Elicited Time Preferences and Behavior in Long-Run Projects

AKIN, ZAFER and YAVAS, ABDULLAH

18 April 2023

Elicited Time Preferences and Behavior in Long-Run Projects

ZAFER AKIN* and ABDULLAH YAVAŞ‡

April 18, 2023

Abstract

We study whether and how the experimentally elicited time preferences of subjects are associated with their behavior in long-run projects. First, risk and time preferences are elicited from time-dated monetary choices to estimate a general discount and utility function at an individual level, then subjects work on a longitudinal project that requires effort in multiple periods. We find that present bias in the form of a fixed cost or variable cost (quasi-hyperbolic discounting) is not supported by monetary choices. Analyses of allocation patterns of work reveal that the estimated utility and discounting models are not compatible with the observed allocations. We find evidence of both present and future bias, although the former is more prevalent and severe, and subjects exhibit naivete in their choice reversals. Furthermore, discount rate and present bias parameters estimated based on monetary choices have predictive power on how work is allocated in the long-run project.

Keywords: time preferences, quasi-hyperbolic discounting, experiment, long-run project

JEL codes: C91, D91

1 Introduction

Most of us regularly undertake *long-run projects* that only provide a payoff upon completion within a specific time frame. For instance, an architect creating a design, a professor preparing a referee report, or a student working on a presentation or pursuing a certification may all be examples of such projects. The challenge is to allocate time and effort *efficiently* to complete the project in a

*Corresponding author at: Department of Decision Sciences and Economics, American University in Dubai, P.O. Box 28282, UAE. Tel.: +971 4 318 3331. Email: zakin@aud.edu. Orcid ID: 0000-0001-5904-0494.

†Real Estate and Urban Land Economics, University of Wisconsin-Madison. Tel.: +1 608 263 7651. Email: ayavas@bus.wisc.edu.

‡Authors thank the Scientific and Technological Council of Turkey (TUBITAK) that provided partial funding for this project. We are grateful to Kalyan Chatterjee, Susanna Esteban, Simon Gaechter, Edward Green, Glenn Harrison, Rosemarie Nagel, and Elisabet Rutström for helpful comments. Fahri Aydos, İbrahim Çiçekli, Tunahan Kökmen, and Aamir Parpia provided excellent research assistance. We also thank the participants of presentations at ASSET Conference, Caltech, and Koç University. Previous versions of this paper circulated under the title "An Experimental Analysis of Time-Inconsistency In Long-Run Projects." Any errors are our own.

way that maximizes payoff given intertemporal preferences and time constraints. Last minute finish ups, scattered completion of parts, requests for deadline extensions, early completion, and incomplete projects for which some effort has already been expended are among the commonly observed outcomes of such projects. Not all these outcomes are ex-ante efficient; for instance, initiating a project, investing time and energy, but then leaving it unfinished. Several factors such as impatience, temptation, uncertainty, risk preferences, and anticipatory feelings may drive intertemporal choices that lead to these outcomes including the seemingly inefficient ones. However, the most commonly employed paradigm when modeling these intertemporal choices is the discounted utility model whose parameters can be elicited by experimental methods. One of the most significant documented behavioral regularities related to discounting is preference reversals. Given the ample evidence on preference reversals both in monetary and real effort domains,[1] it is critical to explore whether intertemporal preferences in one domain carry over into the other.

In this paper, we investigate how players whose risk and time preferences have been elicited behave in a long-run project. The main research question is do the elicited time and risk preferences of people help us explain and predict their time allocation pattern in a project requiring multi-period time investment? If not, which alternative modeling approaches can explain the observed behavior? For the agents with any non-negative and non-increasing (symmetric) discount function (for costs and rewards), it is optimal to delay the costs as much as possible towards the deadline. In order to account for other potential patterns of cost allocation, we have integrated discounting models that feature declining discount rates on intertemporal valuations of future payoffs[2] such as hyperbolic and quasi-hyperbolic discounting that may lead to choice reversals.[3] To do this, we first elicit the risk and time preferences of the subjects with a hybrid method and estimate a general discount function that embeds different specifications (Benhabib, Bisin and Schotter, 2010) and a standard risk parameter. Then, we assigned the subjects a project that required them to invest effort during at least two out of three working periods and analyzed their allocation patterns to determine the consistency between their preferences derived from monetary choices and their preferences demonstrated through the intertemporal allocation of effort.

We find that the support of discounting models obtained from time-dated monetary choices are diverse. General hyperbolic and standard exponential discounting models explain the intertemporal choices of about half of the subjects. Present bias in the form of a fixed cost or variable cost (quasi-hyperbolic discounting) lacks descriptive power in monetary choices. Predictions for time

[1] See Ericson and Laibson (2019) for a detailed discussion.

[2] See Ainslie (1992), Ainslie and Herrnstein (1981), Laibson (1997, 2003), Loewenstein and Prelec (1992), O'Donoghue and Rabin (1999a).

[3] Choice reversals can be explained by both dynamically inconsistent and dynamically consistent preferences. Present-biased preferences -e.g., quasi-hyperbolic discounting, (Laibson, 1997; O'Donoghue and Rabin, 1999a)- are dynamically inconsistent whereas temptation models (e.g., Gul and Pesendorfer, 2001) are dynamically consistent. These reversals can also be the outcome of a specific form of procedural rationality (Rubinstein, 2003), a form of subadditivity (Read, 2001), or multiple self models (Bernheim and Rangel, 2004).

allocations in the long-run project derived from the estimated utility and discounting functions are not compatible with the observed allocations. Analysis of long-run project behavior shows that subjects exhibit time inconsistency, both present and future bias, the former being more prevalent and severe, and there is evidence suggesting that subjects exhibit naivete regarding their preference reversals. Finally, discount rate and present bias parameters estimated based on monetary choices have explanatory power, albeit limited, on how subjects allocate their effort in the long-run project.

There is a large body of research on how to elicit preferences both in Psychology and Economics.[4] *Money Earlier or Later* task (MEL framework, Cohen et al., 2020) that presents time-dated monetary payment options is the most widely used paradigm for estimating time preferences in the laboratory. This framework assumes that choices in MEL experiments and choices over time-dated utility flows are equivalent (Frederick et al., 2002; Andersen et al., 2008; Benhabib, Bisin and Shotter 2010; Halevy 2015).[5] From the time-dated monetary choices in MEL experiments, one can estimate discount functions that determine horizon-dependent utility weights. By using a matching task procedure on money-time pairs, Benhabib, Bisin and Schotter (2010) (from now on BBS) elicit preferences to estimate a general specification of discounting that embeds exponential, hyperbolic, and quasi-hyperbolic discounting frameworks. They also propose a present bias in the form of a fixed cost in their specification. We used a combination of two frequently used designs in MEL experiments, namely, multiple price list (Andersen et al., 2008) and matching task procedure.[6] We follow BBS to estimate the parameters of (eight) different discount functions. We find that no particular discount function stands out among the estimated models. General hyperbola and standard exponential discounting together explain the time discounting behavior of half of the subjects. Quasi-hyperbolic discounting specification is the best model only for 2 (out of 84) subjects. It is a good fit for almost all subjects but most values of present bias parameter, β, are greater than one and not significantly different from one (median β value is greater than one for all models including β, and the average is very close to one). In contrast to BBS, present bias in the form of a fixed cost, b, is not supported by the data. Around one-third of estimated fixed costs are not significantly different from zero, the majority of the values are positive but very small (median values are less than one for all models including b). Our results align with previous research providing evidence of little or no support for present bias for monetary-reward studies (e.g., Augenblick et al., 2015; Dohmen et al., 2012).[7]

[4] See Frederick et al. (2002) for a comprehensive review until 2000s and Cohen et al. (2020) for a review of more recent studies.

[5] For critical work about MEL framework, see Chabris et al. (2008), Augenblick et al. (2015), and Ericson et al. (2015).

[6] For details of these and other procedures, see Freeman et al. (2016) and Cohen et al. (2020).

[7] In their meta-study including 62 studies, Cheung et al. (2021) found evidence for present bias -substantially heterogeneous- with monetary rewards even after correcting publication bias. Imai, Rutter, and Camerer (2021) examined 28 studies that use the convex time budget methodology and found that heterogeneity in the estimates is mainly driven by the type of reward. For monetary-reward studies, the β values are close to one indicating the

Several studies have shown a high correlation between elicited *discount rates*[8] and different field behavior. For example, Bradford et al. (2017) found a significant relationship between elicited discount factors and life outcomes such as overall self-reported health, smoking, drinking, car fuel efficiency, and credit card balance. Chabris et al. (2008) also found a weak but significant correlation between elicited discount rates and field behaviors such as exercise, BMI, and smoking. Golsteyn et al. (2014) found that higher discount rates were associated with lower levels of school performance, health, labor supply, and lifetime income. Additionally, Sutter et al. (2013) showed that experimental measures of time preferences were significant predictors of adolescent behavior, including smoking, drinking, BMI, savings, and school conduct. Experimental measures have also been found to predict other types of behavior, such as overall self-assessed health (Van der Pol 2011), gambling (e.g., Dixon et al., 2003), drug use (e.g., Kirby et al., 1999; Reynolds 2006), alcoholism (e.g., Petry 2001), occupational choices and job attachment (Bonin et al., 2007; Burks et al., 2009), and financial literacy and credit card borrowing (Meier and Sprenger 2010).

A growing body of literature closer to our focus has examined the behavior of individuals in long-term projects. On the theory side, studies show that people with time-inconsistent preferences may put effort into projects they never complete, and they perform worse than time-consistent ones, sophistication not necessarily increases performance but deadlines improve it (Akin, 2012; Herweg and Müller, 2011; O'Donoghue and Rabin, 2008).[9] However, the current theoretical framework is simpler (but still able to capture some findings in the mentioned studies) and only considers allocating a fixed time across limited work periods, without accounting for factors such as deadlines, multiple tasks, partial naivete, learning, and endogenous costs.

On the experimental side, many studies have explored how individuals allocate immediate and future unpleasant tasks to detect inconsistencies. Casari and Dragone (2015) found that the majority of participants completed a 20-minute costly task (listening to an annoying noise) immediately instead of waiting for two or four weeks, which is contrary to the predictions of discounted utility models. This result aligns with previous research showing that people often prefer immediate (small) losses to delayed ones.[10] Additionally, only 20% of participants experienced dynamic choice reversals, and roughly 40% were willing to pay for flexibility. Augenblick et al. (2015) conducted a seven-week longitudinal experiment that found significant present bias in real-effort tasks, but no evidence of significant present bias in monetary rewards. They also showed that subjects identified as present biased chose the commitment device whereas others did not. Augenblick and Rabin (2019) found evidence of present bias in task completion among subjects

absence of present bias.

[8] The evidence regarding the relationship between measured *risk* attitudes and field behavior is mixed. For more details, see Charness et al. (2020), Galizzi et al. (2016), Falk et al. (2018), Lejuez et al. (2002), Lusk and Coble (2005), and Sutter et al. (2013).

[9] For other theoretical papers, see Fischer (1999), Fischer (2001), O'Donoghue and Rabin (2001).

[10] Negative discounting have been observed in different contexts such as small financial losses (Hardisty et al., 2013), electric shocks (Yates and Watts, 1975), health (Chapman, 1996), and some dreadful events (Harris, 2012).

when offered different wages for immediate and future completion across seven weeks. Only 24% of the subjects were found to be sophisticated about their present bias. Bhatia et al. (2021) examined participants' allocation of work and leisure tasks on a 40-minute timeline and found that the initial plans of 55% of the participants demonstrate a preference for improvement (Loewenstein and Prelec, 1993).[11] %76 of the participants who are asked their preference for commitment chose this option. They also found that time discounting cannot fully explain planned behavior, but it can explain some of the participants' changes in plans.

Another strand of literature has focused on using deadlines to address inefficiencies and dynamic inconsistencies. Ariely and Wertenbroch (2002) found that external deadlines are more effective than self-imposed deadlines in enhancing performance. Burger et al. (2011) imposed sub-deadlines on student subjects for a long task and found that interim deadlines led to less task completion and the degree of present-bias was not high. Bisin and Hyndman (2020) studied procrastination among students under different deadline scenarios and found a strong demand for self-imposed deadlines that appeared to be ineffective in increasing task completion rate. They also found evidence for partial naivete when setting deadlines and a relatively widespread present-bias that disappears in the context of repeated similar tasks.[12]

Our study contributes to intertemporal choice research in several ways. We investigate the relationship between risk and time preferences and the completion of costly tasks directly, which has not been previously explored, although some studies have indirectly addressed this topic (e.g. Augenblick et al., 2015). We use a hybrid method for eliciting preferences combining the multiple price list and the matching task procedures that overcomes the limitations of both methods. Our findings support recent studies that suggest time inconsistency is limited in monetary choices (e.g., Andersen et al., 2014). In this sense, ours is yet another study that undermines the MEL frameworks' assumption on the equivalency of monetary choices and choices over time-dated utility flows given the widespread time inconsistencies observed in the field. Differently from previous studies, our study directly tests the applicability of elicited time preferences in another context - behavior in long-run projects. We used the subjects' estimated discount and utility functions to predict their behavior in long-run projects and assessed how different discount models perform. Our finding showing the incompatibility between predicted and actual behavior emphasizes the drawbacks of direct use of discounting models that are estimated from experiments using monetary choices. However, the estimated discount parameters have some explanatory power on how subjects allocate their effort in the long-run project, similar to what some previous studies found (e.g., Bhatia et al., 2021). Our longitudinal real-effort experiment includes a perfectly divisible task and the design is the simplest possible to allow for a multi-period effort allocation (differently

[11]See Barsky et al. (1997) and Angeletos et al. (2001) for the evidence of preference for increasing consumption sequences.

[12]For other types of voluntary or imposed commitments, see Ashraf, Karlan, and Yin (2006), Casari (2009), Duflo, Kremer, and Robinson (2011), Houser et al. (2008), Thaler and Benartzi (2004), and Trope and Fishbach (2000).

from Casari and Dragone, 2015, and Bhatia et al., 2021). Our findings add to the growing body of evidence that time inconsistency is common in real effort tasks, as we observed both present and future biased choices, as well as instances of naive choice reversals. (Ashraf et al., 2006; Augenblick et al., 2015; Augenblick and Rabin, 2019; Casari and Dragone, 2012; Meier and Sprenger, 2010; Takeuchi, 2011).

The rest of the paper is organized as follows. Section 2 provides a general overview of the discounting framework and presents a formal model of behavior in long-run projects based on quasi-hyperbolic discounting. Section 3 outlines the experimental design, while section 4 details the methodology used to analyze the data. Section 5 presents the experiment's results, followed by a discussion in section 6 and a conclusion in section 7.

2 Model

2.1 Discounting and risk behavior

Economic decision-makers face trade-offs between current and future payoffs, which can be analyzed using discounted utility theory. This theory suggests that agents aim to maximize the sum of discounted utilities over time, where the utility function for current payoffs is not discounted, while the utility function for future payoffs is discounted using a decreasing discount function, $d(t)$. Hence, the discounted utility of payoff y earned at time t is expressed as $d(t)u(y)$.

In this paper, we are interested in time-dated monetary payments that are represented as (y, t) where $u(y)$ is the utility of y amount of money in dollar terms and t is the date at which y is earned. We define utility over income and not directly over consumption flows or wealth as in many other studies (BBS and Andersen et al., 2014). The commonly used discount function is exponential discounting where $d(t) = e^{-rt}$ and it is usually written as $d(t) = \delta^t$ where $\delta = e^{-r}$ is the discount factor and r is the discount rate. For the exponential discounting, the discount rate is constant and given by $-\frac{d'(t)}{d(t)} = r = ln(\delta)$. For hyperbolic discounting, $d(t) = \frac{1}{1+rt}$ and the discount rate is decreasing in time and given by $-\frac{d'(t)}{d(t)} = \frac{r}{1+rt}$.

Decreasing discount rate means that the discount function declines at a faster rate in the short run than in the long-run. Quasi-hyperbolic discounting a discrete-time discount function[13] represented as $\{1, \beta\delta, \beta\delta^2, \beta\delta^3, ...\}$ (Phelps and Pollak, 1968; Laibson, 1997) that exhibits decreasing discount rates. This specification reflects a present bias for $\beta < 1$ because it has the feature that there is a sharp drop in the valuation of all future payoffs. BBS introduces a form of present bias called *fixed cost, b,* that is attached to any delayed payoff independent of the amount in which case the discounted utility becomes $u(y)d(t) - b$.

The most commonly used utility function form is the one with constant coefficient of relative risk aversion that can be written as: $u(x) = \frac{x^{1-\sigma}}{1-\sigma}$ where σ is the coefficient of relative risk aversion.

[13] See Pan et al. (2015) and Webb (2016) for extension of quasi-hyperbolic discounting to continuous time.

The widely used method of risk preference elicitation is presenting lotteries to the participants and let them reveal the certainty equivalent of that lottery. Elicitation is through the hybrid method that we use in eliciting time preferences. The elicited values are fitted to the mentioned utility function form to estimate parameter σ. Its negative values refer to risk loving, a value of zero means risk neutrality, and the values between zero and one refer to risk aversion.

2.2 Long-run project

An agent faces a costly long-run project that requires investment and effort in at least two periods to complete. The project cannot be completed in a single period due to time and effort constraints, and completion results in a fixed payoff, v, that is earned one period after completion. Assuming the project must be finished within three periods at most, the agent must allocate their time efficiently among these periods to maximize their net payoff based on their preferences.

The agent's time preferences can take one of two forms: (i) time-consistent exponential discounting, with the sequence of discount factors: $\{1,\ \delta,\ \delta^2,\ \delta^3, ...\}$ or (ii) quasi-hyperbolic discounting with the sequence of discount factors: $\{1,\ \beta\delta,\ \beta\delta^2,\ \beta\delta^3, ...\}$. Here, δ represents the standard time-consistent impatience factor with $\delta \in (0, 1)$ and β represents the time-inconsistent preference for immediate gratification with $\beta \in (0, 1)$. The agent can be either naive or sophisticated. Let $\widehat{\beta}$ be the agent's belief about what his taste for immediate gratification, β, will be in all future periods. For a sophisticated person, $\widehat{\beta} = \beta$ and for a naive person, $\widehat{\beta} = 1$. Note that in this part, we use the term hyperbolic discounting to refer to quasi-hyperbolic discounting and do not allow for partial naivete.

Let C represent the total effort cost that needs to be incurred in order to complete the long-run project[14] and $\bar{c}$ denote the maximum cost that can be incurred in a given period where $C \in (\bar{c}, 2\bar{c}]$. Furthermore, let c_1, c_2, and c_3 denote the cost incurred in periods 1, 2, and 3, respectively, such that $c_1 \leq \bar{c}, c_2 \leq \bar{c}, c_3 \leq \bar{c}$ and $c_1 + c_2 + c_3 \leq C$. If $c_1 + c_2 + c_3 = C$, the fixed payoff v is earned. If $c_1 + c_2 + c_3 < C$, the project fails to be completed, generating a zero payoff.

Timing of the game: In period 0, the agent learns about the project, the allocation restrictions of the cost and the payoff. He then plans how much cost to incur in each period. Depending on the preferences of the agent, the plan may turn out to be time-inconsistent, meaning that the plan and the actual investment behavior may differ.

In period 1, the agent has two choices. One is doing nothing because either postponing is optimal or the project is not worth starting. The other is to incur $0 \leq c_1 \leq \bar{c}$, with the expectation of finishing the project in the future.

In period 2, the agent can either complete the project by investing the remaining cost $c_2 = C - c_1$

[14] The cost is most likely a function of time and effort, $c(t, e)$. However, we assume that it is only a function of time and satisfies $c(t) \geq 0$ (task is not enjoyable), $c'(t) \geq 0$ (constant or increasing) and $c''(t) \geq 0$,(linear or convex) for all $t \geq 0$.

(if $c_1 \geq C - \bar{c}$), choose to do nothing, or invest some but not all of the remaining cost, $c_1 + c_2 < C$. If $c_1 = 0$, he either invests $C - \bar{c} \leq c_2 \leq \bar{c}$ or abandon the project entirely.

In period 3, if $c_1 + c_2 = C$, the agent earns the payoff. If $C - \bar{c} \leq c_1 + c_2 < C$, he can either invest the rest in period 3, complete the project and receive the payoff in period 4, or choose not to finish the project.

Under the assumption of linear cost, our analysis reveals that the set of optimal project allocations is limited for all parameter values. For agents with a non-negative and non-increasing discount function, it is optimal to push the costs as far as possible. However, naives may end up incurring costs without finishing the project, while sophisticates may choose to distribute the costs across two or three periods depending on the specific parameter values. A formal analysis of each agent's behavior is next (see Appendix B for the details of the analysis).

Formal analysis of each type: The investment schedule $(c_1, c_2, c_3; t)$ means that the agent invests c_i in period $i = 1, 2, 3$, and earns the payoff at time t. For example, $(c_1, C - c_1, 0; 3)$ means that the agent invests $C - \bar{c} \leq c_1 \leq \bar{c}$ at $t = 1$, invests the rest at $t = 2$ and gets the payoff at $t = 3$. The analysis assumes risk neutrality.

$$\text{If } c_1 + c_2 + c_3 = C, \text{ then } t = \begin{cases} 3, & \text{if } c_1 + c_2 = C \\ 4, & \text{if } c_1 + c_3 = C,\ c_2 + c_3 = C \text{ or } c_i \neq 0, \text{for all } i = 1, 2, 3 \end{cases}$$

$$\text{If } c_1 + c_2 + c_3 < C, \text{ then we write } (c_1,\ c_2,\ c_3; -)$$

Exponential agent: The exponential agent either does not start the project $(0,\ 0,\ 0; -)$ or finishes it in period 2 $(C - \bar{c},\ \bar{c},\ 0; 3)$. If the project is worthwhile, the agent executes it consistently.

Naive hyperbolic agent: The naive hyperbolic agent either behaves like the exponential agent, or finishes the project in period 3 $(C - \bar{c}, 0, \bar{c}; 4)$, or starts but does not finish it $(C - \bar{c},\ 0,\ 0; -)$ or $(0, C - \bar{c}, 0; -)$. The hyperbolic agent's inability to recognize their preference for instant gratification may prevent them from following their initial plan in the future. Consequently, they may either take a break in period 2 or initiate the project but eventually opt not to complete it.

Sophisticated hyperbolic agent: The sophisticated hyperbolic agent can behave like the exponential agent or finish the project in period 3 $(0,\ C - \bar{c},\ \bar{c}; 4)$. Additionally, he can spread out the total cost over two or three periods if he realizes that he cannot implement $(C - \bar{c},\ \bar{c},\ 0; 3)$. He finds the least costly implementable strategy and implements it. He never initiates a project he won't complete since he accurately forecasts his future behavior.

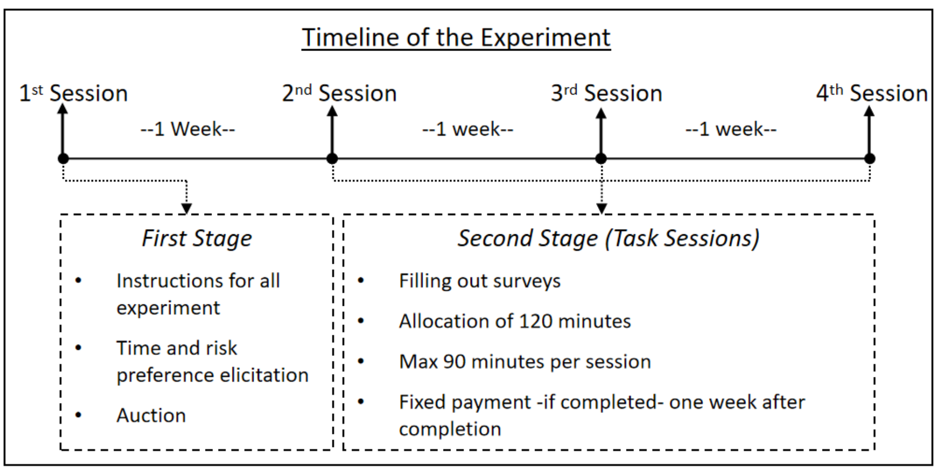
Convext cost specification: The above analysis assumes that the effort cost is linear in time, $C(t) = t$. However, in reality, spending more time on a project may result in decreasing returns to effort, making it more costly. In this case, the cost function becomes convex, where $C(t) = t^{\alpha},\ \alpha > 1$. This implies that it is optimal to allocate costs more evenly than in the linear cost case (see Appendix B for the details).[15]

[15] This model implies that if a subject does not invest in a consecutive manner, they are deemed as naive. If they

The current model generalizes the analysis of O'Donoghue and Rabin (2008) to include three periods. Costs are not homogeneous across periods, unlike Akin (2012). This model will serve as the foundation for the decision problem that participants will face in our experiment.

3 Experimental Design

The experiment was conducted at the experimental laboratory of TOBB University of Economics and Technology, Turkey with 84 participants, including 18 females and 66 males. Divided into four sessions, the experiment had two stages, with the first stage lasting approximately an hour and the second stage lasting two hours. All sessions took place in a computerized environment. During the first session, participants were informed about the experiment's structure and answered questions about their risk and time preferences. The second stage involved "task sessions," where participants completed a long-run task. The experiment timeline is provided below. We emphasized to participants during recruitment that they needed to be available for all four sessions. Although they were not required to stay in the lab for the entire duration of each session, we aimed to reduce exogenous factors that could prevent them from attending any of the sessions, especially in the second stage. The experiment instructions are available in Appendix C.



The first stage of the experiment employed a hybrid method of multiple price list and matching task procedures. The session comprised three parts: eliciting time preference, eliciting risk preference, and conducting the second price auction. In the first two parts, participants were presented

deviate from the specified cost distribution, (first invest $C - \bar{c}$ and then $\bar{c}$), they are considered sophisticated, unless there is an unforeseen external shock. A convex cost structure may result in more even allocations, but it may not be possible to distinguish between sophisticated and naive behavior solely from elicited preferences and behavior. Other factors such as evaluating losses and gains asymmetrically, anticipation utility (Frederick and Loewenstein, 2002), uncertainty, or concave cost structure could also explain different allocation patterns, but these alternatives are not considered in the current theoretical framework.

with multiple price lists containing money-time pairs and lottery/certainty equivalents, respectively, and asked to select their preferred option by clicking on it. The price list consisted of 15 different questions in the format of *option A, option B*, and *indifference.* The hybrid model proposed by the experiment combines the multiple price list method and the matching task procedure, allowing for the estimation of exact parameter values rather than intervals. The last question asked for participants' exact indifference points between options based on the previous 15 questions' answers. This method overcomes the weaknesses of both methods, as the former allows only for interval estimation of parameters, while the latter is cognitively costly and vulnerable to undesirable rule-of-thumb usage that can bias the results (Andersen et al., 2014).

In the first part, each of the 15 questions in the table presents two options using the MEL paradigm. One offers a high amount of money in the future, while the other offers a lower amount of money immediately. The amount offered in the future remains constant for each question, while the amount offered immediately starts at the same value as the future amount and decreases. As expected, almost all subjects switch from choosing the immediate option to the future option at some point, with only 1% of data being incompatible. The final question we ask regarding the time-money pairs is in the following format:

"What amount of money, x Turkish Lira (TL), if paid to you today would make you indifferent to y TL paid to you in t weeks?" ____TL

In the tables, we specify the values of (y, t). A typical question is as follows:

"What amount of money, x TL, if paid to you today would make you indifferent to 300 TL paid to you in 5 weeks?" ____TL

The values of t ranged from 1 to 5 weeks, and the values of y ranged from 50 to 300 Turkish Lira in increments of 50.[16] Therefore, a total of 30 distinct tables were presented to the subjects.

After completing the questions, a table was randomly selected and one of the 16 questions was chosen using a computerized device. Subjects were then paid based on their answer, either immediately or at a later date, using the Becker-DeGroot-Marschak (BDM) incentive mechanism.[17] If the last question was drawn from the chosen table, payment was made as follows: For instance, if subject #1 was asked what amount she would require today to make her indifferent between that amount today and 300 TL to be paid in 5 weeks, and she answered 260 TL, a random number was drawn between 0 and 300 using the computerized randomization device. If the number drawn was smaller than 260, the subject would have to wait for five weeks, after which they would receive 300 TL. If the number drawn was greater than 260, the subject was paid the drawn amount

[16] One US dollar was approximately 1.5 Turkish Lira (TL) at the time of the experiment.

[17] Only seven subjects had a chance to win in a public drawing due to budget constraints (approximately 8% chance of winning). However, since we followed the same method in the risk preference elicitation, the chance of winning was approximately doubled.

immediately. The purpose of this lottery was to incentivize subjects to provide honest responses, thereby preventing random answers.[18]

The second part of the first session is similar to the first and involves eliciting subjects' risk preferences. Each table consists of 15 questions with three options. One is a lottery (same for each table), while the other is a certain amount that reflects the agent's preference over the lottery. The amount starts from a low value and increases up to the higher amount in the lottery. The final option represents indifference. The 16th question asks for the exact amount to make the subject indifferent between the two. It is presented in the following form:

"What amount of money, x TL, if paid to you for sure would make you indifferent to the above lottery?" ____TL

Subjects work on 25 different tables, and each table specifies different lotteries by varying the probabilities and possible amounts. A typical lottery might be:

"0 TL with probability 0.1; 300 TL with probability 0.9"

We increment the probabilities by 0.1 for the first nine tables, and by 0.2 for the remaining lotteries. For tables 10 to 14, we take the indifference amount stated in table 5 and use it as the higher amount (with 0 being the lower amount) for these lotteries. For tables 15 to 19, we use the amount from the previous set of questions as the lower amount (with 300 being the higher amount) for these lotteries. For the final five questions, we use the answers given in tables 12 and 17 as the amounts for the lotteries. Thus, each subject sees a total of 24 different tables and potentially sees different tables after table 9.

After subjects answer all the questions at each table, one of the tables is randomly selected, followed by randomly selecting one of the 16 questions from the chosen table. Based on the subject's response, they will either be paid a certain amount or participate in the lottery.[19] In the case of the last question being drawn from the chosen table, the BDM mechanism is used to determine the payment. Suppose the lottery is "0 TL with probability 0.1; 300 TL with probability 0.9," and the subject is asked what amount they would require today to be indifferent between that amount and the lottery. If the answer is 220 TL, a random number between 0 and 300 is drawn. If the number is smaller than 220, the lottery is played, and if it is greater than 220, the amount drawn is immediately paid to the subject.

In the final part of the first session, subjects participate in a second price auction to determine their cost for completing the two-hour task assigned to them in the second stage of the experiment. They read an information note and take a quiz before filling out a form indicating their plan for

[18]Note that risk preferences were also estimated from lottery responses and controlled for in time preference estimation. We first estimated each individual's risk preference and then imposed it on the time preference estimation.

[19]If one of the first 15 questions is drawn, the agent receives the certain amount if it is chosen. If the lottery is selected, it is played using a randomization device.

completing the task and a bid form indicating the amount of money they are willing to forgo from their fixed earnings of 40 TL for exemption from completing the task. The highest bidder pays the second highest bid, and the winner is exempted from the task and paid according to their indicated plan. The maximum bid in the auction was 39.99, with a minimum of 0 and the second highest bid at 30.5. The average bid was 9 TL. Actual allocations and bids are available in Appendix A.

At the end of the first session, we randomly select 14 individuals to receive payment for the money-time pairs and risk preference elicitation. Payment is given in cash if the subjects are entitled to immediate payment, but if not, they are invited to the laboratory (researcher's office) to receive payment. Reminder emails are sent one day prior to payment day and upcoming task sessions.

In the second part of the experiment, we ask subjects to complete a two-hour task over three consecutive weeks. The task consists of surveys obtained from online resources about the subjects' internet usage, shopping behavior, movie and restaurant preferences, and so on. The task is perfectly divisible and independent of their knowledge, abilities, and experience. The subjects can allocate their two-hour task time among three task sessions scheduled on the same day of the upcoming three consecutive weeks, between 9.30am-11.30am on those specified dates. They are required to attend all three sessions and sign a sign-up sheet to eliminate the impact of traveling time and cost to the experiment site. (See Fernandez-Villaverde and Mukherji (2002) and Augenblick et al. (2015) for similar methods.)

In addition to what they earned from the first stage, subjects were promised a fixed payment of 40 TL if they completed the two-hour task, signed the sign-up sheet at each session, and payment was made one week after task completion. They could work on the task for up to 90 minutes per session. We asked subjects for their task plans before the time preference elicitation questions and at the beginning of each session to observe possible inconsistencies. We administered a quiz after providing instructions, which over 95% of subjects answered correctly, indicating a strong understanding of the experiment's structure and rules. The quiz results were not used to screen participants but to reemphasize the main points of the study.

4 Methodology

The hybrid method we use to elicit risk preferences provides data that can be used to estimate a von Neumann-Morgenstern utility function with a constant coefficient of relative risk aversion. This estimation uses the lotteries and certainty equivalents reported by subjects for each lottery. If the agent's certainty equivalent value is less than the expected value of the lottery (based on a linear utility function), the agent is risk averse, and vice versa. We use the following CRRA utility function in our estimations:

$$u(x) = \frac{x^{1-\sigma}}{1-\sigma}$$

where σ is the coefficient of relative risk aversion (negative values of σ refer to risk loving, value of zero means risk neutrality and values between zero and one refer to risk aversion).[20] By using the data, we estimate the coefficient σ:

$$u(ce) = pu(reward1) + (1-p)u(reward2)$$

$$\frac{(ce)^{(1-\sigma)}}{1-\sigma} = p\frac{(reward1)^{(1-\sigma)}}{1-\sigma} + (1-p)\frac{(reward2)^{(1-\sigma)}}{1-\sigma}$$

For a typical lottery such as "0 TL with probability 0.1; 300 TL with probability 0.9", $p = 0.1$, $reward1 = 0$, $reward2 = 300$ and ce is the certainty equivalent that the subject reports for this lottery.

The econometric method we used to elicit time preferences is very similar to that of BBS. The method involves a four-parameter discounting model as follows:

$$D(y, t; \theta, r, \beta, b) = \beta d(t; \theta, r) - \frac{b}{y}$$

$$\text{where } d(t; \theta, r) = (1 - (1-\theta)rt)^{\frac{1}{1-\theta}}$$

Here, (y, t) is the money-time pair, θ is the curvature of the discount function, β is the quasi-hyperbolic component of present bias, b is the fixed cost component of the present bias, and r is the discount rate when the discounting is exponential though in general, it is a component of discount rate that is independent of time. Exponential, hyperbolic, and quasi-hyperbolic approaches are embedded in this specification. When $\theta = 1$, the discount function becomes exponential discounting:

$$D(t; \theta = 1, r) = e^{-rt}$$

When $\theta = 2$, the discount function becomes hyperbolic discounting:

$$D(t; \theta = 2, r) = \frac{1}{1 + rt}$$

In the first part of the experiment, we determine the indifference points of each subject on money-time pairs using the hybrid method mentioned earlier. This method provides the indifference amount, denoted by x TL, for the specified late payment (y, t) for different combinations of TL amounts and time horizons. Consequently, we obtain 30 observations for each subject $i = 1, 2, ..., 84$ for x where $u(x) = u(y)D(y, t)$, with the functional form of $u(.)$ derived from the risk preference elicitation part.

In the most general form, we assume that the data generating process for each subject i is:

$$u(x) = u(y^i(x, t))D(y^i(x, t), t; \theta^i, r^i, \beta^i, b^i)\varepsilon^i(x, t)$$

[20]For the coefficient of relative risk aversion, r is commonly used but since we will use it to refer to the discount rate, we use σ here instead of r.

where $\varepsilon^i(x,t)$ is assumed to be lognormally distributed[21] and i.i.d. with respect to subjects and questions. The estimation method we used is the non-linear least squares.[22]

For the second stage of the experiment, we employ various statistical techniques to compare the empirical data with the theoretical predictions. The problem of the agent is to solve the following:

$$\max_{\{t_1,t_2\}}\{-u(c(\underbrace{\frac{t_1}{120})^{\alpha}}_{c_1})-D(\frac{7}{365};\theta,r,\beta)u(c(\underbrace{\frac{t_2}{120})^{\alpha}}_{c_2})-D(\frac{14}{365};\theta,r,\beta)u(c(\underbrace{\frac{t_3}{120})^{\alpha}}_{c_3})+D(v,\frac{21}{365};\theta,r,\beta,b)u(v)\}$$

$$\text{subject to } t_1+t_2+t_3=120;\; t_1\leq 90, t_2\leq 90; \alpha\geq 1$$

If $t_1+t_2=120$, the objective function above becomes:

$$-u(c(\underbrace{\frac{t_1}{120})^{\alpha}}_{c_1})-D(\frac{7}{365};\theta,r,\beta,b)u(c(\underbrace{\frac{t_2}{120})^{\alpha}}_{c_2})+D(v,\frac{14}{365};\theta,r,\beta,b)u(v)$$

In the second part of the experiment, we obtained the actual data, denoted by $(t_j^i)^*$ for all periods $j=1,2,3$ and for all subjects $i=1,2,...84$. The best fitting estimated discount function for each subject and the estimated risk preference we obtained from the first part are imposed to the above objective function and a Matlab code that maximizes it is written to estimate the optimal time allocation (predicted values) $\widehat{t_j^i}$ for all $i=1,2,...84$ and for all $j=1,2,3$. Out of the 84 subjects, 64 finished the task sessions and were included in the comparison of their data with the theoretical predictions. We used the following statistics for comparison:

1. We consider the ratio of the sum of squared errors to the maximum error (similar to $1-(R-Square)$). The statistic we calculate is

$$S_1=\frac{\sum_i\sum_j(\widehat{t_j^i}-(t_j^i)^*)^2}{140*90*N}$$

   A closer statistic to *zero* represents a better prediction.[23]

[21] We also estimated the parameters under the assumption that

$$x=y^i(x,t)D(y^i(x,t),t;\theta^i,r^i,\beta^i,b^i)+\varepsilon^i(x,t)$$

where errors, $\varepsilon^i(x,t)$, are assumed to be normally distributed and i.i.d. with respect to subjects and questions. The results did not change significantly.

[22] The estimations are performed both in EViews and Matlab. We are grateful to Prof. Jess Benhabib for providing the Matlab code.

[23] The maximum possible error in predicting the allocations is 180. This can be seen from, for example,

$$(t_j^i)^*=((t_1^i)^*,(t_2^i)^*,(t_3^i)^*)=(0,30,90)\ and\ \widehat{t_j^i}=(\widehat{t_1^i},\widehat{t_2^i},\widehat{t_3^i})=(30,90,0)\ OR$$

$$(t_j^i)^*=((t_1^i)^*,(t_2^i)^*,(t_3^i)^*)=(60,60,0)\ and\ \widehat{t_j^i}=(\widehat{t_1^i},\widehat{t_2^i},\widehat{t_3^i})=(0,30,90)$$

If these are added across the subjects, one obtains $180*N$. The denominator is $140*90*N$ because the maximum deviation for a subject is $(90)^2+(60)^2+(30)^2=140*90$.

2. We then calculate the correlation coefficient indicating the strength and direction of a linear relationship between two random variables. Specifically, the statistics we use is

$$S_2 = correlation(\widehat{t^i_j}, (t^i_j)^*) \ \forall\ j = 1,\ 2,\ 3,$$

where a statistic closer to +1 represents a better prediction.

3. We then compare the first two moments of the actual and predicted data using the following statistics:

$$S_{3a} = \frac{mean(\widehat{t^i_j})}{mean((t^i_j)^*)} \ and\ S_{3b} = \frac{variance(\widehat{t^i_j})}{variance((t^i_j)^*)} \ \forall\ j = 1,\ 2,\ 3.$$

For both of the statistics, a value closer to *one* represents a better prediction.

4. We finally consider the effect size to measure the strength of the relationship between two variables. The most commonly used effect size measure is Cohen's d. It is defined as follows:

$$d = \frac{mean_1 - mean_2}{\sqrt{\frac{(SD_1^2+SD_2^2)}{2}}}$$

where $mean_i$ and SD_i are the mean and standard deviation for group i, for $i = 1, 2$. Here, $mean_1$ and SD_1 are the real allocation mean and standard deviation. The most accepted opinion about the interpretation of the resultant effect size is that 0.2 is indicative of a small effect, 0.5 a medium and 0.8 a large effect size. A larger effect size implies a consistent difference between the two series.

While statistics such as S_1, S_{3a} and d provide valuable information about the predictions, it is more meaningful to compare them with statistics obtained from a random allocation and an equal allocation. If the elicited risk and time preferences are relevant to the context of long-run project completion, we can expect that the statistics for the chosen model will yield better predictions than these two models. In other words, it will have greater predictive power than random and equal allocations.

5 Results

In this section, we present the results of our experiment on risk and time preferences as well as the behavior of participants in the long-run project. We first elicit risk parameters and use them to estimate time preferences. Incorporating agents' risk attitudes leads to more accurate time preference estimates compared to assuming risk neutrality. Finally, we use these estimated parameters to predict each individual's behavior in the long-run project.

5.1 Risk Preference Elicitation

We used the CRRA utility function to estimate the risk parameters of 84 subjects. The analyses are performed in EViews by using the least squares method. There are 24 data points for each subject. The parameters of 22 subjects turn out to be insignificant.[24] Among the significant parameters, 7 subjects were risk-loving, 2 were risk-neutral, and the rest were risk-averse. The average risk parameter was found to be 0.265 (median is 0.221), which is consistent with previous literature (Harrison and Rutström, 2008).[25] Table 1 in Appendix A provides further details.

5.2 Time Preference Elicitation

We analyzed the time preference data from the first part of the experiment using various model specifications described in the methodology section. We employed eight different model specifications. Our first, third, and fourth specifications are the same as those used by BBS. They were specified in the following order:

1. General discount function without any present bias (generalized hyperbola):

$$D(y, t; \theta, r, \beta = 1, b = 0) = (1 - (1 - \theta)rt)^{\frac{1}{1-\theta}}$$

2. The general discount function with quasi-hyperbolic discounting:

$$D(y, t; \theta, r, \beta, b = 0) = \beta(1 - (1 - \theta)rt)^{\frac{1}{1-\theta}}$$

3. The general discount function with present bias in the form of fixed cost:

$$D(y, t; \theta, r, \beta = 1, b) = (1 - (1 - \theta)rt)^{\frac{1}{1-\theta}} - \frac{b}{y}$$

4. The most general discount function:

$$D(y, t; \theta, r, \beta, b) = \beta(1 - (1 - \theta)rt)^{\frac{1}{1-\theta}} - \frac{b}{y}$$

5. Standard exponential discounting function with quasi-hyperbolic discounting:

$$D(y, t; \theta = 1, r, \beta, b = 0) = \beta e^{-rt}$$

6. Standard exponential discounting function with both forms of present bias:

$$D(y, t; \theta = 1, r, \beta, b) = \beta e^{-rt} - \frac{b}{y}$$

[24] We set the level of significance as $\alpha = 0.05$.

[25] Additionally, we found a significant negative correlation between the CRRA and discount factors, which is also consistent with previous research (Anderhub et al., 2001).

7. Standard exponential discounting function with present bias in the form of fixed cost:

$$D(y, t; \theta = 1, r, \beta = 1, b) = e^{-rt} - \frac{b}{y}$$

8. Standard exponential discounting function:

$$D(y, t; \theta = 1, r, \beta = 1, b = 0) = e^{-rt}$$

In the first four specifications, we include the generalized hyperbola. For the last four, the curvature of the discount function is restricted to 1, exponential discounting. Then, present bias is included either in the form of a variable (quasi-hyperbolic) or a fixed cost or both. The criteria we applied to decide whether a model is supported is all coefficients to be significant at 5% level. Although our aim is not to find a discount function satisfying for all/most subjects, we will first evaluate each model and mention how valid it is across subjects, then we evaluate each and choose a winning model for each subject based on different criteria to predict their behavior in the long-run project.

For the first estimation, we find that both the θ and r parameters are significant for 32 out of 84 subjects, while for the remaining subjects, one or both parameters are insignificant. Among the 32 subjects, 4 have θ values that are not significantly different from 2 (hyperbolic discounting), and one has a θ value that is not significantly different from 1 (exponential discounting). For most of the remaining subjects, the θ parameter is not precisely estimated and is consistent with both exponential and hyperbolic discounting. The median value of r is %54 and 69 out of 84 subjects have significant r values. The median r value is the same for the significant ones. 46 values are less than 100%, and 6 values are higher than 300%.

In the second estimation, which includes the present bias parameter in the form of a variable cost, β, the model is only supported for 8 out of 84 subjects. However, for 6 of these 8 subjects, the null hypothesis that $\beta = 1$ cannot be rejected. For the other two subjects, the present bias parameter is significantly greater than 1. For 3 subjects, hyperbolic discounting ($\theta = 2$) and for 2 subjects, exponential discounting ($\theta = 1$) are not rejected. For the remaining subjects, θ is not precisely estimated. The median value for the discount rate r is %45, with 41 out of 84 subjects having significant values, and a median value of %47.

In the third estimation, the present bias parameter in the form of a fixed cost, b, is added to the first model. Contrary to what BBS found in their data, we could not find significant support for the present bias in the form of a fixed cost. It is supported for only 12 subjects. The average value of the fixed cost b is 3.27 TL (excluding an outlier with a value of 24, the average becomes 1.37 TL, with a minimum of -0.88 TL and a maximum of 5.76 TL). The hypothesis of hyperbolic or exponential discounting for all 12 subjects is rejected. The median value for the discount rate r is %22, with 62 out of 84 subjects having significant values, and a median value of %41.

In the fourth model specification, all parameters, $\theta, r, \beta,$ and b, are allowed to vary. However, this model is supported for only 5 out of 84 subjects. Among these 5 subjects, β is greater than 1 for all of them, and for one subject, we cannot reject the hypothesis that $\beta = 1$. The average value of the fixed cost b is around 1.1 TL. Hyperbolic discounting cannot be rejected for only one of these 5 subjects. The median r is %44, and 51 out of 84 subjects have a significant r (the median r is the same for both cases).

Based on the first four models, it can be inferred that the shape of discounting curve (exponential vs. hyperbolic) cannot be accurately estimated using the available data, and for a number of subjects, both exponential and hyperbolic discounting models fit the data equally well. Furthermore, neither the fixed nor variable cost component of present bias is supported by the data. The median discount rate, r, falls between 0.22 and 0.54, which corresponds to an annual discount factor of 0.8 and 0.58, respectively. These values are considered reasonable.

We now move on to the next four model specifications, where we assume an exponential discount function with a fixed curvature of unity ($\theta = 1$). We then add either the quasi-hyperbolic component (β), the fixed cost component (b), both or neither.

The fifth specification assumes exponential discounting with only quasi-hyperbolic component. This model is supported for all but two subjects, for whom convergence could not be achieved. The average value of β is 0.999, with a median of 1.002 and a standard deviation of 0.02. Only 8 out of 82 subjects have significantly different β values from 1, 3 of which are less than 1, and the rest are greater than 1. The median r is %59.

In the sixth specification, we allow both present bias components. This specification is applicable to 50 subjects in our study. However, the average β is 1.014 (with a median of 1.012) and it is less than 1 only for 2 out of 50 subjects. β values are significantly different from 1 for 44 out of 50 subjects. All the fixed cost values are significantly different from zero, with an average and median of 2.49 and 1.29, respectively (average of 1.88 without 3 outliers). Additionally, the minimum and maximum values of fixed cost are -0.95 and 8.88 (without outliers). The median r is %57.

In the seventh specification, we only allow the fixed cost component, b, to change, and we found that it is supported for 37 of the subjects. The average and median values of b are 1.22 and 0.83, respectively, with minimum of -1.3 and maximum of 6.1 (without 2 outliers). The median r is about %51.

Finally, the last specification is the standard exponential discounting model, which is supported for all but one subject, and the median r is %60.

Based on the various model specifications used, we find that the quasi-hyperbolic discounting parameter β is not significantly different from 1 for most subjects, and the fixed cost component of present bias is significant but economically not important. The curvature of discounting (exponential vs. hyperbolic) cannot be precisely estimated with the available data. When restricted to exponential specification, the annual discount rate is estimated to be between 55-60%. This finding is consistent with previous literature that generally does not find significant present bias in monetary rewards (e.g., Augenblick et al. 2015; Andersen et al. 2014; BBS). However, the present study differs from BBS in that present bias in the form of a fixed cost does not find support in the data. While it is not uncommon to find annual discount rates greater than 100% in monetary discounting experiments, the rates we estimated are between 50% and 60%, which suggests reasonable annual discount factors of about 0.6 and 0.55 (close to Coller and Williams, 1999).

By applying certain criteria, we chose the best model for each subject. Firstly, we eliminated any models with insignificant coefficients. Next, for models including the quasi-hyperbolic component, we tested whether $\beta = 1$ and eliminated models where the null hypothesis could not be rejected. Among the remaining models (if there was only one, we used that model), we checked the models in the first four specifications that did not impose any restriction on θ. We also tested whether $\theta = 1$, and if so, we chose the corresponding model in the last four specifications. These criteria allowed us to obtain a unique model for almost all subjects (for three subjects, there was no convergence for all models except the exponential one). Table 2 in Appendix A, shows the chosen discounting models and associated time-preference parameters for all subjects. Among the 84 subjects, model 1, 2, 3, 4, 5, 6, 7, and 8 were selected for 24, 1, 7, 3, 2, 25, 3, and 19 subjects, respectively.

In conclusion, our analysis of data obtained from risk and time preference elicitation using monetary rewards reveals diverse support for different discounting models. While no single model emerges as a clear winner, general hyperbola (model 1), exponential discounting with both forms of present bias (model 6),[26] and exponential discounting alone (model 8) account for over 80% of the subjects' time discounting behavior. Quasi-hyperbolic discounting (model 5) is the best fit for only 2 subjects, and for most subjects, the quasi-hyperbolic discounting parameter β is not significantly different from 1. When using an exponential specification (and including present bias), we obtain a monthly discount factor of approximately 0.95.[27] Our findings are consistent with the literature, as shown in a recent meta-analysis by Imai, Rutter, and Camerer (2021), which found limited present bias for monetary-reward studies.

5.3 Long-Run Project

We had a total of 84 subjects, but 20 of them did not attend the second stage. Out of these 20, three subjects just signed the sign-up sheet in the first task session but never showed up again, while the remaining 17 never showed up after the first session. The histograms for the time spent in each task session are presented in Figure 1 of Appendix A. The average time spent on the first, second,

[26] In the best model chosen for 25 subjects, it was found that $\beta > 1$ for all, with an average value of b being 2. This implies that these subjects do not exhibit present bias in the form of a variable cost, but rather display future bias. Although these subjects exhibit present bias in the form of a fixed cost, it is not of significant economic importance.

[27] Bradford et al. (2017) reported a monthly discount factor of 0.85, which is relatively low but consistent with previous literature that has found relatively low discount factors when using MPLs (Meier and Sprenger 2010, Frederick, Loewenstein and O'Donoghue 2002). By comparison, our estimate appears to be more reasonable.

and third task sessions were 48 (25.5), 38 (26), and 34 (30.6) minutes, respectively, with standard deviations shown in parentheses. The median values were 50, 43.5, and 29.5 minutes, respectively. 8 of the subjects allocated the task equally between the first two periods (+/-5 minutes), 13 took a break in the second period, 26 allocated the task in all three periods, 18 finished the task in the first two periods, 7 worked only in the last two periods, and 6 (7) spent the maximum time in the first (last) period (+/-5 minutes). The subjects were recruited in four groups and came to the lab on different days of the week (Monday, Tuesday, Wednesday, and Thursday). There were no significant differences in completion rate or time spent per session between genders or across groups. (see Table 3 of Appendix A).

Based on how subjects allocated their time, we classified them as front-loaders or back-loaders if they completed at least 60 minutes in the first or last period, respectively (Burger et al., 2011). We label them as full front (back)-loaders if they complete the project in the first (last) two task sessions. Out of the 64 subjects, 22 (3 female) were classified as front-loaders and 16 (4 female) as back-loaders. There were 19 (4 female) full front-loaders and 7 (2 female) full back-loaders (no significant gender differences, p=0.31 and p=0.53).

All monotonically decreasing discounting functional forms predict an increasing trend in time allocation. If subjects discount future at all, we need to see them postponing costly activities. However, in our dataset, the average time spent decreased over time, and the regression of minutes against session periods yielded a significant negative coefficient for the time trend (-6.93, p=0.005, Burger et al. (2011) found no clear trend over time). This observation is also supported by the non-parametric tests. There are significant differences between task sessions 1 - 2 and 1 - 3, but there is no significant difference between 2 and 3 (two-tailed Wilcoxon-Mann-Whitney ranksum test, p=0.04, p=0.005, p=0.27, respectively). Although convex cost function can make the allocation smoother, it cannot reverse it. Discounting also implies no gap between periods. However, out of 64 subjects, only 14 exhibited increasing time allocations, and 13 subjects took a break in the second period. Nearly half of the participants showed a decreasing pattern of time allocation (28/64), and 14 subjects exhibited non-monotonic time allocation. None of these behaviors can be explained by a discounting model as the sole driver for intertemporal choice. Only six of the 14 subjects who showed increasing time allocations had no gaps. Therefore, only about 9.4% (6/64) of our participants exhibited preferences consistent with discounted utility models. This result is similar to that of Casari et al. (2015), who also observed a similar ratio of 6.8% and attributed this behavior to uncertainty (subjects having stochastic utility functions).

Time allocation can also be examined based on the period in which subjects spent the most time. 24 (38%) spent the most time in the first period, 22 (34%) in the second period, and 18 (28%) in the third period. This observation also suggests a declining trend in time allocation.

Do Elicited Risk and Time Preferences predict behavior in the Long-Run Project?

We now present the statistics for different model specifications as defined in the methodology section. Table 4 specifically displays the statistics obtained when linear effort cost is assumed. We first determined the risk parameter for each subject, reflecting the curvature of their utility function. Next, we used this potentially non-linear utility functional form to fit the data for time preferences, and estimated discounting parameters for each of the 8 different discount functions. Using the estimated discounting functions, we then calculated the optimal effort allocation for each subject. The "Chosen" model in Table 4 represents the model that best fits each subject's revealed choices (and their implied optimal effort allocation). "Equal" represents the equal allocation of effort (40 minutes in each session) among sessions. The term "Random" refers to a scenario where the cost is allocated randomly across three task sessions, as determined through simulations.[28]

Table 4: Calculated Statistics for Each Discounting Model and the Best Three among Them based on Each Statistics (*Linear Effort Cost*)

LINEAR COST													
MODEL	**S1**	**S2 (t1)**	**S2 (t2)**	**S2 (t3)**	**S3a (t1)**	**S3a (t2)**	**S3a (t3)**	**S3b (t1)**	**S3b (t2)**	**S3b (t3)**	**d (t1)**	**d (t2)**	**d (t3)**
1	0.530	0.035	0.188	0.189	0.109	0.819	2.469	0.238	0.018	0.372	2.115	0.375	-2.037
2	0.550	0.009	-0.143	-0.048	0.372	0.831	2.084	1.950	0.503	0.992	0.966	0.287	-1.292
3	0.540	0.011	-0.003	0.145	0.159	0.781	2.441	0.306	0.210	0.437	1.943	0.416	-1.962
4	0.550	0.055	-0.085	-0.174	0.329	0.890	2.077	1.792	0.470	0.921	1.060	0.189	-1.304
5	0.540	0.051	-0.088	0.140	0.170	0.768	2.440	0.317	0.232	0.438	1.909	0.436	-1.961
6	0.550	0.054	-0.070	-0.188	0.330	0.894	2.072	1.792	0.468	0.912	1.060	0.182	-1.300
7	0.570	0.032	0.196	0.188	0.109	0.818	2.469	0.237	0.017	0.368	2.116	0.376	-2.040
8	0.530	0.035	-0.029	-0.076	0.460	0.757	2.043	2.276	0.533	1.080	0.787	0.409	-1.221
Chosen	0.570	-0.142	-0.220	-0.140	0.070	0.985	2.335	0.153	0.246	0.410	2.287	0.028	-1.831
Equal	0.185	NA	NA	NA	0.839	1.043	1.184	NA	NA	NA	0.424	-0.089	-0.288
Random	0.325	0.011	0.032	0.012	0.817	1.085	1.082	0.908	0.960	0.799	0.352	-0.126	-0.101
1 (best)	*Equal*	*4*	*7*	*1*	*Equal*	*Chosen*	*Random*	*Random*	*Random*	*2*	*Random*	*Chosen*	*Random*
2	*Random*	*6*	*1*	*7*	*Random*	*Equal*	*Equal*	*5*	*8*	*4*	*Equal*	*Equal*	*Equal*
3	*1 and 8*	*5*	*Random*	*3*	*8*	*Random*	*8*	*3*	*2*	*8*	*8*	*Random*	*8*

S1 is the ratio of the sum of squared errors to the maximum error. S2 is correlation coefficient. S3a is the mean ratio. S3b is the variance ratio.
d is Cohen's d. ti is the time spent in task session i.

S_1 represents the ratio of the sum of squared errors to the maximum error, with smaller values indicating better fits. For example, Model 1 and random allocation explained 47% and 67.5% of the data in terms of squared error, respectively. Equal allocation performed significantly better than all other models, and the random model performed second-best. The values for all other models were quite similar, around 0.55.

S_2 represents the correlation coefficients between actual and predicted allocations, with higher values indicating better fits. Nearly all values were close to zero and most were negative, except for the first task session allocation. While models 4, 6, and 5 (and 7 and 1) had the highest correlation coefficients for t1 (t2 and t3), respectively, the coefficients were so close to zero that it is difficult to conclude that predicted and actual allocations were correlated.

In terms of mean and variance ratios (S_{3a} and S_{3b}), the equal and especially random model are found to be the best. However, it appears that the predictions underestimate (overestimate) the

[28] For each subject, we generated three random numbers that were less than or equal to 90 and added up to 120. We repeated this process 100 times, calculated each statistic, and took the average.

real allocations in the first (third) task session, as can be deduced from the mostly front-loaded observed allocations. This phenomenon may also result in overestimated (underestimated) Cohen's d values for the first (third) task session, which is consistent with the findings presented in the last three columns of Table 4. Among all models, the random and equal models exhibit the best Cohen's d values.

We compared the results obtained from linear and convex effort costs by conducting the same analysis again. The results are presented in Table 5. With convex cost, it is optimal for individuals to allocate the cost more evenly among the periods, as the marginal cost increases with time spent on the task. In our study, we utilized a simple convex cost function with a value of $\alpha = 2$.[29]

Table 5: Calculated Statistics for Each Discounting Model and the Best Three among Them based on Each Statistics (*Convex Effort Cost*)

CONVEX COST													
MODEL	**S1**	**S2 (t1)**	**S2 (t2)**	**S2 (t3)**	**S3a (t1)**	**S3a (t2)**	**S3a (t3)**	**S3b (t1)**	**S3b (t2)**	**S3b (t3)**	**d (t1)**	**d (t2)**	**d (t3)**
1	0.274	0.083	-0.097	-0.026	0.644	0.991	1.518	0.381	0.025	0.579	0.799	0.018	-0.679
2	0.418	0.088	-0.141	0.158	0.365	0.970	1.936	0.946	0.228	0.944	1.202	0.057	-1.127
3	0.293	-0.045	-0.111	-0.068	0.641	0.976	1.540	0.378	0.059	0.611	0.808	0.048	-0.702
4	0.475	0.020	-0.080	0.018	0.280	0.911	2.122	0.773	0.126	0.844	1.427	0.175	-1.381
5	0.279	0.043	-0.143	-0.029	0.664	0.967	1.519	0.333	0.088	0.578	0.769	0.067	-0.680
6	0.475	0.059	-0.103	0.049	0.271	0.904	2.143	0.771	0.122	0.835	1.447	0.188	-1.410
7	0.275	0.080	-0.100	-0.030	0.645	0.989	1.519	0.380	0.024	0.578	0.797	0.022	-0.680
8	0.402	0.050	-0.180	0.140	0.417	0.978	1.854	0.999	0.242	0.895	1.089	0.042	-1.040
Chosen	0.403	0.020	-0.050	0.100	0.343	0.968	1.969	0.527	0.103	0.777	1.402	0.063	-1.209
Equal	0.185	NA	NA	NA	0.839	1.043	1.184	NA	NA	NA	0.424	-0.089	-0.288
Random	0.327	0.009	0.028	0.012	0.815	1.087	1.082	0.908	0.958	0.800	0.352	-0.126	-0.101
1 (best)	*Equal*	*2*	*Random*	*2*	*Equal*	*1*	*Random*	*8*	*Random*	*2*	*Random*	*1*	*Random*
2	*1*	*1*	*Chosen*	*8*	*Random*	*7*	*Equal*	*2*	*8*	*8*	*Equal*	*7*	*Equal*
3	*7*	*7*	*4*	*Chosen*	*5*	*8*	*1*	*Random*	*2*	*4*	*5*	*8*	*1*

S1 is the ratio of the sum of squared errors to the maximum error. S2 is correlation coefficient. S3a is the mean ratio. S3b is the variance ratio.
d is Cohen's d. ti is the time spent in task session i.

As expected, the majority of the statistics have now become closer to their expected values with the convex cost function since our data exhibits a front-loaded pattern. S_1 has improved for all models, except for the "equal" model as its statistics remain unchanged. The "random" model's statistics have also only slightly changed since it is simply an allocation imposed without any underlying risk/time preference or cost structure. However, the equal allocation model is still the best model for explaining the observed behavior. Although the correlation coefficients have improved, they are still far from being close to plus one. For the mean and variance ratios (S_{3a} and S_{3b}), the equal and random models continue to dominate other models.

We can also evaluate the performance of each model by determining how often it is the best predictor of real-time allocations. For the linear cost case, the equal, random, and first models were the best in 31, 15, and 9 cases, respectively. The remaining models performed best in at most 4 cases. Surprisingly, the model we chose based on the elicited risk and time preferences was only

[29] Burger et al. (2011) calibrated the cost function as a simple convex function ($\alpha = 2$). Although time preferences were not elicited in their study, they performed a simulation using the quasi-hyperbolic model of procrastination with different values of β, with and without uncertainty over future studying costs. Similar to our findings, their results suggested that the observed aggregate pattern is not entirely inconsistent with quasi-hyperbolic models, but rules out β values that are substantially less than 1.

the best in 2 cases. In the case of convex cost, the first, equal, and random models were the best in 18, 17, and 10 cases, respectively. Model 2 and 8 were the best in 7 cases, and the remaining models were the best in at most 2 cases. The chosen model performed best in only 4 cases.

Overall, our study aimed to predict time allocation behavior in a long-run project using utility and discount functions obtained from eliciting risk and time preferences through choices over lotteries and time-dated monetary flows. However, our results indicate that neither our chosen model nor any of the other models outperform the equal distribution or random allocation models, regardless of the cost structure. Additionally, our chosen model is the best predictor for only 6% of the subjects. This suggests that the estimated discount and utility models may not be easily transferable to other contexts or domains, as our results imply that the predictive ability of risk and time preferences elicited from lotteries and time-dated monetary payments may be dependent on the specific context in which they are applied. Nevertheless, as we will demonstrate in the following section, there is a correlation between the parameters of the estimated models and the patterns of costly task completion.

Furthermore, our results support the literature that demonstrates the incompatibility of time preferences derived from time-dated monetary and non-monetary choices, especially with regard to present bias behavior (Imai, Rutter, and Camerer, 2021; Cheung et al., 2021). Several studies have found little or no evidence of present biased preferences in monetary choices when controlling for risk, transaction costs, and payment reliability (e.g., Andersen et al., 2008; Augenblick et al., 2015; Dohmen et al., 2012). Similarly, we did not find any evidence of present biased preferences using monetary choices in our study. Other studies have used the cost of working on real-effort tasks (Augenblick et al., 2015; Casari and Dragone, 2012) and intertemporal choices of juices or soda (Brown et al., 2009), and they have found strong evidence of present-bias. The next subsection examines whether our subjects exhibited present bias in their long-run project behavior.

Dynamic Inconsistencies in the Long-Run Project

In this part, we examine possible dynamic inconsistencies by comparing subjects' real effort choices and their plans mentioned at different points during the experiment. In the first session, we asked subjects about their task allocation plan. We repeated this question at the beginning of the first and second task sessions. By comparing the actual time spent on each task session with the advanced plan (made one week before the decision) and the imminent plan (made just before the task began), we can infer whether subjects exhibit choice reversals. There are two possible forms of choice reversals: *time inconsistency (present bias)* where one postpones part or all of a costly task they had planned to do (e.g., procrastination) or chooses immediately available consumption goods/money they had not planned to choose; *reverse time inconsistency (future bias)* where one completes part or all of a costly task they had planned not to do (e.g., precrastination) or defers immediate consumption they had planned to consume. If subjects complete (more) less of the task than what they had planned one week before, they can be considered as (reverse) time inconsistent. We consider plus/minus 5 minute deviations from the plan as no deviations and label these allocations as consistent.

Aggregate Analysis: We begin by comparing the average plans for the first task session that subjects reported in the first session (the advanced plan) with what they reported just before starting the task (the imminent plan), and then comparing both with the actual time spent on the first task session. We use the following notation: p_{ij} represents the plan on how much time they spend on the task at session i about session j where $i = 1, 2, 3; j = 2, 3, 4$ and $i \leq j$. Recall that t_i represents the time spent in session $i + 1$. The results show that, on average, subjects planned to spend more time in advance. Specifically, the advanced plans were $p_{12} = 51.77$ and 53.90 minutes for the whole sample and for those who finished the task, respectively. However, at the time they needed to do it, they planned to spend significantly less time. The average imminent plan was $p_{22} = 47.97$ min, and they actually spent significantly less time ($t_1 = 47.65$ min) than what they had planned in advance (one tailed $t - test$ for two paired samples: $p_{12} = 53.90$ vs. $p_{22} = 47.97$, $p = 0.026$; $p_{12} = 53.90$ vs. $t_1 = 47.65$, $p = 0.024$; $p_{22} = 47.97$ vs. $t_1 = 47.65$, $p = 0.41$).[30]

We can perform similar analyses for the second task session. Subjects reported their plans on how much time they would spend in the third (second task) session, in the first session (two weeks before), in the second session (one week before), and just before they started the third session. The reports were $p_{13} = 43.90$, $p_{23} = 51.27$, and $p_{33} = 38.45$ minutes, respectively. They actually spent an average of $t_2 = 38.36$ minutes in the third session. In the first session, given their plans to finish $p_{12} = 53.90$ minutes in the second session, they planned to spend $p_{13} = 43.90$ minutes in the third session (two-weeks before the task). However, given that they planned to complete only $p_{22} = 47.97$ minutes in the second session (and there was still one week until the third session), they significantly increased their plans to $p_{23} = 51.27$ minutes ($p_{13} = 43.90$ vs. $p_{23} = 51.27$, two tailed $t - test$, $p = 0.024$). But when it came time to work on the task, they planned to complete $p_{33} = 38.45$ and completed $t_2 = 38.36$ minutes (one tailed $t - test$, $p_{13} = 43.90$ vs. $t_2 = 38.36$, $p = 0.06$; $p_{23} = 51.27$ vs. $t_2 = 38.36$, $p < 0.001$).[31] These findings show that, on average, subjects exhibit time inconsistency (are present-biased) in the real effort task.

Individual Analysis: We can conduct an individual analysis by comparing each subject's plan in the first session with what they actually did in the second session, as well as their plan in the second session with what they did in the third session (p_{12} vs. t_1 and p_{23} vs. t_2). Table 6 does this comparison and categorizes the subjects based on their dynamic inconsistencies. If planned

[30]Similar results were obtained using the non-parametric Wilcoxon matched-pairs signed-ranks test, although the second comparison lost significance. When the whole data set was used, the results did not change.

[31]When we use the non-parametric Wilcoxon matched-pairs signed-ranks test, we get the same results except we lose significance in the second comparison. The results are robust to excluding the plans of those who did not finish the task. We did not make any comparisons for the last task session because they are just residuals of the planned/completed times in the first and second task sessions.

time is higher (lower) than the actual, it labels it as present (future) biased. Out of the 64 subjects, 43 exhibited present bias at least once (26 and 30 in the first and second sessions, respectively), meaning that they planned to spend more time in advance but ended up spending less time when the task was imminent (i.e., they had a positive intention-action gap). 13 and 17 subjects exhibited present bias only in the first and second sessions, respectively, while 13 subjects exhibited present bias in both sessions. On the other hand, 32 out of 64 (23 and 13 in the first and second session, respectively) subjects exhibited future bias at least once ($p_{12k} - t_{1k} < 0$ or $p_{23k} - t_{2k} < 0$). 19 and 9 subjects exhibited future bias only in the first and second sessions, respectively, while only 4 subjects were future biased in both sessions. Only 9 subjects were completely time consistent and behaved according to their stated plans (within plus/minus 5 minutes).

Moreover, 20 subjects in the study exhibited both present and future bias in their behavior. Of these, 7 initially displayed present bias but then behaved as future biased, while the remaining 13 showed the opposite pattern. One possible explanation for this mixed behavior is that these individuals attempted to compensate for their initial misplanning. However, they were unable to achieve complete compensation (for both groups, $p_{12k} + p_{23k} > t_{1k} + t_{2k}$). In the first group, for example, they deviated by -38 minutes in the second session but could only compensate for 24 minutes of this deviation in the third session. Similarly, in the second group, they deviated by +17 minutes in the second session but relaxed too much and completed 31 minutes less in the third session. Additionally, we quantified the severity of subjects' inconsistencies by measuring their total deviations from their plans ($p_{12k} + p_{23k} - t_{1k} - t_{2k}$). Thirteen subjects had no deviations, while 36 (15) subjects were overall present (future) biased with an average of 44 (-26) minutes. These findings suggest that present bias is more prevalent and severe than future bias in the sample studied.[32]

Table 6: Summary of Dynamic Inconsistencies

		P_{23} *vs.* t_2			
	# of Subjects / $(P_{12}, P_{23}) \rightarrow (t_1, t_2)$	Present Biased	Future Biased	Consistent	
P_{12} *vs.* t_1	Present Biased	13 *(54, 70) → (27, 30)*	7 *(53, 51) → (15, 75)*	6 *(69, 25) → (44, 25)*	*26* *(57, 55) → (27, 41)*
	Future Biased	13 *(45, 53) → (62, 22)*	4 *(50, 37) → (55, 58)*	6 *(47, 40) → (70, 39)*	*23* *(47, 47) → (63, 32)*
	Consistent	4 *(60, 50) → (60, 7)*	2 *(50, 30) → (51, 56)*	9 *(61, 56) → (61, 55)*	*15* *(60,51) → (60, 42)*
		30 *(51, 60) → (46, 24)*	*13* *(52, 33) → (44, 67)*	*21* *(59, 42) → (59, 42)*	*64* *(54, 51) → (48, 38)*

Naivete: Our findings also suggest that there is evidence of subjects' naivety regarding their choice reversals. Firstly, we observed that the intention-action gap persisted in both directions, even after the subjects gained experience in the first task session. 13 (4) subjects continued to exhibit

[32] Takeuchi (2011) finds that more respondents exhibit future bias than present bias.

present (future) biased behavior.[33] Secondly, at the end of the experiment, subjects reported their plans for allocating time among the task sessions if they were to repeat the task. The reported plans were significantly more optimistic than both their plans and what they accomplished during the experiment, with an average of 60 and 42 minutes for the first and second task sessions, respectively. This indicates that the subjects were overly optimistic. Finally, when asked whether they would commit to a fixed allocation scheme ($t_1 = t_2 = 60$) if they were to repeat the task, only three out of 64 subjects agreed to do so, which suggests that the majority of the subjects did not fully understand their own behavior. However, caution is necessary when interpreting these results due to the limited repetition of tasks, although previous research has shown that present-bias tends to disappear when subjects are given three similar tasks within a two-week period (Bisin and Hyndman, 2020). Furthermore, the commitment question was not incentivized and there may have been other factors, such as uncertainty, that influenced the outcomes.

Overall, these results provide evidence of dynamic choice reversals among participants, as they deviated from their planned allocations in both task sessions. We observed both time consistency (present bias) and reverse time inconsistency (future bias), but the former was more prevalent and severe in our sample. Furthermore, our results suggest that participants in our sample are somewhat naive about their inconsistencies, which aligns with previous research using real effort tasks.

Analysis with Patience Index: We can also analyze subjects' behavior by creating a patience index (PI) based on their actual time allocations, which measures their tendency to front-load or back-load the task time.[34] This index can signal present or future bias of the subjects, and we can calculate it for both their plans and actual time allocations. It is calculated by dividing the total time allocated to the first and second task sessions by the total time allocated to the second and third task sessions (that lies between 0.25 and 4), and then normalizing it to a range of 0 to 1. Let p_{ijk} represent subject $k's$ plan at session i about session j where $k = 1, 2..., 64$; $i = 1, 2, 3; j = 2, 3, 4$ and $i \leq j$. Remember that t_{ik} is the time spent in session $i + 1$ for subject k. We can define the PI for actual allocations and for plans at each session for each subjects k as follows:

$$PI^k_{Real} = \frac{\frac{t_{1k}+t_{2k}}{t_{2k}+t_{3k}} - 0.25}{3.75} = \frac{4t_{1k} + 3t_{2k} - t_{3k}}{15t_{2k} + 15t_{3k}}; PI^k_{S1} = \frac{4p_{12k} + 3p_{13k} - p_{14k}}{15p_{13k} + 15p_{14k}};$$

$$PI^k_{S2} = \frac{4p_{22k} + 3p_{23k} - p_{24k}}{15p_{23k} + 15p_{24k}}; PI^k_{S3} = \frac{4t_{1k} + 3p_{33k} - p_{34k}}{15p_{33k} + 15p_{34k}}$$

To provide an example, the most impatient person will allocate the minimum amount of time

[33] We also examined whether subjects improved in their ability to predict how much of the task time they would complete in the next session and learn from their experience. We created a normalized index based on the deviations from their predictions for both session 1 and 2 and compared them. However, we did not observe a significant difference, indicating that the subjects did not learn from their experience in this regard.

[34] See Bhatia et al., (2021) for a similar index.

possible in the first two task sessions $(0, 30, 90)$ and have a PI of 0. Someone who allocates time equally across all task sessions $(40, 40, 40)$ will have a PI of 0.2. The most patient person will allocate the highest possible time in the first task session and the rest in the second task session $(90, 30, 0)$, resulting in a PI of 1. Therefore, if subjects discount future utility, their PI will range from 0 to 0.2, while those with future bias will have a PI ranging from 0.2 to 1.

Approximately 36% of the subjects (23 individuals) have a PI value of 0.2 or lower, indicating that most subjects exhibit future bias. It is worth noting that only one subject has a PI value of 0, while five subjects have a PI value of 1.[35] The average PI for actual time allocations is $PI_{Real} = 0.329$, which is significantly higher than 0.2 ($p < 0.01$). Participants with $PI \leq 0.2$ have a significantly lower β parameter compared to those with $PI > 0.2$ (0.993 vs. 1.001, one-tailed $t - test$, $p = 0.045$; the former is marginally significantly less than 1, but the latter is not significantly different from 1, $p = 0.06$, $p = 0.29$). The mean PI based on reported plans for the first session is $PI_{S1} = 0.350$. When comparing the index values of participants who completed the task ($PI_{S1-Fin} = 0.369$) and those who did not ($PI_{S1-Unfin} = 0.291$) based on their initial plans in the first session, the difference is marginally significant ($t - test$, $p = 0.058$). This suggests that participants who drop out of the real effort task tend to report more impatient plans. The mean PI for the second session is $PI_{S2} = 0.380$, which is not significantly different from $PI_{S1-Fin} = 0.368$ ($t - test$, $p = 0.77$), but significantly higher than $PI_{Real} = 0.329$ ($t - test$, $p = 0.04$). In the third session, participants reported their plans based on their allocation in the second session. The mean PI for this plan is $PI_{S3} = 0.324$, which is significantly less than $PI_{S2} = 0.380$ ($t - test$, $p = 0.021$). In the last session, participants answered a hypothetical question about how they would allocate their time if they were to do this task again. The mean PI for this allocation is $PI_{S4} = 0.48$, significantly higher than the PI of their actual allocation $PI_{Real} = 0.329$ ($t - test$, $p < 0.001$), and all reported plans ($t{-}test$, $p < 0.05$). These results suggest a gap between intention and action, with participants reporting an intention to behave patiently in the future but failing to do so. Moreover, the last result supports our previous conclusion that participants may be naive about their present bias, as they report very optimistic and patient plans despite their own time-inconsistent behavior.

Table 7 presents a comparison of the patience indexes based on the planned allocations from session 1 and the actual allocations. The majority of the subjects (43 out of 64) planned to front-load the cost, and most of them (31 out of 43) actually followed this plan closely, as indicated by a small change in mean PI ($mean\ PI$ = 0.47→0.51). The ones who did not follow through their plans (12 out of 43) heavily discounted future by postponing the task ($mean\ PI$ = 0.43→0.10). This group can be categorized as mostly *naive present-biased* because they reversed their initial intentions and discounted the future heavily. On the other hand, half of the ones who planned to postpone the task (11 out of 21) postponed it even more than their plan ($mean\ PI$ = 0.18→0.08).

[35] It is important to consider that alternative models may explain this pattern, including a preference for improving sequences (Loewenstein, 1987) or uncertainty (Casari and Dragone, 2015). These alternative explanations will be further discussed in the discussion section

This group, based on what they planned and what they did, can be categorized as *partially naive present-biased* because they correctly anticipated their discounting but underestimated its extent. The remaining 10 out of 21 subjects front-loaded the cost despite planning to postpone the task.

Table 7: Comparing Planned and Actual Patience Indexes

		Actual		
	# of Subjects	PI $\leq$ 0.2	PI > 0.2	
Planned (Session 1)	PI $\leq$ 0.2	11 *Mean PI = 0.18 → 0.08*	10 *Mean PI = 0.19 → 0.31*	*21* *Mean PI = 0.18*
	PI > 0.2	12 *Mean PI = 0.43 → 0.10*	31 *Mean PI = 0.47 → 0.51*	*43* *Mean PI = 0.46*
		23 *Mean PI = 0.09*	*41* *Mean PI = 0.46*	*64* *Mean PI = 0.37 → 0.33*

Determinants of Patience Index: We conducted a regression analysis to examine the determinants of PI, using estimated discount rate r and present bias parameter β (obtained from quasi-hyperbolic discounting model - model 5) based on monetary choices as independent variables. The results are summarized in Table 8, which indicates that the signs of the coefficients for r and β are as expected and are statistically significant. The findings are robust to the inclusion of various control variables. The negative sign for the discount rate suggests that as subjects discount the future more heavily, they tend to postpone the task further. Conversely, the positive sign for β indicates that as subjects exhibit more severe present bias (lower β), they tend to postpone the costly effort to the future. These results imply that estimated discount rate r and present bias parameter β based on monetary choices do have explanatory power in predicting how subjects allocate their effort in the costly task.

Table 8: Predicting Patience Index

Dependent Variable : Patience Index		
	Model 1	Model 2
Discount rate (r)	-0.093**	-0.113**
	(0.039)	(0.045)
β	2.127**	2.689**
	(1.002)	(1.098)
Constant	-1.727	-2.382
	(0.983)	(1.104)
Controls	No	Yes
# observations	64	64
R-squared	0.0643	0.1723

Notes: Coefficients from regression of patience index on elicited individual discounting parameters. Patience index is calculated based on time-allocation behavior in the long run project. Discount rate and β are obtained through monetary choices. Control variables include gender, bid (proxy for cost of the task), elicited risk parameter, and competitiveness. Robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Reasons of Attrition: Finally, we analyzed the possible reasons for attrition in our sample. We mentioned earlier that individuals who did not complete the task reported more impatient plans. However, due to a lack of subject-specific information, we were unable to conduct a detailed analysis of the determinants of attrition. Our correlation analysis revealed that failing to complete the task is correlated with the bid amount, discount rate (r), and present bias parameter (β) in the expected direction, but not with gender or risk parameter. The mean bid amount of the dropouts is significantly higher than that of those who completed the task (13 vs 7.9, one-tailed $t - test$, $p < 0.01$). The same mean difference holds for the discount rate (r) but not for the present bias parameter (β) (one-tailed $t - test$, $p = 0.015$, $p = 0.76$, respectively). When we perform a logistic regression with 'Finished(=1)' as the dependent variable and bid, the discount rate (r), the present bias parameter (β), and some controls as independent variables, all have the expected signs, but only the bid is found to be marginally significant. Thus, monetary present bias measures have no explanatory power over task completion behavior. However, our results suggest that individuals with higher bids and discount rates are more likely to drop out, although this attrition can also be attributed to negative shocks that we cannot control.

6 Discussion

The design, methodology, and evidence presented in the study require some clarification to address potential confounds. It is important to note that no discounting framework can fully explain the phenomenon of front-loaded task completion, where there is a decreasing trend in time allocation. In this experiment, we found that approximately 30% of subjects (19 out of 64) exhibited future bias (similar to Augenblick et al., 2015), as they completed the task in the second session instead of the third session, which would have been optimal if they had been discounting costs. While the usually assumed convex cost framework can better explain more spread out allocations, even convexity cannot account for this behavior.[36] The future bias observed in our experiment may be explained by individuals with preferences for the resolution of uncertainty, as proposed by Kreps and Porteus (1978). Additionally, uncertainty about future utility and cost is likely a significant factor in explaining the observed trends, as the nature of informational environments may vary depending on when plans are formulated and executed. Another dimension of uncertainty is the future costliness of the task. If subjects anticipate the task to be more costly than previously envisioned due to emerging tasks or work, they may choose to complete (more of) their tasks immediately. Since subjects with future uncertainty would benefit from flexibility, the desire not to commit to a suggested plan can be a sign of this effect in our experiment (only three out of 64 subjects chose the commitment plan, but this decision was hypothetical and not incentive

[36] If there are increasing returns to effort, the cost function should be concave. This introduces two competing factors in determining how to allocate the task: the efficiency of working more upfront and the discounting of future costs, which makes postponing optimal. These opposing factors can skew allocation towards the dominant factor.

compatible). However, a limitation of the uncertainty argument is that it can accommodate a broad range of behavioral patterns, making it difficult to disprove.

The intertemporal choices in our experiment could also be driven by anticipation utility (Loewenstein, 1987; Caplin and Leahy, 2001). Anticipation utility refers to the pleasure or dread/anxiety that people derive not only from the consumption of a good or activity (in this case, completing a costly task) but also from anticipating it. This can be a powerful motivator for people to delay consumption (i.e., complete costly tasks early). Additionally, people tend to remember unfinished tasks better than completed ones (known as the Zeigarnik effect; Zeigarnik, 1927), which might have intensified the urge to complete more of the task earlier in our case by increasing anxiety from the anticipation of the costly task.

We observed a discrepancy between planned and implemented allocations in both directions, and we attributed these to the subjects' dynamic inconsistencies. However, it is possible that this discrepancy may be due to simple decision errors rather than dynamic inconsistencies. The fact that subjects have two opportunities to exhibit dynamic inconsistencies in the long-run project part addresses this possibility. Indeed, half of the subjects exhibiting present bias (13 out of 26) and a majority of those who demonstrated dynamic consistency (9 out of 15) displayed similar behavior once more (see table 6). However, future-biased subjects tended to exhibit a marked shift towards present bias or consistency in their subsequent decisions (19 out of 23). This suggests that present-biased or consistent responses may not necessarily be considered decision errors, whereas future-biased behavior, while potentially resulting from a response to novel informational contexts, may be more prone to error. Thus, the stability of present bias over effort increases our confidence that the observed effects are due to dynamic inconsistency.

We employed a general survey completion task, assuming that all participants were familiar with this type of task and provided clear instructions on the nature of the surveys. This may have reduced uncertainty about the task's cost and decreased participants' curiosity to start immediately and complete some of it, but it did not entirely eliminate it. Requiring participants to attend the lab for each session was done to minimize the impact of unexpected shocks on their time allocations on different dates. Assuming that positive and negative shocks were distributed equally among participants is a reasonable assumption, given that they completed the task. Additionally, this requirement may have attracted more patient participants although we found that discount rates were similar to those reported in the literature (e.g., Coller and Williams, 1999). Furthermore, we analyzed the differences between those who dropped out of the experiment after the first part (20 out of 84) and those who completed it. We found that individuals who perceived the task as more costly and had higher discount rates were more likely to drop out. Thus, high perceived cost and discount rates appeared to act as a filter in our experiment.

To account for the heterogeneous costs of the task for each subject, we conducted our analysis using different cost functions, including linear and convex cost, and obtained the subjects' valuations of the task cost through an incentivized second price auction, rather than estimating or calibrating the cost function, as done in Augenblick et al. (2015) and Burger et al. (2011). Although revealing the true valuation was a weakly dominant strategy, some subjects reported a zero valuation (9 out of 84), and others reported very low valuations (5 out of 84). To address this issue, we repeated the analysis using the average bid (9 TL) and minimum wage for two hours (20 TL) for these subjects, but the results remained largely unchanged.

Our sample size of 84 participants, with 64 continuing to the end of the experiment, is similar to that in previous literature, such as Burger et al. (2011) with 87 participants, of whom 74 continued, and Augenblick et al. (2015) with 102 participants, of whom 89 continued. However, our sample is not gender-balanced, with only 22% of the participants being female (18 out of 84). Nevertheless, our analysis showed no appreciable difference in behavior across gender.

Finally, it is important to address concerns about our compensation methodology. While we provided payment to all participants who completed the task, we compensated approximately 15% of the subjects randomly in the preference elicitation section. However, we believe that our results remain robust and unaffected by this payment method since probabilistic payment has been shown to have no or insignificant effect on discounting behavior (Andersen et al., 2014; Weber and Chapman, 2005). Furthermore, we acknowledge that payment uncertainty might have played a role in our results since we pay the subjects the fixed payment one week after they complete the task and some would get their payments from the preference elicitation task in a future date. However, payment for the time and risk preference part was done immediately for most of the participants. Additionally, participants who completed the task in the second session were required to sign up during the third session to receive payment. Lastly, participants who completed the task in the third session or needed payment at a later time visited the researcher's office on campus on a predetermined day to receive payment and were reminded of the payment date by email. Since the participants were students who were regularly on campus, we believe that any potential effects of payment uncertainty are negligible.

7 Conclusion

Individuals often prioritize immediate gratification over long-term benefits, leading them to defer costly tasks and abandon their prior plans. The discounted utility framework is commonly used in the literature to model these intertemporal choices. In this paper, we explore the feasibility of utilizing elicited parameters from discounted utility models to explain and predict time allocation in a multi-period investment project. To achieve this, we conducted a two-part experiment that involved eliciting time and risk preferences and a longitudinal design that required subjects to allocate their time for a two-hour costly task over three periods.

Our study reveals three key findings. Firstly, we found no evidence of quasi-hyperbolic discounting or present bias in the form of a fixed cost in choices over monetary payments. This finding is consistent with recent literature, which suggests that present bias is limited in the monetary domain when accounting for transaction costs and risk preferences. Secondly, while dynamic choice reversals are evident in the overall real effort allocation patterns within the multi-period project, there is substantial heterogeneity at the individual level. We observed both present bias and future bias, with the former being more widespread and severe. Additionally, we identified signs of naivete. These two findings indicate a lack of compatibility between the predicted allocations from the estimated utility and discounting models and the observed time allocations. Lastly, although the estimated discount and utility models may not be directly transferable to other contexts, the discount rates and present bias parameters provide useful information about how subjects allocate their effort in the multi-period project. This final finding supports recent research suggesting a correlation between elicited discount rates and different field behaviors.

Our paper contributes to the growing body of research highlighting the appropriate use of discounting models estimated from monetary choices and their limitations in modeling dynamic choice reversals. Our findings suggest that choices over effort can go a long way in modeling present bias. However, our data has some limitations, such as the absence of high rewards and long time horizons, and a restricted subject pool, which requires caution in generalizing our results. To better understand the reasons for observed inconsistencies, future research can involve asking subjects to explain why their planned and implemented allocations diverged. Additionally, qualitative data can be obtained to explore the motivations behind commitment decisions, and diverse samples and field studies can be employed. Investigating the relationship between inconsistencies and personality traits and exploring the role of uncertainty on choice reversals are also promising areas for future research.

REFERENCES

1. Ainslie, G. (1992). *Picoeconomics*. Cambridge University Press.

2. Ainslie, G., Herrnstein R.J. (1981). Preference Reversals and Delayed Enforcement. *Animal Learning and Behavior*, 9, 476-82.

3. Akin Z. (2012). Intertemporal Decision making with Present Biased Preferences. *Journal of Economic Psychology,* 33-1, 30-47.

4. Anderhub, V., Gneezy U., Güth, W., Sonsino D. (2001). On the interaction of risk and time preferences: An experimental study. *German Economic Review*, 2(3), 239-253.

5. Andersen, S., Harrison, G. W., Lau, M. I., Rutström, E. E. (2008). Eliciting Risk and Time Preferences. *Econometrica* 76 (3): 583–618.

6. Andersen, S., Harrison, G. W., Lau, M. I., Rutström, E. E. (2014). Discounting behavior: A reconsideration. *European Economic Review,* 71, 15-33.

7. Angeletos, G. M., Laibson, D., Repetto, A., Tobacman, J., Weinberg, S. (2001). The hyperbolic consumption model: Calibration, simulation, and empirical evaluation. *Journal of Economic perspectives*, 15(3), 47-68.

8. Ariely, D. and Wertenbroch, K. (2002). Procrastination, deadlines, and performance: self-control by precommitment. *Psychological Science,* 13, 219-224.

9. Ashraf, N., Karlan, D., Yin, W. (2006). Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines. *The Quarterly Journal of Economics*, 121(2), 635-672.

10. Augenblick, N., Niederle, M., Sprenger, C. (2015). Working over time: Dynamic inconsistency in real effort tasks. *The Quarterly Journal of Economics*, 130(3), 1067-1115.

11. Augenblick, N., Rabin, M. (2019). An experiment on time preference and misprediction in unpleasant tasks. *Review of Economic Studies*, 86(3), 941-975.

12. Benhabib J., Bisin A., Schotter A. (2010). Present-Bias, Quasi-Hyperbolic Discounting and Fixed Costs. *Games and Economic Behaviour*, 69, 205-223.

13. Bhatia, S., Crawford, M. M., McDonald, R. L., Moreno, M. A., Read, D. (2021). Inconsistent Planning and the Allocation of Tasks Over Time. Working paper.

14. Bisin, A., Hyndman, K. (2020). Present-bias, procrastination and deadlines in a field experiment. *Games and economic behavio*r, 119, 339-357.

15. Bradford, D., Courtemanche, C., Heutel, G., McAlvanah, P., Ruhm, C. (2017). Time preferences and consumer behavior. *Journal of Risk and Uncertainty*, 55(2), 119-145.

16. Burger, N., Charness, G., Lynham, J. (2011). Field and online experiments on self-control. *Journal of Economic Behavior and Organization*, 77(3), 393-404.

17. Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics*, 112(2), 537-579.

18. Casari, M. (2009). Pre-commitment and exibility in a time decision experiment. *Journal of Risk and Uncertainty*, 38(2), 117-41.

19. Casari, M., Dragone, D. (2015). Choice reversal without temptation: A dynamic experiment on time preferences. *Journal of Risk and Uncertainty*, 50(2), 119-140.

20. Chabris, C. F., Laibson, D., Morris, C. L., Schuldt, J. P., Taubinsky, D. (2008). Individual laboratory-measured discount rates predict field behavior. *Journal of risk and uncertainty*, 37(2), 237-269.

21. Caplin, A., Leahy, J. (2001). Psychological expected utility theory and anticipatory feelings. *The Quarterly Journal of Economics*, 116(1), 55-79.

22. Chapman, G. B. (1996). Temporal discounting and utility for health and money. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 22, 771–791.

23. Charness, G., Garcia, T., Offerman, T., Villeval, M. C. (2020). Do measures of risk attitude in the laboratory predict behavior under risk in and outside of the laboratory? *Journal of Risk and Uncertainty*, 60(2), 99-123.

24. Cheung, S. L., Tymula, A., Wang, X. (2021). Quasi-hyperbolic present bias: A meta-analysis. Life Course Centre Working Paper, (2021-15).

25. Cohen, J., Ericson, K. M., Laibson, D., White, J. M. (2020). Measuring time preferences. *Journal of Economic Literature*, 58(2), 299-347.

26. Coller, M., Williams, M.B., (1999). Eliciting individual discount rates. *Experimental Economics,* 2, 107–127.

27. Dohmen, T., Falk, A., Huffman, D., Sunde, U. (2012). The intergenerational transmission of risk and trust attitudes. *The Review of Economic Studies*, 79(2), 645-677.

28. Duflo, E., M. Kremer, and J. Robinson (2011). Nudging Farmers to Use Fertilizer: Evidence From Kenya. *American Economic Review*, 101(6), 2350-2390.

29. Ericson, K. M., White, J. M., Laibson, D., Cohen, J. D. (2015). Money earlier or later? Simple heuristics explain intertemporal choices better than delay discounting does. *Psychological science*, 26(6), 826-833.

30. Ericson, K. M., Laibson, D. (2019). Intertemporal choice. In *Handbook of Behavioral Economics: Applications and Foundations 1* (Vol. 2, pp. 1-67). North-Holland.

31. Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., Sunde, U. (2018). Global evidence on economic preferences. *The Quarterly Journal of Economics*, 133(4), 1645–1692.

32. Fernandez-Villaverde, J., Mukherji, A. (2002). Can we really observe hyperbolic discounting? Available at SSRN 306129.

33. Fischer, C., (1999). Read this paper even later: procrastination with time-inconsistent preferences. Resources for the Future Discussion Paper 99-20. Resources for the Future, Washington, DC.

34. Fischer, C. (2001), Read this paper later: procrastination with time-consistent preferences. *Journal of Economic Behavior and Organization*, 46, 249-69.

35. Frederick S., Loewenstein G., O'Donoghue T. (2002). Time Discounting and Time Preference: A Critical Review. *Journal of Economic Literature*, 40, 351-401.

36. Frederick S., Loewenstein G. (2002). The Psychology of Sequence Preferences. Working Paper, Sloan School, MIT.

37. Freeman, D., Manzini, P., Mariotti, M., Mittone, L. (2016). Procedures for eliciting time preferences. *Journal of Economic Behavior and Organization*, 126, 235-242.

38. Galizzi, M. M., Machado, S. R., Miniaci, R. (2016). Temporal stability, cross-validity, and external validity of risk preferences measures: Experimental evidence from a UK representative sample.

39. Golsteyn, B. H., Grönqvist, H., Lindahl, L. (2014). Adolescent time preferences predict lifetime outcomes. *The Economic Journal*, 124(580), F739-F761.

40. Halevy, Y. (2015). Time Consistency: Stationarity and Time Invariance. *Econometrica* 83(1): 335-352.

41. Hardisty, D. J., Appelt, K. C., Weber, E. U. (2013). Good or bad, we want it now: Fixed-cost present for gains and losses explains magnitude asymmetries in intertemporal choice. *Journal of Behavioral Decision Making*, 26, 348-361.

42. Harris, C. R. (2012). Feelings of dread and intertemporal choice. *Journal of Behavioral Decision Making*, 25(1), 13-28.

43. Harrison, G.W., Rutström, E.E. (2008). Risk aversion in the laboratory. In *Risk aversion in experiments* (pp. 41–196) Emerald Group Publishing Limited.

44. Herweg, F., Müller, D. (2011). Performance of procrastinators: On the value of deadlines. *Theory and Decision*, 70(3), 329-366.

45. Houser, D., Schunk, D., Winter, J., Xiao, E. (2018). Temptation and Commitment in the Laboratory. *Games and Economic Behavior*, 107, 329-344.

46. Imai T., Rutter T. A., Camerer C. F., (2021). Meta-Analysis of Present-Bias Estimation using Convex Time Budgets. *The Economic Journal*, Volume 131, Issue 636, 1788–1814.

47. Kreps, David M. and Evan L. Porteus (1978). Temporal Resolution of Uncertainty and Dynamic Choice Theory. *Econometrica*, 1978, 46 (1), 185–200.

48. Laibson, D. (2003). *Intertemporal Decision Making*. Encyclopedia of Cognitive Science, Nature Publishing Group, London.

49. Laibson, D. (1997). Golden Eggs and Hyperbolic Discounting. *Quarterly Journal of Economics*, 62, 443-77.

50. Lejuez, C.W., Read, J.P., Kahler, C.W., Richards, J.B., Ramsey, S.E., Stuart, G.L., Strong, D.R., Brown, R.A. (2002). Evaluation of a behavioral measure of risk taking: the balloon analogue risk task (bart). *Journal of Experimental Psychology: Applied*, 8(2), 75–84.

51. Loewenstein, G. (1987). Anticipation and the valuation of delayed consumption. *The Economic Journal*, 97(387), 666-684.

52. Lowenstein, G., Prelec, D. (1992). Anomalies in intertemporal choice: Evidence and an interpretation, *Quarterly Journal of Economics*, 107, 573-598.

53. Loewenstein, G., Prelec, D. (1993). Preferences for sequences of outcomes. *Psychological Review*, 100(1), 91-108.

54. Lusk, J.L., Coble, K.H. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics*, 87(2), 393–405.

55. Meier, S., Sprenger, C. (2010). Present-biased preferences and credit card borrowing. *American Economic Journal: Applied Economics*, 2(1), 193-210.

56. O'Donoghue, T. and Rabin M. (1999a). Doing It Now or Later. *American Economic Review*, 891, 103-124.

57. O'Donoghue, T. and Rabin, M. (1999b). Incentives for procrastinators. *Quarterly Journal of Economics* 114, 769-816.

58. O'Donoghue, T. and Rabin, M. (2001). Choice and procrastination. *Quarterly Journal of Economics,* 116, 121-160.

59. O'Donoghue, T. and Rabin, M. (2008). Procrastination on long-term projects. *Journal of Economic Behavior and Organization*, 66:2, 161-175.

60. Pan, J., Webb, C. S., Zank, H. (2015). An extension of quasi-hyperbolic discounting to continuous time. *Games and Economic Behavior*, 89, 43-55.

61. Phelps, ES., Pollak, RA. (1968). On Second-best National Saving and Game-equilibrium Growth. *Review of Economic Studies*, 35, 185-199.

62. Sutter, M., Kocher, M. G., Glätzle-Rützler, D., Trautmann, S. T. (2013). Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review,* 103(1), 510-31.

63. Takeuchi, K. (2011). Non-parametric test of time consistency: Present bias and future bias. *Games and Economic Behavior*, 71(2), 456-478.

64. Thaler, R. H., and S. Benartzi (2004). Save More Tomorrow: Using Behavioral Economics to Increase Employee Saving. *Journal of Political Economy*, 112(1), 164-187.

65. Trope, Y., and A. Fishbach (2000). Counteractive Self-Control in Overcoming Temptation. *Journal of Personality and Social Psychology*, 79(4), 493-506.

66. Yates, F. J., Watts, R. A. (1975). Preferences for deferred losses. *Organizational Behavior and Human Performance*, 13, 294–306.

67. Weber, B. J., Chapman, G. B. (2005). The combined effects of risk and time on choice: Does uncertainty eliminate the immediacy effect? Does delay eliminate the certainty effect? *Organizational Behavior and Human Decision Processes*, 96(2), 104-118.

68. Webb, C. S. (2016). Continuous quasi-hyperbolic discounting. *Journal of Mathematical Economics*, 64, 99-106.

69. Zeigarnik, B. (1927). Das Behalten erledigter und unerledigter Handlungen [The retention of completed and uncompleted actions]. Psychologische Forschung, 9, 1-85.

APPENDIX A

Table 1: Risk Preferences, Time Allocations, and Bids for Participants

Estimated Relative Risk Aversion Coefficient			Actual Time Allocations (min.)			*Bid (TL)*	Estimated Relative Risk Aversion Coefficient			Actual Time Allocations (min.)			*Bid (TL)*
Subject	*Risk Parameter (σ)*	*Std. Err.*	*T1*	*T2*	*T3*		*Subject*	*Risk Parameter (σ)*	*Std. Err.*	*T1*	*T2*	*T3*	
01	0.043792	(0.064)				30	43	-0.300381**	(0.12)	44	47	29	8.99
02	-0.015484	(0.091)	20	90	10	8	44	0.367609****	(0.065)	63	57	0	10.5
03	-0.228441*	(0.122)	69	0	51	2.6	45	0.298338****	(0.052)	64	28	28	16
04	0.127562	(0.078)				0	46	0.441242****	(0.049)	57	0	63	10
05	0.092849	(0.064)	0	30	90	5	47	0.240704**	(0.089)	50	42	28	12
06	0.216916****	(0.033)	50	57	13	6	48	0.543801****	(0.072)	60	0	60	8
07	0.259375***	(0.086)	36	45	39	18.1	49	0.280677****	(0.06)	34	0	86	5
08	0.054308	(0.059)	0	51	69	19.8	50	0.314913****	(0.052)	12	65	43	9.99
09	0.422115****	(0.034)	77	0	43	30.5	51	-0.271941**	(0.106)	0	70	50	8
10	0.179512**	(0.08)				25	52	0.520817****	(0.052)	35	75	10	5
11	0****	(0)	67	30	23	5	53	0.16456****	(0.04)	90	25	5	9.99
12	0.466105****	(0.05)	37	57	26	6	54	0.476565****	(0.074)				39.99
13	0.684843****	(0.049)	61	59	0	8	55	-0.000941	(0.023)	48	72	0	3.5
14	0.262695****	(0.069)	68	0	52	10	56	-0.07986	(0.064)	60	60	0	0
15	0.158346***	(0.056)				15	57	0.164161	(0.097)				0
16	0.427655****	(0.055)				5	58	0.243454**	(0.088)	30	0	90	5
17	0.535769****	(0.055)	36	0	84	23	59	-0.129901	(0.098)	90	30	0	0.5
18	0.225222***	(0.061)	0	47	73	9.99	60	-0.079825	(0.091)	33	30	57	5
19	0.670537****	(0.043)	0	57	63	5	61	-0.362034***	(0.115)				8
20	0.429984****	(0.036)	67	53	0	8	62	0.052642	(0.081)	33	0	87	30
21	0.547446****	(0.05)	63	57	0	10	63	0.180761***	(0.055)				10
22	0.447631****	(0.077)				22	64	0.287613****	(0.053)				5
23	0.236644***	(0.072)				0	65	0.306751****	(0.071)	52	25	43	21.75
24	0.139787	(0.1)	41	25	54	5	66	-0.230612**	(0.096)	58	62	0	1
25	0.569822****	(0.062)				10	67	0.340486****	(0.088)				2
26	0.33196****	(0.085)	53	50	17	0	68	0.047135**	(0.019)	90	30	0	2.5
27	0.02576	(0.063)				20.01	69	-0.144718	(0.132)	44	76	0	10.5
28	-0.144665*	(0.084)	47	60	13	0	70	0.257148***	(0.084)	15	10	85	10.99
29	0.204239*	(0.11)	0	90	30	5	71	-0.204109**	(0.087)	46	60	15	10
30	0.199159****	(0.033)	35	55	30	0	72	-0.502193***	(0.155)	59	60	0	21.1
31	0.007809	(0.111)				10.51	73	0.213275***	(0.065)	58	62	0	11.11
32	0.312696****	(0.067)				0	74	-0.162409***	(0.055)				22
33	0.168193****	(0.036)				8.7	75	0.48151****	(0.054)	50	60	10	6
34	0.359666****	(0.053)	67	53	0	2	76	0.122082**	(0.047)	50	35	35	5
35	0.151827*	(0.083)	65	55	0	7	77	0.047982	(0.09)	90	30	0	10
36	0.323766****	(0.056)	26	30	64	3.75	78	0.383095****	(0.087)	0	80	40	5.1
37	0.242323***	(0.066)	80	0	40	4	79	0.200469**	(0.086)	70	0	50	3
38	0.402065****	(0.091)	90	30	0	6.99	80	0.552892****	(0.085)	27	5	88	0.15
39	0.365248****	(0.052)	58	0	62	5	81	0.071166	(0.045)				27
40	-0.029047	(0.037)	58	40	22	0	82	0.554975****	(0.055)	42	45	30	5
41	0.447331****	(0.092)	48	0	72	0.5	83	0.382788****	(0.075)	75	45	0	10.33
42	0.125364**	(0.059)	12	18	90	10	84	0.245534****	(0.038)	90	30	0	3

***** if p< 0.001; *** if p< 0.01; ** if p< 0.05; * if p< 0.1*

Table 2: Chosen Discounting Models and Associated Time-Preference Parameters for All Subjects

Discounting Models

1. D(y,t;θ,r,β=1,b=0)=	(1-(1- θ)rt)^(1/(1- θ))
2. D(y,t;θ,r,β,b=0)=	β(1-(1- θ)rt)^(1/(1- θ))
3. D(y,t;θ,r,β=1,b)=	(1-(1- θ)rt)^(1/(1- θ)) - b/y
4. D(y,t;θ,r,β,b)=	β(1-(1- θ)rt)^(1/(1- θ)) - b/y
5. D(y,t;θ=1,r,β,b=0)=	βe^(-rt)
6. D(y,t;θ=1,r,β,b) =	βe^(-rt) - b/y
7. D(y,t;θ=1,r,β=1,b)=	e^(-rt) - b/y
8. D(y,t;θ=1,r,β=1,b=0)=	e^(-rt)

Subject	Disc. Mod.	β	θ	r	b
01	1	-	-6.192 **	0.949 ****	-
06	1	-	16.574 ****	3.593 ****	-
07	1	-	-279.019 ***	0.035 ****	-
15	1	-	-7.884 **	0.745 ****	-
16	1	-	11.942 **	3.523 ***	-
19	1	-	-503.954 **	0.021 **	-
20	1	-	-233.752 **	0.035 ****	-
23	1	-	4.178 ***	2.228 ****	-
26	1	-	-27.296 ***	0.227 ****	-
33	1	-	-83.923 ****	0.100 ****	-
35	1	-	-32.086 ****	0.240 ****	-
41	1	-	-39.404 **	0.203 ****	-
43	1	-	-71.278 ****	0.144 ****	-
46	1	-	-39.817 **	0.162 ****	-
48	1	-	2.198 ****	1.203 ****	-
50	1	-	-22.314 **	0.367 ****	-
56	1	-	13.870 ****	4.940 ****	-
57	1	-	8.447 **	3.950 ***	-
60	1	-	6.099 ***	3.174 ****	-
61	1	-	-20.075 ***	0.409 ****	-
69	1	-	-8.021 ***	0.899 ****	-
71	1	-	-8.667 ***	0.797 ****	-
78	1	-	16.355 **	2.293 ***	-
81	1	-	2.965 **	1.983 ****	-
10	2	1.059 ****	3.911 ***	3.844 ****	-
03	3	-	-124.670 **	0.079 ***	3.872 ***
37	3	-	-61.483 ***	0.154 ***	0.882 ****
53	3	-	-65.800 **	0.141 ***	1.651 ****
55	3	-	-98.715 **	0.085 ****	0.481 **
72	3	-	-26.874 ***	0.332 ****	24.160 ***
73	3	-	-44.994 ****	0.195 ****	0.614 ****
74	3	-	-47.284 ***	0.195 ****	5.761 ****
22	4	1.024 ****	-30.523 **	0.305 ***	1.130 ****
54	4	1.036 ****	-18.417 **	0.393 ****	1.005 ****
77	4	1.010 ****	-31.021 ***	0.261 ****	1.961 ****
24	5	0.902 ****	-	1.074 **	-
66	5	0.967 ****	-	0.727 ***	-
04	6	1.026 ****	-	0.169 ****	2.814 ****
05	6	1.026 ****	-	0.611 ****	3.418 ***
09	6	1.032 ****	-	0.700 ****	1.017 ***
12	6	1.037 ****	-	0.571 ****	1.140 ****
13	6	1.035 ****	-	0.181 ***	0.483 ****

Subject	Disc. Mod.	β	θ	r	b
27	6	1.041 ****	-	0.494 ****	6.595 ****
29	6	1.026 ****	-	0.403 ****	2.867 ****
30	6	1.011 ****	-	0.569 ****	1.326 ***
32	6	1.015 ****	-	0.401 ****	0.801 ****
36	6	1.025 ****	-	0.342 ****	2.117 ****
38	6	1.080 ****	-	0.825 ****	2.859 ****
39	6	1.022 ****	-	0.574 ****	1.270 ****
40	6	1.028 ****	-	1.058 ****	7.985 ****
42	6	1.011 ****	-	0.352 ****	1.904 ****
44	6	1.014 ****	-	0.501 ****	0.814 ***
52	6	1.037 ****	-	0.546 ****	0.904 ****
59	6	1.006 ****	-	0.148 ****	1.621 ****
62	6	1.018 ****	-	0.500 ****	2.419 ****
65	6	1.011 ****	-	1.780 ****	0.346 **
70	6	1.040 ****	-	0.340 ****	3.536 ****
75	6	1.021 ****	-	0.357 ****	0.900 ****
76	6	1.011 ****	-	0.254 ****	1.165 ****
79	6	1.013 ****	-	0.155 ****	0.917 ****
80	6	1.058 ****	-	0.303 ****	1.351 ****
84	6	1.004 ****	-	0.069 ****	0.225 ****
08	7	-	-	2.250 ****	2.770 ****
17	7	-	-	0.778 ****	0.168 **
18	7	-	-	0.694 ****	0.837 **
02	8	-	-	0.527 ****	-
11	8	-	-	0.311 ****	-
14	8	-	-	0.064 ****	-
21	8	-	-	1.225 ****	-
25	8	-	-	0.979 ****	-
28	8	-	-	0.186 ****	-
31	8	-	-	2.287 ****	-
34	8	-	-	0.842 ****	-
45	8	-	-	0.054 ****	-
47	8	-	-	0.129 **	-
49	8	-	-	1.742 ****	-
51	8	-	-	3.150 ****	-
58	8	-	-	1.059 ****	-
63	8	-	-	1.630 ****	-
64	8	-	-	0.201 ****	-
67	8	-	-	0.648 ****	-
68	8	-	-	0.036 ****	-
82	8	-	-	1.242 ****	-
83	8	-	-	1.415 ****	-

**** if p< 0.001; *** if p< 0.01; ** if p< 0.05; * if p< 0.1

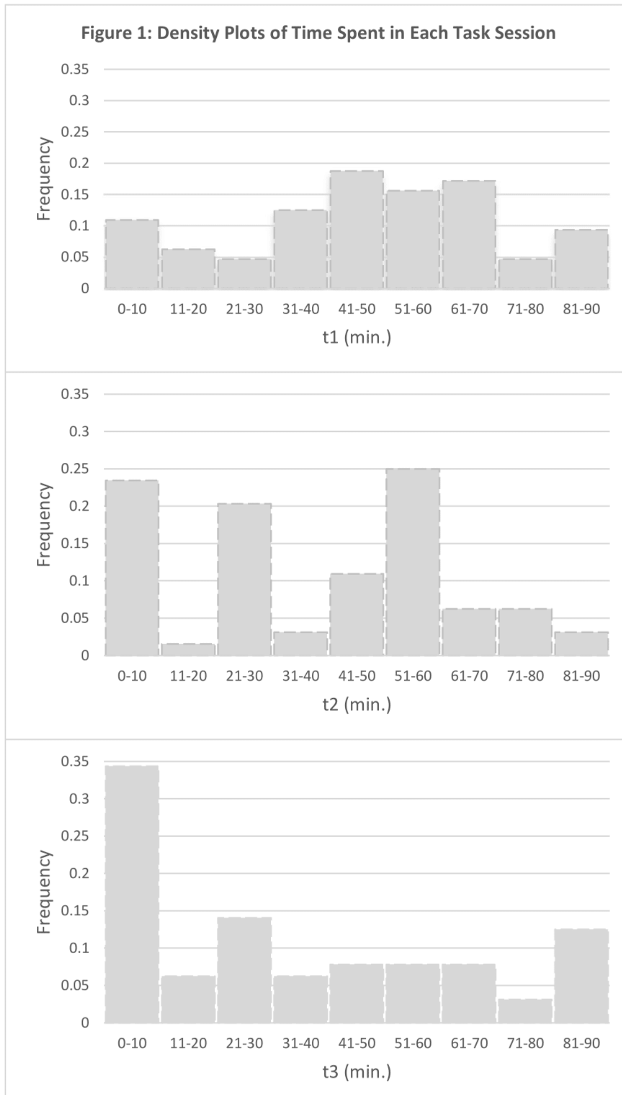


Figure 1: Density Plots of Time Spent in Each Task Session
Frequency
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0-10
11-20
21-30
31-40
41-50
51-60
61-70
71-80
81-90
t1 (min.)
t2 (min.)
t3 (min.)

Table 3: Completion of the Task and Average Time Allocations by Gender and Group

	Gender					
	Female		Male		Total	
# of Subjects	18 (%22)		66 (%78)		84	
	Completed (C)	Not Completed (NC)	C	NC	C	NC
# of Subjects	15 (%83)	3 (%17)	49 (%74)	17 (%26)	64 (%76)	20 (%24)
t1 (min.)	51 (26.3)	27 (23.1)	47 (25.4)	48 (21.5)	48 (25.5)	45 (22.5)
t2 (min.)	34 (29.4)	53 (11.5)	40 (25.1)	41 (20.9)	38 (26.0)	43 (20.0)
t3 (min.)	35 (29.8)	40 (20.0)	33 (31.1)	31 (23.4)	34 (30.6)	32 (22.7)

	Group							
Group No	1		2		3		4	
# of Subjects	22		18		22		22	
	C	NC	C	NC	C	NC	C	NC
# of Subjects	16 (%73)	6 (%27)	12 (%67)	6 (%33)	19 (%86)	3 (%14)	17 (%77)	5 (%23)
t1 (min.)	40 (28.7)	32 (23.8)	52 (24.3)	53 (10.3)	45 (23.9)	46 (11.8)	51 (27.5)	50 (33.2)
t2 (min.)	40 (27.1)	51 (21.5)	40 (25.7)	43 (13.6)	33 (28.0)	27 (23.0)	42 (24.1)	44 (23.0)
t3 (min.)	40 (30.6)	38 (29.6)	28 (23.4)	24 (18.6)	42 (33.8)	47 (11.3)	23 (29.7)	26 (21.9)

Standard Deviations for average time allocations are in parenthesis.
The time allocations for the ones who did not complete the task are their planned allocations reported in the first session.

APPENDIX B - Formal Analysis

In period 0, it is optimal to incur the maximum cost, $\bar{c}$, at the finishing stage for almost all the agents ($\beta \in (0,1]$). To see this, consider the fact that the agent tries to maximize the following discounted utility by choosing c_1 and c_2,

$$P^*(c_1,c_2) = \max_{\{c_1,c_2\}} P(c_1,c_2) = \max\{0, -u(c_1) - \beta\delta u(c_2) - \beta\delta^2 u(C-c_1-c_2) + \beta\delta^3 u(v)\} \text{ if } c_1+c_2 < C,$$

$$P^*(c_1,c_2) = \max_{\{c_1,c_2\}} P(c_1,c_2) = \max\{0, -u(c_1) - \beta\delta u(c_2) + \beta\delta^2 u(v)\} \text{ if } c_1+c_2 = C.$$

Given that the agent is risk neutral, it is clear that for any given β, δ, C, and v values, if $c_2 \neq C - c_1$, then since $P(c_1,c_2)$ is decreasing both in c_1 and c_2, the following are true

$$-c_1 - \beta\delta c_2 - \beta\delta^2(C-c_1-c_2) + \beta\delta^3 v \overset{c_1 \to 0}{<} -\beta\delta c_2 - \beta\delta^2(C-c_2) + \beta\delta^3 v < -\beta\delta(C-\bar{c}) - \beta\delta^2\bar{c} + \beta\delta^3 v$$

$$-c_1 - \beta\delta c_2 - \beta\delta^2(C-c_1-c_2) + \beta\delta^3 v \overset{c_2 \to 0}{<} -c_1 - \beta\delta^2(C-c_1) + \beta\delta^3 v < -(C-\bar{c}) - \beta\delta^2\bar{c} + \beta\delta^3 v$$

however,

$$-\beta\delta(C-\bar{c}) - \beta\delta^2\bar{c} + \beta\delta^3 v > -(C-\bar{c}) - \beta\delta^2\bar{c} + \beta\delta^3 v$$

On the other hand, if $c_2 = C - c_1$, then by the same reasoning above, the agent should choose $c_1 = C - \bar{c}$. Then the above problem can be written as follows:

$$P^*(c_1,c_2) = \max\{0, -(C-\bar{c}) - \beta\delta\bar{c} + \beta\delta^2 v, -\beta\delta(C-\bar{c}) - \beta\delta^2\bar{c} + \beta\delta^3 v\}$$

Depending on the parameter values (as long as both expressions are greater than zero), one of them will give us the maximizing allocation as either $c_1 = C - \bar{c}$ and $c_2 = \bar{c}$ or $c_2 = C - \bar{c}$ and $c_3 = \bar{c}$. If the agent is not risk neutral, given the utility function, the agent maximizes the discounted utility by choosing c_1 and c_2. We now analyze each agents' behavior in detail.

1. Exponential agent: Since the exponential agent is time-consistent, his investment schedule will be either $(0,\ 0,\ 0; -)$ or $(C-\bar{c},\ \bar{c},\ 0; 3)$. He plans to follow an investment schedule and he follows it as such. His plan of finishing the project or not doing it depends on whether the project is worth doing regardless of the period from which he looks ahead. If condition 1 below is satisfied, then the exponential agent investment schedule will be $(C-\bar{c},\ \bar{c},\ 0; 3)$:

$$-(C-\bar{c}) - \delta\bar{c} + \delta^2 v \geq 0 \tag{1}$$

If the above condition is not satisfied, then the exponential agent will not start the project, $(0,\ 0,\ 0; -)$. So, since for the exponential agent $\beta = 1$, postponing is not optimal.

2. Naive hyperbolic agent: Given that the project is worthwhile, in period 1, he will compare the expressions in condition 2 below:

$$\underbrace{-(C-\bar{c}) - \beta\delta\bar{c} + \beta\delta^2 v}_{(C-\bar{c},\ \bar{c},\ 0;3)} \geq \underbrace{-\beta\delta(C-\bar{c}) - \beta\delta^2\bar{c} + \beta\delta^3 v}_{(0, C-\bar{c},\ \bar{c};4)} \geq 0 \tag{2}$$

If condition 2 is satisfied, then the agent starts doing the project. If condition 3 below is also satisfied, then the naive agent finishes the project in the second period and gets the payoff in period 3 $(C-\bar{c},\ \bar{c},\ 0;3)$:

$$\beta\delta v-\bar{c}\geq\beta\delta^2 v-\beta\delta\bar{c}\geq 0 \tag{3}$$

However, if $\beta\delta^2 v-\beta\delta\bar{c}\geq\beta\delta v-\bar{c}\geq 0$, then the agent follows the investment schedule $(C-\bar{c},0,\bar{c};4)$. In addition, if $\beta\delta v-\bar{c}\leq 0\leq\delta v-\bar{c}$, then he does not finish the project, $(C-\bar{c},\ 0,\ 0;-)$.

If condition 2 is not satisfied,

$$0\leq\underbrace{-(C-\bar{c})-\beta\delta\bar{c}+\beta\delta^2 v}_{(C-\bar{c},\ \bar{c},\ 0;3)}\leq\underbrace{-\beta\delta(C-\bar{c})-\beta\delta^2\bar{c}+\beta\delta^3 v}_{(0,C-\bar{c},\ \bar{c};4)} \tag{4}$$

then he postpones the project to period 2. In period 2, he invests $C-\bar{c}$. In period 3, if $\beta\delta v-\bar{c}\geq 0$, then $(0,C-\bar{c},\bar{c};4)$. If $\beta\delta v-\bar{c}\leq 0\leq\delta v-\bar{c}$, then $(0,C-\bar{c},0;-)$.

If the following is satisfied, then he never starts, $(0,0,0;-)$;

$$\underbrace{-(C-\bar{c})-\beta\delta\bar{c}+\beta\delta^2 v}_{(C-\bar{c},\ \bar{c},\ 0;3)}\leq\underbrace{-\beta\delta(C-\bar{c})-\beta\delta^2\bar{c}+\beta\delta^3 v}_{(0,C-\bar{c},\ \bar{c};4)}<0$$

3. Sophisticated hyperbolic agent: The sophisticated agent thinks ahead and perceives what he will do in the future. He then works backwards and decides what to do now. If conditions 2 and 3 are satisfied, then he follows $(C-\bar{c},\ \bar{c},\ 0;3)$. If 3 and 4 are satisfied, then, he follows $(0,\ C-\bar{c},\ \bar{c};4)$. As opposed to a naive agent, sophisticated agent will never incur any cost without getting any payoff because he knows how he will behave in the future.

We can also observe an outcome where the cost incurred is not equal to $\bar{c}$. This is because the agent knows how he will actually evaluate payoffs in the future, thus he can arrange the costs to make each stage worth investing. If condition 2 is satisfied, but condition 3 is not, then he knows that he cannot implement $(C-\bar{c},\ \bar{c},\ 0;3)$. Instead, he will figure out the least costly implementable strategy and compare it with $(0,\ C-\bar{c},\ \bar{c};4)$ because this is surely implementable by his future self. The least costly implementable strategy is the one that makes the second period self indifferent between postponing the remaining time to the last period and finishing it in the second period. It is given by the following equation:

$$\beta\delta v-c^*=\beta\delta^2 v-\beta\delta c^*$$

where $c^*=\frac{\beta\delta(1-\delta)v}{1-\beta\delta}$ is the maximum amount of cost/time that sophisticated agent can allocate for the second period because any $c>c^*$ will make him postpone the completion of the project to the third period. Then, he will choose and implement $max\{(0,C-\bar{c},\bar{c};4),(C-c^{**},c^{**},0;3)\}$ strategy, where $c^{**}=max\{C-\bar{c},c^*\}$ and $c^{**}=c^*$ (note that by definition, $c^*<\bar{c}$.) If $c^{**}=C-\bar{c}$, then least costly implementable strategy is $(C-\bar{c},c^*,\bar{c}-c^*;4)$, and net payoff of this is obviously lower than that of $(0,C-\bar{c},\bar{c};4)$.

Convext cost specification: The problem of the agent is now as follows:

$$\max_{\{t_1,t_2\}}\{-\underbrace{c(\frac{t_1}{T})^{\alpha}}_{c_1}-\beta e^{-rl_1}\underbrace{c(\frac{t_2}{T})^{\alpha}}_{c_2}-\beta e^{-rl_2}\underbrace{c(\frac{T-t_1-t_2}{T})^{\alpha}}_{C-c_1-c_2}+\beta e^{-rl_3}v\}$$

where T is the total time to be allocated, c is the total cost for T, t_i is the time allocated to the period i and $\alpha > 1$. In linear cost case, $\alpha = 1$, c_i represents the monetary cost of spending t_i minutes in period i and $c_i = c\frac{t_i}{T}$ where c is the cost of spending T minutes on the project. By taking the first order conditions and doing the necessary calculations, we find that

$$\begin{aligned}
t_1^* = t_2^*(\beta e^{-rl_1})^{\frac{1}{\alpha-1}} &= \frac{T(\beta e^{-rl_1})^{\frac{1}{\alpha-1}}}{1+e^{\frac{-r(l_1-l_2)}{\alpha-1}}+(\beta e^{-rl_1})^{\frac{1}{\alpha-1}}} \\
t_2^* &= \frac{T}{1+e^{\frac{-r(l_1-l_2)}{\alpha-1}}+(\beta e^{-rl_1})^{\frac{1}{\alpha-1}}} \\
T-t_1^*-t_2^* &= \frac{Te^{\frac{-r(l_1-l_2)}{\alpha-1}}}{1+e^{\frac{-r(l_1-l_2)}{\alpha-1}}+(\beta e^{-rl_1})^{\frac{1}{\alpha-1}}}
\end{aligned}$$

Note that $t_1^* \to \frac{T}{3}; t_2^* \to \frac{T}{3}$, and $T - t_1^* - t_2^* \to \frac{T}{3}$ as $\alpha \to \infty$. In the experiment, we use $T = 120, l_1 = \frac{7}{365}, l_2 = \frac{14}{365}, l_3 = \frac{21}{365}$, β and r are subject specific and convergence is achieved for $\alpha \geq 3$. Thus, convex costs might offer a better explanation of more even time allocations.

APPENDIX C - Instructions

First Session

Thank you for participating in this study on individual decision making. The instructions are simple and if you follow them closely, you will earn cash. How much and when you get paid will be based on your decisions. The data collected in this experiment will be used in economic decision analysis, and the identity and choices of participants will be kept confidential.

This is the first session of a sequence of four sessions. The remaining three sessions will be held on April 20 (Thursday), April 27 (Thursday), and May 4 (Thursday). At the end of today's session, you will earn either a certain amount today or a different amount in the future, depending on your decisions and a lottery process. In the remaining three sessions, your payoff will again depend on what you do in those sessions. The details will be explained shortly.

In this session, you will be asked thirty simple questions, and your answers will determine when and how much you will be paid. The payment amount will be determined by a lottery process and by your answers to these questions.

For example, here are two of the thirty questions you will be asked to answer:

"What amount of money, if paid to you today, would make you indifferent to 10 TL paid to you in 5 days?"

"What amount of money, if paid to you today, would make you indifferent to 50 TL paid to you in 1 month?"

After you answer all thirty questions, one of the questions will be drawn randomly. Suppose, for example, that the second question above is drawn, and you answered 40 TL. Then, we will draw a random number between 0 and 50, where all the numbers between 0 and 50 have an equal probability of being drawn. We will draw this number separately for each participant in the experiment. If the number drawn for you is smaller than the indifference amount you stated (i.e., if the number drawn is smaller than 40), you will have to wait for one month, at which time you will be paid 50 TL. If the number drawn is greater than the indifference amount you stated, then the amount drawn will be paid to you today. Note that the smaller the indifference amount you chose as your response to the question drawn, the higher the chances that you will be paid today, and the smaller the expected amount that you will be paid today.

In the three sessions that will follow today's session (which we will refer to as "task sessions"), the main objective will be to complete a two-hour task that involves filling out some simple surveys. You have the flexibility to allocate the two-hour task time among the three task sessions scheduled for April 20 (Thursday), April 27 (Thursday), and May 4 (Thursday). You must come to each of the three task sessions and sign a sign-up sheet. You will be paid a fixed amount of 40 TL only if you complete this two-hour task and sign the sign-up sheet in each of the three task sessions. You can work on the task for at most 90 minutes (1.5 hours) in a given session. This means that you will need to work on the task in at least two of the three task sessions to complete the task. Note that even if you complete the two-hour task in two of the three sessions, you still have to come and sign the sign-up sheet in the other session. We will send you reminder emails one day before the task sessions.

The payoff 40 TL will be paid one week after you finish the task. For example, if you complete the task on May 4, then 40 TL will be paid on May 11. Note again that even if you complete the task on April 27, you need to come to the third task session on May 4 and sign the sign up sheet. There is no session on May 11, which is a date of payment for those who choose to complete the two-hour task on May 4.

As mentioned earlier, you can divide the two-hour time period to complete the task in any way you like among the three task sessions. Please indicate your plan regarding the task by filling out the schedule below. These plans are not binding. Changing your plans will not affect your payoff as long as you complete the task and sign the sign up sheet in all the three task sessions.

APRIL 20: ____ minutes; APRIL 27: ____ minutes; MAY 4: ____ minutes;

We next ask you to answer the following questions in the space provided: *Questions for time preference and risk preference elicitation...*

Now, we will conduct a simple auction. You indicated your plan regarding the task. Now we will give you the following option: we ask each of you to fill out a "bid form" that will be distributed to you momentarily. You will be bidding for the right to be exempted from the requirement of completing the two-hour task. Your bid is how much money you are willing to give up out of your 40 TL fixed earnings in order to be exempted from the requirement of completing the two-hour task. The participant with the highest bid will win the auction and will not have to complete the two-hour task. The highest bidder will pay the second highest bid; hence his/her earnings will be 40 TL minus the second highest bid. You cannot bid more than 40 TL.

Example: Suppose you bid 35 TL and turns out that the highest bid from the other participants is 18 TL. Since you are the highest bidder, you win the auction and get paid 40-18 = 22. Your payment date will be based on the plan that you submitted above. If, for instance, you indicated in your plan (the one you have filled today) that you would finish the task in the session on April 27, then 22 TL will be paid to you on May 4. If you indicated that you would finish the task in the session on May 4, then 22 TL will be paid on May 11. Note that even if you win the auction, you still have to come to the next three sessions and sign the sign up sheet. Otherwise, you will not be paid anything. Now please indicate how much money you are willing to bid to be exempted from completing the two-hour task. Write your bid on the bid form within the next two minutes. Do not show your bid to anybody. Your bids will be collected at the end of the two-minute period and the winner will be announced. In case of a tie for the highest bid, we will randomly determine the winner. (Bids are collected and the winner is determined. The first session ends.)

Second Session (First Task Session)

Welcome back! As a reminder, the objective of the three task sessions (including today's session) is to complete a two-hour task that involves filling out some surveys. You have the flexibility to allocate the two-hour task time among the three task sessions scheduled for today, April 27 (Thursday), and May 4 (Thursday). To get paid, you must come back for each of the remaining two task sessions and sign a sign-up sheet.

You will be paid a fixed amount of 40 TL only if you complete this two-hour task and sign the sign-up sheet in all three task sessions. You can work on the task for a maximum of 90 minutes during any given task session. This means that you will need to work on the task during at least two of the three task sessions to complete it. Note that even if you allocate the two hours between two of the three sessions, you must still come and sign the sign-up sheet during the other session.

Since you cannot work on the task for more than 90 minutes during any of the task sessions, the earliest session in which you can complete the task is the next task session on April 27 (Thursday). You can also complete the task during the third task session on May 4 (Thursday). If you complete it on May 4, you will be paid on May 11. Note that if you complete it on April 27, you still need to come to the third task session and sign the sign-up sheet on May 4 to receive payment.

Remember that you can allocate the two-hour task time however you like among the three task sessions. Now, please indicate your plan for completing the task by filling out the schedule below. These plans are not binding, and changing your plans will not affect your payoff as long as you complete the task and sign the sign-up sheet during all three task sessions. You have one minute to fill out the schedule:

TODAY: ____ minutes, APRIL 27: ____ minutes; MAY 4: ____ minutes;

Now, the time is –:– , You can start filling out the surveys. You can spend up to 90 minutes on the surveys today. It is important that you do not engage in any other activity (using the computer or cell phone, etc.) during the time you spend on the surveys. Please take your time to fill out the surveys carefully. Note that you do not have to complete all the surveys by the end of the two-hour period. (Filling out surveys...)

After you are done with the surveys for the day, come and sign the sign up sheet. We will note your ending time on your forms.

Third Session (Second Task Session)

Welcome back. Today is the third session (second task session). Given the number of minutes you spent on the task in the second session (first task session); please indicate your plan for the remaining minutes to complete the two-hour task by filling out the schedule below. These plans are not binding. Changing your plans will not affect your payoff as long as you complete the task and sign the sign up sheet in all the three task sessions.

TODAY: ____ minutes, MAY 4: ____ minutes;

(Filling out surveys...)

After you are done with the surveys for the day, come and sign the sign up sheet. We will note your ending time on your forms.

Fourth Session (Third Task Session)

This is the final (fourth) session (third task session). Today you will spend the remaining minutes, if any, to complete the two-hour requirement on the task.

If you have any remaining minutes, start filling out the surveys now... (Filling out surveys...)

Please answer the following questions before you leave:

QUESTION 1: Your answer will not impact your payoffs. Suppose we maintained the requirement of coming to all the three task sessions and signing a sign up sheet. Suppose also that we now give you the same two-hour task as we did at the beginning of the experiment. Now, how would have you allocated your time among the task sessions?

APRIL 20: ____ minutes; APRIL 27: ____ minutes; MAY 4: ____ minutes;

QUESTION 2: Your answer will not impact your payoffs. Suppose we maintained the requirement of coming to all the three task sessions and signing a sign up sheet and gave you the choice between the following two options. Please choose one:

Option 1: You get to determine the allocation of the two-hour time as you wish (as has been the case for this experiment).

Option 2: Distribution of the two-hour time is determined by the experimenter as one hour on April 20 and one hour on April 27.

This is the end of the experiment. If you completed the two hour task in the previous session, the experimenter will pay 40 TL today. Otherwise, finish the task today and you will be paid next week (May 4).

Thank you for your participation.

QUIZ

Please circle T for true and F for false.

1. I can finish the whole task in one day. T F (False)
2. I can finish the task either in the second task session or in the third task session. T F (True)
3. I will be paid as soon as I complete the task. T F (False)
4. My main decision is how to allocate the two hour task time among the three task sessions. T F (True)
5. I have to finish the task, once I started it. T F (False)
6. I can earn partial payoff by completing a portion of the task. T F (False)
7. I cannot work on the task for more than 90 minutes (1.5 hour) in one task session. T F (True)
8. Although I come and sign the sign up sheet in all the three task sessions, I will not be paid 40 TL if I do not complete the task. T F (True)
9. Although I complete the two hour task, I will not be paid 40 TL if I do not come and sign the sign up sheet in all three task sessions. T F (True)