

In Part I, we informed subjects that each contract's deadline was 60 seconds. Therefore, if they choose a contract from a pair and the pair is selected for payment, they would have 60 seconds to solve $\mathcal{L}$'s associated maze. For each pair of contracts, subjects had to either choose one contract in the pair or declare they were indifferent between them. Therefore, subjects effectively chose (i) the baseline contract, (ii) the alternative contract, or (iii) or declared they were indifferent between the two.

Figure 2 displays an example of the sample screen in Part I. For each pair of contracts, the subjects stated their choices by clicking the button with the contract's label they preferred or by clicking the 'Either V or W' button if they were indifferent. We randomized the order in which the eight pairs of contracts were presented to a subject and the order in which the contracts in a pair were displayed on the screen (i.e., either on the left or on the right).

The subjects did not receive any feedback between choices, nor did they see the mazes associated with each contract. They were told that at the end of the experiment, i.e., after

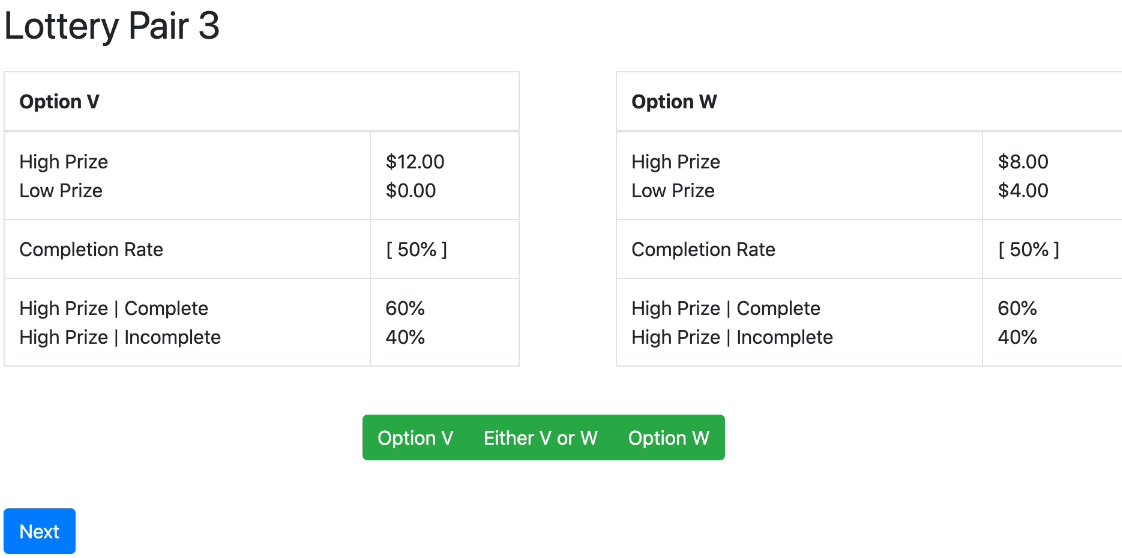

Figure 2: Sample Screen from Part I

completing Parts I, II, and III, one of the pairs in Part I would be randomly selected for payment, and they would then get to solve the maze associated with the contract they chose from the pair in at most 60 seconds. If a subject clicked on ‘Either V or W,’ we randomly selected a contract and, hence, the maze the subject had to solve.

4.2 Part II: Allocating Time Between Contracts

After completing Part I, subjects proceeded to Part II. In Part II, we presented subjects with the same eight pairs of contracts and asked them to state how much of 120 seconds they would allocate between the contracts (the mazes associated with the contracts). Figure 2 displays a sample screen presented to subjects in Part II.

Subjects had to input an integer in the corresponding field to indicate how many seconds they wanted to allocate to each option. If a subject stated that she would allocate 40 seconds to Option V, the software automatically assigned 80 seconds to Option W. In this way, we ensured that subjects exhausted their time budget.

Similarly to Part I, we randomized the order in which the eight pairs of contracts were presented to a subject and the order in which the contracts in a pair were displayed on the screen (i.e., either on the left or on the right).

Subjects did not receive feedback between time allocation decisions or see the mazes associated with each contract. They were told that one of the pairs in Part II would be randomly selected for payment at the end of the experiment, i.e., after completing Parts I,

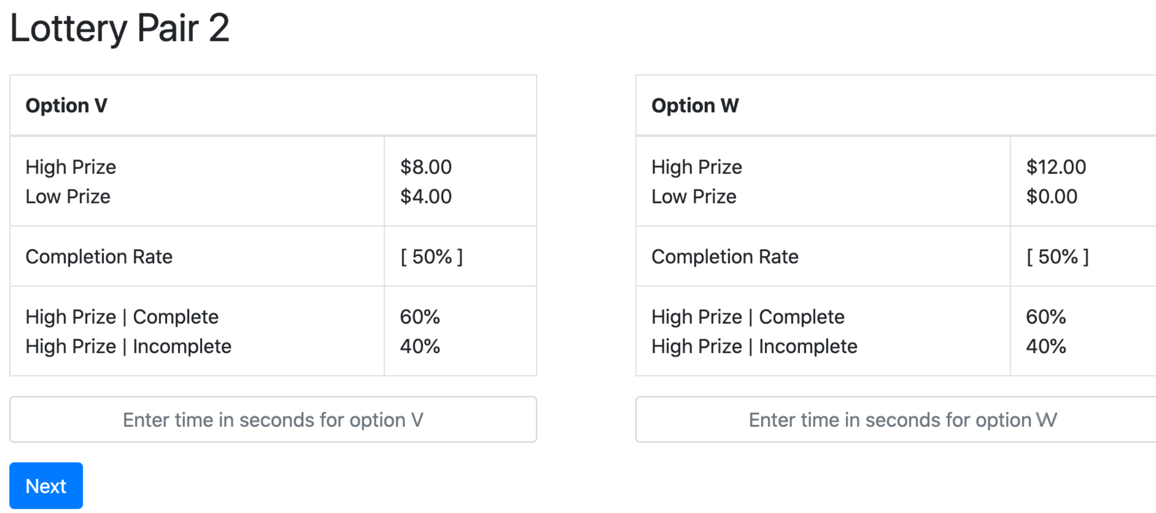

Figure 3: Sample Screen from Part 2

II, and III. They would then get to solve the two mazes associated with the selected pair of contracts under the time allocation they stated for that pair.

4.3 Part III: Eliciting Subjects' Characteristics

In Part III, subjects faced eight different elicitation tasks. The tasks elicited the characteristics required to test the model's predictions: confidence, risk, and ambiguity attitudes. Importantly, we pay subjects in these tasks so that if they behave as the model prescribes, the elicitation tasks we use can be shown to be incentive compatible. We also elicited other characteristics, e.g., attitudes toward reducing compound lotteries and alternative measures of confidence and risk attitudes. See Appendix B.2 for further details.

4.4 Payoffs

A subject's payoff in the experiment was the sum of her payoffs in three tasks, each randomly drawn from one of the Parts of the experiment. In the randomly drawn task from Part I, the subject had 60 seconds to solve the maze associated with the contract she chose. The subjects' payoff in this task was the outcome of playing the lottery, which the contract specifies, given their success or failure in solving the maze.

In the randomly drawn task from Part II, the subject had to solve the mazes associated with both contracts in the pair under the time allocation she stated. The subjects' payoff in this task was the sum of the outcomes of the two lotteries the contracts specify, given their success or failure in solving the mazes.

In the randomly drawn task from Part III, the subjects' payoffs were a function of the randomly chosen elicitation task. We discuss the payoffs of each elicitation task in Appendix B.2.

4.5 Implementation

The experiment was conducted at the Center for Experimental Social Science (CESS) laboratory at New York University, using oTree (Chen et al. (2016)) during February and March of 2020. We conducted four sessions, with 99 participants recruited from the general population of NYU students using *hroot* (Bock et al. (2014)).[10] The experiment lasted approximately 60 minutes, and average earnings, including a \$10 show-up fee, were \$31 and ranged from \$18 to \$46.

5 Results

We now proceed to the experiment's results and what they imply about Lessons 1, 2, and 3. We then study how effective the types of contracts we consider are against the baseline contract. Finally, we study how well the standard model of choice and time allocation that we used to design the experiment can account for our subjects' behavior.

5.1 The Three Lessons and Their Implications to Contract Design

Lesson 1: Flat Fees are Important in Contract-Choice. Table 3 summarizes choices in the experiment. For each pair of contracts, it displays the percentages of subjects who chose the baseline contract ($\mathcal{L}_B$), who were indifferent ('Indifferent'), and who chose the other contract in a pair (Not $\mathcal{L}_B$). Consider first the case of dominated contracts. Here things go as expected. The baseline contract should dominate these contracts in contract-choice. Both $\mathcal{L}_{D_1}$'s flat fee and bonus are lower than those of $\mathcal{L}_B$. Moreover, although $\mathcal{L}_{D_2}$'s bonus is higher than that of $\mathcal{L}_B$, its flat fee is so low relative to $\mathcal{L}_B$'s that it is still dominated by $\mathcal{L}_B$. Incidentally, only a few subjects chose a dominated contract over the baseline, which suggests that our subjects reacted to the contractual incentives.

Consider now confidence contracts. Most subjects choose $\mathcal{L}_{C_1}$ over $\mathcal{L}_B$, whereas subjects are split between $\mathcal{L}_B$ and $\mathcal{L}_{C_2}$. This suggests that whereas some subjects are willing to accept $\mathcal{L}_{C_1}$'s lower flat fee for its higher bonus, they no longer do so for $\mathcal{L}_{C_2}$. We conjecture that this is so because they judge $\mathcal{L}_{C_2}$'s flat fee as "too" low— getting the low prize

[10] For the first session, we do not have subjects' choices and time allocations in the pair $(\mathcal{L}_B, \mathcal{L}_{C_2})$.

Table 3: Choice and time allocation to contract pairs

Pairs	*Choice (percentage)*		
	$\mathcal{L}_B$	Indifferent	Not $\mathcal{L}_B$
$\mathcal{L}_B$ vs $\mathcal{L}_{C_1}$	17.2	8.1	74.7
$\mathcal{L}_B$ vs $\mathcal{L}_{C_2}$	43.5	11.6	44.9
$\mathcal{L}_B$ vs $\mathcal{L}_{R_1}$	35.4	12.1	52.5
$\mathcal{L}_B$ vs $\mathcal{L}_{R_2}$	50.5	6.1	43.4
$\mathcal{L}_B$ vs $\mathcal{L}_{D_1}$	92.9	3.0	4.0
$\mathcal{L}_B$ vs $\mathcal{L}_{D_2}$	96.0	1.0	3.0
$\mathcal{L}_B$ vs $\mathcal{L}_{A_1}$	34.3	30.3	35.4
$\mathcal{L}_B$ vs $\mathcal{L}_{A_2}$	54.5	19.2	26.3

for sure—compared to that of $\mathcal{L}_B$, which still offers a 40% chance of getting the high prize. However, the model predicts that a subject should choose $\mathcal{L}_{C_1}$ over $\mathcal{L}_B$ if and only if the subject chooses $\mathcal{L}_{C_2}$ over $\mathcal{L}_B$. These results suggest that the flat fee indeed matters but that the model underestimates the importance of flat fees when they are "too" low.

Consider now risk contracts. Most of our subjects prefer $\mathcal{L}_{R_1}$ to $\mathcal{L}_B$ but prefer $\mathcal{L}_B$ to $\mathcal{L}_{R_2}$. Again, the issue is similar to the one with confidence contracts: whereas subjects are willing to trade-off $\mathcal{L}_{R_1}$'s lower flat fee for its higher bonus relative to $\mathcal{L}_B$, $\mathcal{L}_{R_2}$'s flat fee is considered too low, and hence, its higher bonus relative to $\mathcal{L}_B$ does not compensate for it. Curiously, contrary to the case of confidence contracts, the model is more successful in predicting choice on the pair $\mathcal{L}_{R_2}$ and $\mathcal{L}_B$ than on $\mathcal{L}_B$ to $\mathcal{L}_{R_1}$. This is so because the model predicts that most of our subjects should choose $\mathcal{L}_B$ over $\mathcal{L}_{R_1}$ and $\mathcal{L}_{R_2}$. This indeed happens for $\mathcal{L}_{R_2}$, but not for $\mathcal{L}_{R_1}$. Therefore, in this case, the model overestimates the importance of flat fees when they are *not* "too" low.

Finally, consider ambiguous contracts. When ambiguity is low, as in the case of $\mathcal{L}_{A_1}$, roughly a third of the subjects choose $\mathcal{L}_B$, the other third chooses $\mathcal{L}_{A_1}$, and the remaining third declares indifference. However, as soon as ambiguity increases, as in the case of $\mathcal{L}_{A_2}$most subjects choose $\mathcal{L}_B$. The problem seems to be that although these contracts have the same flat fee and bonus, the weight subjects assign to each depends on how ambiguous the contract is. When ambiguity increases, subjects become worried that the task will be too hard (i.e., α will be too low). In this case, they will be more likely to only get the flat fee, but not the bonus. Therefore, they prefer to go with the contract with a task of known difficulty.

These results suggest that flat fees indeed matter for choice, consistent with Lesson 1. However, our model implies that a subject's marginal rate of substitution between the flat fee and the bonus is constant. In contrast, our results suggest that it is decreasing: the lower the flat fee, the higher the bonus required to compensate for it.

Lesson 2: Bonuses and Contract Time Allocation Table **??** summarizes time allocations in the experiment. It displays the average time subjects allocate to the baseline ($\mathcal{L}_B$) and the other contract in the pair (Not $\mathcal{L}_B$). Risk and confidence contracts have a higher bonus than the baseline contract, and correspondingly, they receive more time, on average, than the baseline contract. However, $\mathcal{L}_{C_2}$ is not much more effective on average than $\mathcal{L}_{C_1}$ in attracting time over $\mathcal{L}_B$, although the bonus of $\mathcal{L}_{C_2}$ is 5 times that of $\mathcal{L}_B$, whereas that of $\mathcal{L}_{C_1}$ is 3 times. In fact, the difference in the averages displayed in the table is not statistically significant. Similarly, $\mathcal{L}_{R_1}$ and $\mathcal{L}_{R_2}$ are equally effective in attracting time, although the bonus of $\mathcal{L}_{R_2}$ is 3 times that of $\mathcal{L}_B$, whereas that of $\mathcal{L}_{C_1}$ is 2 times.

Time allocation between the baseline and dominated contracts is even more puzzling. Although the bonus of $\mathcal{L}_B$ is "only" two times that of $\mathcal{L}_{D_1}$, the difference in time allocated to $\mathcal{L}_B$ and $\mathcal{L}_{D_1}$ is the largest in the pairs we consider, namely 38.8 seconds in favor of $\mathcal{L}_B$. To put things into perspective, the bonus of $\mathcal{L}_{C_2}$ is five times that of $\mathcal{L}_B$, but the difference in the time allocated to $\mathcal{L}_{C_2}$ and $\mathcal{L}_B$ is "only" 22.8 seconds in favor of $\mathcal{L}_{C_2}$. Finally, and surprisingly, although $\mathcal{L}_{D_2}$ has a higher bonus than $\mathcal{L}_B$, $\mathcal{L}_B$ attracts significantly more time than $\mathcal{L}_{D_2}$.

Table 4: Choice and time allocation to contract pairs

Pairs	*Time (seconds)*	
	$\mathcal{L}_B$	Not $\mathcal{L}_B$
$\mathcal{L}_B$ vs $\mathcal{L}_{C_1}$	52.0	68.0
$\mathcal{L}_B$ vs $\mathcal{L}_{C_2}$	48.6	71.4
$\mathcal{L}_B$ vs $\mathcal{L}_{R_1}$	54.0	66.0
$\mathcal{L}_B$ vs $\mathcal{L}_{R_2}$	54.9	65.1
$\mathcal{L}_B$ vs $\mathcal{L}_{D_1}$	79.4	40.6
$\mathcal{L}_B$ vs $\mathcal{L}_{D_2}$	73.5	46.5
$\mathcal{L}_B$ vs $\mathcal{L}_{A_1}$	60.3	59.7
$\mathcal{L}_B$ vs $\mathcal{L}_{A_2}$	63.3	56.7

To further investigate the relevance of bonuses to time allocation, we ran the following regression:

$$t^i_{(\mathcal{L}_B,\mathcal{L}_X)} = \beta_0 + \beta_1 \left(\frac{\Delta^i_{\mathcal{L}_B}}{\Delta^i_{\mathcal{L}_X}} - 1 \right),$$

where for each subject i and $X \in \{C_1, C_2,\ R_1, R_2,\ D_1, D_2\}$,[11] $t^i_{(\mathcal{L}_B, L_X)}$ is the amount of time subject i allocates to contract $\mathcal{L}_B$ in the pair $(\mathcal{L}_B, \mathcal{L}_X)$, and $\left(\frac{\Delta_{\mathcal{L}^i_B}}{\Delta_{\mathcal{L}^i_X}} - 1 \right)$ is the *normalized* ratio of bonuses for subject i.

For each pair $(\mathcal{L}_B, \mathcal{L}_X)$, when the normalized ratio of bonuses is 0 for subject i, that is, when $\Delta^i_{\mathcal{L}_B} = \Delta^i_{\mathcal{L}_X}$, the model predicts that the subject should allocate the same amount of time to $\mathcal{L}_B$ and $\mathcal{L}_X$. Therefore, if the model is correct (on average), we expect $\beta_0 = 60$. The model also predicts that $\beta_1 > 0$.

Table 5 displays the results of the regression. Consistent with the model, $\beta_1 = 10.77 > 0$, which means that if the bonus of $\mathcal{L}_B$ is twice that of $\mathcal{L}_X$, subjects allocate roughly 11 more seconds to $\mathcal{L}_B$. This suggests that subjects understand the importance of bonuses for time allocation. However, the magnitude of $\beta_0 = 65.64$, which is statistically different from 60, is puzzling given that the model predicts that the baseline contract should receive less than 60 seconds in five out of the six pairs of contracts included in the regression.

Table 5: Time Allocation and Bonuses

	Coefficient	*Robust Std. Err.*	*p-value*
β_0	65.64	1.37	0.00
β_1	10.77	2.47	0.00

What explains the magnitude of β_0? The pair of contracts $\mathcal{L}_B$ and $\mathcal{L}_{D_2}$ suggests that instead of basing their time allocation exclusively on the ratio of bonuses, subjects are allocating more time to the contract they would choose in a pair and, hence, find more attractive. If this is true, our previous discussion about the relevance of flat fees for choice implies that flat fees also matter for time allocation.

We call this pattern the *attractiveness bias* and conjecture that it is a particular case of a process Kahneman et al. (2002) named *attribute substitution*. When asked how they want to allocate their time between two contracts, a question some subjects might deem complex, they substitute it with the more straightforward question of what contract they find more attractive (and, hence, would choose). They then instinctively allocate more time to the

[11] These are the pairs for which the model makes predictions about time allocation.

more attractive contract but adjust this instinctive reaction using the contracts' bonuses.

To test whether the data supports the attractiveness bias, we ran a modified version of our first regression, where we condition time allocation on the contract the subjects chose in each pair:

$$t^i_{(\mathcal{L}_B,\mathcal{L}_X)} = \sum_{k\in\{B,X,\text{Indiff}\}} \mathbf{1}^i_{\{Choice_{(\mathcal{L}_B,\mathcal{L}_X)}=\mathcal{L}_k\}} \left[\beta^k_0 + \beta^k_1 \left(\frac{\Delta^i_{\mathcal{L}_B}}{\Delta^i_{\mathcal{L}_X}} - 1\right)\right],$$

where for each subject i and $X \in \{C_1, C_2, R_1, R_2, D_1, D_2\}$, $t^i_{(\mathcal{L}_B,\mathcal{L}_X)}$ is the amount of time subject i allocates to contract $\mathcal{L}_B$ in the pair $(\mathcal{L}_B, \mathcal{L}_X)$, $\left(\frac{\Delta^i_{\mathcal{L}_B}}{\Delta_{\mathcal{L}^i_X}} - 1\right)$ is the *normalized* ratio of bonuses, and $\mathbf{1}^i_{\{Choice_{(\mathcal{L}_B,\mathcal{L}_X)}=\mathcal{L}_k\}}$ is an indicator variable that, for each $k \in \{B, X, \text{Indiff}\}$, takes value 1 when subject i chooses $\mathcal{L}_k$, and 0 otherwise.

Running this regression is equivalent to running three separate regressions: one for the observations where subjects chose the baseline contract, one for the observations where subjects chose the other contract, and one for the observations where subjects declared indifference between the contracts. For each case, we run a simple linear regression between the time allocated to the baseline in a pair and the normalized ratio of bonuses. For each pair $(\mathcal{L}_B, \mathcal{L}_X)$ and each $k \in \{B, X, \text{Indiff}\}$, the model again implies that $\beta^k_0 = 60$ and $\beta^k_1 > 0$.

Table 6 displays the results of the regression. On average, subjects that choose $\mathcal{L}_B$ allocate more time to it than the model predicts they should when the contracts have the same bonus ($\beta^B_0 = 70.57$). Similarly, on average, subjects that choose $\mathcal{L}_X$ allocate more time to it than the model predicts when the contracts have the same bonuses ($\beta^X_0 = 50.6$). Finally, subjects that declare indifference allocate roughly the same amount of time to both contracts ($\beta^{\text{Indiff}}_0 = 57.73$). Therefore, subjects allocate, on average, more time to the contract that attracts them when choosing.

When choosing the baseline contract or declaring indifference, subjects react to the increase in the ratio of bonuses as predicted by the model ($\beta^B_1 = 12.35$ and $\beta^{\text{Indiff}}_1 = 5.31$ are statistically significant) but not when choosing the other contract in the pair (β^X_1 is not statistically significant).

Lesson 3: The Trade-Off and Implications to Contract Design The attractiveness bias can account for the time allocation results that are at odds with the model's predictions. As discussed in detail in the next section, it explains why the baseline contract effectively attracts time over dominated contracts, even when the model predicts it should not. It

	Coefficient	*Robust Std. Err.*	*p-value*
β_0^k			
Choose B ($k = B$)	70.57	1.62	0.00
Indifference ($k =$ **Indiff**)	57.73	3.83	0.00
Choose Other ($k = X$)	50.60	1.91	0.00
β_1^k			
Choose B ($k = B$)	12.35	1.70	0.00
Indifference ($k =$ **Indiff**)	5.31	2.58	0.04
Choose Other ($k = X$)	-1.26	1.38	0.36

Table 6: The Attractiveness Bias

also explains why the two confidence (risk) contracts are almost as effective: $\mathcal{L}_{C_1}$ ($\mathcal{L}_{R_1}$) is more attractive in choice than $\mathcal{L}_{C_2}$ ($\mathcal{L}_{R_2}$). More importantly, the attractiveness bias qualifies Lesson 3. That is, it reduces the trade-off a resource-constrained Principal faces in designing contracts. Contracts $\mathcal{L}_{C_1}$ and $\mathcal{L}_{R_1}$ perform well both in contract-choice and contract-time allocation.

Therefore, our experimental results suggest that when a resource-constrained Principal designs contracts, she must ensure that the flat fee is not too low because subjects find contracts with low flat fees unattractive when choosing. By the attractiveness bias, low flat fees will also affect the contract's effectiveness in attracting time. Finally, once the principal allocates enough resources to increase the flat fee, the remaining resources should go into increasing the bonus because, as we have seen, our subjects react to it when allocating time.

5.2 The Effectiveness of The Different Types of Contracts

We now explore how effective the four types of contracts are in competing against the baseline contract. Table 7 joins the information in Tables 3 and Table 4. Recall that the contracts we used in the experiment are derived from the baseline by varying some of its parameters while ensuring that their expected cost is, at most, that of the baseline.

How effective are contracts that increase the probability spread while keeping expected costs constant? That is, how effective are confidence contracts? Table 7 shows that confidence contracts are effective in contract-choice. However, as argued above, their effectiveness decreases if we increase the spread in probabilities too much by reducing their flat fee. Whereas three out of four subjects choose $\mathcal{L}_{C_1}$ over $\mathcal{L}_B$, less than two out of four subjects

Table 7: Choice and time allocation to contract pairs

Pairs	*Choice (percentage)*			*Time (seconds)*	
	$\mathcal{L}_B$	Indifferent	Not $\mathcal{L}_B$	$\mathcal{L}_B$	Not $\mathcal{L}_B$
$\mathcal{L}_B$ vs $\mathcal{L}_{C_1}$	17.2	8.1	74.7	52.0	68.0
$\mathcal{L}_B$ vs $\mathcal{L}_{C_2}$	43.5	11.6	44.9	48.6	71.4
$\mathcal{L}_B$ vs $\mathcal{L}_{R_1}$	35.4	12.1	52.5	54.0	66.0
$\mathcal{L}_B$ vs $\mathcal{L}_{R_2}$	50.5	6.1	43.4	54.9	65.1
$\mathcal{L}_B$ vs $\mathcal{L}_{D_1}$	92.9	3.0	4.0	79.4	40.6
$\mathcal{L}_B$ vs $\mathcal{L}_{D_2}$	96.0	1.0	3.0	73.5	46.5
$\mathcal{L}_B$ vs $\mathcal{L}_{A_1}$	34.3	30.3	35.4	60.3	59.7
$\mathcal{L}_B$ vs $\mathcal{L}_{A_2}$	54.5	19.2	26.3	63.3	56.7

choose $\mathcal{L}_{C_2}$ over $\mathcal{L}_B$.

In time allocation, the average amount of time subjects allocate to $\mathcal{L}_{C_1}$ is not statistically different from the one they allocate to $\mathcal{L}_{C_2}$. The attractiveness bias can account for this fact. Given that 72.5% of subjects choose $\mathcal{L}_{C_1}$ over $\mathcal{L}_B$ and 44.9% choose $\mathcal{L}_{C_2}$ over $\mathcal{L}_B$, the attractiveness bias implies that subjects allocate more time, on average, to $\mathcal{L}_{C_1}$ relative to $\mathcal{L}_B$ and allocate less time to $\mathcal{L}_{C_2}$ relative to $\mathcal{L}_B$ than the model predicts, making the average amount of time allocated to $\mathcal{L}_{C_1}$ and $\mathcal{L}_{C_2}$ closer than what the model predicts.

We reach similar conclusions on the efficacy of spreading prizes while keeping expected costs constant. 51.7% of subjects chose $\mathcal{L}_{R_1}$ over $\mathcal{L}_B$, while 36.7% chose $\mathcal{L}_B$ over $\mathcal{L}_{R_1}$. In contrast, only 41.7% of our subjects chose $\mathcal{L}_{R_2}$ over $\mathcal{L}_B$, whereas 51.7% chose $\mathcal{L}_B$ over $\mathcal{L}_{R_2}$. This again suggests that subjects shy away from contracts with flat fees that are too low. In time allocation, although both risky contracts attract more time than the baseline contract, $\mathcal{L}_{R_2}$ attracts, on average, roughly the same amount of time over $\mathcal{L}_B$ as $\mathcal{L}_{R_1}$ over $\mathcal{L}_B$. Once more, the attractiveness bias can explain these results.

Although confidence and risky contracts are both effective in competing against the baseline for time allocation, Table 7 suggests, and statistical tests corroborate, that confidence contracts attract, on average, more effective than risky ones. This suggests that influencing soft incentives, i.e., the Agent's beliefs, is more effective than influencing hard incentives, both for contract-choice and contract-time allocation.

The model suggests that one way the Principal can compete for people's time against the baseline contract at a lower expected cost is to increase the spread in probabilities $(p_S - p_F)$ while decreasing the sum of these probabilities $(p_S + p_F)$ relative to the baseline contract.

This is what $\mathcal{L}_{D_2}$ does. However, Table 7 shows that it is ineffective in both contract-choice and contract-time allocation. Once more, the attractiveness bias rationalizes this pattern. The attractiveness bias also explains why $\mathcal{L}_B$ attracts much more time than $\mathcal{L}_{D_1}$ despite the ratio of spreads between these contracts being much lower than the ratio of spreads between $\mathcal{L}_{C_2}$ and $\mathcal{L}_B$.

How effective are ambiguous contracts? Subjects chose $\mathcal{L}_{A_1}$ as often as $\mathcal{L}_B$, which indicates that, on average, subjects are not averse to a small amount of (symmetric) ambiguity in the completion rate. However, subjects choose $\mathcal{L}_B$ twice as often as $\mathcal{L}_{A_2}$, which suggests that subjects want to avoid the possibility of highly unfavorable outcomes, such as the completion rate of the ambiguous contract being 0. Interestingly, both ambiguous contracts attract roughly the same time, on average, as the baseline contract. Therefore, ambiguity in the completion rate does not seem to affect subjects' time allocation as much.

5.3 Testing the Model

To assess the model's performance in the experiment, we introduce the notion of a prediction matrix.

Definition 1 *Given $N \in \mathbb{N}$ subjects and $M \in \mathbb{N}$ predictions, a* ***prediction matrix*** $(P_{ij})_{i=1,\ldots,N}^{j=1,\ldots,M}$ *is a $N \times M$ matrix where*

$$P_{ij} \coloneqq \begin{cases} 1, & j \textit{ is true of } i \\ 0, & j \textit{ is false of } i \\ NA, & j \textit{ does not apply to } i \end{cases}.$$

A prediction matrix summarizes the model's performance for each subject and each prediction. For each subject i and each prediction j, P_{ij} can take one of three values. If prediction j is correct for subject i, $P_{ij} = 1$. If prediction j is incorrect for subject i, $P_{ij} = 0$. In either of these cases, we say that prediction j is *valid* for subject i. However, if prediction j cannot be tested for subject i, either because an assumption is needed to test it fails or because of missing data, $P_{ij} = NA$, we say it is *invalid* (for subject i in prediction j). For the assumptions each prediction requires to be declared valid, see Appendix A, particularly Tables 9 to 12.

Given a prediction matrix, we can calculate how well the model describes each subject's behavior and its degree of success for each prediction, which leads to the following definitions.

Definition 2 *The* ***model's degree of success for subject*** $i^\star \in \{1, \ldots, N\}$ *is defined as*

$$C_{i^\star} := \frac{\sum_{\{j : P_{i^\star j} \neq NA\}} P_{i^\star j}}{|\{j : P_{i^\star j} \neq NA\}|}$$

Definition 3 *The* ***model's degree of success in prediction*** $j^\star \in \{1, \ldots, M\}$ *is defined as*

$$P_{j^\star} := \frac{\sum_{\{i : P_{ij^\star} \neq NA\}} P_{ij^\star}}{|\{j^\star : P_{ij^\star} \neq NA\}|}$$

The model's degree of success for subject i measures how well the model describes the subject i's behavior in the experiment when we restrict attention to valid predictions. The model's degree of success in prediction j is the percentage of subjects that conform to prediction j when we restrict attention to valid predictions.

Table 8: Summary of Valid Predictions

Prediction Category	All	Choice	Time	Choice ND
Degree of success	62.0	65.5	59.4	51.7

Table 8 summarizes model's degree of success for all predictions. We find that 62% of all valid predictions are correct. Once we split the predictions between choice and time allocation predictions, we find that 65.5% of the model's choice predictions are correct, whereas 59.4% of its time predictions are correct. However, choice predictions about dominated contracts follow from a simple dominance argument because the baseline contract awards lotteries that first-order stochastically dominate the lotteries awarded by dominated contracts no matter whether a subject completes the task. Therefore, any "reasonable" model of choice between contracts should predict that the agent should choose the baseline over a dominated contract. This implies that getting these predictions right only provides weak evidence for the model's predictive success. Once we exclude the choice predictions about dominated contracts, we see that 51.7% of choice predictions are correct, suggesting that the model better predicts time allocations than choice. And indeed, the model predicts 2/3 of our subjects' time allocations better than their choices.[12]

[12] If instead of ignoring the invalid predictions, we consider them incorrect, we find that 56% of the model's predictions are correct. Suppose we further split the predictions between choice and time allocation. In that case, we find that 52.5% of choice predictions are correct, and if we exclude choice predictions about dominated contracts, 38% of choice predictions are correct. The percentage of correct time predictions does not change.

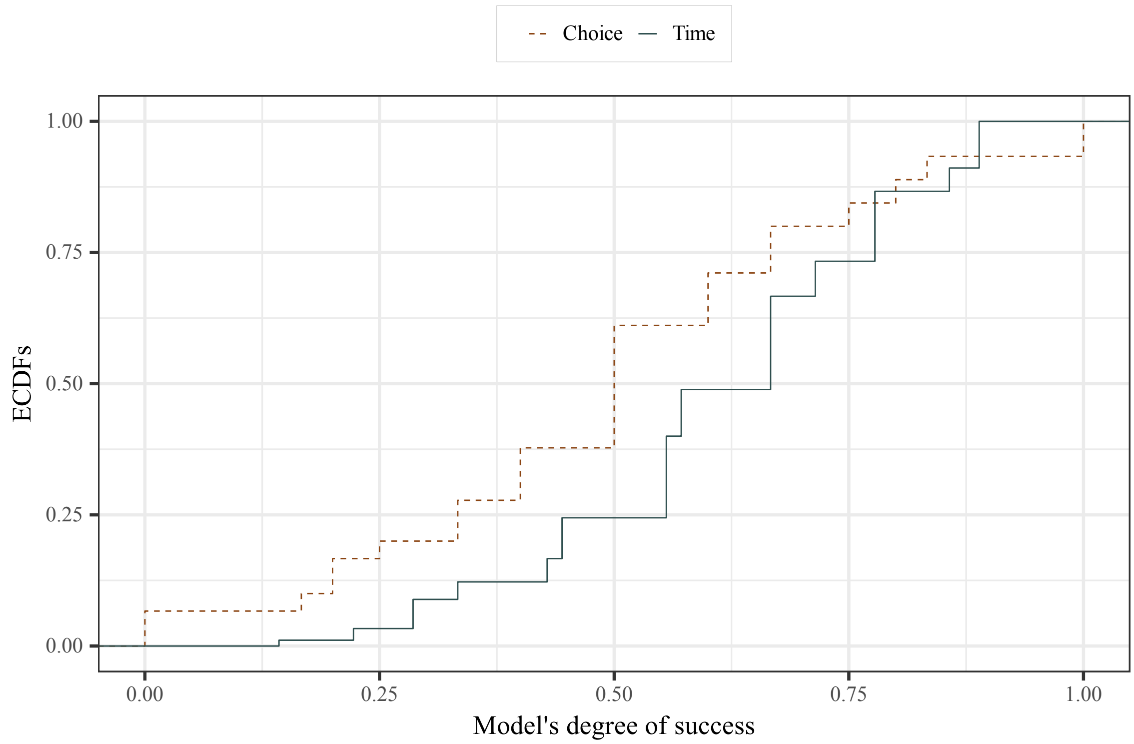

Figure 4: ECDFs of the Model's Degree of Success for Subjects by Type of Prediction (Dominance Excluded)

Figure 4 provides further evidence for this claim. It plots two empirical CDFs (ECDFs). The first is the ECDF of the model's degree of success across subjects when we only consider (valid) choice predictions (excluding those about dominated contracts). The second is the corresponding ECDF for the time predictions. We then see that the second ECDF "almost" first-order stochastically dominates the first indicating the model's greater success in predicting time allocations than choices.

Figure 5 plots the model's degree of success subject by subject, decomposing its degree of success in predicting a subject's choice (circles) (excluding dominated contracts) and time allocations (triangles). On the x-axis, we ordered subjects by the model's degree of success in predicting their choices. There are three points of interest in Figure 5. First, there is a large degree of heterogeneity in the model's degree of success across subjects, ranging from 18% to 88%. Second, although we can again see that the model better accounts for most subjects' time allocations than for their choices, there is a significant proportion of subjects for whom the opposite is true. Third, subjects differ greatly regarding how frequently they adhere to our model's choice and time predictions. Looking at Figure 5 from left to right, we can spot subjects that conform to the model very well in one type of task but not in the other, and these differences in the model's performance across tasks can be sizable.[13]

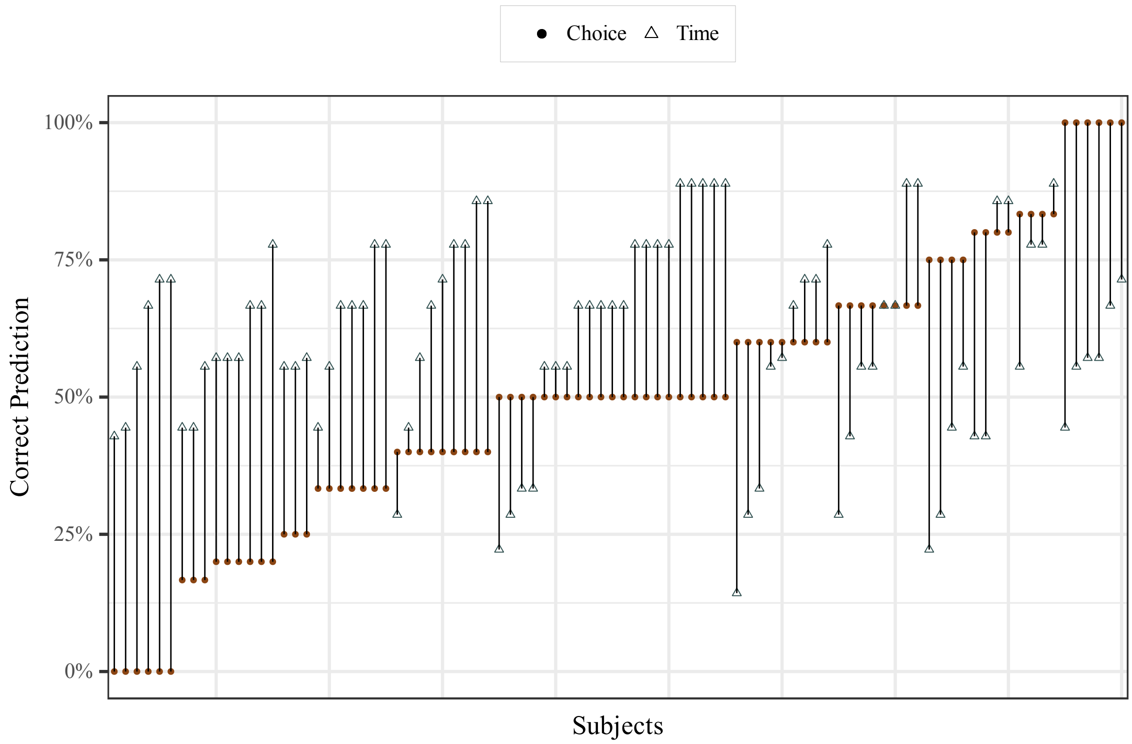

Figure 5: Model's Success by Subject (Dominance Excluded)

While Figures 4 and 5 look at the model's performance across subjects, Figure 6 displays the model's success across predictions. There is a good deal of heterogeneity here as well, with the model's success rate ranging from 11% to 96%. The most successful predictions are the predictions about choice involving dominated contracts, whereas the least successful prediction is about the time allocation between the baseline and the second dominated contract. Note also that the predictions Time_C_r, Time_R_r, and Time_D_r are particularly successful, which again suggests that subjects do react to bonuses when allocating time.

[13] Once we exclude predictions about dominated contracts, 9 of our subjects have no valid predictions, so we exclude them from the graph. Moreover, although invalid predictions in choice (see Appendix A, particularly A.5) lead to an overestimation of the model's success in choice, the qualitative results about the two layers of heterogeneity of the model's success across subjects would still hold if we only considered subjects for whom all choice predictions are valid.

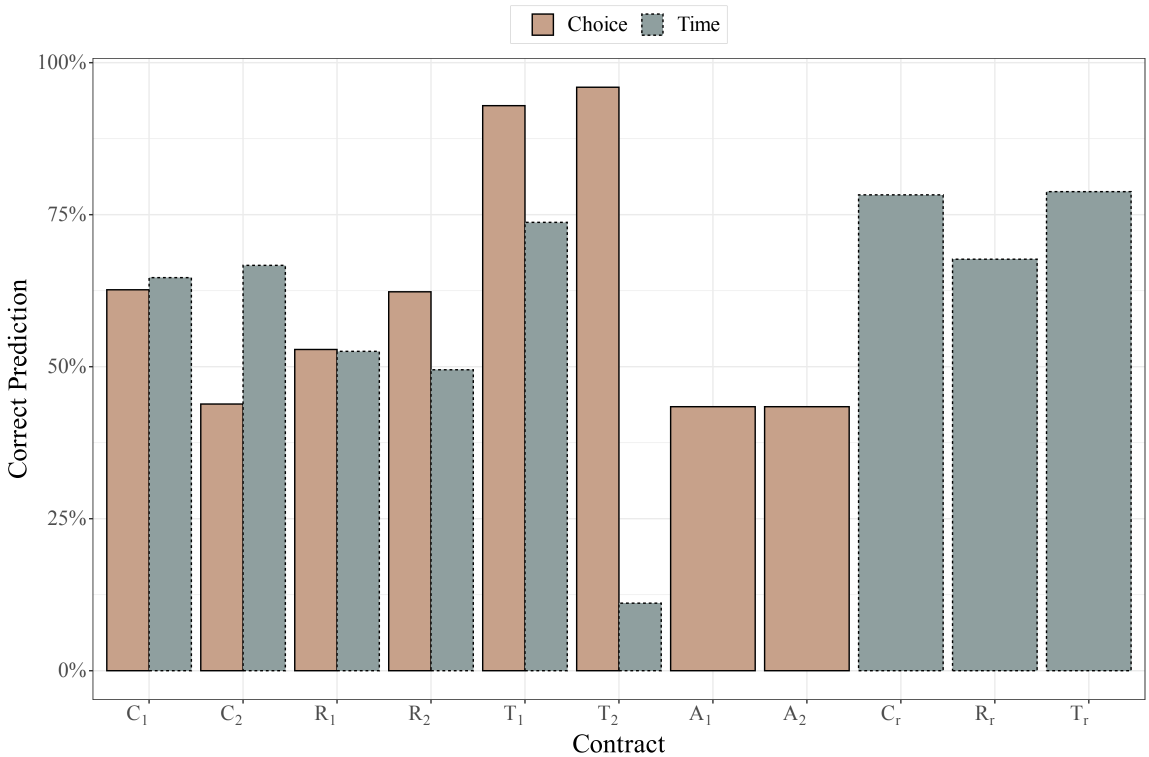

Figure 6: Degree of Success by Prediction

Two reasons account for the model's higher degree of success in predicting time allocations. First, as discussed extensively in Appendix A.6, the time allocation predictions about risk and especially confidence contracts would hold for a broad class of preferences over contracts. Second, if the elicitation of the characteristics we need for the model's choice predictions is subject to measurement error (cf., Gillen et al. (2019)), we might incorrectly conclude that the model predictions fail. [14]

6 Concluding remarks

This paper addresses how people choose and allocate time between bonus-based contracts. We have seen that a standard choice and time allocation model implies that flat fees are more important than bonuses for choice and that only bonuses should matter for time allo-

[14] For instance, given how we elicit the confidence function when $\alpha = 0.5$ and $t = 60$, we might be overestimating subjects' confidence (Benoît et al. (2022)), which can explain why the prediction Choice C_2 fails for more than half of our subjects. However, measurement error provides — at best — a partial explanation for the model's failures in predicting choices. For instance, if we ignore indifferences, the model predicts that a subject chooses $\mathcal{L}_B$ over $\mathcal{L}_{C_1}$ and $\mathcal{L}_{C_2}$ or $\mathcal{L}_{C_1}$ and $\mathcal{L}_{C_2}$ over $\mathcal{L}_B$. Although this prediction is unaffected by measurement error, the choices of 51% of our subjects do not conform to it.

cation. However, our results suggest that people also care about the overall attractiveness of a contract when allocating time, which implies that flat fees also matter for time allocation. This tendency, which we call the attractiveness bias, can lead agents to allocate time across contracts sub-optimally if their goal is to allocate time to maximize the payment they get.

Moreover, the model suggests that a resource-constrained principal faces a trade-off in designing a contract that performs well in both contract-choice and contract-time allocation. This trade-off is relevant if the Principal is unsure how the Agent will engage with the contract. For instance, suppose the Principal is uncertain about the Agent's time budget. If the Agent is very time-constrained, he might be forced to choose one among the offered contracts, whereas if the Agent has enough time to allocate between several projects, he must decide how to split his time between the offered contracts.

The attractiveness bias, however, suggests that this trade-off is less pronounced than the model predicts. In particular, our results indicate that to design a contract that performs well in contract-choice and time allocation, the Principal must make sure that the flat fee is not "too low," lest the contract becomes unappealing for an Agent that chooses between contracts and, by the attractiveness bias, also to an Agent that allocates time between contracts. The Principal should then allocate her remaining resources to increasing the bonus to attract the Agent's time. Therefore, principals should first set a sufficiently high flat fee to secure initial engagement, and then direct any remaining budget toward the bonus.

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Appendices

A Derivation of the Predictions

This section derives the model's predictions for the four contract types. We also state the specific choice and time allocation predictions of the model for the pairs in the experiment. Recall that, given two contracts $\mathcal{L}_1$ and $\mathcal{L}_2$, $\mathcal{L}_1$ is chosen from the menu $\{\mathcal{L}_1, \mathcal{L}_2\}$ if and only if

$$\boldsymbol{p}(\alpha_1, t_1)\Delta_{\mathcal{L}_1} - \boldsymbol{p}(\alpha_2, t_2)\Delta_{\mathcal{L}_2} + (U_F^{\mathcal{L}_1} - U_F^{\mathcal{L}_2}) \geqslant 0,$$

and that the amount of time allocated to $\mathcal{L}_1$ satisfies

$$\frac{\boldsymbol{p}'(\alpha_2, T - t_{\mathcal{L}_1})}{\boldsymbol{p}'(\alpha_1, t_{\mathcal{L}_1})} = \frac{\Delta_{\mathcal{L}_1}}{\Delta_{\mathcal{L}_2}}.$$

In the following, we refer to the first expression as the Choice Formula and the second expression as the Time Allocation Formula.

A.1 Confidence Contracts

A confidence contract $\mathcal{L}_C$ relative to $\mathcal{L}_B$ is one in which $H_C = H_B$, $L_C = L_B$, $\alpha_C = \alpha_B$,

$$p_F^C < p_F^B < p_S^B < p_S^C \text{ and } p_F^C + p_S^C = p_F^B + p_S^B.$$

Manipulating the Choice Formula, we see that $\mathcal{L}_C$ is chosen from the menu $\{\mathcal{L}_B, \mathcal{L}_C\}$ if and only if

$$\frac{\boldsymbol{p}(\alpha_B, t)}{1 - \boldsymbol{p}(\alpha_B, t)} \geqslant \frac{p_F^B - p_F^C}{p_S^C - p_S^B}.$$

Since $\frac{\boldsymbol{p}(\alpha_B,t)}{1-\boldsymbol{p}(\alpha_B,t)}$ is an increasing function of $\boldsymbol{p}(\alpha_B, t)$, a sufficiently confident Agent, i.e., one that assigns a sufficiently high probability to succeed in the task, should choose $\mathcal{L}_C$ over $\mathcal{L}_B$.

Manipulating the Time Allocation Formula, we get that the amount of time $t_{\mathcal{L}_C}$ allocated to $\mathcal{L}_C$ satisfies

$$\frac{\boldsymbol{p}'(T - t_{\mathcal{L}_C}, \alpha_B)}{\boldsymbol{p}'(t_{\mathcal{L}_C}, \alpha_B)} = \frac{p_S^C - p_F^C}{p_S^B - p_F^B}$$

Since the left-hand side increases with $t_{\mathcal{L}_C}$ and the right-hand side is greater than one, we have that $t_{\mathcal{L}_C} > \frac{T}{2}$. That is, the Agent should always allocate more time to a confidence contract. Moreover, $t_{\mathcal{L}_C}$ should increase with $p_S^C - p_F^C$.

We use two confidence contracts in the experiment, $\mathcal{L}_{C_1}$ and $\mathcal{L}_{C_2}$ in Table 2. For both contracts, the model predicts that subjects should choose $\mathcal{L}_{C_i}$ from the menu $\{\mathcal{L}_B, \mathcal{L}_{C_i}\}$ if and only if $\boldsymbol{p}(0.5, 60) \geqslant 0.5$. The model also predicts that subjects should always allocate more time to $\mathcal{L}_{C_i}$ than $\mathcal{L}_B$ for each $i \in \{1, 2\}$, i.e., $t_{\mathcal{L}_{C_i}} > 60$. Finally, given that $p_S^{C_2} - p_F^{C_2} > p_S^{C_1} - p_F^{C_1}$, the model predicts that subjects should allocate more time to $\mathcal{L}_{C_2}$ (relative to $\mathcal{L}_B$) than to $\mathcal{L}_{C_1}$ (relative to $\mathcal{L}_B$), i.e., $t_{\mathcal{L}_{C_2}} > t_{\mathcal{L}_{C_1}}$.

A.2 Risk Contracts

A risk contract $\mathcal{L}_R$ relative to $\mathcal{L}_B$ is one in which $p_S^R = p_S^B$, $p_F^R = p_F^B$, $\alpha_R = \alpha_B$,

$$L_R < L_B < H_B < H_R \quad \text{and} \quad H_R + L_R = H_B + L_B$$

Manipulating the Choice Formula, we get that $\mathcal{L}_R$ is chosen from the menu $\{\mathcal{L}_R, \mathcal{L}_B\}$ if and only if

$$K_{(H_B,L_B)}^{(H_R,L_R)}(u) \geqslant \frac{1 - \boldsymbol{q}(\alpha_B, t)}{\boldsymbol{q}(\alpha_B, t)},$$

where $K_{(H_B,L_B)}^{(H_R,L_R)}(u) := \frac{u(H_R)-u(H_B)}{u(L_B)-u(L_R)}$ measures the Agent's risk attitude (see Appendix B.2), and $\boldsymbol{q}(\alpha_B, t) := \boldsymbol{p}(\alpha_B, t)p_S^B + (1 - \boldsymbol{p}(\alpha_B, t))p_F^B$ is the total probability of getting the high prize, which increases with a subject's confidence.

Therefore, a sufficiently risk-seeking Agent will always choose $\mathcal{L}_R$.[15] Similarly, a sufficiently risk-averse Agent will always choose $\mathcal{L}_B$.[16] Since the right-hand side is a decreasing function of $\boldsymbol{p}(\alpha_B, t)$, for intermediate values of $K_{(H_B,L_B)}^{(H_R,L_R)}(u)$, the more confident the Agent is, i.e., the higher $\boldsymbol{p}(\alpha_B, t)$, the more prone she is to choose $\mathcal{L}_R$ from $\{\mathcal{L}_R, \mathcal{L}_B\}$.

Manipulating the Time Allocation Formula, we get that the amount of time $t_{\mathcal{L}_R}$ allocated to $\mathcal{L}_R$ satisfies

$$\frac{\boldsymbol{p}'(T - t_{\mathcal{L}_R}, \alpha_B)}{\boldsymbol{p}'(t_{\mathcal{L}_R}, \alpha_B)} = \frac{u(H_R) - u(L_R)}{u(H_B) - u(L_B)}.$$

Since the left-hand side is increasing in $t_{\mathcal{L}_R}$ and the right-hand side is greater than 1, if we assume that u is strictly increasing, we have that $t_{\mathcal{L}_C} > \frac{T}{2}$. That is, the Agent should always allocate more time to $\mathcal{L}_R$. Moreover, $t_{\mathcal{L}_R}$ should increase with $u(H_R) - u(L_R)$.

We use two risk contracts in the experiment, $\mathcal{L}_{R_1}$ and $\mathcal{L}_{R_2}$ in Table 2. The model

[15] This will happen whenever $K_{(H_B,L_B)}^{(H_R,L_R)}(u) \geqslant p_S^B / p_F^B$

[16] This will happen if $K_{(H_B,L_B)}^{(H_R,L_R)}(u) < \frac{p_{N,B}}{p_{S,B}}$.

predicts that subjects should choose $\mathcal{L}_{R_1}$ from the menu $\{\mathcal{L}_B, \mathcal{L}_{R_1}\}$ if and only if

$$K^{(10,2)}_{(8,4)}(u) \geqslant \frac{1 - \boldsymbol{q}(0.5, 60)}{\boldsymbol{q}(0.5, 60)},$$

and choose $\mathcal{L}_{R_2}$ from the menu $\{\mathcal{L}_B, \mathcal{L}_{R_2}\}$ if and only if

$$K^{(12,0)}_{(8,4)}(u) \geqslant \frac{1 - \boldsymbol{q}(0.5, 60)}{\boldsymbol{q}(0.5, 60)}.$$

The model also predicts that subjects should always allocate more time to $\mathcal{L}_{R_i}$ than to $\mathcal{L}_B$ for each $i \in \{1, 2\}$, i.e., $t_{\mathcal{L}_{R_i}} > 60$. Finally, the model predicts that subjects should allocate more time to $\mathcal{L}_{R_2}$ (relative to $\mathcal{L}_B$) than to $\mathcal{L}_{R_1}$ (relative to $\mathcal{L}_B$).

A.3 Dominated Contracts

A dominated contract $\mathcal{L}_D$ relative to $\mathcal{L}_B$ is one in which $H_D = H_B$, $L_D = L_B$, $\alpha_D = \alpha_B$,

$$p^D_S < p^B_S \text{ and } p^D_F < p^B_F.$$

Manipulating the Choice Formula, we get that $\mathcal{L}_D$ is chosen from the menu $\{\mathcal{L}_B, \mathcal{L}_D\}$ if and only if

$$\frac{\boldsymbol{p}(\alpha_B, t)}{1 - \boldsymbol{p}(\alpha_B, t)} \leqslant \frac{p^B_F - p^D_F}{p^D_S - p^B_S}.$$

Since the left-hand side is always positive $\frac{\boldsymbol{p}(\alpha_B,t)}{1-\boldsymbol{p}(\alpha_B,t)}$ and the right-hand side is always negative, the Agent should only choose $\mathcal{L}_B$ from the menu $\{\mathcal{L}_B, \mathcal{L}_D\}$.

Manipulating the Time Allocation Formula, we get that the amount of time $t_{\mathcal{L}_D}$ allocated to $\mathcal{L}_D$ satisfies

$$\frac{\boldsymbol{p}'(T - t_{\mathcal{L}_D}, \alpha_B)}{\boldsymbol{p}'(t_{\mathcal{L}_D}, \alpha_B)} = \frac{p^D_S - p^D_F}{p^B_S - p^B_F}$$

Since the left-hand side is increasing in $t_{\mathcal{L}_D}$, if $\frac{p^D_S - p^D_F}{p^B_S - p^B_F} > 1$, then $t_{\mathcal{L}_D} > \frac{T}{2}$. If $\frac{p^D_S - p^D_F}{p^B_S - p^B_F} < 1$, then $t_{\mathcal{L}_D} < \frac{T}{2}$. Moreover, the amount of time allocated to $\mathcal{L}_D$ is increasing in $p^D_S - p^D_F$.

We use two dominated contracts in the experiment, namely $\mathcal{L}_{D_1}$ and $\mathcal{L}_{D_2}$ in Table 2. The model predicts that subjects should always choose $\mathcal{L}_B$ over $\mathcal{L}_{D_1}$ and $\mathcal{L}_{D_2}$. The model also predicts that subjects should allocate more time to $\mathcal{L}_B$ than to $\mathcal{L}_{D_1}$, i.e., $t_{\mathcal{L}_B} > 60$, but more time to $\mathcal{L}_{D_2}$ than to $\mathcal{L}_B$, i.e., $t_{\mathcal{L}_B} < 60$. Finally, given that $p^{D_2}_S - p^{D_2}_F > p^{D_1}_S - p^{D_1}_F$, the model predicts that subjects should allocate more time to $\mathcal{L}_{D_2}$ (relative to $\mathcal{L}_B$) than to $\mathcal{L}_{D_1}$ (relative to $\mathcal{L}_B$), i.e., $t_{\mathcal{L}_{D_2}} > t_{\mathcal{L}_{D_1}}$.

A.4 Ambiguous Contracts

An ambiguous contract $\mathcal{L}_A$ relative to $\mathcal{L}_B$ is one in which $H_A = H_S$, $L_A = L_S$, $p_S^A = p_S^B$, $p_F^A = p_F^B$, but, for some $\varepsilon > 0$,

$$\alpha_A \in [\alpha_B - \varepsilon, \alpha_B + \varepsilon]$$

We postulate that the Agent evaluates $\mathcal{L}_A$ in two steps. She first resolves the ambiguity with respect to α_A, i.e., she decides which contract among those in the set $\{\mathcal{L}_x : x \in [\alpha - \varepsilon, \alpha + \varepsilon]\}$ she is facing, and then evaluates the resulting contract using (1).

She resolves the ambiguity with respect to α_A by substituting it by

$$\alpha_\varepsilon := \gamma_\varepsilon(\alpha_B + \varepsilon) + (1 - \gamma_\varepsilon)(\alpha_B - \varepsilon),$$

for some weight γ_ε, which measures the agent's ambiguity attitude.

Manipulating the Choice Formula, we get that $\mathcal{L}_A$ is chosen from the menu $\{\mathcal{L}_B, \mathcal{L}_A\}$ if and only if $\boldsymbol{p}(\alpha_\varepsilon, t) \geqslant \boldsymbol{p}(\alpha_B, t)$. If we assume that $p(\cdot, t)$ is strictly increasing, we have that $\mathcal{L}_A$ is chosen from $\{\mathcal{L}_A, \mathcal{L}_B\}$ if and only if $\alpha_\varepsilon \geqslant \alpha_B$. Or, equivalently, if

$$\gamma_\varepsilon \geqslant 1/2.$$

Therefore, $\mathcal{L}_A$ is chosen from $\{\mathcal{L}_A, \mathcal{L}_B\}$ if and only if the Agent is ambiguity seeking (see Appendix B.2).

Manipulating the Time Allocation Formula, we get that the amount of time allocated to $\mathcal{L}_A$ satisfies

$$\frac{\boldsymbol{p}'(T - t_{\mathcal{L}_A}, \alpha_B)}{\boldsymbol{p}'(t_{\mathcal{L}_A}, \alpha_\varepsilon)} = 1$$

Therefore, the predictions about time allocation rely on the assumptions about the cross-derivative of the belief function with respect to time and the completion rate. We refrain from making an assumption about this cross-derivative and, hence, from making predictions about time allocation for ambiguous contracts.

In the experiment, we use two ambiguous contracts, namely $\mathcal{L}_{A_1}$ and $\mathcal{L}_{A_2}$ (see Table 2). The model predicts that subjects should choose $\mathcal{L}_{A_i}$ from the menu $\{\mathcal{L}_B, \mathcal{L}_{A_i}\}$ if and only if $\alpha_{\varepsilon_i} \geqslant 0.5$.

A.5 The Model's Predictions in the Experiment

Tables 9 to 12 summarize the model's predictions about choice and time allocation in each pair of contracts in the experiment.

Table 9: Confidence contracts - Predictions

	$(\mathcal{L}_B, \mathcal{L}_{C_1})$	$(\mathcal{L}_B, \mathcal{L}_{C_2})$
Choice C$_i$	$p(0.5, 60) > 0.5$ iff $\{\mathcal{L}_{C_1}\}$ $p(0.5, 60) = 0.5$ iff $\{\mathcal{L}_B, \mathcal{L}_{C_1}\}$ $p(0.5, 60) < 0.5$ iff $\{\mathcal{L}_B\}$	$p(0.5, 60) > 0.5$ iff $\{\mathcal{L}_{C_2}\}$ $p(0.5, 60) = 0.5$ iff $\{\mathcal{L}_B, \mathcal{L}_{C_2}\}$ $p(0.5, 60) < 0.5$ iff $\{\mathcal{L}_B\}$
Time C$_i$	$t_{\mathcal{L}_{C_1}} > t_{\mathcal{L}_B}$	$t_{\mathcal{L}_{C_2}} > t_{\mathcal{L}_B}$
	$t_{\mathcal{L}_{C_2}} > t_{\mathcal{L}_{C_1}}$	

*Assumption(s):

(i) Successful elicitation of $p(0.5, 60)$

Table 10: Risk contracts - Predictions

	$(\mathcal{L}_B, \mathcal{L}_{R_1})$	$(\mathcal{L}_B, \mathcal{L}_{R_2})$
Choice R$_i$	$K^{(8,2)}_{(6,4)}(u) > \frac{1-\boldsymbol{q}(0.5,60)}{\boldsymbol{q}(0.5,60)}$, iff $\{\mathcal{L}_{R_1}\}$ $K^{(8,2)}_{(6,4)}(u) = \frac{1-\boldsymbol{q}(0.5,60)}{\boldsymbol{q}(0.5,60)}$ iff $\{\mathcal{L}_B, \mathcal{L}_{R_1}\}$ $K^{(8,2)}_{(6,4)}(u) < \frac{1-\boldsymbol{q}(0.5,60)}{\boldsymbol{q}(0.5,60)}$ iff $\{\mathcal{L}_B\}$	$K^{(10,0)}_{(6,4)}(u) > \frac{1-\boldsymbol{q}(0.5,60)}{\boldsymbol{q}(0.5,60)}$, iff $\{\mathcal{L}_{R_2}\}$ $K^{(10,0)}_{(6,4)}(u) = \frac{1-\boldsymbol{q}(0.5,60)}{\boldsymbol{q}(0.5,60)}$ iff $\{\mathcal{L}_B, \mathcal{L}_{R_2}\}$ $K^{(10,0)}_{(6,4)}(u) < \frac{1-\boldsymbol{q}(0.5,60)}{\boldsymbol{q}(0.5,60)}$ iff $\{\mathcal{L}_B\}$
Time R$_i$	$t_{\mathcal{L}_{R_1}} > t_{\mathcal{L}_B}$	$t_{\mathcal{L}_{R_2}} > t_{\mathcal{L}_B}$
	$t_{\mathcal{L}_{R_2}} > t_{\mathcal{L}_{R_1}}$	

*Assumption(s):

(i) Successful elicitation of $p(0.5, 60)$

(ii) For $(\mathcal{L}_B, \mathcal{L}_{R_1})$, the elicited u must satisfy $u(10) \geqslant u(8) \geqslant u(4) > u(2)$

(iii) For $(\mathcal{L}_B, \mathcal{L}_{R_2})$, the elicited u must satisfy $1 \geqslant u(8) \geqslant u(4) > 0$

Table 11: Ambiguity contracts - Predictions

	$(\mathcal{L}_B, \mathcal{L}_{A_1})$	$(\mathcal{L}_B, \mathcal{L}_{A_2})$
Choice A$_i^*$	$\alpha_{[0.4,0.6]} > 0.5$, iff $\{\mathcal{L}_{A_1}\}$ $\alpha_{[0.4,0.6]} = 0.5$ iff $\{\mathcal{L}_B, \mathcal{L}_{A_1}\}$ $\alpha_{[0.4,0.6]} < 0.5$ iff $\{\mathcal{L}_B\}$	$\alpha_{[0,1]} > 0.5$, iff $\{\mathcal{L}_{A_2}\}$ $\alpha_{[0,1]} = 0.5$ iff $\{\mathcal{L}_B, \mathcal{L}_{A_2}\}$ $\alpha_{[0,1]} < 0.5$ iff $\{\mathcal{L}_B\}$
Time A$_i$	—	—
	—	

*Assumption(s):

(i) Successful elicitation of $\boldsymbol{p}(x, 1)$, for $x \in \{0.2, 0.5, 0.8\}$

(ii) $\boldsymbol{p}(0.8, 60) > \boldsymbol{p}(0.5, 60) > \boldsymbol{p}(0.2, 60)$

Table 12: Dominated contracts - Predictions

<table>
<tr><td></td><td>$(\mathcal{L}_B, \mathcal{L}_{D_1})$</td><td>$(\mathcal{L}_B, \mathcal{L}_{D_2})$</td></tr>
<tr><td>Choice D$_i$</td><td>$\{\mathcal{L}_B\}$</td><td>$\{\mathcal{L}_B\}$</td></tr>
<tr><td rowspan="2">Time D$_i$</td><td>$t_{\mathcal{L}_{D_1}} < t_{\mathcal{L}_B}$</td><td>$t_{\mathcal{L}_{D_2}} > t_{\mathcal{L}_B}$</td></tr>
<tr><td colspan="2">$t_{\mathcal{L}_{D_2}} > t_{\mathcal{L}_{D_1}}$</td></tr>
</table>

A.6 Robustness of Time Predictions

The model's time predictions on confidence and risk contracts would still hold for different preferences over contracts. In fact, assume that subjects evaluate contracts using the formula

$$U(\mathcal{L}|t) = \rho(\alpha, t)V(L_{\text{Success}}) + (1 - \rho(\alpha, t))V(L_{\text{Failure}}),$$

where $\rho(\alpha, t) : [0, 1] \times \mathbb{R}_+ \to [0, 1]$ is a decision weight, V a functional over lotteries, and L_{Success} and L_{Failure} the lotteries one gets if one succeeds and fails in the task associated with $\mathcal{L}$. Assume that $\rho(\alpha, \cdot)$ is increasing, concave, and continuously differentiable. Taking first-order conditions of the time allocation problem

$$\max_{t\in[0,T]} \left[U(\mathcal{L}_B|t) + U(\mathcal{L}_X|T - t)\right]. \tag{6}$$

and assuming that $\alpha_1 = \alpha_2 =: \alpha$, we get to

$$\frac{\rho'(\alpha, T - t_{\mathcal{L}_B})}{\rho'(\alpha, t_{\mathcal{L}_B})} = \frac{V(L^B_{\text{Success}}) - V(L^B_{\text{Failure}})}{V(L^X_{\text{Success}}) - V(L^X_{\text{Failure}})}.$$

Assume first that we have, for any lottery $(p, H; 1 - p, L)$, we can write

$$V((p, H; 1 - p, L)) = f(p, H) + f(1 - p, L),$$

for some super-modular function $f : [0, 1] \times \mathbb{R} \to \mathbb{R}$. That is, f satisfies the following property: for every $p_1, p_2 \in [0, 1]$ and $x_1, x_2 \in \mathbb{R}$,

$$f(\max\{p_1, p_2\}, \max\{x_1, x_2\}) - f(p_1, x_1) \geqslant f(p_2, x_2) - f(\min\{p_1, p_2\}, \min\{x_1, x_2\}),$$

and this inequality is strict whenever (p_1, x_1) and (p_2, x_2) are strictly ranked by the component-wise ordering of $\mathbb{R}^2$.

Recall that in the baseline, confidence, and risk contracts, the probabilities of getting the high prize if one succeeds and fails sum up to 1. Therefore,

$$\frac{V(L^B_{\text{Success}})-V(L^B_{\text{Failure}})}{V(L^C_{\text{Success}})-V(L^C_{\text{Failure}})}=\frac{[f(p^B_S,H)-f(p^B_S,L)]-[f(1-p^B_S,H)-f(1-p^B_S,L)]}{[f(p^C_S,H)-f(p^C_S,L)]-[f(1-p^C_S,H)-f(1-p^C_S,L)]},$$

and, for risk contracts,

$$\frac{V(L^B_{\text{Success}})-V(L^B_{\text{Failure}})}{V(L^R_{\text{Success}})-V(L^R_{\text{Failure}})}=\frac{[f(p_S,H_B)-f(1-p_S,H_B)]-[f(p_S,L_B)-f(1-p_S,L_B)]}{[f(p_S,H_R)-f(1-p_S,H_R)]-[f(p_S,L_R)-f(1-p_S,L_R)]}.$$

Since f is super-modular,

$$\max\left\{\frac{V(L^B_{\text{Success}})-V(L^B_{\text{Failure}})}{V(L^C_{\text{Success}})-V(L^C_{\text{Failure}})},\frac{V(L^B_{\text{Success}})-V(L^B_{\text{Failure}})}{V(L^R_{\text{Success}})-V(L^R_{\text{Failure}})}\right\}<1,$$

and, hence, $t_{\mathcal{L}_B} < T/2$.

As an illustration, assume that $f(p,x) = w(p)u(x)$, where $w : [0,1] \to [0,1]$ and $u : \mathbb{R} \to \mathbb{R}$ are strictly increasing. We can interpret w as a probability weighting function. Then, f is super-modular; hence, time predictions about risk and confidence contracts are robust to probability weighting.

Time predictions about confidence contracts are even more robust because they still hold, provided only that V is (strictly) increasing with respect to first-order stochastic dominance. In fact, since

$$L^C_{\text{Success}} \succ_{FOSD} L^B_{\text{Success}} \succ_{FOSD} L^B_{\text{Failure}} \succ_{FOSD} L^c_{\text{Failure}},$$

where $\succsim_{FOSD}$ is the ranking of lotteries according to first-order stochastic dominance, we get that

$$\frac{V(L^B_{\text{Success}})-V(L^B_{\text{Failure}})}{V(L^C_{\text{Success}})-V(L^C_{\text{Failure}})}<1,$$

and, hence, $t_{\mathcal{L}_B} < T/2$.

B Further details on the experimental design

B.1 Maze selection

We employed an algorithm to generate what are known as "perfect" mazes. The algorithm's key parameters are width, height, Compactness Factor (CF), and Dead End Index (DEI). The width and height parameters dictate the dimensions of the maze by specifying the number of cells it comprises. Meanwhile, the CF serves as a metric for assessing maze compactness. A high CF value indicates a compact structure in that the solution path of the maze is short relative to the overall maze size. In contrast, a low CF value indicates a less compact arrangement, with the solution path traversing a larger portion of the maze. The DEI quantifies the distribution of dead ends in a maze. A maze with a high DEI features a dispersed arrangement of lengthy dead ends, whereas a maze with a low DEI value exhibits a concentrated distribution of shorter dead ends.

A separate group of subjects played many mazes of width and height equal to 20 but with varying CF and DEI. These subjects had a 60-second deadline to solve each maze and were paid for the total number of mazes they solved. We used these subjects' performances to find mazes with the completion rates we needed for our experiment. That is, if a contract states a completion rate of 50%, the contract would have a maze that 50% of these subjects solved in, at most, 60 seconds.

Figure 7 presents a sample screen for completing a maze. The subjects had to navigate the blue square to the green dot using the keyboard's up, down, left, and right arrow keys.

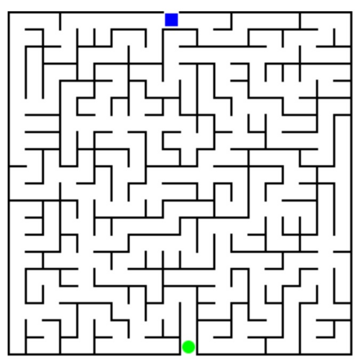

Figure 7: Sample screen of a maze

B.2 Details of Part III: The Characteristics and their Measurement

In Part III of the experiment, we elicit the characteristics of subjects needed to test the predictions of our model and some other characteristics of our subjects.

B.3 Task 1: Confidence Attitude

The agent's belief in her probability of success in solving the maze associated with a contract, i.e., the function $\boldsymbol{p}$, plays a crucial role in our analysis. It captures how confident a subject is, as the following definition formalizes.

Definition 4 *Given $t \geqslant 0$ and a completion rate α, we say that an Agent is* ***over-confident*** *at (α, t) if $\boldsymbol{p}(\alpha, t) > \alpha$;* ***confident-neutral*** *if $\boldsymbol{p}(\alpha, t) = \alpha$; and* ***under-confident*** *if $\boldsymbol{p}(\alpha, t) < \alpha$.*

Given $(\alpha, t) \in [0,1] \times \mathbb{R}_+$, we can elicit $\boldsymbol{p}(\alpha, t)$ as follows. Consider the contract $\mathcal{L} = (H, L, 1, 0, \alpha, t)$. The value of this contract is

$$U(\mathcal{L}) = \boldsymbol{p}(\alpha, t)u(H) + (1 - \boldsymbol{p}(\alpha, t))\, u(L).$$

For each $p \in [0, 1]$, define the contract $\mathcal{L}_p$ that pays the lottery $L_p := (p, H; 1 - p, L)$ for sure and note that, according to the model,

$$U(\mathcal{L}_p) = pu(H) + (1 - p)u(L).$$

Assuming that u is strictly increasing, there exists a unique value of $p^\star(\alpha, t) \in [0, 1]$ such that $U(\mathcal{L}) = U(\mathcal{L}_{p^\star})$. We then have that $U(\mathcal{L}_p) \geqslant U(\mathcal{L})$ if and only if $p \geqslant p^\star(\alpha, t)$.

In Task 1, we elicit $\boldsymbol{p}(0.2, 60)$, $\boldsymbol{p}(0.5, 60)$, and $\boldsymbol{p}(0.8, 60)$ through a multiple price list. More specifically, for each of these probabilities, we use a multiple price list with 11 lines, in which on every line $\ell \in \{0, \ldots, 10\}$, we ask the subject to choose between the $\mathcal{L}$ and the contract $\mathcal{L}_{0.1\ell}$. If at line $\ell^\star \in \{0, \ldots, 10\}$, the subject switches from the choice of $\mathcal{L}$ to the choice of $\mathcal{L}_{0.1\ell^\star}$, then we know that

$$p(\alpha, t) \in (0.1(\ell^\star - 1), 0.1\ell^\star].$$

B.4 Task 2: Ambiguity Attitude

Recall that given an ambiguous contract $\mathcal{L}_A$ (relative to $\mathcal{L}_B$), where $\alpha_A \in [\alpha_B - \varepsilon, \alpha_B + \varepsilon]$, we assume that the Agent first resolves the ambiguity with respect to α_A by setting it equal to

$$\alpha_\varepsilon := \gamma_\varepsilon(\alpha_A + \varepsilon) + (1 - \gamma_\varepsilon)(\alpha_A - \varepsilon),$$

for some weight γ_ε. We interpret γ_ε as the agent's attitude towards ambiguity and say that she is *ambiguity-averse* if $\gamma_\varepsilon < \frac{1}{2}$; *ambiguity-neutral* if $\gamma_\varepsilon = \frac{1}{2}$; and *ambiguity-loving* if $\gamma_\varepsilon > \frac{1}{2}$.

In Task 2, we use a Multiple Price List to elicit bounds for $\alpha_{0.1}$ and $\alpha_{0.5}$ in the same way we did for $\boldsymbol{p}(\alpha, t)$ in Task 1.

B.5 Task 3: Risk Attitude

In our model, the curvature of the agent's (Bernoulli) utility function u captures her risk attitude. Therefore, the decision-maker is *risk-averse* if and only if u is concave; *risk-neutral* if and only if u is linear; and *risk-loving* if and only if u is convex.

From now on, we focus on a risk-averse agent, but what we say can be easily adapted to a risk-neutral or risk-seeking agent. Fix $H_1, H_2, L_1, L_2 \in \mathbb{R}$ with $H_2 > H_1 > L_1 > L_2$ and $H_2 - H_1 = L_1 - L_2$. Define

$$K_{(H_1,L_1)}^{(H_2,L_2)}(u) \coloneqq \frac{u(H_2) - u(H_1)}{u(L_1) - u(L_2)}.$$

If u is strictly increasing, this is well-defined, and we have that $K_{(H_1,L_1)}^{(H_2,L_2)}(u) \leqslant 1$ whenever u is concave. Moreover, given any strictly increasing concave function φ, we have that[17]

$$K_{(H_1,L_1)}^{(H_2,L_2)}(\varphi \circ u) = \frac{\varphi(u(H_2)) - \varphi(u(H_1))}{\varphi(u(L_1)) - \varphi(u(L_2))} \leqslant \frac{u(H_2) - u(H_1)}{u(L_1) - u(L_2)} = K_{(H_1,L_1)}^{(H_2,L_2)}(u).$$

Hence, the more concave u is,[18] the smaller $K_{(H_1,L_1)}^{(H_2,L_2)}(u)$ will be. Hence, $K_{(H_1,L_1)}^{(H_2,L_2)}(u)$ captures the Agent's risk attitude.

We can then elicit subjects' risk attitude by eliciting u and calculating $K_{(H_1,L_1)}^{(H_2,L_2)}(u)$. To elicit u, we proceed as follows. Fix two prizes $\bar{L}, \bar{H} \in \mathbb{R}$ with $\bar{L} < \bar{H}$, and set $u(\bar{L}) = 0$ and $u(\bar{H}) = 1$. To elicit $x \in (\bar{L}, \bar{H})$, notice that there exists a unique $p_x \in (0,1)$ such that

$$u(x) = U(x) = U(L_x) = p_x u(\bar{H}) + (1 - p_x) u(\bar{L}) = p_x,$$

where $L_x = (p_x, \bar{H}; 1 - p_x, \bar{L})$ Therefore, to elicit $u(x)$, we need to elicit the probability the probability p_x that would make her indifferent between the contract $(p_x, \bar{H}; 1 - p_x, \bar{L})$ and receiving x for sure. To make the elicitation of p_x incentive compatible, we use the BDM mechanism (Becker et al. (1964)).

[17] By the concavity of φ, whenever $H_2 > H_1 > L_1 > L_2$, we have that

$$\frac{\varphi(u(H_2)) - \varphi(u(H_1))}{u(H_2) - u(H_1)} \leqslant \frac{\varphi(u(H_1)) - \varphi(u(L_1))}{u(H_1) - u(L_1)} \leqslant \frac{\varphi(u(L_1)) - \varphi(u(L_2))}{u(L_1) - u(L_2)}.$$

[18] Given two strictly increasing and concave functions $u_1, u_2 : \mathbb{R}^n \to \mathbb{R}$, we say that u_1 is *more concave than* u_2 if there exists a concave $\varphi : \mathbb{R} \to \mathbb{R}$ such that $u_1 = \varphi \circ u_2$.

B.6 Tasks 4 to 8: curvature, risk, over-placement

Task 4 provides information about the curvature of the function $p(0.5, \cdot)$. This task is a modified version of the procedure introduced in Avoyan and Romagnoli (2023). Subjects were told they would have 3 minutes to solve a maze with a completion rate of 50% but could decide how they wanted to be compensated.

They could choose between three payment options. In Option A, the subject would earn \$10 if she solved the maze in at most 2 minutes and \$0 otherwise. In Option B, with a 50% probability, the subject would earn \$10 if she has successfully solved the maze in, at most, 1 minute and \$0 otherwise. If the coin lands on Tails, the subject would earn \$10 if they solved the maze in 3 minutes and \$0 otherwise. In Option C, the subject declared to be indifferent between Options A and B. By choosing Option A, they reveal that $p(0.5, \cdot)$ is concave. By choosing Option B, they reveal that $p(0.5, \cdot)$ is convex. By choosing Option C, they reveal that $p(0.5, \cdot)$ is linear.[19]

Tasks 5 was an alternative risk aversion elicitation task using a price-list procedure from Holt and Laury (2002). *Task 6* measures subjects over precision (Moore and Healy (2008)), which elicits a subject's belief about how sure she is about the truth of a given statement. More specifically, subjects were asked how far the moon was from the Earth. They were also asked to what percentage of subjects their answer was closer to the truth than. For example, if they answered 75% to the second question, they believed their answer was closer to the actual distance than 75% of the other subjects. They were rewarded for the accuracy of both guesses.

Tasks 7 and 8 were used by Agranov and Ortoleva (2017) to elicit subjects' attitudes towards compound lotteries. In *Task 7*, subjects are asked to allocate 100 tokens between a safe and risky investment. The risky investment had a 50 percent chance of success and returned two and a half times the investment if successful and nothing otherwise. *Task 8* repeats Task 7, but the risky investment was a compound lottery, which, when reduced, was equivalent to the risky investment in Task 7. Subjects with neither aversion nor attraction to compound lotteries should invest the same number of tokens in both tasks. In contrast, subjects who dislike (like) compound lotteries will invest less (more) in Task 8 (see Agranov and Ortoleva (2017)).

[19] This is analogous to eliciting risk preference by offering a sure payment versus a convex combination of payments whose mean is the sure payment.