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Do Job Seekers (Really) Procrastinate?*

Maxime Le Bihan[†]

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Abstract

We experimentally investigated whether job seekers' short-run and long-run time preferences over money and effort influence job search intensity and outcomes. Our findings indicate that long-run impatience impacts search effort and the reservation wage, but only when elicited in the effort domain. Both procrastination and present bias over money reduce job search efforts, with procrastination negatively influencing early search outcomes and present bias affecting the exit from unemployment. Preferences over financial trade-offs and leisure arbitrages also affect job search, but this is only observed when time preferences are elicited using the Double Multiple Price List method, not the Convex Time Budget method.

Keywords: Time discounting, present bias, job search, labor market, experiment

JEL: C91, J64, D91

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1 Introduction

Public spending on unemployment benefits in OECD countries averaged 0.58% of GDP in 2019, and it even exceeded 1.5% in countries such as France, Spain, and Finland (*source: OECD*).¹ Despite the essential role these benefits play in supporting job seekers, public discourse often accuses job seekers of abusing the system. This narrative overlooks the complexity of job search processes and job seekers' involuntary behavioral biases.

In response to the limitations of standard theories in explaining job search anomalies,² economists have explored various behavioral biases that could prolong job search duration through sub-optimal search effort and reservation wage updating (for surveys, see Charness and Kuhn, 2011; Cooper and Kuhn, 2020). Time preferences have emerged as a natural suspect (DellaVigna and Paserman, 2005; Paserman, 2008) because time inconsistencies lead to decision errors in many areas (Loewenstein and Thaler, 1989; Laibson, 1997).³ In addition to exponential discounting of future consumption, some individuals exhibit present bias: while many prefer immediate smaller rewards to larger but delayed ones, they tend to switch preferences when all the rewards are shifted to the future. Similarly, when the cost of effort is immediate while its benefits can only be reaped in the future (like when seeking a job), present-biased individuals have trouble sticking to their plans and may be naive about it. These features have been captured by models of quasi-hyperbolic discounting (Laibson, 1997; O'Donoghue and Rabin, 1999).

However, despite compelling evidence of the impact of short-run and long-run impatience on decision-making in various domains, such as finances or health, the empirical consequences of time inconsistencies and their nature on job search intensity and outcomes remain largely unknown.⁴ This constitutes the main aim of our study. The seminal theoretical contribution of DellaVigna and Paserman (2005) and Paserman (2008) explained how present-biased job seekers could fall prey to procrastination and exert less search effort than they intend to. Their estimations supported hyperbolic discounting, showing that impatience correlates with longer unemployment but not with the reservation wage.

¹<https://data.oecd.org/socialexp/public-unemployment-spending.htm>. Accessed on August 14, 2024. In 2020, expenditures on unemployment-related benefits in the EU-27 also represented 7.3% of total expenditures on social benefits. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Social_protection_statistics_-_unemployment_benefits. Accessed on August 14, 2024.

²For early experimental evidence, see Braunstein and Schotter (1982); Cox and Oaxaca (1989, 1992).

³Other behavioral factors influencing search and reservation wage include reference dependence in terms of resources or consumption and loss aversion (*e.g.*, Schunk, 2009; Damgaard, 2017; DellaVigna et al., 2017; Marinescu and Skandalis, 2021), errors and heuristics (*e.g.*, Dohmen et al., 2009; Schunk, 2009; Brown et al., 2011), learned helplessness (*e.g.*, Bjørnstad, 2006), overconfidence and biased treatment of information (*e.g.*, Falk et al., 2006; Spinnewijn, 2015; Golman et al., 2017; Gee, 2018; Belot et al., 2018; Mueller et al., 2021), and an external locus of control (*e.g.*, Caliendo et al., 2015; McGee and McGee, 2016; Preuss and Hennecke, 2018).

⁴Interestingly, while economists have little explored the effects of procrastination on job search, one can find plenty of applications and blogs on the Internet that claim to help individuals overcome their job search procrastination (for example, <https://www.sparkacareer.com/post/nine-ways-to-stop-job-search-procrastination/>; <https://blogs.jobget.com/blog/steps-to-defeat-job-search-procrastination/>; <https://camdenkelly.com/how-to-overcome-job-search-procrastination/>; <https://www.europelanguagejobs.com/blog/procrastination-job-search.php>). Accessed on August 14, 2024.

Since this early contribution, there have been very few attempts to document the effects of time inconsistencies on job search, and none exploring their exact nature. This raises major empirical challenges that we address here with an experimental approach.

For estimating their model, DellaVigna and Paserman (2005) used proxy variables for impatience (*e.g.*, smoking or having life insurance) from survey data (PSID and NLSY in the US). However, these proxies constitute indirect and noisy measures of time preferences that do not permit disentangling between short-run and long-run discounting, only enabling the estimation of an average global effect.⁵ Using also a survey method, van Huizen and Plantenga (2014) measured Dutch job seekers' time preferences more directly through a psychological questionnaire on future orientation; they found support for the hyperbolic discounting model. However, these measures rely on self-reported and non-incentivized time preferences, which may restrain their validity.

The experimental approach constitutes an alternative to both survey methods and the structural approach.⁶ Apart from our study, Belot et al. (2024) provides the only attempt so far to elicit unemployed job seekers' risk and time preferences experimentally to directly infer discounting parameters and link them to survey and administrative data. They found a negative correlation between present bias and the number of job interviews received.⁷ The main interest of such an approach lies in the low number of assumptions on which the inference of the parameters relies, compared to the structural approach, and in the use of data directly collected for the purpose of inferring preferences.

We aimed to experimentally explore how time preferences impact job search effort and outcomes, using an incentivized elicitation of time preferences, and to investigate the nature of the mechanism: if present bias affects job search effort negatively, is it due to financial trade-offs that place excessive weight on sooner financial streams, or is it because of a tendency to procrastinate in terms of effort over leisure? To this aim, we designed a longitudinal online experiment with French job seekers to measure short- and long-run discounting parameters over both money and effort. Our first contribution is estimating the time preferences of a population that differs substantially in terms of both status and age from the student subjects. We combine experimental measures of these parameters with survey and administrative data from the French Public Employment Service ("Pole Emploi" and "UNEDIC") database. These data allow us to test DellaVigna

⁵Several methods have been developed since then to collect more direct measures of time discounting through surveys (*e.g.*, Dohmen et al., 2011, 2012), but none have been used yet in the context of job search.

⁶The structural approach was implemented by Paserman (2008) who used the NLSY survey data to calibrate a model of hyperbolic discounting and to recover short and long-run discounting from effort choices, reemployment wages, and duration of unemployment spells. They found a higher present bias for individuals with lower wages before becoming unemployed. A concern with this method is its strong dependence on the structure of the model, especially the assumed wage distribution.

⁷Meyer (2018) elicited the time preferences of low-skill workers in Ethiopia experimentally and correlated these measures with survey data, showing that present bias decreased the time spent on job search by 57%. His study includes on-the-job search and time-dated monetary allocations, while we consider unemployed individuals and measure time preferences over both money and effort, which also differs from Belot et al. (2024).

and Paserman (2005)’s model predictions regarding search behavior and outcomes in the labor market.

Our second contribution is varying two dimensions in the elicitation of time preferences to investigate the mechanism through which discounting and present bias affect job search. First, we manipulated within-subjects the domain of time preferences we elicited, which has never been done with job seekers. The literature has shown that patience is higher for monetary than for primary rewards (*e.g.*, Estle et al., 2007; Reuben et al., 2010; Ubfal, 2016; Cheung et al., 2022), and present bias is more pronounced for consumption than for money (see reviews and meta-analyses by Cohen et al., 2016; Cheung et al., 2021; Imai et al., 2021).⁸ Recent studies even show no evidence of present bias for money (*e.g.*, Andersen et al., 2014; Andreoni and Sprenger, 2012). In particular, Augenblick et al. (2015) found that individuals exhibit present bias over effort but are time-consistent when allocating money. Whether this would hold for job seekers is unknown. Because job search involves both real effort and monetary trade-offs, we elicited the same individuals’ time preferences for both monetary rewards and effort allocations over time to investigate which dimension influences job search and its outcomes more.

Second, we varied the method used to elicit time preferences between subjects. Although the measurement of time preferences has been on the economists’ agenda for a long (see, *e.g.*, Frederick et al., 2002), there is still no consensus on which method provides the most accurate estimates. Several methods have emerged (Laury et al., 2012; Attema et al., 2016; Belot et al., 2024), but among the most frequently used are the Double Multiple Price List (DMPL) of Andersen et al. (2008) and the Convex Time Budget (CTB) of Andreoni and Sprenger (2012). We adopted both methods in our study. With the DMPL method, individuals make binary allocation choices between a sooner and a later date in an increasing price list; the switching point from which they start preferring the later payment informs on their preferences. The CTB method introduces a convex choice environment, allowing individuals to choose how to allocate a budget between a sooner and a later date at different exchange rates. These methods also differ in their estimation of utility curvature. With the DMPL method, risk preferences are identified through choices in risky lotteries, using the Holt and Laury lottery procedure (Holt and Laury, 2002), while time preferences are recovered from riskless choices. In contrast, the CTB method recovers utility curvature and time preferences simultaneously from a set of riskless choices.

Our third contribution lies in using two types of rewards (money and leisure) and two elicitation methods (DMPL and CTB) to assess which type of reward and which method explain better job search behavior and success.

⁸In their meta-analysis of estimates of the present bias parameter in 62 studies, Cheung et al. (2021) found, on average, present bias for both monetary ($\beta = 0.82$) and non-monetary rewards ($\beta = 0.66$), with substantial heterogeneity depending notably on the measurement method and the type of reward.

Our study involved 250 job seekers registered with the French Public Employment Service (PES). The experiment spanned three sessions over seven weeks. The allocation of monetary rewards was made in the second session, with various time horizons, front-end delays, and exchange rates. To elicit time preferences over effort, participants had to perform a real-effort task. The allocation of effort occurred across the first and second sessions, with the realization of effort in the second and third sessions.

We found that regardless of the method used, job seekers discount effort more than they discount money, which aligns with Augenblick et al. (2015). Even after accounting for prospects in the labor market, the gap between discounting in the two domains persisted. However, we noted substantial discrepancies in the estimates between the DMPL and CTB methods.⁹ In the CTB treatment, the sample exhibited, on average, a long-run discount factor equal to one and a short-run factor greater than one, indicating an unexpected *future* bias for monetary payoffs. In contrast, both estimates of discounting for effort did not differ significantly from one, suggesting no present bias or future bias for effort allocation. In contrast, using the DMPL treatment, consistent with prior research, the estimates of participants' short-run and long-run discounting for money did not differ significantly from one. However, for effort allocation, participants exhibited present bias on average, indicating a tendency to procrastinate. The long-run discounting parameter did not differ significantly from one.

The model by DellaVigna and Paserman (2005) predicts that, with exponential time preferences, more impatient individuals (those with a higher long-run discount rate) tend to search less than more patient individuals because they place less value on the present value of the future wages they could potentially earn. Meanwhile, because they value present gains and the immediate consumption they permit more than future ones, they tend to lower their reservation wage and increase their likelihood of accepting lower wage offers. Overall, the effects of long-run discounting on search duration are twofold. The search effort effect lengthens the unemployment duration, whereas the reservation wage effect shortens it. With exponential time preferences, the effect on the reservation wage dominates, leading more impatient job seekers to exit unemployment faster. Hyperbolic discounting (characterized by high short-run and low long-run discounting) alters this prediction by strengthening the effect of short-run impatience on search behavior. Job seekers who are present biased engage in less search due to the current disutility of job search efforts for payoffs accruing in the future. Since wages only provide utility in the future, present bias should be unrelated to the reservation wage. Thus, under hyperbolic discounting, higher impatience should correlate negatively with exiting unemployment,

⁹In Cheung et al. (2021)'s meta-analysis, the CTB method is more likely to reject present bias compared to choice lists, although the difference is no longer significant when covariates are considered. In our study, these differences remained pronounced even after controlling for individual characteristics. In their meta-analysis, Matousek et al. (2022) also found large differences in the estimates of individual discount rates across studies. They highlight a sizable publication bias against unintuitive results and large differences depending on whether studies are conducted with students (who are typically less patient) or a more diverse sample of the population.

as present-biased individuals may delay their search efforts.

We found that long-run impatience affects both search effort and the reservation wage when time preferences were elicited in the effort domain: more impatient job seekers in the long run search less and report a lower reservation wage. As predicted by DellaVigna and Paserman (2005), present bias over money reduced the number of hours searched and did not affect the reservation wage. Similarly, procrastination in the effort domain decreased the number of direct actions undertaken to find a job but it did not impact the reservation wage. However, these effects were evident only when using the DMPL method for eliciting time preferences. The time preferences elicited with the CTB method did not show a significant impact on job search, except for a surprisingly positive effect of present bias for money on the time spent searching. This effect was driven by individuals with moderate levels of short-run discounting. One interpretation could be that impatience for money creates a sense of urgency to return to work, suggesting a mechanism different from that in DellaVigna and Paserman (2005).

Regarding the outcomes of job search observed at the time of the survey, the impact of short-run and long-run impatience over money on the probability of receiving interviews and job offers did not reach statistical significance. However, when short-run impatience over money was elicited using the DMPL method, it negatively impacted the hazard rate measured approximately a year after the experiment. Procrastinators identified using the DMPL method received fewer job interviews during their early unemployment spells. In line with DellaVigna and Paserman (2005), one interpretation is that procrastinators delay their search efforts, which subsequently reduces their early job opportunities. However, the pure effect of procrastination appears to only hit at the beginning of the spell, while present bias over money seems to affect longer-run perspectives.

Based on this analysis, three final remarks can be drawn. First, present bias over money and procrastination describe different individuals in the context of job search. Second, in the long run, job search is more affected by impatience in terms of financial trade-offs than by arbitrage over leisure. This finding challenges simplistic narratives about job seekers' motivation and suggests that policy interventions should focus on supporting job seekers with hyperbolic time preferences in two directions: in the monetary dimension, helping them focus on the current value of the future financial streams attached to the exit from unemployment, and in the real dimension, providing commitment devices to encourage concrete and planned job search actions. Finally, the link between time preferences and job search efforts is highly sensitive to the method used to elicit these preferences. We highlight discrepancies in results between the DMPL and CTB methods that underscore the need for a more systematic investigation into the efficacy of these two most popular methods in predicting real-world behavior.

Section 2 introduces the theoretical background. Section 3 outlines our empirical strategy. Section 4 presents our findings. Section 5 discusses these results and concludes.

2 Theoretical background

The model proposed by DellaVigna and Paserman (2005) (DVP hereafter) extends the classical framework by Lippman and McCall (1976) by incorporating a hypothesis on the discounting of future utility streams. Conventional job search models assume time-consistent behavior where future utility is discounted exponentially. A future wage utility at time t is assigned a weight δ^t , where δ represents the discount factor. This exponential discounting assumption has an elegant property: the weight given to future utility depends solely on the time horizon t , and any utility unit at time t is valued at δ times as much as a utility unit at time $t - 1$. A decision should remain unchanged if the option to modify it later exists. However, research showed that decision time can influence outcomes: when a decision is made in advance of its implementation, individuals sometimes alter this choice as the implementation date approaches (Thaler, 1980). The novelty of their model lies in the introduction of present bias in the context of job search.

A notable finding in the recent empirical literature is that individuals exhibit present bias when allocating effort units, but this bias is less pronounced when allocating monetary units (Augenblick et al., 2015; Cheung et al., 2021). Thus, we hypothesize that in our sample, due to present bias, job seekers will tend to disproportionately delay effort allocation to a later date when decisions are made on the day the task should be performed. In contrast, we expect allocations of monetary units to remain consistent, irrespective of when the decisions are made. This leads us to formulate the following hypothesis:

Hypothesis 1: *Time inconsistencies prevail in job seekers' allocation of effort over time but not in their allocation of money over time.*

However, we anticipate that job seekers may exhibit heterogeneity in their available time and financial situation over time, which could be influenced by their subjective prospects in the job market. If job seekers believe they will exit unemployment quickly, they might prioritize income stream in the present to smooth background consumption and perform the task early while they have more time available (Belot et al., 2024). Controlling for these prospects could reduce the differences in patience over time and money.

Hypothesis 2: *The disparity in time inconsistencies between the monetary and effort dimensions diminishes when subjective job search prospects in the labor market are accounted for.*

The following hypotheses derive from the model of DVP, which incorporates a β - δ quasi-hyperbolic utility discounting à la Laibson (1997). This model augments the

⁹These hypotheses, along with the experimental design and data analysis plan, were preregistered at AsPredicted (#68035). The order of presentation of the hypotheses has been slightly revised.

exponential discount factor δ by a parameter β when decision timing coincides with the present date. This means future values are discounted β times more when decisions are made on the present date, reverting to exponential discounting when planning is ahead of the present. At time t , a job seeker selects a search effort, s_t , and a stopping condition for the wage to maximize the following program:

$$\underset{s_t \in [0,1]}{\text{Max}} \quad b - c(s_t) + \beta\delta[s_t E\{\max(V_{t+1}^E(w), V_{t+1}^U)\} + (1 - s_t)V_{t+1}^U] \quad (1)$$

where b is the unemployment benefit, c the cost of search with $c(\cdot)$ an exponential function, and w the wage level. The job seeker decides on the amount of search and then, receives the immediate utility of staying unemployed, which is equal to the utility of unemployment, b , minus the search cost, $c(s_t)$. Given the chosen search level, she also receives the discounted value of the expected utility of the next period. This utility results from two possible situations. First, with probability s_t , she receives a job offer at wage w , accepts it, and receives the future value of employment at that wage, $V_{t+1}^E(w)$. Alternatively, if she rejects the offer, she gets the utility of remaining unemployed in the next period, V_{t+1}^U . Second, with probability $(1 - s_t)$, she remains unemployed and receives the continuation payoff, V_{t+1}^U . A reservation wage strategy maximizes this program as follows:

$$w^* = (1 - \delta)V^U \quad (2)$$

and the first-order condition of the program yields:

$$c'(s_t) = \frac{\beta\delta}{1 - \delta(1 - q)} \left[\int_{w^*}^{\bar{x}} (u - w^*) dF(u) \right] \quad (3)$$

The reservation wage setting does not directly involve short-run discounting, which explains why present bias does not affect the reservation wage, or affects it only marginally. In terms of job search behavior, at equilibrium, the marginal cost of search equals its marginal expected benefit, which directly depends on both the short-run and the long-run discounting factors. Thus, whether job seekers are sophisticated or naive, those with present bias tend to search less than they would ideally prefer to.

In a standard model where job seekers simultaneously determine their reservation wage and search effort level, the costs of search are incurred in the present, while the values of future potential incomes accrue in the future and are discounted accordingly. Since only the discount factor δ matters, two effects come into play at equilibrium. On the one hand, impatient individuals, characterized by a lower δ , heavily discount the future. This results in a lower valuation of potential future wages, leading them to reduce their search effort. On the other hand, impatient individuals are more likely to accept lower

wages compared to more patient individuals. This is because impatient individuals place a higher value on immediate gains and are less willing to wait for potentially better offers in the future. The first effect leads to a negative correlation between unemployment duration and the discount factor δ through its impact on search effort, whereas the second one implies a positive correlation between unemployment duration and δ through its effect on the reservation wage.

DVP show that heterogeneity matters. For high values of δ , individuals wait too long in their job search to secure higher-wage job offers, thereby prolonging their unemployment spell. The overall effect of δ on exiting unemployment forms a hump-shaped curve: the exit rate increases with δ up to a certain threshold beyond which it decreases with δ because the search becomes more selective. We propose the following hypotheses:

Hypothesis 3: *Job seekers with a higher discount factor δ exert greater job search effort and set higher reservation wages. This relationship holds true for both monetary and effort dimensions, as decisions related to job search effort and reservation wage setting involve both real effort and financial trade-offs.*

Hypothesis 4: *Job seekers with a higher discount factor δ tend to exit unemployment faster when the effect of discounting on search effort outweighs its effect on the reservation wage. However, for very high levels of δ , the opposite occurs: the higher reservation wage outweighs the effect on search effort, resulting in longer unemployment spells.*

Since the short-run discount factor, β , increases the discounting of future values, the model with hyperbolic discounting predicts a stronger effect of discounting on search effort. Indeed, effort levels are decided at the beginning of the unemployment spell, but effort is realized throughout the spell. Naive agents fail to anticipate that when the time to search arrives, they will both overestimate their future effort provision and undervalue the future return of their search. Procrastination exacerbates these two effects, causing job seekers to put in less effort than initially planned. In contrast, short-run impatience does not directly affect the reservation wage. Both short-run and long-run discount factors positively correlate with search effort, while only the long-run discount factor positively correlates with the reservation wage, as it reflects long-run considerations.¹⁰ Hyperbolic discounters ($\beta < 1$) search less compared to exponential discounters ($\beta = 1$), but their reservation wage is similar. Thus, short-run impatience (lower β) delays job seekers' exit from unemployment. Based on this argument, and given its strong focus on effort allocation inconsistencies, we introduce our final hypothesis:

Hypothesis 5: *Present-biased job seekers in the effort domain tend to provide lower search effort, thereby delaying their exit from unemployment. Present bias does not significantly affect the reservation wage that implies trade-offs made in the distant future.*

¹⁰Sophisticated present biased agents may anticipate their tendency to search less in the future and marginally adjust their reservation wage downwards, although this effect is relatively small according to DVP.

3 Empirical strategy

Our data originate from three sources: an online experiment designed to measure the time preferences of a sample of job seekers in France, a pre-experimental survey, and an administrative dataset providing individual labor market histories of the same job seekers. This section introduces our sampling procedures, details the administrative data, and outlines the pre-experimental survey and experimental design.

3.1 Sampling and administrative data

Participants to our study were sampled from the French Public Employment Service (PES) database.¹¹ In France, individuals can register with Pôle Emploi for receiving support in their job search. Registering is mandatory for eligible unemployed persons to receive unemployment benefits from UNEDIC. Those receiving unemployment benefits are legally requested to update their job search information monthly until they find employment.¹² The PES database contains comprehensive socio-demographic information (such as age, education, gender), work history (including previous unemployment spells, wages, and contract types, the reason for the termination of the previous labor contract), and details about job search (type of jobs sought and duration of the unemployment spell). Leveraging this dataset, we selected our sample and tracked each participant’s labor market history from their initial registration. We also monitored updates on their job search status with the PES about one year after the experiment concluded.¹³

A statistical power analysis conducted using G*Power 3 (Faul et al., 2007) determined that we required 210 participants to detect a medium-size effect ($d=0.5$) with 95% power and a significance level of 5%. Anticipating the heterogeneity in job seekers’ decisions, which could increase variance and reduce power, we aimed to recruit a sample of 300 participants who would complete the three sessions of the experiment.¹⁴

Based on our expectations regarding response and attrition rates during the experiment, we selected a sample of 40,000 individuals from among all the unemployed job seekers eligible for unemployment benefits. Our predictions were derived from an environment without on-the-job search, so we excluded employed job seekers from the sample. Additionally, due to specific characteristics of their job market, we excluded job seekers

¹¹This database maintained by Pôle Emploi is called the “Fichier National des Allocataires (FNA)”.

¹²Once the eligibility period for receiving unemployment benefits ends, a job seeker is no longer requested to update information every month, except if he or she is willing to continue to receive the assistance of a caseworker, which remains accessible even to job seekers who no longer receive benefits.

¹³A limitation is that while the dataset informs us if participants continued their job search at a certain date, it does not confirm definitively whether they found employment if they stopped registering. PES estimates that over 80% of unemployed job seekers who cease registering before their benefits expire do so because they have secured employment, entered training, or started an internship.

¹⁴These numbers were pre-registered (AsPredicted #68035). The pre-registration also mentioned a pilot study involving 20 data points that we conducted to test the experimental platform, but these data were not used in the analysis.

over 55 years old and below 18. To measure time preferences without any potential bias from the duration of unemployment, we only selected job seekers who had registered with the PES at most four months before our invitation. This time frame was chosen for operational reasons, as it may take up to four months for the database to be updated with the necessary information to select our sample. We conducted the experiment with the agreement of the PES, but we framed the study as academic research to avoid desirability bias in responses about job search efforts. As a result, we needed to invite a larger sample since the expected response rate was lower than that for an official survey by the PES.¹⁵

We emailed each participant in the sample with a link to register for our online experiment. Before registering, participants were invited to answer a pre-experimental survey (see next section). Out of the initial 40,000 individuals in the sample, 38,000 had valid email addresses, and we obtained a response rate of 8% (3,066 job seekers). Among these, 937 completed the survey and 616 registered for the experiment. The attrition rate between registration and the first session was 51%, leaving us with 304 participants. Of these, 235 participants completed all three sessions. The final sample used in the data analysis consists of the 250 participants who completed sessions 1 and 2, the sessions in which decisions were made.¹⁶

Table C1 in Appendix C compares the socio-demographic characteristics of the 40,000 job seekers who received an invitation to participate and those of the 250 job seekers who completed at least the first two sessions. Two-tailed t-tests show that, compared to the initial population, our final sample over-represents job seekers older than 25 years, those holding at least a Master’s degree, and those working in communication and firm support occupations. Conversely, it under-represents those with at most a high-school degree, new entrants, and those in transport, banking, and commerce occupations.

3.2 Pre-experimental survey

Before registering for the experiment, invited job seekers had to answer a survey. Out of 937 respondents, 750 fully completed questionnaires. This survey provides unincentivized measures of risk aversion, time discounting, and present bias, using the Falk et al. (2018) method. Eliciting these preferences allowed us to control for differences in time preferences between the participants who actually completed the experiment and those who did not. Moreover, for the sub-sample that completed the experiment, this allowed us to compare the predictive value of these unincentivized measures in terms of search

¹⁵In France, online surveys of newly unemployed participants typically have a response rate between 5% and 9% (source: personal communication with the PES). We anticipated an even lower response rate because the invitation required a commitment to participate in three successive online experimental sessions.

¹⁶As pre-registered, we excluded participants who provided inconsistent values for the reservation wage. A valid value had to lie within a range of 0.5 to 1.5 times the previous wage, as recovered from individual administrative data. For new entrants, we excluded those indicating values below the minimum wage and above the last decile of the wage distribution in France. Contrary to the pre-registration, we included the 15 participants who did not participate in session 3, as there were no decisions to be made in the last session.

effort and outcomes with the incentivized measures obtained during the experiment.

These measures consisted of a weighted average of the answers to two types of questions (see Appendix A). In the first set of questions, job seekers reported their agreement with three statements related to risk, patience, and the tendency to procrastinate, using 0-10 Likert scales.¹⁷ The second set of questions included staircase measures of risk and patience. For risk, participants chose between five successive hypothetical sure values and a 50/50 gamble between receiving 300€ and 0€. The sure value changed depending on their previous choice, increasing when the gamble was chosen, and decreasing otherwise. For patience, respondents made five hypothetical choices between receiving 100€ immediately and a varying amount in a year. Here again, the value of the future amount depended on their previous choice, increasing when the immediate payment was chosen, and decreasing otherwise. In both staircase measures, there were 32 possible values of risk and patience, depending on the respondent’s successive choices. The final measures of risk and patience combine the Likert scale measures and the staircase measures. The present bias measure is the self-assessment of one’s tendency to procrastinate.

We also collected several measures of search effort over the past four weeks, including the number of weekly hours spent searching, the frequency of use of eight search channels (online search engines, Public Employment Services (PES), local newspapers, friends, previous co-workers, interim agencies, social networks, and direct contact with employers), and the number of actions undertaken to find a job (training, sending resumes, attending job speed dating meetings). Additionally, we inquired about the tendency to set a search target in terms of hours searched or the number of resumes sent, as well as its time horizon (not used). We asked questions about the reservation wage and the minimum and maximum wages expected for the position sought. We asked about the number of interviews and job offers received. Respondents also reported their prospects regarding their exit from unemployment in the next four weeks, two, three, and six months.

Table C2 in Appendix C compares three groups: the 250 job seekers who completed the experiment, the 50 who started but did not finish, and the 450 who completed the survey but did not register for the experiment. The table reveals no significant differences between those who started the experiment but did not finish and those who completed it. However, compared to our final sample, those who completed the survey but did not register for the experiment spent significantly more hours searching, exhibited higher search intensity, and engaged in more active job search. They reported significantly lower reservation wages and received a higher number of job offers, and they reported less patience. This suggests that our experiment may over-represent job seekers with less urgency to return to work and higher job expectations.

¹⁷For risk: “In general, how willing are you to take risks?”; for patience: “How willing are you to give up something that would benefit you today to enjoy it more in the future?”; for procrastination: “ I tend to postpone the tasks to be done even though I know it would be better to do them right away.”

3.3 Experimental Design

Procedures – By registering for our experiment, job seekers committed to participate three times over a seven-week period, with each participation scheduled exactly three weeks apart. After completing the survey, they were invited to register and choose a day and time for their first session, knowing that the subsequent two sessions would be scheduled on the same day three and six weeks later, respectively. All sessions were conducted online. The experiment was programmed in Java. In session 1, participants received instructions on their screen and could ask questions through a chat platform. Since the instructions were almost identical across sessions, the chat was replaced by an email contact for sessions 2 and 3. Participants could log in to our online platform any-time between 8:30 am and midnight on their chosen day for sessions 2 and 3. Reminders were sent two days before each session. In each session, we reminded the nature of the tasks, the decisions to be made, and the timeline.

Treatments – The experiment used a 2x2 factorial design. One dimension manipulated the method used to elicit time preferences between subjects. In our two treatments, participants had to allocate units between two different dates. In the Double Multiple Price List (DMPL) treatment, based on Andersen et al. (2008), all units had to be allocated either to one date or the other (binary choices). In the Convex Time Budget (CTB) treatment, based on Andreoni and Sprenger (2012), participants could allocate a combination of units to a sooner or later date. In the DMPL treatment, we used the Holt and Laury (2002) measure of risk attitudes.¹⁸ To create a common experimental assessment of risk attitude, we added the Bomb Risk Elicitation Task (Crosetto and Filippin, 2013) (BRET) at the very end of session 1 for both treatments.¹⁹

The other dimension manipulated within subjects was the nature of the units to be allocated, either monetary or effort units (see choice sets in Tables D1 and D2 in Appendix D). In one condition, participants made 24 allocation decisions for monetary units between two dates, with six gross interest rates, two time horizons, and two front-end delays. In the other condition, they made 12 allocation decisions regarding a number of tasks to perform at either a sooner or later date, with 12 exchange rates. These decisions were made once in session 1 and once in session 2, totaling 24 decisions. Participants had to perform the task in sessions 2 and/or 3, according to one of their choices, which was randomly selected.²⁰ Figure 1 summarizes the timeline of the experiment.

¹⁸Subjects were presented with 10 ordered choices between two lotteries. Lottery A paid either €8.0 or €6.4, while Lottery B paid either €15.4 or €0.4. The probability that both lotteries paid the high payoff varied from 10% to 90%. The later subjects switched from the safer Lottery A to Lottery B, the more risk averse they were.

¹⁹A grid represented 100 boxes. Opening a box paid €0.05, but one box contained a bomb that, if opened, nullified the gains. The higher the number of boxes opened by participants, the less risk-averse they are.

²⁰The allocation of effort was done in two steps, while the allocation of money was done in a single session. This design aimed to preserve the independence of these decisions and prevent monetary decisions from compensating for effort choices. Requiring the first effort allocation decisions to be made in session 1 also avoided asking

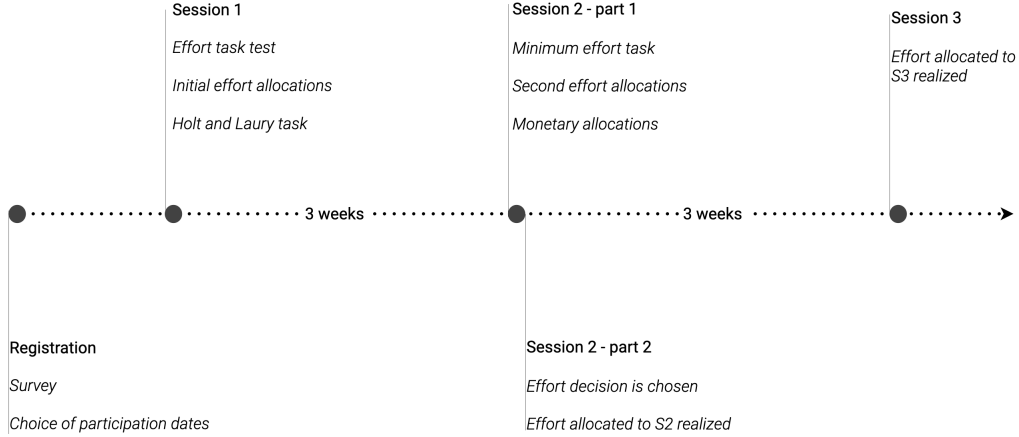


Figure 1: Timeline of the experiment

Monetary Allocations – All the intertemporal decisions regarding monetary allocations were made in session 2, after the effort allocations were made but before one of them was selected for implementation. Participants made their 24 decisions in four sets of six decisions, with one choice set per screen. They were informed that one decision would be randomly selected at the end of the session for payment. We varied the time horizon, with $k = (3, 10)$ weeks, between the first two and the last two sets of decisions. For a given time horizon, we varied the front-end delay on the sooner payment for each set of six decisions, with $t = (0, 3)$ weeks. The first two sets had a time horizon of three weeks. Allocations had to be made between session 2 and session 3 in the first set, and between session 3 and three weeks after session 3 (six weeks after the decision date) in the second set. The last two sets had a time horizon of 10 weeks. Allocations had to be made between session 2 and 10 weeks after session 2 in the third set, and between session 3 and 10 weeks after session 3 (13 weeks after the decision date) in the fourth set.

The decisions consisted of allocating monetary payments, c , at two dates, t and $t+k$, subject to the following budget constraint:

$$Pc_t + c_{t+k} = y \quad (4)$$

where $P \in [1.05, 1.11, 1.18, 1.25, 1.43, 1.82]$ is the gross interest rate, and y is the maximum amount that could be allocated to the later date, with $y = \text{€}15$. Within a (t, k) choice set, each decision was associated with a different interest rate, presented in increasing order. The four sets included the same rates. In addition, to maintain a constant transaction cost between sessions and regardless of the allocation decisions, a $\text{€}6$ fixed fee was paid at each of the two dates, which was not counted toward the monetary allocations.

The allocation decisions were made by moving a slider. The gross interest rate was displayed on the left of the slider, and as the participant moved the slider, the amounts participants to return for a fourth session to perform tasks assigned to the later date.

allocated to each date were displayed on top of it (see Figure B2 in Appendix B). In the CTB treatment, any feasible allocation on the slider bar was allowed.²¹ In contrast, in the DMPL treatment, only choices at the extremes were allowed.

Effort allocations – Subjects made 12 allocation decisions between two dates with varying exchange rates, both in session 1 and session 2. In session 1, after practicing, they allocated tasks between two future dates, while in session 2 they allocated tasks between the present and a future date. Participants were informed that only one of these 24 decisions would be selected randomly and implemented, with decisions made in session 2 having a 90% chance of being selected compared to a 10% chance for those made in session 1. As in Augenblick et al. (2015), this allowed subjects to maintain flexibility while experiencing their potential present bias when reallocating effort in session 2. Performing the tasks paid a one-time completion bonus of €27 at the end of session 3, conditional on having participated in all sessions.

The tasks involved entering references of scientific articles published in economic journals into a computer. By clicking on provided links, participants accessed the table of contents of one journal issue. They had to copy and paste the titles of the first three articles and the names of their authors (see Figure B3 in Appendix B). This counted as one “page”. The decisions consisted of allocating a number of pages, e , between a sooner date t and a later date $t + k$, subject to the following budget constraint:

$$e_t + Re_{t+k} = m \tag{5}$$

where $R \in [0.2, 0.25, 0.33, 0.5, 0.66, 0.75, 1, 1.2, 1.25, 1.33, 1.5, 1.66]$ is the exchange rate between sooner and later tasks. Each rate indicates how much each page allocated to the sooner date diminishes the number of pages allocated to the later date. For example, a rate of 0.33 indicates that one page at the sooner date reduces by 0.33 the number of pages allocated at the later date. A lower value of R means that the relative cost of performing the tasks at the sooner date is lower. m is the maximum number of pages that could be allocated to the sooner date, with $m = 15$. We assume that the effort cost function is convex, time-separable, and stationary.

Each screen displayed six slider bars with allocation decisions between sooner and later dates. For each decision, the exchange rate of sooner *vs.* later tasks was indicated on the left side of the bar. As participants moved the slider, the number of pages to complete in each session was displayed on top of the bar (see Figure B3 in Appendix B). To proceed to the next decision, participants had to move the slider. In the CTB treatment,

²¹In Andreoni and Sprenger (2012), participants had to allocate 100 tokens between two dates, knowing the fixed value of one token in US dollars at the late date and the varying value of one token at the sooner date. Here, we indicated the varying value at the late date of €1 at the early date, and moving the slider directly gave the resulting net payments in € at each of the two dates.

participants could choose any inner allocations on the slider, while in the DMPL treatment, only extreme allocations were allowed.²² To ensure that all participants faced the same transaction costs, independently from their choices, and to eliminate any show-up cost effects, a minimum work requirement of five pages was imposed in each of the three sessions. This number was not counted toward the allocation decisions.

Payment procedures – Previous research has highlighted the importance of payment credibility in measuring time preferences (Andreoni and Sprenger, 2012). To equalize transaction costs for time-dated payments, participants’ earnings were wired to their bank account by the National Center for Scientific Research (CNRS). CNRS is France’s principal public research institution. Its longstanding presence and recognition in French public life lend significant credibility to the payment processes. Credibility was further enhanced by noting the support of the PES in our study. However, paying through bank transfers means that funds were actually made available during the week following a session. This delay is a limitation, as research indicates that present bias is highly sensitive to same-day immediate payments (*e.g.*, Balakrishnan et al., 2020). Consequently, we may have underestimated short-run impatience in the monetary dimension. In contrast, the effort was performed in the hour. On average, participants earned €70.36 (S.D.=3.77) in total for their decisions, including a total show-up fee of €18 (€6 per session).

4 Results

In this section, we first outline our estimation strategies. Next, we present our estimates of time preferences over money and effort. Finally, we examine the extent to which time preferences correlate with job search and its outcome.

4.1 Estimation strategies

Recovering risk and time preferences from choice data requests making very stringent assumptions on the utility functions. Using two methodologies, we were able to assess to what extent the preference estimates were sensitive to changes in the assumptions. We adopted the framework of the quasi-hyperbolic discounting model (Laibson, 1997; O’Donoghue and Rabin, 2001) in a situation in which agents have to make intertemporal choices and define an individual’s objective function at date t as:

$$T(u_t, u_{t+k}) = (u_t + \omega_1)^\theta + \beta^{1_{t=0}} \delta^k (u_{t+k} + \omega_2)^\theta \quad (6)$$

²²Because the number of pages was discrete, only a restricted set of decisions within the defined ranges could be selected. Higher levels of R had fewer inner choices than lower levels, leading to greater variance in decisions at higher rates and thus, weaker statistical power for effects driven by differences in choices with these rates.

where u represents the argument traded off over time. In one condition, participants allocated tasks over two dates, t and $t + k$. In this situation, u takes the value e and θ the value $\gamma > 1$, reflecting effort aversion through the cost function's curvature, identified through the variations in the exchange rates. In the other condition, they allocated monetary units at two dates, in which case u takes the value c . Here, we adopted a simple power utility function in which θ takes the value α that reflects risk aversion.

The parameters β and δ account for the utility discounting over time. δ is the long-run discount factor that accounts for future utility devaluation. The lower δ is, the more impatient an agent is. β is the short-run discount factor that captures a greater utility discounting when $t = 0$. The lower β is, the more present-biased an agent is, discounting future utilities more when having to make a choice in the present. This form returns to the standard exponential model when $\beta = 1$, that is, when future utility is discounted in the same way, irrespective of the decision time.

Finally, the Stone Geary parameters ω enable the element u to be integrated with background monetary streams or effort present in the same time unit. They can represent background consumption (Andersen et al., 2008; Andreoni and Sprenger, 2012) or minimum effort requirement (Augenblick et al., 2015).

Convex Time Budget estimation – To recover the parameters of interest α , β , and δ , the CTB method relies on choices where monetary and effort units can be freely distributed over the two dates.²³ An agent maximizes (6) under the constraints (4) for money and (5) for effort. For money, the maximization yields the tangency condition:

$$\frac{c_t + \omega_1}{c_{t+k} + \omega_2} = (P\beta^{\mathbb{1}_{t=0}}\delta^k)^{\left(\frac{1}{\alpha-1}\right)} \quad (7)$$

For effort, the maximization yields the tangency condition:

$$\frac{e_t + \omega_1}{e_{t+k} + \omega_2} = \left(\frac{1}{R}\beta^{\mathbb{1}_{t=0}}\delta^k\right)^{\left(\frac{1}{\gamma-1}\right)} \quad (8)$$

In both cases, $\mathbb{1}_{t=0}$ takes value 1 if $t = 0$ and value 0 if $t > 0$. Both equations can be estimated using Ordinary Least Squares (OLS) regressions after log-linearization. The estimated equations take the form:

$$\ln\left(\frac{u_t + \omega_1}{u_{t+k} + \omega_2}\right) = \left(\frac{\ln\beta}{\theta - 1}\right)\mathbb{1}_{t=0} + \left(\frac{\ln\delta}{\theta - 1}\right)k + \left(\frac{1}{\theta - 1}\right)\ln(Rate) \quad (9)$$

The variable *Rate* takes the value P for money and $-\frac{1}{R}$ for effort, while $\theta = \alpha$ for money and $\theta = \gamma \geq 1$ for effort. After estimation, the parameters α , β , and δ are recovered via

²³Estimating these parameters requires subjects to respond to the exchange rate. Only 6 participants in the CTB treatment never changed their task allocations while 78 never changed their payment allocations. Including or excluding these participants from the aggregate estimates does not affect qualitatively the results.

a non-linear combination of the regression coefficients. Indeed, this structural approach implies that both ω parameters are known. Since the ratio $\ln(\frac{u_t + \omega_1}{u_{t+k} + \omega_2})$ is undefined for $\omega = 0$, we set it equal to the show-up fee for the monetary decisions (€6) and to the minimum effort (five pages) for the effort decisions. However, to avoid using a defined value for the Stone Geary parameters, equations (4) and (5) can be estimated using Non-Linear least Squares, which allows us to both directly estimate the parameters and avoid the log transformation. We acknowledge that each decision was bounded by the choice set limits.²⁴ While the positive probability of corner solutions represents a caveat of the NLS approach, it can be accounted for by Two-Limit Tobit regressions (Wooldridge, 2010). We thus provide all three estimates. Standard errors were clustered at the individual levels and they were estimated using the delta method.

Double Multiple Price List estimation – The approach to recovering our parameters from DMPL choices differs from that used for CTB choices, using two distinct tasks. The task used to identify discounting parameters relies on choices where effort and money are allocated either to the sooner or later date. Most studies estimate discounting through the ratio between sooner and later utilities, assuming risk neutrality. In contrast, the DMPL method allows us to account for utility function curvature, using the choices made in the Holt and Laury (2002) risk elicitation task, which results in higher discount rates in the presence of risk aversion.

Although we could strictly apply this method, using risk preferences and the allocation task simultaneously for the monetary dimension, the use of a separate task in the effort dimension presents challenges because curvature arises from effort aversion, which cannot be estimated using an adaptation of a Holt and Laury (2002) task for effort. Thus, we employed a two-step process. First, we estimated effort aversion and discounting in the CTB sample. We then incorporated the estimated average effort aversion level into the likelihood function to evaluate discounting parameters in the DMPL sample. We followed a similar two-step strategy to estimate risk aversion and time discounting in the monetary dimension. First, we estimated risk aversion using the Holt and Laury (2002) task and then estimated discounting levels.²⁵

Following Andersen et al. (2008), we related the allocation choices and the theoretical model by defining a choice probability index for each choice alternative. The present value of choosing the sooner (PV_S) and later (PV_L) alternatives were defined as follows:

$$PV_S = (u_t + \omega_1)^\theta + \beta^{1-t=0} \delta^k (\omega_2)^\theta \quad (10)$$

²⁴Corner choices represent the situations in which either c_t or c_{t+k} are null. These cases represent the bounds $[\frac{0+\omega_1}{u_{t+k}+\omega_2}, \frac{u_{t+k}+\omega_1}{0+\omega_2}]$ that change for each exchange rate and decision made by each participant.

²⁵Estimating these parameters requires that participants respond to the various exchange rates. In our sample, 3 participants in the DMPL treatment never changed their task allocations, and 77 never changed their payment allocations. Including or excluding these participants from the aggregate estimates does not affect the results.

$$PV_L = (\omega_1)^\theta + \beta^{1-t} \delta^k (u_{t+k} + \omega_2)^\theta \quad (11)$$

We made the simplifying assumption that the amounts received in the experiment were immediately consumed, as implicitly done in the CTB approach. We then built the following choice probability indexes based on the stochastic choice model of Luce (1959):

$$P(\text{choice} = S) = \frac{PV_S^{\frac{1}{\mu}}}{PV_S^{\frac{1}{\mu}} + PV_L^{\frac{1}{\mu}}} \quad (12)$$

$$P(\text{choice} = L) = 1 - P(\text{choice} = S) \quad (13)$$

We assumed that a given option is chosen whenever its choice probability index exceeds $\frac{1}{2}$. To account for the positive probability of errors in the statistical specification adopted, we introduced the error parameter μ , as is common in the literature (Andersen et al., 2008; Andreoni et al., 2015). When μ is large, this probability becomes random, whereas it approaches a perfectly deterministic model when $\mu \rightarrow 0$. Following Holt and Laury (2002), we utilized the fact that the index is already in the form of a Cumulative Distributive Function to define our log-likelihood functions, allowing us to estimate our parameters of interest through Maximum Likelihood:

$$\ln(L(\theta, \beta, \delta, \mu, \omega_1, \omega_2)) = \sum_i [(\ln(P(\text{choice} = S)) | \text{choice} = S) + (\ln(P(\text{choice} = L)) | \text{choice} = L)] \quad (14)$$

We replicated the strategy at the individual level for both the DMPL and the CTB estimation techniques. In the next subsections, we present the aggregate results for each treatment before using the individual estimates for the job search analysis.

4.2 Short- and long-run time discounting

We first present the results on time preferences over money followed by the results on time preferences over effort.

Discounting money over time – Figures 2 and 3 display the average amount of money allocated to the sooner date for each gross interest rate (P) and time horizon in the CTB and the DMPL treatments, respectively (see values in Tables E1 and E2 in Appendix E). All curves are downward sloping, consistently with the law of demand.²⁶ Allocations to the sooner date are, on average, lower in the CTB treatment compared to the DMPL

²⁶At the individual level, 12 participants out of 128 had non-monotonically decreasing allocations in the CTB treatment and 9 out of 124 switched multiple times in the DMPL treatment. In the CTB treatment, 49 participants always chose the same allocation (either sooner or later) regardless of the gross interest rate; the corresponding number in the DMPL treatment is 46. It is not possible to estimate individual parameters for these individuals. They were included in the aggregate analysis; however, removing them from the estimates does not alter the results. We report estimates excluding these participants in Appendix G.

treatment because job seekers in the CTB treatment utilized the possibility to distribute their monetary units across two dates.

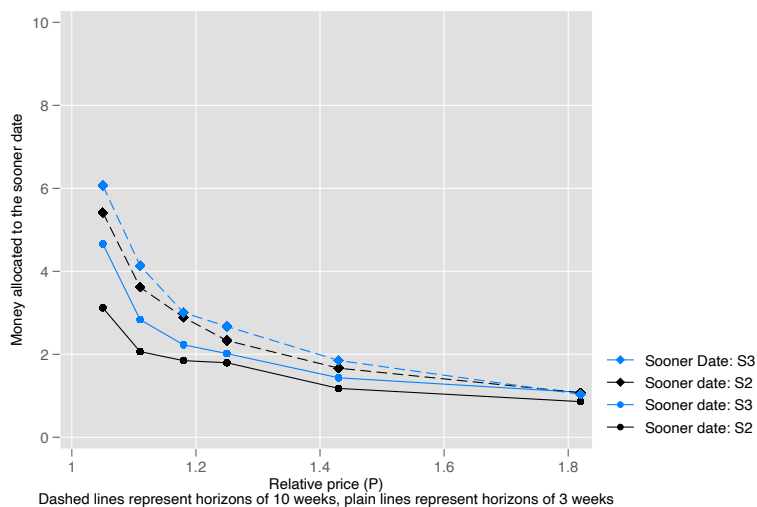


Figure 2: Monetary allocations in the CTB treatment

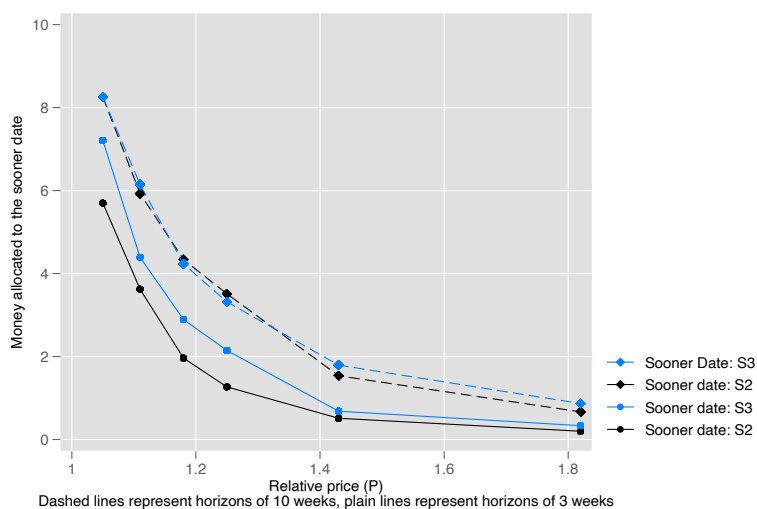


Figure 3: Monetary allocations in the DMPL treatment

Notes: The figures represent, for each treatment, the average number of monetary units allocated to the sooner date, for each gross interest rate (P) and time horizon. Plain curves are for a three-week horizon and dashed curves are for a ten-week horizon. S2 is for session 2 and S3 is for session 3.

The figures reveal that subjects in both treatments exhibited increased impatience as the time horizon extended. They allocated more units to the sooner date when the time horizon was longer: in both figures, the dashed curves ($k = 10$ weeks) always lie above the solid curves ($k = 3$ weeks). Controlling for the gross interest rates, participants allocated on average €0.88 (s.e.=0.15) more to the sooner date when the time horizon was 10 weeks compared to three weeks in the CTB treatment ($p < 0.001$), and €1.5 (s.e.=0.2) more in the DMPL treatment ($p < 0.001$). In the short run, however, participants displayed future bias in both treatments. They allocated larger amounts to the sooner date when

the sooner date was in the future: in both figures, the curves where the sooner date is session 3 always lie above those where the sooner date is session 2. Controlling for the gross interest rates, participants allocated on average €0.57 (s.e.=0.19) less to the sooner date when it was in the present ($t = 0$) compared to when it was in the future ($p = 0.002$) in the CTB treatment, and €0.73 (s.e.=0.26) less in the DMPL treatment ($p = 0.005$). Most pairwise differences within²⁷ and between²⁸ time horizons are highly significant.

Pooling the data from all the participants (excluding only those with inconsistent –non-monotonic– choices, Table 1 reports the aggregate estimates of the risk and time preference parameters in the CTB treatment (models (1) to (3)) and the DMPL treatment (models (4) and (5)), with standard errors clustered at the individual level. Model (1) reports the estimates from OLS, model (2) those from a Two-Limit Tobit, and model (3) those from NLS. Models (4) and (5) are Maximum Likelihood Estimates.

The long-run discounting estimates indicate that, on average, individuals exhibited patience: the daily discount factor δ is very close to 1 across all estimates (and close to the 0.998 estimated in Augenblick et al. (2015) with a Two-Limit Tobit).²⁹ For short-run discounting, both linear and Tobit estimates reveal a strong future bias in the CTB treatment ($\beta = 1.187$ and 1.162, respectively), indicating a preference for deferring payment to the future. When accounting for non-linearities in how parameters enter the objective function, the level of future bias drops to 1.050 but remains significantly greater than 1 (χ^2 test, $p < 0.001$). These levels are higher than the 1.004 estimated in Andreoni and Sprenger (2012) with NLS and 0.988 in Augenblick et al. (2015) with a Two-Limit Tobit.³⁰ The DMPL estimate of β is closer to the CTB estimate using NLS (1.043). Overall, the average level of future bias implies that when comparing choices between €15 at a sooner date and a free amount three weeks later, individuals would be willing to pay approximately €0.9 to receive the earnings in the future, that is, when the sooner date is in the future rather than in the present.

For risk preferences, the low OLS estimate of α (0.392) can be attributed to non-linearities and bounded choices. The estimate using Non-Linear Least squares is 0.902 (close to the 0.920 estimated in Andreoni and Sprenger (2012) with the same method).

²⁷Two-tailed t -tests conducted on the average allocations to the sooner date in the CTB and DMPL treatments, respectively, yield: $p = 0.003$ and $p = 0.007$ when comparing session 2 *vs.* session 3 with session 3 *vs.* session 3+3, but $p = 0.207$ and $p = 0.841$ when comparing session 2 *vs.* session 3+7 with session 3 *vs.* session 3+10.

²⁸Two-tailed t -tests conducted on the average allocations to the sooner date in the CTB and DMPL treatments are all highly significant ($p < 0.001$) when comparing session 2 *vs.* session 3 with session 2 *vs.* session 3+7, and when comparing session 3 *vs.* session 3+3 with session 3 *vs.* session 3+10.

²⁹The large number of decisions allows us to detect small effects up to three decimals. However, because our horizons are relatively short, we have limited ability to infer discounting over very long horizons, where such a degree of precision may be more critical. Although the χ^2 test is significant for models (1) and (2), for the horizons in our settings we can reasonably assume that δ is economically close to 1 in the CTB estimations.

³⁰A meta-analysis of articles using the CTB method (Imai et al., 2021) shows that, on average, individuals are not present-biased over money (β close to 1). However, there is heterogeneity across studies, with a few observing $\beta > 1$ (Andreoni and Sprenger, 2012; Aycinena et al., 2015; Aycinena and Rentschler, 2018; Brocas et al., 2018). Present bias is less frequent in field studies compared to lab studies, and it tends to be higher when the sooner reward is delivered in the hours following the experiment, as already shown by (Balakrishnan et al., 2020).

Table 1: Average estimates of time preferences over money

	CTB			DMPL	
	OLS (1)	Two-Limit Tobit (2)	NLS (3)	(4)	MLE (5)
α	0.392*** (0.031)	0.862*** (0.027)	0.902*** (0.011)	0.732*** (0.041)	-
δ	1.002*** (0.0007)	1.001*** (0.0006)	1.000*** (0.0002)	-	0.999*** (0.0003)
β	1.187*** (0.019)	1.162*** (0.019)	1.050*** (0.008)	-	1.043*** (0.012)
$H_0: \delta = 1, p$	0.000	0.024	0.141	-	0.000
$H_0: \beta = 1, p$	0.000	0.000	0.000	-	0.000
N	2760	2760	2760	1350	2760
N clusters	115	115	115	135	115

Notes: α is for risk attitude, δ for long-run discounting, β for short-run discounting. The computations of δ are based on daily rates. Standard errors in parentheses are clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The estimate using the Two-Limit Tobit model (0.862) also shows a small level of curvature (smaller than Andreoni and Sprenger (2012) and the 0.974 found in Augenblick et al. (2015), using the same method); however, because of the constraints of the model, this value is only identified up to a proportionality constant which dampens its precision and makes the value 0.902 more reliable. In contrast, a substantial degree of risk aversion, showing a preference for smooth consumption, is found in the DMPL treatment, using the Holt and Laury method. According to these estimates, a certainty equivalent between €3.6 and €5.75 would be required to make an agent indifferent to a 50/50 gamble between €15 and €0. This higher curvature found in the DMPL compared to the CTB treatment is aligned with the findings of Andersen et al. (2008) and Andreoni et al. (2015).

Discounting effort over time – Figures 4 and 5 display the average number of effort units allocated to the sooner date (*i.e.*, session 2) for each exchange rate between sooner and later effort (R), depending on the decision date (session 1 or 2) in the CTB and DMPL treatments, respectively (see detailed values in Tables E3 and E4 in Appendix E). The curves are downward sloping in both treatments: participants allocate less effort to the sooner date as the exchange rate increases. The curves also exhibit some concavity for the most advantageous rates, signaling effort aversion. This general pattern is consistent with the findings of Augenblick et al. (2015).³¹

Regarding discounting patterns, there is no evidence of present bias in the CTB treatment, as the two curves in Figure 4 largely overlap. When participants had to

³¹At the individual level, the total number of inconsistent patterns aligns with the monetary analysis: 12 participants out of 128 exhibited preference reversals in the CTB treatment, while 9 out of 124 showed non-monotonic choices in the DMPL treatment. In the CTB treatment, 6 participants consistently allocated all their effort to either the sooner or the later date, with no variation; 3 participants in the DMPL treatment followed the same pattern. These participants are thus excluded from the analysis.

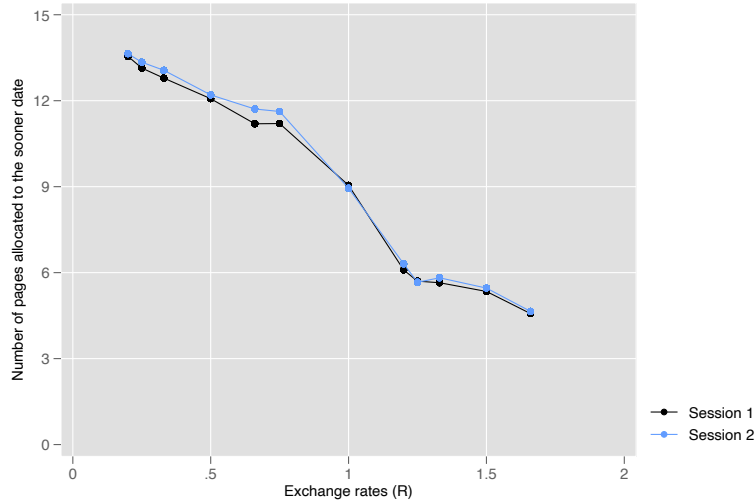


Figure 4: Effort allocations in the CTB treatment

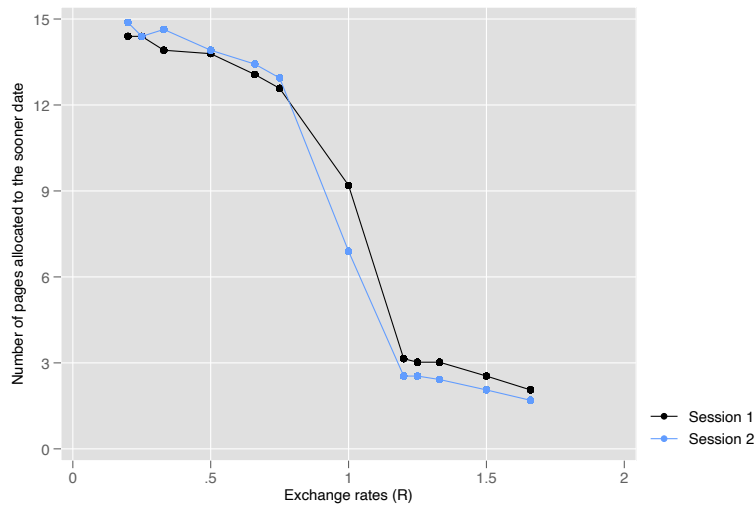


Figure 5: Effort allocations in the DMPL treatment

Notes: The figures represent, for each treatment and each decision date (session 1 or 2), the average number of pages allocated to the sooner date (session 2), depending on the exchange rate of sooner *vs.* later effort (R).

allocate all their effort to a single date, in Figure 5 the curve for the sooner date allocations of effort made in session 2 lies below the curve for decisions made in session 1 when $R = 1$ and when sooner tasks become relatively more expensive to perform ($R > 1$). This suggests a tendency to postpone effort more when the sooner date for performing the task was today, but the difference is not significant.³² Controlling for gross interest rates, participants allocated, on average, the same number of pages to the sooner date whether it was in the present ($t = 0$) or in the future, in both the CTB and DMPL

³²Two-tailed t -tests indicate that the average effort allocation to the sooner date was not significantly different when decisions were made in session 1 or in session 2, in both the CTB and DMPL treatments ($p = 0.554$ and $p = 0.776$, respectively).

treatments (respectively, the mean differences are 0.10 and -0.07 , with tests of equality of means indicating $p = 0.44$ and $p = 0.69$).

Table 2 reports the aggregate estimates of participants' time preference parameters over effort in the CTB treatment (models (1) to (3)) and the DMPL treatment (model (4)). The preferences in the CTB treatment are estimated through OLS (model (1)), Two-Limit Tobit (model (2)), and NLS regressions (model (3)). The CTB estimates based on the OLS and Tobit models indicate a time-consistent behavior, with β and δ not significantly different from one. The NLS estimate reveals a significant $\delta > 1$, but it remains very close to one. In contrast, the estimates for the DMPL treatment show significant present bias ($\beta = 0.969$), whereas the long-run patience parameter is close to one but marginally significantly different from one ($\delta = 0.997$). Finally, the curvature parameter (γ), which captures effort aversion, varies across models, with the Two-Limit Tobit estimate being the smallest and the NLS estimate being the largest. Overall, the rates are close in magnitude to the rate of 1.589 reported in Augenblick et al. (2015).

Table 2: Average estimates of time preferences over effort

	CTB			DMPL
	OLS (1)	Two-Limit Tobit (2)	NLS (3)	MLE (4)
γ	1.308*** (0.030)	1.171*** (0.025)	1.750*** (0.117)	-
δ	1.003*** (0.004)	1.003*** (0.003)	1.006*** (0.003)	0.997*** (0.001)
β	1.018*** (0.067)	1.009*** (0.067)	1.045*** (0.066)	0.969*** (0.015)
$H_0: \delta = 1, p$	0.372	0.402	0.038	0.065
$H_0: \beta = 1, p$	0.785	0.896	0.495	0.049
N	2784	2784	2784	2760
N clusters	116	116	116	115

Notes: γ for effort aversion, δ for long-run discounting, β for short-run discounting. The computations of δ are based on daily rates. Standard errors in parentheses are clustered at the individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To summarize, our findings support Hypothesis 1. Job seekers in the DMPL treatment displayed a behavior close to exponential discounting for monetary decisions but exhibited present biasedness in the effort dimension. In contrast, those in the CTB treatment exhibited a pronounced future bias in monetary decisions, whereas their behavior in the effort dimension did not significantly deviate from exponential discounting. Notably, although this future bias is atypical, participants exhibited lower short-run discounting (β) over effort than over money, which is again consistent with Hypothesis 1 and the literature. This leads to our first result:

Result 1 (Time preferences at the aggregate level): Job seekers are on average less patient over effort than over money. In the DMPL treatment, they exhibit present

bias when allocating effort over time, but time consistency when allocating money. In the CTB treatment, they exhibit future bias over money but time consistency over effort.

Individual estimates – At the individual level, a significant proportion of job seekers exhibited present bias ($\beta < 1$), especially in the effort dimension, despite substantial differences according to the elicitation method. Using OLS for the CTB treatment, we estimated that the percentage of present-biased job seekers is 15% in the money domain and 55% in the effort domain. Using MLE for the DMPL treatment, the respective equivalent percentages are 53% and 31%.³³

We estimated the correlation between individual time and risk preferences, controlling for the elicitation method and individual characteristics, with two objectives: i) to explore whether the elicitation method significantly affects the estimated value of the parameters, and ii) to test Hypothesis 2 regarding individual heterogeneity, particularly the possible role of job seekers' expectations in the labor market. The expectation of a quick exit might lead job seekers to prefer a positive income stream in the present to smooth background consumption and to exhibit less procrastination, as they may have more time available now than in the near future. Table F1 in Appendix F reports OLS regressions of α , δ , and β estimated at the individual level in each dimension. The independent variables include the CTB treatment and a series of individual socio-demographic and economic characteristics, including the prospect of finding a job in the next four weeks, [1-3] months, [3-6] months, and after six months.

First, controlling for individual characteristics, the CTB method revealed a significantly lower tendency to smooth consumption (at the 5% level), higher long-run impatience over money, and a lower tendency to procrastinate in the task (both significant at the 1% level) compared to the DMPL method. Analyses of the role of time preferences on job search and outcomes should control for the elicitation method. Second, we found no significant correlation between any of the estimated parameters and job seekers' subjective prospects in the labor market, nor with their characteristics. Thus, we reject Hypothesis 2 and its prediction that accounting for job prospects would reduce the difference between patience over time and money. This is summarized in Result 2.

Result 2 (Subjective prospects): Job seekers' subjective prospects on their future exit from unemployment do not correlate with time preferences in any dimension; thus, these prospects cannot reduce the difference in patience over money and over time.

4.3 Time preferences and job search

In this section, we focus on the effects of time preferences on the effort provided in job search within the labor market. We built three measures of search effort based on

³³See also Figures B4, B5, and B6 in Appendix B that display the distributions of the individual estimates of long-run and short-run time preferences over effort and money, and the distribution of risk preferences, respectively.

respondents’ answers in the pre-experimental survey. “Hours searched” is the number of hours spent each week on searching over the past four weeks. “Search channel index” is an index equal to the sum of the ordinal frequencies of use of each of the eight search channels, weighted by the number of channels used. “Active search” is the number of search actions undertaken to exit unemployment (*e.g.*, sending a CV, contacting a firm directly).³⁴ We also analyzed how time preferences impacted the log of the reservation wage reported by the participants in the survey.

Table 3 presents the estimates of OLS regressions on the pooled sample of participants from the CTB and the DMPL treatments. The dependent variables are the three measures of search and the reservation wage. The independent variables include the standardized individual estimates of time preferences over money (models (1) to (4)) or over effort (models (5) to (8)). Time preferences are those estimated by OLS in the CTB treatment and by Maximum Likelihood in the DMPL treatment.³⁵ To control for risk preferences, we used the BRET measure, as it provides an estimate using a common method for all participants.³⁶ In all models, each preference parameter was interacted with a dummy for the DMPL treatment because Table F1 in Appendix F showed that some estimates were affected by the estimation method. We controlled for socio-demographic variables (gender, age, and education) and unemployment characteristics (number of past registrations with the PES and motive of the last registration) (Table H1 in Appendix H displays the detailed coefficients of these controls).^{37, 38}

Table 3 shows that the preference for smooth consumption had no significant impact on the intensity of job search or the reservation wage, and the risk measure was not significant in any model. Hypothesis 3 stated that the long-run discount factor, δ , should positively correlate with both search effort and the reservation wage, irrespective of the time dimension. Table 3 provides mixed support for this hypothesis. While long-run patience over money had no significant effect in any model, long-run patience over effort had the expected significant positive impact on both active search and reservation wage, but only in the DMPL treatment. In an exploratory perspective, Table I1 in Appendix I shows that, in the CTB sample, participants in the upper quartile of the distribution

³⁴The variable has four levels: “less than 5” to “15 and more”, with increasing steps of five actions per level. We report estimates using OLS but obtained similar results using an ordered logit model.

³⁵Because of the large discrepancy in variance between the Maximum Likelihood and OLS methods, the standardized δ parameters were multiplied by 100 to ease interpretation.

³⁶We also considered using the pre-experimental measure of risk from the global preference survey method. However, we preferred using the BRET due to its higher correlation with the value of α inferred from the Holt and Laury task (correlation of 21% with $p = 0.034$).

³⁷For these regressions, we excluded from the sample of 250 participants those with unreliably high values of discounting, search effort, or reservation wages, leaving us with 125 observations for the regressions using monetary discounting measures and 202 observations for the regressions using effort discounting measures.

³⁸The Stone Geary parameters were assumed to be equal to 0.01 for time preferences over money and to 5 for time preferences over effort. This choice was guided by the fact that these estimates provide the highest correlation to the choices made in the experiment. Indeed, when participants made their choices, they were more likely to consider all the tasks they were asked to perform (the five-page minimum requirement), whereas it is not clear that they integrated all the monetary streams.

of δ over effort set significantly higher reservation wages (at the 5% level). This pattern holds for all quartiles compared to the first one in the DMPL sample, as shown in Table I2). We interpret this as a reflection of the value that high δ job seekers may attribute to their ability to consistently plan efforts.

The effect of long-run patience over effort on active search and the reservation wage in the DMPL treatment is robust but less significant when estimating time preferences with a Two-Limit Tobit (see Table I3 in Appendix I). Surprisingly, it negatively affects the number of hours searched in the CTB treatment. Using instead NLS estimates reveals a positive and significant effect of long-run patience over effort on the number of hours searched and the search channel index in both treatments and on active search in the DMPL treatment. However, it indicates a negative effect on the reservation wage in the DMPL treatment (see Table I4 in Appendix I). This suggests that the effect of long-run patience over effort on the reservation wage is more fragile.

Finally, we explored possible non-linear effects of long-run patience on search efforts. In the monetary domain, assuming a non-linear effect of δ revealed a negative and convexly decreasing effect of long-run patience on the search effort index (see model (2) in Table I5 in Appendix I). In the effort domain, the same assumption revealed an increasing and concave effect of long-run patience on the reservation wage.

We summarize our analysis as follows:

Result 3 (Long-run impatience and search effort): Less long-run impatience over effort tends to increase both search effort and, with more variable evidence, the reservation wage. In contrast, long-run impatience over money does not have a significant impact on either search intensity or the reservation wage.

Regarding short-run impatience, Hypothesis 5 posits that present bias over effort (procrastination) should lead to postponing search effort without affecting the reservation wage, as the latter reflects trade-offs made in the distant future. Table 3 provides some support for this hypothesis, but only in the DMPL treatment. Consistent with DVP, active search increased significantly (at the 1% level; model (7)) with higher values of β in this treatment. A 0.1 increase in β in the DMPL estimates raised the likelihood of sending at least 15 applications in the past four weeks by 10.6%. This positive effect is driven by job seekers in the top quartile of the β distribution (see Table I2 in Appendix I). In contrast, in the CTB treatment, the coefficients did not achieve standard levels of significance, and Table I1 in Appendix I shows no difference across quartiles. As expected, the effect of short-run impatience on the reservation was not significant in any treatment.

Table 3: Time preferences and job search effort

	Search and time preferences over money				Search and time preferences over effort			
	Hours	Search channel	Active	Reservation	Hours	Search channel	Active	Reservation
	searched	index	search	wage	searched	index	search	wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk (BRET)	-0.024 (0.042)	0.005 (0.004)	-0.002 (0.006)	-0.00002 (0.001)	0.002 (0.032)	0.003 (0.003)	-0.002 (0.004)	0.0007 (0.001)
δ (money)	0.013 (0.055)	-0.007 (0.006)	-0.011 (0.008)	-0.0003 (0.002)	-	-	-	-
DMPL \times δ (money)	-0.011 (0.054)	0.006 (0.006)	0.010 (0.008)	0.0007 (0.002)	-	-	-	-
β (money)	-3.943*** (1.370)	-0.170 (0.148)	-0.267 (0.205)	0.060 (0.065)	-	-	-	-
DMPL \times β (money)	6.591*** (1.889)	0.242 (0.163)	0.276 (0.245)	-0.013 (0.077)	-	-	-	-
δ (effort)	-	-	-	-	0.001 (0.006)	0.0003 (0.001)	-0.0003 (0.001)	0.0005 (0.0005)
DMPL \times δ (effort)	-	-	-	-	-0.011 (0.381)	0.017 (0.030)	0.106*** (0.039)	0.0318** (0.012)
β (effort)	-	-	-	-	-1.186* (0.683)	-0.160* (0.095)	-0.176 (0.109)	-0.048 (0.034)
DMPL \times β (effort)	-	-	-	-	0.382 (1.381)	0.228* (0.135)	0.651*** (0.169)	0.112* (0.067)
DMPL treatment	2.046 (2.260)	0.032 (0.220)	-0.117 (0.322)	-0.034 (0.080)	2.586 (6.180)	0.511 (0.487)	1.769*** (0.662)	0.514** (0.209)
Observations	125	125	125	125	202	202	202	202
R^2	0.216	0.180	0.124	0.379	0.080	0.132	0.135	0.389
Adjusted R^2	0.083	0.041	-0.024	0.274	-0.011	0.046	0.050	0.328

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In an exploratory analysis, we also examined the effect of short-run impatience in the monetary domain on search efforts. While no significant effect was observed on the reservation wage, we found that a 0.1 increase in β over money led to an additional 27

minutes per week spent searching for a job in the DMPL treatment (significant at the 1% level in the model (1)). In contrast, in the CTB treatment, an increase in β over money was associated with a significant decrease in search effort by 39 minutes. We reject the notion that this effect was driven by a strong future bias for money observed in this treatment. In fact, there was no significant effect of β over money on search effort among participants in the top quartile of the distribution (see Table I1 in Appendix I).

Could the positive correlation between the value of β over money and effort and job search effort in the DMPL treatment hide an effect of financial and time prospects, as suggested by Belot et al. (2024)? We can dismiss this interpretation. Recall that we asked participants about their perceived likelihood of finding a job in one, two, three, and six months. We regressed these stated probabilities on the discounting parameters for money and effort. Regression results presented in Table I6 in Appendix I show that $t\beta$ values for both money and effort do not correlate with the subjective probability of finding a job in any time horizon (see models (1) to (4), and (5) to (8), respectively). This indicates that those who exhibited greater short-run impatience did not show particular optimism about their short-run prospects.

Overall, our analysis leads to Result 4:

Result 4 (Short-run impatience and search effort): Procrastination discourages active job search, and short-run impatience over money reduces the weekly time spent searching for a job. These effects are observed only when using the DMPL method. There is no evidence that short-run impatience affects the reservation wage.

4.4 Time preferences and job search outcomes

4.4.1 Early outcomes

Hypotheses 4 and 5 predicted that both long-run impatience and procrastination would negatively affect exit from unemployment. Specifically, more patient job seekers were expected to find a job faster due to their higher search effort. An exception was anticipated for individuals with very high levels of δ , whose extreme patience might make them overly selective, delaying their return to work. We tested these hypotheses using the responses from the pre-experimental questionnaire, which asked about the number of interviews and job offers received since the beginning of their unemployment spell. We acknowledge that these measures are an imperfect proxy for search outcomes, as participants had only experienced two to four months of unemployment at the time of the experiment and we could not observe job finding directly. Consequently, the search effort reported at the time of the survey is likely to have had its effect later in the unemployment spell.³⁹ De-

³⁹The mean unemployment spell lasted 329 days in France in 2021 - source : *Pôle-Emploi* - "https://www.pole-emploi.org/statistiques-analyses/demandeurs-demploi/trajec-toires-et-retour-a-lemploi/duree-de-chomage-4e-trimestre-2021.html?type=article" Accessed on August 14, 2024.

spite its limitations, these responses should still be correlated with unemployment exit and provide insight into the return to search.

Table 4 reports Logit regressions where the dependent variable is the probability of having received at least one job interview (models (1) and (3)) or at least one job offer since the beginning of the unemployment spell (models (2) and (4)).⁴⁰ We regressed the same set of preference variables, interaction terms, and controls as those used in Table 3 on both outcomes. The first two models account for time preferences over money, while the last two models for preferences over effort (see Table H2 in Appendix F for the coefficients of the control variables).

Table 4: Time preferences and job search outcomes

	Time preferences over money		Time preferences over effort	
	Got interviews (1)	Got offers (2)	Got interviews (3)	Got offers (4)
Risk (BRET)	-0.002 (0.010)	0.00002 (0.011)	-0.003 (0.007)	0.002 (0.007)
δ (money)	-0.009 (0.014)	-0.017 (0.017)	-	-
DMPL \times δ (money)	0.006 (0.014)	0.029 (0.033)	-	-
β (money)	-0.366 (0.367)	-0.066 (0.422)	-	-
DMPL \times β (money)	0.743 (0.483)	-0.008 (0.676)	-	-
δ (effort)	-	-	-0.002 (0.002)	-0.004 (0.003)
DMPL \times δ (effort)	-	-	0.105 (0.077)	0.054 (0.079)
β (effort)	-	-	-0.388 (0.315)	-0.482 (0.363)
DMPL \times β (effort)	-	-	0.878** (0.419)	0.396 (0.466)
DMPL treatment	0.058 (0.573)	-0.330 (0.622)	1.649 (1.255)	1.118 (1.295)
Observations	127	124	207	203

Notes: The regressions are Logit models. The dependent variables are the probability to get job interviews (models (1) and (3)) and the probability to get a job offer (models (2) and (4)). Robust standard errors are in parentheses. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the motive of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Although long-run impatience over effort was associated with decreased active search and a lower reservation wage (see Table 3), Table 4 shows no significant effect of δ on the likelihood of getting an interview or job offer in either dimension. To more directly test Hypothesis 4, which predicts a non-linear effect of discounting on search outcomes, we

⁴⁰We also performed Tobit regressions on the raw number of interviews and offers obtained to account for the proportion of null responses. Specifically, 47% of the sample had received no interview and 73% had received no job offer since the start of their unemployment spell. The results from these Tobit models were qualitatively similar to those reported in Table 4.

estimated a specification using the quartiles of the distribution of long-run discounting (see Tables J1 and J2 in Appendix H). We found no evidence of a hump-shaped effect in the direction predicted by the model. The effects of long-run impatience over money did not reach standard levels of significance in the DMPL treatment. In the CTB treatment, the effects appeared convex, with individuals in the second quartile of the distribution showing a lower probability of receiving interviews and offers (both significant at the 5% level; models (1) and (2)). This suggests that in this treatment, both the most impatient and the most patient individuals were more likely to receive offers compared to those who were closer to indifference between the future and the present. For long-run impatience over effort, the only significant (at the 1% level) and positive effect of δ was found for the second quartile in the DMPL treatment concerning the probability of getting an interview (model (3)). Overall, we can reject Hypothesis 4.

Short-run impatience over money had no significant effect on outcomes in any treatment under our preferred specification. However, using NLS and Two-Limit Tobit models instead of OLS to estimate β revealed that the effects of short-run impatience over money on search outcomes were consistent with those on search effort (available upon request). Job seekers with low levels of short-run impatience in the CTB treatment searched less and had poorer outcomes whereas those with low impatience in the DMPL treatment experienced the opposite. In the CTB treatment, the negative effect is driven by the bottom 25% of the distribution who searched more and had better early outcomes. In contrast, procrastinators were less likely to get a job interview (significant at the 5% level; model (3) in Table 4). This is consistent with DVP’s prediction and not surprising given the lower level of search among procrastinators (Table 3). This effect was observed only with the DMPL method.

4.4.2 Late outcomes

To further investigate job search outcomes, we utilized our administrative dataset to track participants through their unemployment spells until they found a job up to a year after they registered at the PES.⁴¹ Table J3 in Appendix J presents the estimates of three Cox proportional hazards models ((1), (3), and (5)), which analyze the hazard rate based on the duration of unemployment spells, and three logit models ((2), (4), and (6)), which analyze the probability of finding a job (up to a year after registration in the unemployment system). The first two regressions account for time preferences over money, the next two consider time preferences over effort, as elicited in the experiment, and the last two use unincentivized measures of risk and time preferences from the pre-

⁴¹In the administrative database, a job seeker’s record ends either when they report finding a job or when they stop registering with the PES. The reason for stopping registration is not always provided, and various factors, such as pregnancy, can lead to cessation of registration without necessarily indicating job finding. This feature introduces some noise in our long-term outcome measure. To mitigate this, we report results using only confirmed cases of job finding.

experimental survey, including all survey participants.

The results in Table J3 show that long-run impatience over both effort and money does not explain long-run outcomes in any specification or treatment, consistent with findings for short-run outcomes. We also found no evidence of a hump-shaped effect of long-run impatience on the hazard rate, thereby rejecting Hypothesis 4. Regarding short-term preferences, the pattern aligns with the search effects found in the previous section. Specifically, individuals with high short-run impatience over money (who also tend to exhibit lower search effort) display a lower hazard rate (significant at the 5% level). This effect is observed only in model (1) when preferences are estimated using the DMPL method, while preferences elicited using the CTB method suggest the opposite trend. No effect of procrastination on the hazard rate or the probability of finding a job was detected, regardless of whether procrastination was measured in the experiment or self-reported in the survey. This contrasts with its negative effects on active job search and the probability of getting interviews in the short run (observed in the DMPL treatment).

We conclude that biases affecting the ability to plan effort over time influence job market outcomes only in the short run, while biases related to the perceived value of future income streams impact long-term outcomes. This suggests that effort and monetary decisions reflect two distinct dimensions of time preferences. Overall, our analysis of outcomes rejects Hypothesis 4 and leads us to our last result:

Result 5 (Time preferences and job search outcomes): Long-run impatience over money or effort does not impact search outcomes measured at the time of the survey or later on. Procrastination reduces the likelihood of receiving a job interview early in the unemployment spell, while short-run impatience over money is associated with a lower probability of exiting unemployment later. Both short-run impatience effects only hold when using the DMPL method.

4.5 Robustness test

How do estimates based on other methods for measuring time preferences compare with these results? In our pre-experimental survey, we elicited risk attitudes, patience in the monetary domain, and procrastination as a general tendency to delay tasks in an abstract setting, using the unincentivized measures of Falk et al. (2018). Table 5 displays the same regressions as those in Tables 3 and 4 with preferences derived from this survey.

In Table 5, consistent with our earlier findings showing no effect of long-run impatience over money on search effort and outcomes, the survey measure of patience had no significant effect in any model. This holds even when estimating these regressions on the sole job seekers who completed the experiment. In contrast, Table 5 reveals a significant negative effect of the self-reported tendency to procrastinate on search effort and, consequently, on search outcomes, as predicted by DVP. This aligns with the results based on procrastination measured with the DMPL method, but contradicts those obtained with

Table 5: Search effort and outcomes - Parameters from the pre-experimental survey

	Search effort			Search outcomes		
	Hours searched (1)	Search channel index (2)	Active search (3)	Reservation wage (4)	Got interviews (5)	Got offers (6)
Risk aversion	0.589 (0.508)	0.102** (0.050)	0.172* (0.100)	0.073** (0.034)	0.165* (0.085)	0.225** (0.095)
Patience	0.163 (0.477)	-0.017 (0.045)	-0.089 (0.094)	-0.022 (0.024)	-0.113 (0.085)	-0.050 (0.090)
Procrastination	-1.046** (0.458)	-0.094** (0.041)	-0.316*** (0.086)	-0.054* (0.029)	-0.169** (0.079)	-0.202** (0.087)
Individual controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Unemployment controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
N Observations	713	713	680	713	713	680
R^2	0.027	0.034	0.061	0.199	-	-
Adjusted R^2	0.006	0.014	0.040	0.181	-	-

Notes: The regressions are OLS models ((1) to (4)) and Logit models ((5) and (6)). Robust standard errors are in parentheses. The reservation wage is expressed in log. In models (5) and (6), the dependent variable is the probability to get at least one job interview or at least one job offer, respectively. Risk and time preferences are those elicited in the pre-experimental survey, based on the procedures of Falk et al. (2018). The individual controls include gender, age and education. The unemployment controls include the motive of the last registration to the PES and the number of past registrations to the PES. The number of observations varies because of missing observations in some variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the CTB method. This negative effect persists when we restrict the sample to the job seekers who completed the experiment, who on average exhibited similar levels of procrastination as the full survey sample. Thus, the discrepancies observed with the CTB method cannot be attributed to attrition. Overall, using the survey measures supports the conclusions drawn from the DMPL method more than those from the CTB method.

5 Conclusion

In this study, we investigated whether job search efforts can be influenced by unintentional time inconsistencies, using two popular experimental methods: the Double Multiple Price List and the Convex Time Budget methods. The DMPL method indicated that job seekers do not exhibit present bias when making monetary trade-offs, aligning with the existing literature. Conversely, the CTB method revealed evidence of future bias, suggesting that individuals may prefer receiving money at a later date rather than sooner, which contrasts with the prevailing literature and seems counter-intuitive. In the effort domain, the DMPL estimates indicated the presence of procrastination, whereas the CTB estimates suggested overall time consistency. Despite these methodological differences, our findings show that job seekers discount utility related to effort more heavily than utility related to money, a pattern consistent with similar studies on time preferences

conducted with different populations (*e.g.*, Augenblick et al., 2015).

Individual-level estimates showed that time preferences significantly influence job search behavior, particularly using the DMPL method. Consistent with DellaVigna and Paserman (2005), the DMPL treatment revealed that both long-run and short-run impatience over effort negatively correlate with active search effort. These impatiences also negatively correlate with the reservation wage, although DVP’s model only predicts this for long-run impatience. For job seekers exhibiting long-run impatience over effort, the future utility of a potential wage offer may provide a weaker motivation compared to more patient people. Present-biased individuals tend to search less than an exponential job search model would predict. Conversely, no significant effect of long-run impatience over money was found on job search effort or reservation wage, diverging from DVP’s predictions. The policy implications of these findings include the need for interventions to help job seekers plan and maintain regular search efforts since the outset of their unemployment. Since short-run impatience over money decreases job search time, policies aimed at helping job seekers manage their income streams over time could also be beneficial.

Using the CTB method, we observed minimal effects of time preferences on job search effort and reservation wage. The only notable exception was an unexpected positive effect of short-run impatience over money on the number of hours spent searching, suggesting that present-biased individuals over money might search with increased urgency.

Regarding job search outcomes, long-run impatience over money or effort did not explain early or later job market outcomes. However, procrastinators were less likely to receive job interviews early in their unemployment spell, and present-biased job seekers in the monetary domain had a lower probability of exiting unemployment. These effects were observed exclusively with the DMPL method.

Overall, our study highlights significant discrepancies based on the elicitation method used for time preferences. The DMPL method provided aggregate estimates of long-run and short-run impatience consistent with existing literature. In contrast, the CTB method indicated a general future bias over money, which is rare in the literature and unexpected for job seekers. The DMPL method’s findings regarding the impact of impatience over effort and money on job search effort and outcomes align with DellaVigna and Paserman (2005), whereas the CTB method did not reveal these associations. This suggests that the choice of elicitation method can greatly influence conclusions about the relationship between time preferences and job search behavior.

The samples assigned to the two treatments did not differ in individual characteristics, suggesting that differences in preferences are unlikely driven by such demographic factors. Delays in early reward payments due to bank transfers might have led to an underestimation of short-run impatience over money, but this should have uniformly affected all measures regardless of the elicitation method. Thus, it is likely that the method itself accounts for these discrepancies. One potential explanation is that the CTB method’s

more flexible allocation of effort or money over time may increase complexity and noise in decision-making, suggesting that increasing the sample size could enhance the precision of patience parameters with this method. Further systematic methodological comparisons are needed to understand these discrepancies and determine the most reliable method for studying the influence of time preferences on behavior.

Research into how time preferences impact behavior in the labor market should consider the nature of elicited preferences. Our study’s content of certain payments and task performance differs from the uncertainty of job search, where outcomes are not guaranteed. Future experiments should investigate time preferences under conditions of uncertainty to better reflect the preferences that influence real-world job market behavior.

Bibliography

ANDERSEN, S., G. W. HARRISON, M. I. LAU, AND E. E. RUTSTRÖM (2008): “Eliciting Risk and Time Preferences,” *Econometrica*, 76, 583–618.

——— (2014): “Discounting behavior: A reconsideration,” *European Economic Review*, 71, 15–33.

ANDREONI, J., M. A. KUHN, AND C. SPRENGER (2015): “Measuring time preferences: A comparison of experimental methods,” *Journal of Economic Behavior & Organization*, 116, 451–464.

ANDREONI, J. AND C. SPRENGER (2012): “Estimating time preferences from convex budgets,” *American Economic Review*, 102, 3333–3356.

ATTEMA, A. E., H. BLEICHRODT, Y. GAO, Z. HUANG, AND P. P. WAKKER (2016): “Measuring discounting without measuring utility,” *American Economic Review*, 106, 1476–94.

AUGENBLICK, N., M. NIEDERLE, AND C. SPRENGER (2015): “Working over time: Dynamic inconsistency in real effort tasks,” *Quarterly Journal of Economics*, 130, 1067–1115.

AYCINENA, D., S. BLAZSEK, L. RENTSCHLER, AND B. SANDOVAL (2015): “Smoothing, discounting, and demand for intrahousehold control for recipients of conditional cash transfers,” *Journal of Applied Economics*, 22, 219–242.

AYCINENA, D. AND L. RENTSCHLER (2018): “Discounting and Digit Ratio: Low 2D:4D Predicts Patience for a Sample of Females,” *Frontiers in Behavioral Neuroscience*, 11.

- BALAKRISHNAN, U., J. HAUSHOFER, AND P. JAKIELA (2020): “How soon is now? Evidence of present bias from convex time budget experiments,” *Experimental Economics*, 23, 294–321.
- BELOT, M., P. KIRCHER, AND P. MULLER (2018): “Providing advice to jobseekers at low cost: an experimental study on online advice,” *Review of Economic Studies*, 86, 1411–1447.
- (2024): “Eliciting time preferences when income and consumption vary: Theory, validation & application to job search,” *American Economic Journal: Microeconomics*.
- BJØRNSTAD, R. (2006): “Learned helplessness, discouraged workers, and multiple unemployment equilibria,” *Journal of Socio-Economics*, 35, 458–475.
- BRAUNSTEIN, Y. AND A. SCHOTTER (1982): “Labor market search: an experimental study,” *Economic Inquiry*, 20, 133–144.
- BROCAS, I., J. D. CARRILLO, AND J. TARRASÓ (2018): “How long is a minute?” *Games and Economic Behavior*, 111, 305–322.
- BROWN, M., C. J. FLINN, AND A. SCHOTTER (2011): “Real-Time Search in the Laboratory and the Market,” *American Economic Review*, 101, 948–974.
- CALIENDO, M., D. A. COBB-CLARK, AND A. UHLENDORFF (2015): “Locus of Control and Job Search Strategies,” *Review of Economics and Statistics*, 97, 88–103.
- CHARNESS, G. AND P. KUHN (2011): “Lab Labor: What Can Labor Economists Learn from the Lab?” *Handbook of Labor Economics*, 4, 229–330.
- CHEUNG, S. L., A. TYMULA, AND X. WANG (2021): “Quasi-Hyperbolic Present Bias: A Meta-Analysis,” *Life Course Centre Working Paper*.
- (2022): “Present Bias for Monetary and Dietary Rewards,” *Experimental Economics*, 25, 1202–1233.
- COHEN, J. D., K. M. ERICSON, D. LAIBSON, AND J. M. WHITE (2016): “Measuring time preferences,” in *National Bureau of Economic Research*, 22455.
- COOPER, M. AND P. KUHN (2020): “Behavioral Job Search,” in *Handbook of Labor, Human Resources and Population Economics*, ed. by K. Zimmermann, Springer, 1–22.
- COX, J. C. AND R. L. OAXACA (1989): “Laboratory experiments with a finite-horizon job-search model,” *Journal of Risk and Uncertainty*, 2, 301–329.
- (1992): “Direct Tests of the Reservation Wage Property,” *The Economic Journal*, 102, 1423.

- CROSETTO, P. AND A. FILIPPIN (2013): “The “bomb” risk elicitation task,” *Journal of Risk and Uncertainty*, 47, 31–65.
- DAMGAARD, M. (2017): “Labor market search effort with reference-dependent preferences,” *Economics Letters*, 156, 99–101.
- DELLAVIGNA, S., A. LINDNER, B. REIZER, AND J. SCHMIEDER (2017): “Reference-dependent job search: evidence from Hungary,” *The Quarterly Journal of Economics*, 132, 1969–2018.
- DELLAVIGNA, S. AND M. D. PASERMAN (2005): “Job Search and Impatience,” *Journal of Labor Economics*, 23, 527–588.
- DOHMEN, T., A. FALK, D. HUFFMAN, F. MARKLEIN, AND U. SUNDE (2009): “Biased probability judgment: Evidence of incidence and relationship to economic outcomes from a representative sample,” *Journal of Economic Behavior & Organization*, 72, 903–915.
- DOHMEN, T., A. FALK, D. HUFFMAN, U. SUNDE, J. SCHUPP, AND G. G. WAGNER (2011): “Individual risk attitudes: Measurement, determinants, and behavioral consequences,” *Journal of the European Economic Association*, 9, 522–550.
- DOHMEN, T. J., A. FALK, D. HUFFMAN, AND U. SUNDE (2012): “Interpreting Time Horizon Effects in Inter-Temporal Choice,” *CEPR Working Paper Series*.
- ESTLE, S., L. GREEN, J. MYERSON, AND D. HOLT (2007): “Discounting of monetary and directly consumable rewards,” *Psychological Science*, 18, 58–63.
- FALK, A., A. BECKER, T. DOHMEN, B. ENKE, D. HUFFMAN, AND U. SUNDE (2018): “Global evidence on economic preferences,” *The Quarterly Journal of Economics*, 133, 1645–1692.
- FALK, A., D. HUFFMAN, AND U. SUNDE (2006): “Do I Have What it Takes? Equilibrium Search With Type Uncertainty and Non-Participation,” *IZA Discussion Paper*, 2531.
- FAUL, F., E. ERDFELDER, AND A. G. E. A. LANG (2007): “G*Power 3: A flexible statistical power analysis program for the social, behavioral and biomedical sciences,” *Behavior Research Methods*, 39, 175–191.
- FREDERICK, S., G. LOEWENSTEIN, AND T. O. DONOGHUE (2002): “Time discounting and time preference A critical review,” *Journal of Economic Literature*, 40, 351–401.
- GEE, L. K. (2018): “The More You Know: Information Effects on Job Application Rates in a Large Field Experiment,” *Management Science*, 65, 2077–2094.

- GOLMAN, R., D. HAGMANN, AND G. LOEWENSTEIN (2017): “Information Avoidance,” *Journal of Economic Literature*, 55, 96–135.
- HOLT, C. A. AND S. K. LAURY (2002): “Risk aversion and incentive effects,” *American Economic Review*, 92, 1644–1655.
- IMAI, T., T. A. RUTTER, AND C. F. CAMERER (2021): “Meta-analysis of present-bias estimation using Convex Time Budgets,” *The Economic Journal*, 131, 1788–1814.
- LAIBSON, D. (1997): “Golden eggs and hyperbolic discounting,” *The Quarterly Journal of Economics*, 112, 443–478.
- LAURY, S. K., M. M. MCINNES, AND J. TODD SWARTHOUT (2012): “Avoiding the curves: Direct elicitation of time preferences,” *Journal of Risk and Uncertainty*, 44, 181–217.
- LIPPMAN, S. A. AND J. J. MCCALL (1976): “Job search in a dynamic economy,” *Journal of Economic Theory*, 12, 365–390.
- LOEWENSTEIN, G. AND R. H. THALER (1989): “Anomalies: intertemporal choice,” *Journal of Economic Perspectives*, 3, 181–193.
- LUCE, R. D. (1959): *Individual choice behavior*, John Wiley.
- MARINESCU, I. AND D. SKANDALIS (2021): “Unemployment Insurance and Job Search Behavior,” *The Quarterly Journal of Economics*, 136, 887–931.
- MATOUSEK, J., T. HAVRANEK, AND Z. IRSOVA (2022): “Individual discount rates: a meta-analysis of experimental evidence,” *Experimental Economics*, 25, 318–358.
- MCGEE, A. AND P. MCGEE (2016): “Search, effort, and locus of control,” *Journal of Economic Behavior & Organization*, 126, 89–101.
- MEYER, C. J. (2018): “In search of a better life: Self-control in the Ethiopian labor market,” in *European University Institute WP*.
- MUELLER, A., J. SPINNEWIJN, AND G. TOPA (2021): “Job Seekers’ Perceptions and Employment Prospects: Heterogeneity, Duration Dependence and Bias,” *American Economic Review*, 111, 324–363.
- O’DONOGHUE, T. AND M. RABIN (1999): “Doing it now or later,” *American Economic Review*, 89, 103–124.
- (2001): “Choice and procrastination,” *The Quarterly Journal of Economics*, 116, 121–160.

- PASERMAN, M. D. (2008): “Job Search and Hyperbolic Discounting: Structural Estimation and Policy Evaluation,” *The Economic Journal*, 118, 1418–1452.
- PREUSS, M. AND J. HENNECKE (2018): “Biased by success and failure: How unemployment shapes locus of control,” *Labour Economics*, 53, 63–74.
- REUBEN, E., P. SAPIENZA, AND L. ZINGALES (2010): “Time discounting for primary and monetary rewards,” *Economics Letters*, 106, 125–127.
- SCHUNK, D. (2009): “Behavioral heterogeneity in dynamic search situations: Theory and experimental evidence,” *Journal of Economic Dynamics and Control*, 33, 1719–1738.
- SPINNEWIJN, J. (2015): “Unemployed but optimistic : Optimal insurance design with biased beliefs,” *Journal of the European Economic Association*, 13, 130–167.
- THALER, R. (1980): “Toward a positive theory of consumer choice,” *Journal of Economic Behavior & Organization*, 1, 39–60.
- UBFAL, D. (2016): “How general are time preferences? Eliciting good-specific discount rates,” *Journal of Development Economics*, 118, 150–170.
- VAN HUIZEN, T. AND J. PLANTENGA (2014): “Job Search Behaviour and Time Preferences: Testing Exponential Versus Hyperbolic Discounting,” *De Economist (Netherlands)*, 162, 223–245.
- WOOLDRIDGE, J. M. (2010): *Econometric analysis of cross section and panel data*, MIT Press.

6 Appendices

Appendix A: Instructions (translated from French)

Instructions week 1

Hello,

We thank you for having taken part to this study.

Before going on, please read carefully the present consent and ask to the persons in charge in the (virtual) room all the questions you judge necessary in order to be fully informed about the implementation of the study.

Do not forget that your participation is entirely voluntary. You can withdraw from the experiment at any moment without having to give any justification.

Scope of the experiment

This research study aims at improving the understanding of the job search. For your registration, we have asked you a range of questions regarding your job search. Next, you are going to take different decisions and to realize several simple tasks for each session of the study. The exact instructions for these decisions and these tasks will be reveal to you after the phase of consent.

Your answers will only be used in the context of the research project, in the respect of your rights and on an anonymous basis.

Expected payments

To guarantee the validity of our study, it is of the utmost importance that you participate at each of the 3 sessions to which you have been invited. If you are here to each of the 3 sessions and that you realize all the tasks asked, you will receive 7€ for each session as well as a compensation of 30€ for having completed the study, which makes in total 51€. Furthermore, you can increase importantly your gains in function of the decisions you will take during the 3 sessions.

You will receive your realized gains of this session of today in the next 7 days. Your realized gains for each next session of the study will follow in the next 7 working days after the session. This corresponds to the administrative delay of bank transfers.

If you were unable to pursue the experiment until the third session, we ask you to inform us by email and if it is possible, to tell us the reason of your decision. If you do so, you will receive 7€ by session you attend to thank you for having taken part to this study.

Our email:

etude_recherche_emploi@gate.cnrs.fr

Participation and consent

You have been selected to participate to this study following a draw at random realized among the persons seeking employment registered in the data bases Pôle Emploi/Unedic in the metropolitan area of Lyon.

The data collected regarding your situation will be the object of a processing realized by Maxime Le Bihan, PhD student under contract CIFRE at Unédic, and Marie Claire Villeval, head of research at CNRS.

The legal base of the processing, in accordance to the article 6 of the RGPD, lies on the participants' consent to this study and on their personal data processing.

To this end, you should only participate if you are in agreement with the mentioned elements of this page.

Confidentiality and security

Your data will be anonymized before any dissemination of the study's results.

Your email address will be deleted after the data collection.

Your banking data will be retained by the CNRS's accountability services only to assure the banking transfer of your gains for the study.

Your identity will be concealed thanks to an ID assigned randomly for all the types of data collected.

Only the persons in charge of the study hold the correspondence table allowing to make the link between your email and the random number assigned in the different files.

Raw data, in the form of computer encrypted files, will be stored on a secure server or our laboratory, the GATE. The final database will be stored on an external drive and protected by a password only known by the persons in charge of the study.

Your personal data will be stored in active base only until the publication of the study's results. After this date, your data will be definitely archived on an anonymous basis.

Dissemination and transfer of data

Your anonymized data could be transferred outside the European Union as part of submission for publication of research works of this study in international journals.

The study's results could be disseminated on an anonymous basis in professional and scientific seminars.

Legal rights of people

You can have access and get a copy of your personal data, oppose the processing of these data, rectify them or delete them. You have also a right regarding the limitation of the processing of your data.

You can exercise these rights or ask question regarding this project at any moment by communicating with the persons in charge at: etude_recherche_emploi@gate.cnrs.fr.

You can also contact the Délégué à la Protection des Données of the laboratory at the following address: DPD — 17 rue Notre Dame des Pauvres — 54519 — Vandoeuvre lès Nancy Cedex – dpd.demandes@cnrs.fr.

After contacting us, if you feel that your Informatique et Libertés rights are not respected, you have the possibility to lodge an online or written claim at the CNIL.

CNIL, 3 Place de Fontenoy, TSA 80715 — 75334 Paris Cedex 07 (<https://www.cnil.fr/>)

Screen : Session 1

Hello and welcome to the first session of our study.

Screen: Your ID

To begin, you need to log in using the ID that you created for the first session. To remind you, we have advised you to determine it the following way (without space, without dash, without cedilla, without capital letter):

- Your month and year of birth (in the form MMY);
- First letter of the first name of your mother;
- First letter of the first name of your father.

Screen:

In this study, your main task will consist in collecting data regarding scientific papers for our laboratory.

To get you familiar with this task, we will first explain it to you and allow you to test it.

Then, you should decide when to realize a range of similar tasks. This decision will occur between the different sessions of the study and its specific modalities will be explained to you as soon as you have finished the test of the task.

Screen: Your task

The task we ask you to realize consist in accessing tables of contents of in line scientific journals and to report the headlines of the papers in those tables of contents with the names of the authors.

It is important for us that the information you report is comprehensive and exact.

Please click on “following” to access the procure to be followed to search for this information on internet.

Screen: How to find the information to report?

Firstly, click on the link of the issue of the journal that will be provided to you.

The page returned by the link reveal a list of papers as in the example below.

In order to realize your task:

1. Copy (ctrl + c) the headline of the paper (in blue in the example) and paste it (ctrl + v) in the box of the form bearing the mention “name of the article”.
2. Then, return to the page of the journal, copy (ctrl + c) the name of the author(s) (circled in red in the example) in the line below the headline of the article and paste (ctrl+v) the name(s) in the box of the form bearing the mention “name of the authors”.
3. Click on “validate” to finish your entry and move on to the following link.

You should repeat this operation for the three first articles of each journal’s issue.

Although the articles are in English, you do not need to understand it to realize the task.

Screen: Your task: Test

In this screen, you will be able to test the task you should realize in this study.

In the lines below, please report the 3 first papers of the volume that will be display by clicking on the following link: [link 1](#)

Once you have completed your entries, please check there is no space before and after each of them, then click on the button “Validate”.

Screen: Your 5 minimum pages

For each session (included the session of today), we will ask you to realize a minimum of 5 pages.

We call « page » the 3 first papers and their authors appearing in the table of contents of a journal. You will be able to realize these 5 pages for today's session in the next screen.

We will then explain to you the process of all the sessions.

Click on “following” as soon as you are ready to begin.

Screen: Your 5 required pages

Please report the 3 first papers of the following volume: [link 1](#)

Screen: Today (session 1):

Thanks for having completed your 5 pages for this session!

Your second task for today will be to take 12 decisions.

Each of those 12 decisions consists in choosing **how many pages** you wish to realize during the **session 2** (that will take place in 3 weeks) AND how many during the **session 3** (that will take place in 6 weeks). You are free to allocate the number of pages among the two sessions as you want.

To take each of your 12 decisions, you should move a cursor on the position of your choice as in the example below (you can move freely the cursor).

To move the cursor, click on it and move your mouse on the right or on the left. Above the cursor, you see the number of pages to realize during the session 2 and during the session 3.

The values used in this example are only here to illustrate and are not intended to influence you.

Screen: How the experiment will proceed

What is changing between the 12 decisions?

A reported page in session 2 do not always diminish as such the number of pages to report in session 3.

Among the 12 decisions, reporting an additional page in session 2 will modify of one unit more, or less, the number of pages to report in session 3. The trade-off to realize will be different in each of the decisions.

Screen: Testing the different rates

In that screen, you can freely move the cursors to test the rates by clicking on it. These choices will not count for the next phase of the study.

Screen

The values used in this example are only here to illustrate and are not intended to influence you.

In the example below, to be able to do one page less in session 2, I need to do two pages more in session 3.

(For the number of pages to remain entire, the pages are reported to the nearest whole number.)

Screen: How the experiment will proceed

Explanatory scheme

It is your choice in the decision drawn at random that will determine the number of pages that you will effectively have to report in the session 2 and the number in the session 3.

In case you choose to do not attend the session 2 or the session 3 or if you don't realize at each of the session, you will not be able to finish the study and you will only receive the minimum gain of 6€ for all the study.

Screen: Procedure for the random draw of one of your 24 decisions:

So, today (session 1), you will take 12 decisions on the number of pages to report in session 2 and in session 3, and **in session 2 (in three weeks) you will take again these 12 decisions.**

There are two steps to draw at random which of your 24 decisions will effectively be taking place.

The first step will determine if this decision is one of those you had taken in session 1 or in session 2. For the session 2, we will invite you to draw at random a number between 1 and 10. If the number drawn at random is 1, then the decision that will apply will be one of your 12 decisions taken today. If the number is different from 1, it will be one of your 12 decisions taken in session 2. Therefore, the decision drawn at random will be issue from session 1 with one chance in ten and will be issue from session 2 with nine chances in ten.

The step 2 will determine which decision will apply eventually. For the session drawn at random, you will draw at random a number between 1 and 12. Each of your 12 decisions during this session has the same chance to be drawn at random.

You will now be able to take your decisions.

Screen:

Comprehension Questions

Question 1: How many sessions of this study do you need to attend to complete and receive all your payments?

Question 2: Of how many weeks are spaced the sessions of the study?

Question 3: Do you need to complete the 5 pages minimum at each session?

Question 4: In that study, you should allocate some tasks to realize, how many decisions of allocation should you realize altogether (in session 1 and 2)?

Question 5: The following affirmation is true or false?

A draw at random will be realized to determine the session from which will be provided the decision that will apply. This draw at random will select the session 1 with 1 in 10 chances and the session 2 with 9 in 10 chances.

Question 6: Observe the situation below and determine if the affirmation is true or false:

In that situation, if I want to do 2 pages less in session 2, I have to do 3 pages more in session 3. This is 13 pages in session 2 and 3 pages in session 3.

Screen:

Thank you for completing the form. You are now going to decide how many pages to realize in sessions 2 and 3. Please click on the following button to move on.

Screen: Your choice of pages

Please decide how many pages to realize in session 2 and in session 3.

Session 2 will take place in 3 weeks, session 3 in 6 weeks.

Be careful, the exchange rate varies from one decision to another:

Screen:

Set of decision 1

Screen:

Set of decision 2

Screen:

Thank you for having taken your decisions. Before finishing this session, we will propose to you to increase your gains by achieving one last simple task. Please click on « following » to get the instructions.

Screen: What is your favorite lottery ?

In the next screen, you should **choose 10 times** between two different options: the **lottery A** and the **lottery B**. These choices will be presented to you under the form of a chart into which each line corresponds to a new decision.

Your payment in this part will be decided by the draw of a number between 1 and 10. The lotteries A and B correspond to options of payment in function of the draw?

Example: the lines of the chart can be read the following way.

The line presented in this example corresponds to the first decision you will take. The 9 other decisions are similar, but the more you go down the chart and more the chances to obtain the highest payment of each option increase.

One of this decision, and the number between 1 and 10 will be draw at random to determine your gain in this part.

Please, note also that when you will take your first decisions, the others will be filled automatically. You can however change each of those decisions at your convenience.

Click on follow to begin.

Screen : Instructions : the Bomb Task

The picture below represents a grid of 100 boxes. Behind one of these boxes is hidden a bomb. The 99 other boxes are empty. Each box has the same number of chances to hide the bomb. Therefore, the more you choose boxes, the more you can earn money if the bomb is not behind one of the boxes chosen. But also, the more you choose boxes, more you have chances that the bomb is hidden behind one of the boxes chosen.

grid

Your task consists in choosing a number of boxes to be revealed, between 1 and 100.

Screen: Your task

If you chose the number X of cases, the program will reveal all the boxes sorted between the first box in the top left corner of the grid and the box X.

Si vous choisissez le nombre X de cases, le programme découvrira toutes les cases rangées entre la première case en haut à gauche de la grille et la case X.

If the bomb is not hidden behind one of the boxes you have selected, you will earn 5 cents of Euro by box selected. We will multiply your number of boxes chosen by 0.05€.

If the bomb is behind one of the boxes you have selected, you will earn 0€ for this task.

You will be informed at the end of the study of your gain in this part.

To take your decision, you will indicate in the following screen the number of cases that you wish to select. You should confirm your choice by clicking on OK.

Screen:

Bomb task

Screen:

Payments of the experiment

Screen :

Thanks

Reminder of the timing of the sessions and sending of reminders and payments

Instructions week 2

Screen: Welcome to the session 2 of the study:

Thank you for taking part to the second session of our study!

How the session of today will proceed (session 2 of the study)

In the session of today, we are asking you in the first place, to realize the minimum number of pages to report in the task that has been explained to you during our first session. As a reminder, the tasks consist in reporting the headline and the name of the authors of the three first articles of a scientific journal's issue.

Once you have reported the minimum number of pages required, we will ask you again to take 12 decisions. Each of those 12 decisions consists in choosing how many pages you wish to realize during the session 2 (today) and how many during the session 3 (that will take place in 3 weeks). You are free to allocate the number of pages among the two sessions as you want.

We will give you then the last instructions for this session.

Screen: Reminder: How to find the information to report?

Firstly, click on the link of the issue of the journal that will be provided to you.

The page returned by the link reveal a list of papers as in the example below.

In order to realize your task:

1. Copy (ctrl + c) the headline of the paper (in blue in the example) and paste it (ctrl + v) in the box of the form bearing the mention “name of the article”.
2. Then, return to the page of the journal, copy (ctrl + c) the name of the author(s) (circled in red in the example) in the line below the headline of the article and paste (ctrl+v) the name(s) in the box of the form bearing the mention “name of the authors”.
3. Click on “validate” to finish your entry and move on to the following link.

You should repeat this operation for the three first articles of each journal’s issue.

Although the articles are in English, you do not need to understand it to realize the task.

Screen: Your task: Test

In this screen, you will be able to test the task you should realize in this study.

In the lines below, please report the 3 first papers of the volume that will be display by clicking on the following link: [link 1](#)

Once you have completed your entries, please check there is no space before and after each of them, then click on the button “Validate”.

Screen: Reminder: Your decisions

Thank you for having completed the minimum number of pages.

Now, as in the first session, you will be confronted to decisions of allocations as in the following example:

(example of decision)

The values used in this example are only here to illustrate and are not intended to influence you.

What is changing between the 12 decisions?

Contrary to the example shown above, a reported page in session 2 do not always diminish as such the number of pages to report in session 3. Among the 12 decisions, reporting an additional page in session 2 will modify of one unit more, or less, the number of pages to report in session 3. The trade-off to realize will be different in each of the decisions.

For each decision, you are free to fix the exact number of pages to realize to each session. However, the number of pages that you should realize if you allocate all your tasks to session 2 is of 15 pages. The maximum number o pages if you choose to allocate all your tasks to session 3 is variable et will depend of an exchange rate.

You will be informed of the trade-off's conditions (that is to say, of the exchange rate) before taking each of your 12 decisions.

Screen: Reminder: The choice of the “decision that matters”

In session 1 (3 weeks ago), you have taken 12 decisions about the number of exercises to realize in session 2 and in session 3, and in session 2 (today), you will take again those 12 decisions. **This makes in total 24 decisions of allocation of efforts.** Finally, only one of those decisions will be selected to be the decision that matters.

There are two steps to draw at random which of your 24 decisions will effectively be taking place.

The first step will determine if this decision is one of those you had taken in session 1 or in session 2. For the session 2, we will invite you to draw at random a number between 1 and 10. If the number drawn at random is 1, then the decision that will apply will be one of your 12 decisions taken today. If the number is different from 1, it will be one of your 12 decisions taken in session 2. Therefore, the decision drawn at random will be issue from session 1 with one chance in ten and will be issue from session 2 with nine chances in ten.

The step 2 will determine which decision will apply eventually. For the session drawn at random, you will draw at random a number between 1 and 12. Each of your 12 decisions during this session has the same chance to be drawn at random.

To begin to take your allocation decisions, click on “following”.

Screen: Your choice of pages

Please take your decisions by moving the cursor in each line.

Reminder: the session 2 is the session of today and the session 3 will take place in 3 weeks.

Screen: The decision that matters

Thank you for having taken your 12 decisions. You will now be able to draw at random the decision that matters.

Screen:

Please click on “following” to begin.

Firstly, you will trigger the draw at random of the session from which will provide your decision. Click on turn at the center of the wheel to trigger the draw.

Screen:

Now, you will draw at random the decision that will be used to determine the number of pages that you should report. Click on turn at the center of the wheel to draw at random.

The number of the decision is...

Screen:

Please click on “following” to begin to complete your task.

Screen: Your tasks to realize

Screen: Part 2

Thank you for having completed the part 1. We now present you the part 2. This part 2 is independent from the part 1.

In the following screens, your task will consist in **allocating monetary gains over time**. Please click on “following” to begin this part.

Screen: Part 2

To thank you for having continued the experiment this far, we will add 6€ to your 6€ of compensation for your participation at this session.

On top of that 12€ that are due to you for compensation of participation to this session, you could earn an amount of money that will be payed to you at two different dates. You should take 24 decisions regarding the allocation of the payment of this amount between these 5 possible dates:

1. In the next 7 days (Session 2)
2. In the next 3 weeks (Session 3)
3. In the next 6 weeks
4. In the next ten weeks
5. In the next twelve weeks

Screen:

The 24 decisions will be allocated in 4 sets of 6 decisions. In each set of decisions, you should allocate an amount between two dates;

-In the first set of decisions, you should allocate the amount **between the session 2 (today) and the session 3 (in three weeks)**.

-In the second set of decisions, you should allocate the amount between the session 3 (in three weeks) and in six weeks.

-In the third set of decisions, you should allocate the amount between the session 2 (today) and in ten weeks.

-In the fourth set of decisions, you should allocate the amount between the session 3 (in three weeks) and in twelve weeks.

This means that you can receive gains this week as the soonest and in twelve weeks at the latest.

Screen:

Once you have taken all your decisions, one of your 24 decisions will be drawn at random to determine at which dates these amounts will be transferred on your account.

Please, note that the 12€ that are due to you for compensation for your participation to the session of today will be also paid at the two dates corresponding to the dates in the decision drawn at random (6€ will be added to the first transfer and 6€ will be added to the second transfer).

Be careful: All of your gains will be transferred on your account by banking transfer thanks to the information you have communicated to us.

Screen:

In the next screens, you will take 24 decisions. Each line stands for one decision and is numbered from 1 to 24.

These decisions consist to choose **between a gain at a closer date AND a gain at a farther date.**

Among the 24 decisions, an increase of the amount at the closer date will cause a reduction more or less important of the farther gain.

The intensity of this reduction will vary across the decisions and will depend on the exchange rate.

You will be informed of the trade off's conditions before taking each of your 24 decisions.

To take each of your 24 decisions, you should move a cursor on the position of your choice. You will be able to test in the following screen.

Screen: testing the different rates

You can freely move on the cursors to test the rates. This choice will not count for the next phase.

The values displayed are only here to illustrate and are not intended to influence you.

Screen: Procedure for the random draw of one of your 12 decisions

Once your 24 decisions will be taken, you will draw one at random thanks to a wheel including 24 numbers. This draw at random will determine the amounts and the dates of the amounts' payments, in accordance with the choice you have made in the decision drawn at random.

Be careful: each of the decisions you will take can be the decision that will be implemented. Therefore, we ask you to treat each of those decisions as if it were the one that will determine the effective dates of the payment of your gains.

Screen: Your decisions

Please click on "following" to begin.

Screen: Please, take your decisions

Please, take your decisions by moving the cursor in each line.

Screen: The decision that matters

You will now be able to proceed to the drawn at random of the decision that will determine your gains. Please click on turn to begin.

The decision drawn is the number...

Screen: Gains of the study

Instructions week 3

Screen: Session 3

Hello and welcome to the last session of this study.

Screen: Welcome to the session of today (session 3 of the study)

In the session of today, we are asking you in the first place, to realize the minimum required exercise. As in the two previous sessions, you should report the headline and the name of the authors of the three first articles of 5 scientific journals.

You should then complete the number of exercises that you have allocated to the session 3 in the decision drawn at random among your choices three weeks ago. You will be reminded of this number of exercises after the minimum exercise.

Reminder: the completion of this tasks will unfreeze your gain of 27€ to which we will add 6€ for your participation to today's session. A summary of your gains will be indicated to you at the end of the session.

Screen: Reminder: How to find the information to report?

Firstly, click on the link of the issue of the journal that will be provided to you.

The page returned by the link reveal a list of papers as in the example below.

In order to realize your task:

1. Copy (ctrl + c) the headline of the paper (in blue in the example) and paste it (ctrl + v) in the box of the form bearing the mention "name of the article".
2. Then, return to the page of the journal, copy (ctrl + c) the name of the author(s) (circled in red in the example) in the line below the headline of the article and paste (ctrl+v) the name(s) in the box of the form bearing the mention "name of the authors".
3. Click on "validate" to finish your entry and move on to the following link.

You should repeat this operation for the three first articles of each journal's issue.

When you are ready, please click on the "following" button.

Screen: Your decision of pages:

Thank you for having completed your minimum exercise.

In accordance to the decision drawn at random during the previous session, you should report X pages in that session. You will be able to report this number of pages on the following screen.

Please click on “following” to begin.

Screen: Your pages to report

Screen: Summary of your gains in that study

On that page, we summarize all the gains you have earned throughout this study.

-x€ earned following session 1

-x€ earned following session 2

-x€ that you will receive in the next 7 days

-x€ that you will receive in the next 2 weeks

-x€ that you will receive in the next 8 weeks

- x€ that you will receive in the next 10 weeks

We thank you for having taken part to that study.

Screen:

Payments information.

Appendix B: Additional figures

Dans les lignes ci-dessous, veuillez reporter les 3 premiers articles du volume qui s'affichera en cliquant sur le lien suivant : [lien 1](#)

Article 1
Titre :
Auteur(s) :

Article 2
Titre :
Auteur(s) :

Article 3
Titre :
Auteur(s) :

Figure B1: Screenshot of the real effort task

Notes: The figure represents a screenshot of the real effort task to perform in the experiment. Translation from French: “In the following lines, please report the first three articles of the journal issue that will be displayed when clicking the following link. Article/Title/Author(s).”

Décision 1
1 € cette semaine
vaut 1.05 €
dans 3 semaines

cette semaine : 14.3 €
dans 3 semaines : 0 €

Décision 2
1 € cette semaine
vaut 1.11 €
dans 3 semaines

cette semaine : €
dans 3 semaines : €

Décision 3
1 € cette semaine
vaut 1.18 €
dans 3 semaines

cette semaine : €
dans 3 semaines : €

Décision 4
1 € cette semaine
vaut 1.25 €
dans 3 semaines

cette semaine : €
dans 3 semaines : €

Figure B2: Screenshot of the monetary allocation decisions

Notes: The figure represents how the monetary allocation decisions were presented to the participants. The relative price of sooner *vs.* later effort is displayed on the left of each slider. Translation from French: “€1 this week is worth €1.05 in three weeks.”

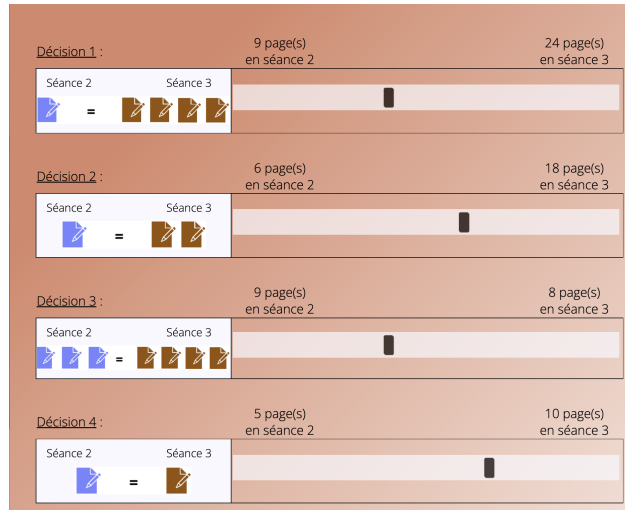


Figure B3: Screenshot of the effort allocation decisions

Notes: The figure represents how the effort allocation decisions were presented to the participants. The exchange rate of sooner *vs.* later effort is displayed on the left of each slider. Translation from French: “Reminder: Session 2 is today; session 3 will be in three weeks from now.”

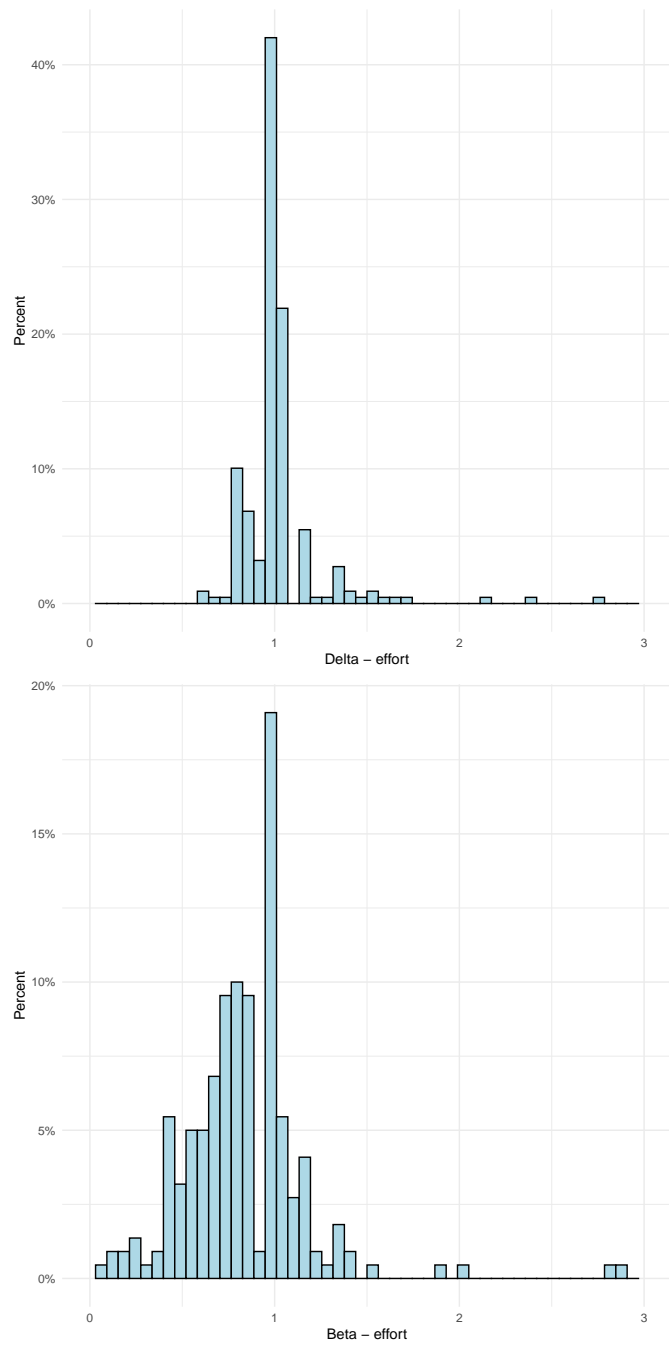


Figure B4: Distribution of the individual estimates of time preferences over effort

Notes: The figures represent the distributions of individual time preferences over effort. The top panel is for long-run patience (δ); the bottom panel is for short-run patience (β). The figures pool the data from the CTB and DMPL treatments. The estimates are based on OLS models for the CTB treatment and MLE for the DMPL treatment.

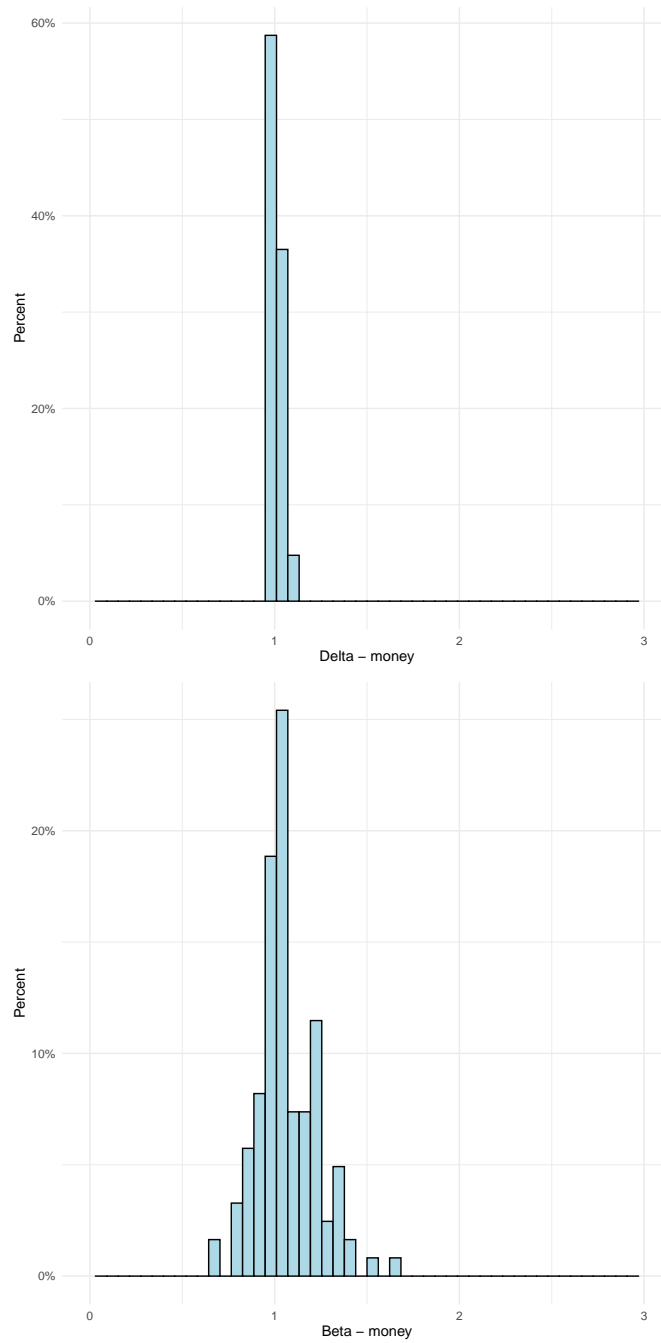


Figure B5: Distribution of the individual estimates of time preferences over money

Notes: The figures represent the distributions of individual time preferences over money. The top panel is for long-run patience (δ); the bottom panel is for short-run patience (β). The figures pool the data from the CTB and DMPL treatments. The estimates are based on OLS models for the CTB treatment and MLE for the DMPL treatment.

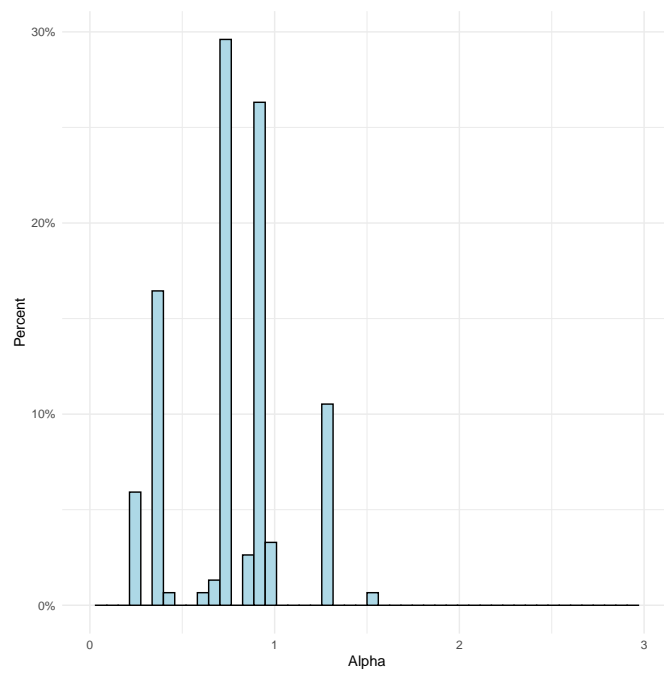


Figure B6: Distribution of the individual estimates of risk preferences

Notes: The figure represents the distribution of individual risk preferences (α) directly recovered from the individual choices in the CTB treatment or estimated from choices in the Holt and Laury lotteries in the DMPL treatment.

Appendix C: Individual characteristics, job search characteristics, and attrition

Table C1: Socio-demographic characteristics of the initial and final samples of job seekers

	Invited sample	Final sample	p-values t-tests
<u>Gender</u>			
Proportion of females	0.52	0.48	0.149
<u>Age categories</u>			
18/24	0.54	0.33	0.000
25/49	0.38	0.56	0.000
50+	0.08	0.11	0.023
<u>Education</u>			
Less than HS (high-school degree)	0.19	0.02	0.000
Professional training	0.18	0.02	0.000
HS	0.24	0.11	0.000
HS+2	0.11	0.12	0.810
HS+3/4	0.13	0.15	0.345
HS+5 and more	0.16	0.58	0.000
<u>Previous daily wage</u>	76.62	81.55	0.578
<u>Motive of the last registration to the PES</u>			
Voluntary unemployment (resignations)	0.13	0.14	0.509
Unvoluntary unemployment (contract end plant closure)	0.20	0.20	0.962
New entrants, reorientation	0.22	0.16	0.026
Other motives	0.24	0.16	0.003
<u>Number of past registrations to the PES</u>	1.05	1.02	0.089
<u>Occupation</u>			
Agriculture	0.04	0.00	0.012
Art, entertainment, catering, hotels	0.08	0.07	0.634
Bank, commerce	0.18	0.09	0.004
Communication and firm support	0.21	0.39	0.000
Construction, maintenance, industry	0.20	0.17	0.387
Health and related	0.21	0.27	0.094
Transport	0.07	0.01	0.010
N observations	40,000	250	-

Notes: The initial sample includes the 40,000 job seekers who registered in the French PES in the last four months before we draw our sample and who received an invitation to participate in our study. The final sample includes the job seekers who completed the survey, registered to the experiment and participated at least in sessions 1 and 2. The previous daily wage is expressed in Euro.

Table C2: Job search characteristics of the participants and attrition

Variables	In experiment until the end (1)	Started experiment but did not finish (2)	In survey but not in experiment (3)
<u>Search effort</u>			
Hours spent searching	9.98	10.46 (0.750)	12.69 (0.003)
Search intensity index	12.55	13.48 (0.249)	14.70 (0.000)
Active search actions	2.74	3.24 (0.144)	3.12 (0.021)
<u>Expected wage</u>			
Reservation wage	2183.81	2113.10 (0.705)	1863.78 (0.000)
Min expected wage	2054.93	1859.60 (0.433)	1685.68 (0.000)
Max expected wage	3706.66	3536.73 (0.807)	3299.98 (0.221)
<u>Search outcomes</u>			
Number of interviews	1.25	1.43 (0.507)	1.44 (0.13)
Number of offers	0.42	0.56 (0.298)	0.69 (0.000)
<u>Preferences</u>			
Risk preference	0.05	0.24 (0.108)	-0.01 (0.308)
Patience	0.24	0.12 (0.325)	-0.08 (0.000)
Procrastination	4.71	4.78 (0.853)	4.70 (0.973)
<u>Gender</u>			
Females	0.52	0.62 (0.214)	0.49 (0.410)
<u>Age</u>			
18/24	0.33	0.36 (0.676)	0.42 (0.013)
25/49	0.55	0.56 (0.913)	0.52 (0.013)
50+	0.12	0.08 (0.427)	0.09 (0.259)
<u>Education</u>			
Less than High School	0.03	0.04 (0.651)	0.15 (0.000)
Professional training	0.02	0.02 (1.000)	0.10 (0.000)
High School degree	0.12	0.14 (0.635)	0.19 (0.006)
HS+2	0.12	0.18 (0.289)	0.11 (0.489)
HS+3/4	0.18	0.22 (0.465)	0.16 (0.442)
HS+5 and more	0.54	0.40 (0.080)	0.30 (0.000)
N observations	250	50	750

Notes: This table summarizes the average characteristics of the job seekers measured in the pre-experimental survey, according to whether they completed the experiment (1), they started the experiment but did not finish it (2), or they did not register to the experiment after filling the survey (3). The expected wage variables are expressed in Euros per month. The preference variables are those elicited with the unincentivized procedures of Falk et al. (2018); higher values indicate, respectively, more risk seeking, more patience, and a higher tendency to procrastinate. Numbers in parentheses are the p-values from t-tests of equality of means, with the sample of job seekers who completed the experiment taken as the reference category.

Appendix D: Choice sets for the allocation of monetary and effort units in the CTB and DMPL treatments

Table D1: Money choice sets

<u>Rates</u>																
<u>1.05</u>																
Money at sooner date	14.3	13.3	12.3	11.3	10.3	9.3	8.3	7.3	6.3	5.3	4.3	3.3	2.3	1.3	0.3	0
Money at later date	0	1.5	2.1	3.15	4.2	5.25	6.3	7.35	8.4	9.45	10.5	11.55	12.6	13.65	14.7	15
<u>1.11</u>																
Money at sooner date	13.5	12.5	11.5	10.5	9.5	8.5	7.5	6.5	5.5	4.5	3.5	2.5	1.5	0.5	-	0
Money at later date	0	1.11	2.22	3.33	4.44	5.55	6.66	7.77	8.88	9.99	11.1	12.21	13.32	14.43	-	15
<u>1.18</u>																
Money at sooner date	12.7	11.7	10.7	9.7	8.7	7.7	6.7	5.7	4.7	3.7	2.7	1.7	0.7	-	-	0
Money at later date	0	1.18	2.36	3.54	4.72	5.9	7.8	8.26	9.44	10.62	11.8	12.98	14.16	-	-	15
<u>1.25</u>																
Money at sooner date	12	11	10	9	8	7	6	5	4	3	2	1	-	-	-	0
Money at later date	0	1.25	2.5	3.75	5	6.25	7.5	8.75	10	11.25	12.5	13.75	-	-	-	15
<u>1.43</u>																
Money at sooner date	10.5	9.5	8.5	7.5	6.5	5.5	4.5	3.5	2.5	1.5	0.5	-	-	-	-	0
Money at later date	0	1.43	2.86	4.29	5.72	7.15	8.58	10.1	11.44	12.87	14.3	-	-	-	-	15
<u>1.82</u>																
Money at sooner date	8.2	7.2	6.2	5.2	4.2	3.2	2.2	1.2	0.2	-	-	-	-	-	-	0
Money at later date	0	1.82	3.64	5.46	7.28	9.1	10.92	12.74	14.56	-	-	-	-	-	-	15

Notes: Rates correspond to the relative price of money at the sooner *vs.* later date. In the first set of decisions, the sooner and later dates correspond, respectively, to session 2 and session 3. In the second set of decisions, they correspond to, respectively, session 3 and 3 weeks after session 3; in the third set, to session 2 and 10 weeks after session 2; and in the fourth set, to session 3 and 10 weeks after session 3.

Table D2: Effort choice sets

<u>Rates</u>																
<u>0.2</u>																
Pages attributed to the sooner date	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Pages attributed to the late date	0	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75
<u>0.25</u>																
Pages attributed to the sooner date	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Pages attributed to the late date	0	4	8	12	16	20	24	28	32	36	40	44	48	52	56	60
<u>0.33</u>																
Pages attributed to the sooner date	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Pages attributed to the late date	0	3	6	9	12	15	18	21	24	27	30	33	36	39	42	45
<u>0.5</u>																
Pages attributed to the sooner date	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Pages attributed to the late date	0	2	4	6	8	10	12	14	16	18	20	22	24	26	28	30
<u>0.66</u>																
Pages attributed to the sooner date	15	-	13	-	11	-	9	-	7	-	5	-	3	-	1	0
Pages attributed to the late date	0	-	3	-	6	-	9	-	12	-	15	-	18	-	21	23
<u>0.75</u>																
Pages attributed to the sooner date	15	-	-	12	-	-	9	-	-	6	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	4	-	-	8	-	-	12	-	-	16	-	-	20
<u>1</u>																
Pages attributed to the sooner date	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
Pages attributed to the late date	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
<u>1.2</u>																
Pages attributed to the sooner date	15	-	-	-	-	-	9	-	-	-	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	-	-	-	5	-	-	-	-	-	10	-	-	13
<u>1.25</u>																
Pages attributed to the sooner date	15	-	-	-	-	10	-	-	-	-	5	-	-	-	-	0
Pages attributed to the late date	0	-	-	-	-	4	-	-	-	-	8	-	-	-	-	12
<u>1.33</u>																
Pages attributed to the sooner date	15	-	-	-	11	-	-	-	7	-	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	-	3	-	-	-	6	-	-	-	9	-	-	12
<u>1.5</u>																
Pages attributed to the sooner date	15	-	-	12	-	-	9	-	-	6	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	2	-	-	4	-	-	6	-	-	8	-	-	10
<u>1.66</u>																
Pages attributed to the sooner date	15	-	-	-	-	10	-	-	-	-	5	-	-	-	-	0
Pages attributed to the late date	0	-	-	-	-	3	-	-	-	-	6	-	-	-	-	9

Notes: Rates correspond to the exchange rate between sooner and later effort. The early date corresponds to session 2 and the later date to session 3. The 12 allocation decisions (one with each rate) were to be made twice, once in session 1 and once in session 2, three weeks later.

Appendix E: Descriptive statistics on the effort and budget shares allocated to the sooner dates

Table E1. Share of *monetary units allocated to the sooner date (CTB treatment)*

Relative prices	Sooner date later than session 2	Sooner date = session 2	p-values t-test
Decision set 1 (Time horizon = 3 weeks)			
1.05	0.48	0.38	0.097
1.11	0.32	0.27	0.331
1.18	0.23	0.15	0.146
1.25	0.18	0.11	0.101
1.43	0.07	0.05	0.584
1.82	0.04	0.02	0.474
Decision set 2 (Time horizon = 10 weeks)			
1.05	0.58	0.58	1.000
1.11	0.45	0.44	0.799
1.18	0.33	0.34	0.893
1.25	0.28	0.29	0.779
1.43	0.17	0.15	0.602
1.82	0.11	0.08	0.513

Notes: The table reads as follows: in session 2, participants allocated on average 48% of their budget to session 3 when €1 in session 3 was worth €1.05 three weeks after session 3; for the same relative price and time horizon, they allocated on average 38% of their budget to the sooner date when this date was today (session 2). This is evidence of future bias, as they allocated a higher share of their budget to the sooner date when this sooner date was later in the future.

Table E2: *Share of monetary units allocated to the sooner date (DMPL treatment)*

Relative prices	Sooner date later than session 2	Sooner date = session 2	p-values t-test
Decision set 1 (Time horizon = 3 weeks)			
1.05	0.33	0.22	0.020
1.11	0.21	0.15	0.121
1.18	0.18	0.15	0.396
1.25	0.17	0.15	0.601
1.43	0.14	0.11	0.424
1.82	0.13	0.10	0.367
Decision set 2 (Time horizon = 10 weeks)			
1.05	0.42	0.38	0.387
1.11	0.31	0.27	0.409
1.18	0.24	0.23	0.837
1.25	0.22	0.19	0.497
1.43	0.18	0.16	0.652
1.82	0.13	0.13	0.895

Notes: The table reads as follows: in session 2, participants allocated on average 31% of their budget to session 3 when €1 in session 3 was worth €1.05 three weeks after session 3; for the same relative price and time horizon, they allocated on average 21% of their budget to the sooner date when this date was today (session 2). This is evidence of future bias, as they allocated a higher share of their budget to the sooner date when this sooner date was later in the future.

Table E3: Share of effort units allocated to the sooner date (CTB treatment)

Exchange rates	Decisions made in session 1	Decisions made in session 2	p-values t-test
Decision set 1			
0.25	0.88	0.89	0.460
0.5	0.80	0.81	0.588
0.75	0.74	0.78	0.209
1	0.60	0.60	0.824
1.25	0.40	0.38	0.650
1.5	0.37	0.36	0.938
Decision set 2			
0.2	0.90	0.91	0.730
0.33	0.85	0.87	0.398
0.66	0.74	0.78	0.137
1.2	0.42	0.42	0.930
1.33	0.39	0.39	0.857
1.66	0.32	0.31	0.830

Notes: In these decisions, the sooner date is always session 2. The table reads as follows: in session 1, participants allocated on average 88% of the pages to be done in session 2 when one page in session 2 was worth 0.25 page in session 3; for the same exchange rate, in session 2 participants allocated on average 89% of the pages to be done in session 2.

Table E4: Share of effort units allocated to the sooner date (DMPL treatment)

Exchange rates	Decisions made in session 1	Decisions made in session 2	p-values t-test
Decision set 1			
0.25	0.97	0.96	0.744
0.5	0.91	0.93	0.561
0.75	0.84	0.86	0.630
1	0.57	0.46	0.063
1.25	0.18	0.17	0.749
1.5	0.17	0.14	0.441
Decision set 2			
0.2	0.95	0.99	0.062
0.33	0.91	0.98	0.030
0.66	0.85	0.90	0.256
1.2	0.19	0.17	0.647
1.33	0.20	0.16	0.441
1.66	0.13	0.11	0.640

Notes: In these decisions, the sooner date is always session 2. The table reads as follows: in session 1, participants allocated on average 97% of the pages to be done in session 2 when one page in session 2 was worth 0.25 page in session 3; for the same exchange rate, in session 2 participants allocated on average 96% of the pages to be done in session 2.

Appendix F: Individual determinants of risk and time preferences

Table F1: Individual determinants of risk and time preferences

	α	δ (money)	β (money)	δ (effort)	β (effort)
CTB treatment	0.396** (0.165)	-0.941*** (0.139)	0.092 (0.209)	0.139 (0.139)	0.445*** (0.150)
Female	0.279* (0.152)	-0.078 (0.159)	0.195 (0.203)	-0.117 (0.169)	0.097 (0.161)
Age: 25/49	-0.083 (0.194)	0.006 (0.193)	-0.089 (0.134)	-0.105 (0.149)	0.040 (0.177)
Age: 50+	0.161 (0.300)	0.586 (0.409)	-0.253 (0.261)	0.393 (0.386)	-0.401 (0.339)
Educ: Less than HS (High School)	0.920* (0.511)	0.678 (0.695)	-0.879 (0.621)	-0.0003 (0.221)	-0.533 (0.532)
Educ: HS+2	0.751** (0.375)	-0.046 (0.171)	-0.769 (0.634)	0.638 (0.563)	-0.340 (0.299)
Educ: HS+3/4	0.374* (0.221)	0.205 (0.266)	-0.664 (0.595)	0.077 (0.117)	-0.380* (0.214)
Educ: HS+5 and more	0.434** (0.193)	-0.022 (0.148)	-0.513 (0.523)	0.084 (0.105)	-0.130 (0.196)
Educ: Professional training	1.644 (1.042)	0.066 (0.594)	-1.053 (0.688)	0.385 (0.244)	0.322 (0.715)
Nb past registrations PES	-0.007 (0.163)	-0.193 (0.323)	0.131 (0.098)	0.120 (0.147)	-0.062 (0.181)
Contract end, layoff	0.016 (0.227)	0.133 (0.163)	-0.066 (0.127)	-0.227 (0.215)	-0.400 (0.405)
New entrants, career change	-0.182 (0.265)	0.377 (0.255)	-0.259 (0.199)	-0.075 (0.168)	-0.601* (0.331)
Other	-0.203 (0.254)	0.156 (0.192)	0.073 (0.189)	-0.322 (0.327)	-0.617** (0.282)
Job Prospect: [1-3] months	0.157 (0.243)	0.318 (0.211)	-0.585 (0.434)	0.060 (0.138)	-0.266 (0.193)
Job Prospect:]3-6] months	-0.017 (0.204)	-0.052 (0.155)	-0.256 (0.297)	0.165 (0.248)	-0.092 (0.313)
Job Prospect: > 6 months	0.329 (0.210)	-0.059 (0.169)	-0.348 (0.353)	-0.035 (0.100)	-0.335 (0.208)
Singe-use goods	0.016 (0.109)	-0.011 (0.167)	0.009 (0.072)	0.074 (0.128)	-0.050 (0.105)
Average-life goods	0.015 (0.099)	-0.094 (0.088)	0.039 (0.048)	-0.001 (0.045)	0.098 (0.099)
Durable goods	0.016 (0.081)	0.256** (0.127)	-0.073 (0.053)	-0.079* (0.048)	0.017 (0.064)
Depression Index	0.078 (0.159)	0.049 (0.137)	-0.139 (0.214)	-0.146 (0.114)	-0.088 (0.116)
Constant	-0.936* (0.526)	0.419 (0.517)	1.035 (1.355)	0.163 (0.459)	0.945 (0.649)
N Observations	185	185	185	185	185
R^2	0.163	0.332	0.114	0.096	0.170
Adjusted R^2	0.061	0.251	0.006	-0.014	0.068

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The value of α is directly recovered from the individual choices in the CTB treatment or estimated from choices in the Holt and Laury lotteries in the DMPL treatment. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). “Single-use goods” (food, oil, medicines, ...), “Average-life goods” (shoes, clothes, toys, leather goods, ...), and “Durable goods” (domestic appliances, furniture, cars, ...) correspond to recent purchases since they became unemployed. “depression index” is defined as the sum of the scores of 3 questions from the Beck depression index. The reference categories are 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES; believing to find a job in less than a month for the subjective prospect regarding the exit of unemployment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix G: Aggregate preferences with exclusion of participants who never switched decisions

Table G1: Preferences parameters for money excluding non-switchers

	CTB			DMPL	
	OLS (1)	Two-Limit Tobit (2)	NLS (3)	(4)	MLE (5)
α	0.481*** (0.037)	0.807*** (0.039)	0.868*** (0.018)	0.732*** (0.041)	-
δ	0.999*** (0.0006)	0.998*** (0.0006)	0.998*** (0.0003)	-	0.997*** (0.0004)
β	1.131*** (0.023)	1.126*** (0.024)	1.055*** (0.013)	-	1.017*** (0.015)
<i>Ho</i> : $\delta = 1$, p	0.018	0.001	0.000	-	0.000
<i>Ho</i> : $\beta = 1$, p	0.000	0.000	0.000	-	0.257
N	1584	1584	1584	1350	1656

Notes: α is for risk attitude, δ for long-run discounting, β for short-run discounting. The computations of δ are based on daily rates. Standard errors in parentheses are clustered at the individual level. We used χ^2 tests of null hypotheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G2: Preferences parameters for effort excluding non-switchers

	CTB			DMPL	
	OLS (1)	Two-Limit Tobit (2)	NLS (3)	MLE (4)	
γ	1.291*** (0.027)	1.172*** (0.025)	1.661*** (0.096)	-	
δ	1.000*** (0.003)	0.999*** (0.002)	1.004*** (0.002)	0.996*** (0.001)	
β	1.018*** (0.067)	1.009*** (0.067)	1.042*** (0.062)	0.969*** (0.002)	
<i>Ho</i> : $\delta = 1$, p	0.865	0.825	0.099	0.011	
<i>Ho</i> : $\beta = 1$, p	0.785	0.888	0.495	0.051	
N	2640	2640	2640	2688	

Notes: γ for effort aversion, δ for long-run discounting, β for short-run discounting. The computations of δ are based on daily rates. Standard errors in parentheses are clustered at the individual level. We used χ^2 tests of null hypotheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix H: Regression tables for search effort and outcomes with details of the control variables

Table H1: Time preferences and job search effort - Full regressions

	Search and time preferences over money				Search and time preferences over effort			
	Hours searched	Search channel index	Active search	Reservation wage	Hours searched	Search channel index	Active search	Reservation wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk (BRET)	-0.024 (0.042)	0.005 (0.004)	-0.002 (0.006)	-0.00002 (0.001)	0.002 (0.032)	0.003 (0.003)	-0.002 (0.004)	0.0007 (0.001)
δ (money)	0.013 (0.054)	-0.007 (0.006)	-0.011 (0.008)	-0.0003 (0.002)	-	-	-	-
D MPL \times δ (money)	-0.011 (0.054)	0.006 (0.006)	0.010 (0.008)	0.0007 (0.002)	-	-	-	-
β (money)	-3.943*** (1.370)	-0.170 (0.148)	-0.267 (0.205)	0.060 (0.065)	-	-	-	-
D MPL \times β (money)	6.591*** (1.889)	0.242 (0.163)	0.276 (0.245)	-0.013 (0.078)	-	-	-	-
δ (effort)	-	-	-	-	0.001 (0.006)	0.0003 (0.001)	-0.0003 (0.001)	0.0005 (0.0005)
D MPL \times δ (effort)	-	-	-	-	-0.011 (0.381)	0.017 (0.030)	0.106*** (0.039)	0.032** (0.012)
β (effort)	-	-	-	-	-1.186* (0.683)	-0.160* (0.095)	-0.176 (0.109)	-0.048 (0.034)
D MPL \times β (effort)	-	-	-	-	0.382 (1.381)	0.228* (0.135)	0.651*** (0.169)	0.112* (0.067)
D MPL treatment	2.046 (2.260)	0.032 (0.220)	-0.117 (0.322)	-0.034 (0.080)	2.586 (6.180)	0.511 (0.487)	1.769*** (0.662)	0.514** (0.209)
Female	0.937 (1.876)	-0.031 (0.154)	-0.219 (0.243)	-0.230*** (0.062)	0.129 (1.458)	-0.141 (0.130)	-0.312* (0.173)	-0.217*** (0.049)
25/49 years old	1.166 (2.292)	0.295 (0.192)	-0.085 (0.277)	0.200*** (0.070)	2.028 (1.958)	0.216 (0.145)	-0.102 (0.224)	0.119** (0.058)
50+	8.979** (3.835)	0.882** (0.370)	0.097 (0.418)	0.394*** (0.136)	6.034** (2.776)	0.534** (0.265)	-0.125 (0.330)	0.449*** (0.112)
Less than HS (High School)	-5.644 (4.599)	-1.090* (0.565)	-0.299 (0.720)	0.132 (0.141)	-2.255 (3.741)	-0.960*** (0.292)	-0.302 (0.472)	-0.062 (0.148)
HS+2	-3.327 (4.225)	-0.232 (0.411)	0.087 (0.584)	0.274* (0.145)	-0.056 (2.499)	-0.166 (0.260)	0.235 (0.403)	0.143 (0.111)
HS+3/4	-0.914 (4.307)	-0.291 (0.387)	0.374 (0.585)	0.168* (0.096)	0.851 (3.066)	-0.345 (0.255)	-0.209 (0.375)	0.109 (0.091)
HS+5 and more	-2.675 (3.912)	-0.482 (0.359)	0.038 (0.517)	0.353*** (0.092)	1.009 (2.521)	-0.520** (0.221)	-0.207 (0.322)	0.284*** (0.075)
Professional training	-7.714 (5.327)	-0.411 (0.860)	-0.839 (0.524)	0.027 (0.133)	-6.497** (2.623)	-0.342 (0.609)	-1.180*** (0.358)	0.107 (0.164)
Number of registrations (PES)	6.647 (9.047)	-0.413 (0.762)	-0.634* (0.334)	0.413*** (0.077)	3.656 (5.750)	-0.366 (0.353)	-0.848*** (0.182)	0.326*** (0.096)
Contract end and econ layoff	5.646** (2.670)	0.494** (0.242)	0.581* (0.329)	-0.0541 (0.106)	3.110 (1.916)	0.364* (0.190)	0.294 (0.249)	-0.149** (0.0716)
New entrants and career change	4.568 (3.034)	0.256 (0.269)	0.343 (0.359)	-0.099 (0.109)	5.131** (2.456)	0.455** (0.202)	0.403 (0.290)	-0.189** (0.0751)
Other	3.103 (2.591)	0.298 (0.265)	0.278 (0.323)	-0.114 (0.127)	2.625 (2.035)	0.227 (0.193)	0.093 (0.249)	-0.075 (0.085)
Constant	0.945 (10.59)	-0.146 (0.942)	1.715* (0.869)	7.005*** (0.215)	-0.186 (6.314)	-0.292 (0.479)	2.119*** (0.465)	7.153*** (0.142)
Observations	125	125	125	125	202	202	202	202
R^2	0.216	0.180	0.124	0.379	0.080	0.132	0.135	0.389
Adjusted R^2	0.083	0.041	-0.024	0.274	-0.011	0.046	0.050	0.328

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the D MPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table H2: Time preferences and job search outcomes - Full regressions

	Time preferences over money		Time preferences over effort	
	Got interviews (1)	Got offers (2)	Got interviews (3)	Got offers (4)
Risk (BRET)	-0.002 (0.010)	0.00002 (0.011)	-0.003 (0.007)	0.002 (0.007)
δ (money)	-0.009 (0.014)	-0.017 (0.017)	-	-
D MPL \times δ (money)	0.006 (0.014)	0.030 (0.033)	-	-
β (money)	-0.366 (0.367)	-0.066 (0.422)	-	-
D MPL \times β (money)	0.743 (0.483)	-0.008 (0.676)	-	-
δ (effort)	-	-	-0.002 (0.002)	-0.004 (0.003)
D MPL \times δ (effort)	-	-	0.105 (0.077)	0.054 (0.079)
β (effort)	-	-	-0.388 (0.315)	-0.482 (0.363)
D MPL \times β (effort)	-	-	0.878** (0.419)	0.396 (0.466)
D MPL treatment	0.058 (0.573)	-0.330 (0.622)	1.649 (1.255)	1.118 (1.295)
Female	-0.478 (0.419)	-0.572 (0.490)	-0.448 (0.307)	-0.129 (0.333)
25/49 years old	0.342 (0.459)	0.544 (0.626)	0.186 (0.373)	-0.176 (0.429)
50+	0.918 (0.882)	0.375 (1.097)	0.294 (0.579)	-0.237 (0.612)
Less than HS (High School)	-2.927* (1.577)	-1.804 (1.541)	-1.014 (0.983)	0.109 (0.968)
HS+2	-2.559** (1.006)	-2.005* (1.104)	-0.885 (0.700)	-0.881 (0.669)
HS+3/4	-0.506 (0.843)	-1.937* (1.042)	-0.877 (0.652)	-1.197* (0.651)
HS+5 and more	-1.032 (0.754)	-2.882*** (0.933)	-0.824 (0.580)	-1.120** (0.531)
Professional training	-1.958 (1.732)	0 (.)	-2.203* (1.278)	0 (.)
Number of registrations (PES)	-0.587 (1.202)	1.267 (1.251)	-0.597 (0.878)	1.084 (1.023)
Contract end and econ layoff	1.103* (0.653)	1.488* (0.767)	0.574 (0.422)	-0.130 (0.491)
New entrants and career change	0.213 (0.696)	0.888 (0.909)	0.530 (0.502)	-0.415 (0.583)
Other	0.341 (0.691)	0.960 (0.764)	0.382 (0.433)	0.008 (0.489)
Constant	1.597 (1.799)	-0.707 (2.060)	1.419 (1.198)	-1.148 (1.287)
Observations	127	124	207	203

Notes: The regressions are Logit models. The dependent variables are the probability to got job interviews (models (1) and (3)) and the probability to get a job offer (models (2) and (4)). Robust standard errors are in parentheses. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the bomb task. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the D MPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the motive of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix I: Regression tables on search effort with alternative specifications

Table I1: Time preferences and job search effort: Quartile specification, CTB treatment

	Search and time preferences over money				Search and time preferences over effort			
	Hours searched (1)	Search channel index (2)	Active search (3)	Reservation wage (4)	Hours searched (5)	Search channel index (6)	Active search (7)	Reservation wage (8)
Risk (BRET)	-0.001 (0.043)	0.005 (0.005)	-0.012* (0.006)	0.002 (0.003)	0.026 (0.037)	0.009** (0.004)	0.006 (0.006)	0.002 (0.002)
<u>δ (money)</u>								
25% < δ (money) < 50%	3.720 (3.161)	-0.166 (0.358)	-0.923** (0.443)	0.056 (0.181)	-	-	-	-
50% < δ (money) < 75%	6.347** (2.863)	0.459 (0.329)	-0.158 (0.451)	-0.132 (0.170)	-	-	-	-
75% < δ (money)	2.443 (4.245)	-0.0161 (0.400)	-0.0821 (0.595)	0.0698 (0.150)	-	-	-	-
<u>β (money)</u>								
25% < β (money) < 50%	-6.905** (3.025)	-1.083*** (0.377)	-1.550*** (0.405)	0.069 (0.152)	-	-	-	-
50% < β (money) < 75%	-8.890*** (3.263)	-1.152*** (0.360)	-0.836 (0.539)	0.0257 (0.152)	-	-	-	-
75% < β (money)	-5.833 (4.365)	-0.298 (0.369)	-0.543 (0.425)	0.199 (0.200)	-	-	-	-
<u>δ (effort)</u>								
25% < δ (effort) < 50%	-	-	-	-	-0.400 (2.640)	0.038 (0.273)	0.187 (0.364)	0.045 (0.086)
50% < δ (effort) < 75%	-	-	-	-	-0.252 (2.677)	-0.186 (0.284)	-0.339 (0.395)	0.064 (0.127)
75% < δ (effort)	-	-	-	-	-0.016 (3.033)	0.445 (0.329)	0.150 (0.437)	0.333** (0.129)
<u>β (effort)</u>								
25% < β (effort) < 50%	-	-	-	-	1.778 (2.442)	0.356 (0.256)	0.467 (0.341)	0.0629 (0.122)
50% < β (effort) < 75%	-	-	-	-	1.500 (3.158)	0.166 (0.339)	0.599 (0.402)	-0.029 (0.115)
75% < β (effort)	-	-	-	-	-1.190 (2.674)	-0.051 (0.309)	-0.391 (0.320)	0.006 (0.111)
Female	3.615 (3.415)	0.459 (0.289)	-0.282 (0.408)	-0.113 (0.136)	2.225 (1.809)	0.092 (0.223)	-0.561** (0.281)	-0.154* (0.080)
25/49 years old	3.779 (2.554)	0.293 (0.331)	0.095 (0.415)	0.225* (0.117)	4.330 (2.813)	-0.074 (0.238)	0.053 (0.368)	0.023 (0.096)
50+	7.691 (4.938)	1.154** (0.566)	-0.304 (0.575)	0.261 (0.173)	8.019** (3.651)	0.484 (0.394)	0.493 (0.427)	0.324* (0.167)
Less than HS (High School)	10.59 (7.246)	-1.429 (0.868)	3.214*** (0.875)	0.128 (0.347)	5.354 (5.172)	-1.158*** (0.424)	-0.004 (0.726)	-0.357 (0.330)
HS+2	-0.097 (7.163)	-0.988* (0.494)	-0.333 (0.583)	0.240 (0.278)	0.676 (3.016)	-0.394 (0.395)	-0.069 (0.582)	0.150 (0.196)
HS+3/4	6.215 (5.984)	-0.732 (0.490)	1.025* (0.569)	0.020 (0.225)	6.025 (4.573)	-0.506 (0.381)	-0.044 (0.528)	0.088 (0.134)
HS+5 and more	-0.978 (4.935)	-0.885* (0.437)	-0.194 (0.516)	0.362 (0.239)	0.609 (2.710)	-0.631** (0.297)	-0.477 (0.468)	0.338*** (0.125)
Professional training	-1.187 (4.835)	-0.681 (0.789)	-0.330 (0.500)	-0.225 (0.243)	-2.427 (3.561)	-0.903 (1.111)	-1.613*** (0.590)	-0.160 (0.208)
Number of registrations (PES)	0 (.)	0 (.)	0 (.)	0 (.)	-0.819 (7.532)	-0.427 (0.456)	-1.008* (0.575)	0.106 (0.119)
Contract end and econ layoff	2.790 (3.322)	0.364 (0.427)	-0.154 (0.506)	0.030 (0.194)	3.232 (2.549)	0.441 (0.309)	0.165 (0.329)	0.002 (0.102)
New entrants and career change	4.792 (3.492)	0.374 (0.472)	-0.218 (0.481)	0.095 (0.199)	7.098** (3.177)	0.429 (0.285)	0.748 (0.459)	-0.091 (0.114)
Other	2.404 (3.787)	0.970** (0.473)	0.004 (0.405)	0.242 (0.246)	3.831 (2.510)	0.615* (0.323)	-0.126 (0.358)	0.115 (0.146)
Constant	2.538 (6.805)	-0.310 (0.703)	2.619*** (0.901)	7.080*** (0.400)	-2.175 (8.496)	-0.623 (0.653)	1.828** (0.840)	7.099*** (0.206)
Observations	55	55	55	55	95	95	95	95
R^2	0.435	0.494	0.464	0.409	0.194	0.257	0.285	0.458
Adjusted R^2	0.153	0.241	0.196	0.113	-0.010	0.069	0.103	0.321

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I2: Time preferences and job search effort: Quartile specification, DMPL treatment

	Search and time preferences over money				Search and time preferences over effort			
	Hours searched	Search channel index	Active search	Reservation wage	Hours searched	Search channel index	Active search	Reservation wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk (BRET)	-0.049 (0.072)	0.002 (0.006)	0.002 (0.009)	0.00007 (0.001)	-0.006 (0.049)	0.001 (0.004)	-0.007 (0.005)	0.0002 (0.001)
<u>δ (money)</u>								
25% < δ (money) < 50%	3.573 (3.812)	-0.519 (0.357)	-0.095 (0.510)	0.227* (0.132)	-	-	-	-
50% < δ (money) < 75%	-6.510* (3.293)	-0.806*** (0.277)	-0.717 (0.446)	-0.063 (0.085)	-	-	-	-
75% < δ (money)	4.286 (6.187)	-0.525 (0.487)	-0.437 (0.819)	0.243 (0.150)	-	-	-	-
<u>β (money)</u>								
25% < β (money) < 50%	1.184 (5.750)	-0.065 (0.447)	0.372 (0.695)	0.194 (0.130)	-	-	-	-
50% < β (money) < 75%	3.011 (4.433)	-0.101 (0.402)	0.885 (0.552)	0.346*** (0.115)	-	-	-	-
75% < β (money)	9.082 (5.867)	-0.150 (0.478)	0.405 (0.658)	0.452*** (0.146)	-	-	-	-
<u>δ (effort)</u>								
25% < δ (effort) < 50%	-	-	-	-	-7.976* (4.503)	-0.657* (0.353)	-0.688 (0.604)	0.475*** (0.109)
50% < δ (effort) < 75%	-	-	-	-	5.532* (3.108)	0.231 (0.229)	0.708* (0.382)	0.402*** (0.120)
75% < δ (effort)	-	-	-	-	1.783 (4.760)	-0.024 (0.355)	0.964** (0.433)	0.345** (0.143)
<u>β (effort)</u>								
25% < β (effort) < 50%	-	-	-	-	-1.656 (4.430)	-0.132 (0.299)	0.151 (0.344)	0.053 (0.109)
50% < β (effort) < 75%	-	-	-	-	5.882 (6.056)	0.626 (0.497)	1.250* (0.746)	-0.135 (0.180)
75% < β (effort)	-	-	-	-	1.054 (4.557)	0.286 (0.332)	1.222*** (0.455)	0.237 (0.148)
Female	-0.025 (2.514)	-0.047 (0.205)	0.116 (0.337)	-0.188*** (0.063)	-0.729 (2.255)	-0.174 (0.177)	-0.040 (0.223)	-0.194*** (0.063)
25/49 years old	2.147 (4.208)	0.359 (0.329)	-0.354 (0.529)	0.140 (0.105)	1.148 (3.075)	0.233 (0.197)	-0.244 (0.309)	0.062 (0.074)
50+	7.789 (6.313)	0.670 (0.555)	-0.326 (0.652)	0.407** (0.187)	2.338 (4.653)	0.277 (0.430)	-0.852* (0.454)	0.534*** (0.140)
Less than HS (High School)	-12.85* (6.416)	-0.511 (0.654)	-0.792 (0.966)	0.0369 (0.105)	-8.254 (5.484)	-1.074** (0.482)	-0.439 (0.733)	0.040 (0.133)
HS+2	-7.249 (6.883)	0.072 (0.579)	0.609 (1.064)	0.229 (0.192)	-2.087 (4.792)	-0.365 (0.387)	0.228 (0.612)	0.024 (0.128)
HS+3/4	-3.846 (6.927)	0.143 (0.587)	0.434 (0.973)	0.277** (0.108)	-3.440 (5.188)	-0.198 (0.389)	-0.180 (0.545)	0.095 (0.124)
HS+5 and more	-4.128 (6.335)	-0.170 (0.523)	0.397 (0.924)	0.378*** (0.108)	-0.814 (4.717)	-0.421 (0.330)	0.110 (0.487)	0.191* (0.102)
Professional training	-9.492 (7.030)	-0.146 (0.703)	-0.249 (0.905)	0.528*** (0.134)	-7.345 (6.348)	-0.126 (0.549)	-1.211 (0.747)	0.271* (0.140)
Number of registrations (PES)	3.783 (7.772)	-0.847 (1.031)	-0.809 (0.625)	0.363** (0.142)	4.456 (10.18)	-0.605 (0.644)	-0.746** (0.327)	0.551*** (0.142)
Contract end and econ layoff	8.349* (4.888)	0.545 (0.392)	0.624 (0.578)	-0.049 (0.142)	1.490 (3.246)	0.405 (0.277)	0.304 (0.377)	-0.164 (0.115)
New entrants and career change	6.508 (5.155)	0.202 (0.389)	0.239 (0.600)	-0.241* (0.135)	3.531 (4.023)	0.403 (0.298)	0.394 (0.424)	-0.281*** (0.103)
Other	1.842 (4.700)	-0.054 (0.395)	-0.058 (0.557)	-0.457*** (0.134)	0.117 (3.398)	-0.094 (0.280)	0.170 (0.353)	-0.127 (0.109)
Constant	4.242 (10.40)	0.740 (1.292)	1.372 (1.249)	6.765*** (0.257)	5.767 (12.49)	0.287 (0.857)	1.376* (0.774)	6.723*** (0.252)
Observations	70	70	70	70	113	113	113	113
R^2	0.259	0.305	0.189	0.646	0.129	0.139	0.207	0.517
Adjusted R^2	-0.023	0.042	-0.120	0.511	-0.048	-0.037	0.045	0.418

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I3: Job search effort and time preferences estimated by Interval Censored Tobit (CTB treatment) or Maximum Likelihood (DMPL treatment)

	Search and time preferences over money				Search and time preferences over effort			
	Hours searched	Search channel index	Active search	Reservation wage	Hours searched	Search channel index	Active search	Reservation wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk (BRET)	-0.010 (0.0423)	0.003 (0.003)	-0.002 (0.006)	-0.0002 (0.001)	0.00006 (0.033)	0.002 (0.003)	-0.003 (0.004)	0.0006 (0.001)
δ (money)	0.041 (0.059)	-0.008 (0.005)	0.001 (0.007)	-0.001 (0.002)	-	-	-	-
DMPL \times δ (money)	-0.039 (0.060)	0.007 (0.005)	-0.002 (0.007)	0.001 (0.002)	-	-	-	-
β (money)	-1.297 (0.965)	-0.243** (0.106)	-0.273** (0.128)	0.031 (0.043)	-	-	-	-
DMPL \times β (money)	4.275** (1.812)	0.329** (0.130)	0.285 (0.191)	0.020 (0.063)	-	-	-	-
δ (effort)	-	-	-	-	-0.0291*** (0.009)	-0.001 (0.001)	0.001 (0.002)	0.0005 (0.0004)
DMPL \times δ (effort)	-	-	-	-	0.043 (0.036)	0.002 (0.003)	0.009** (0.004)	0.002* (0.001)
β (effort)	-	-	-	-	-1.079 (0.719)	-0.117 (0.083)	-0.180* (0.095)	0.0271 (0.028)
DMPL \times β (effort)	-	-	-	-	-0.397 (1.780)	0.245 (0.167)	0.820*** (0.205)	0.060 (0.093)
DMPL treatment	3.408 (2.095)	0.055 (0.195)	0.298 (0.284)	-0.098 (0.082)	2.985** (1.333)	0.306** (0.131)	0.179 (0.172)	0.019 (0.054)
Female	1.661 (1.877)	0.008 (0.148)	-0.170 (0.245)	-0.241*** (0.062)	0.107 (1.490)	-0.131 (0.133)	-0.287 (0.175)	-0.217*** (0.050)
25/49 years old	1.025 (2.386)	0.288 (0.187)	-0.116 (0.278)	0.205*** (0.073)	1.715 (1.958)	0.191 (0.148)	-0.170 (0.221)	0.137** (0.056)
50+	9.766** (4.072)	0.958** (0.381)	0.166 (0.426)	0.382*** (0.136)	4.910* (2.626)	0.518* (0.263)	-0.133 (0.316)	0.430*** (0.111)
Less than HS (High School)	-4.408 (4.908)	-1.007* (0.547)	-0.273 (0.731)	0.122 (0.143)	-1.143 (3.869)	-0.917*** (0.302)	-0.323 (0.485)	-0.070 (0.159)
HS+2	-2.153 (4.245)	-0.156 (0.410)	0.087 (0.602)	0.271* (0.148)	0.151 (2.431)	-0.306 (0.270)	0.112 (0.387)	0.102 (0.108)
HS+3/4	1.029 (4.289)	-0.286 (0.384)	0.387 (0.572)	0.147 (0.095)	0.351 (2.950)	-0.377 (0.257)	-0.295 (0.368)	0.124 (0.087)
HS+5 and more	-1.599 (3.942)	-0.425 (0.351)	0.054 (0.518)	0.347*** (0.092)	0.961 (2.519)	-0.551** (0.222)	-0.249 (0.319)	0.285*** (0.075)
Professional training	-7.696* (4.027)	-0.830* (0.461)	-1.172* (0.621)	0.028 (0.144)	-3.960 (3.727)	-0.160 (0.604)	-1.030*** (0.394)	0.117 (0.155)
Number of registrations (PES)	7.189 (9.272)	-0.401 (0.706)	-0.592* (0.323)	0.403*** (0.077)	4.414 (7.164)	-0.224 (0.420)	-0.751*** (0.201)	0.345*** (0.113)
Contract end and econ layoff	5.646* (2.859)	0.591** (0.246)	0.634* (0.336)	-0.051 (0.106)	3.122 (1.991)	0.315 (0.200)	0.244 (0.260)	-0.171** (0.078)
New entrants and career change	4.509 (3.135)	0.332 (0.274)	0.398 (0.360)	-0.093 (0.108)	4.447* (2.434)	0.346 (0.216)	0.303 (0.288)	-0.193** (0.078)
Other	2.702 (2.607)	0.278 (0.271)	0.258 (0.332)	-0.107 (0.130)	3.145 (2.040)	0.109 (0.207)	0.118 (0.256)	-0.087 (0.090)
Constant	-3.909 (10.54)	-0.271 (0.854)	1.224 (0.781)	7.080*** (0.189)	-0.788 (7.656)	-0.332 (0.526)	2.122*** (0.478)	7.144*** (0.156)
Observations	125	125	125	125	200	200	200	200
R^2	0.185	0.206	0.120	0.378	0.106	0.111	0.131	0.398
Adjusted R^2	0.047	0.071	-0.030	0.272	0.017	0.023	0.044	0.338

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by Interval Censored Tobit) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I4: Job search effort and time preferences estimated by Non Linear Squares (CTB treatment) or Maximum Likelihood (DMPL treatment)

	Search and time preferences over money				Search and time preferences over effort			
	Hours searched (1)	Search channel index (2)	Active search (3)	Reservation wage (4)	Hours searched (5)	Search channel index (6)	Active search (7)	Reservation wage (8)
Risk (BRET)	-0.005 (0.045)	0.005 (0.004)	0.0003 (0.006)	-0.0003 (0.001)	0.014 (0.034)	0.002 (0.003)	-0.001 (0.004)	0.0003 (0.001)
δ (money)	-0.048*** (0.018)	-0.004* (0.002)	-0.006* (0.004)	0.0007 (0.0008)	-	-	-	-
DMPL $\times \delta$ (money)	0.049*** (0.018)	0.003 (0.003)	0.005 (0.004)	-0.0003 (0.001)	-	-	-	-
β (money)	-2.947*** (0.610)	-0.033 (0.117)	-0.177 (0.155)	0.024 (0.029)	-	-	-	-
DMPL $\times \beta$ (money)	6.820*** (2.099)	0.148 (0.153)	0.209 (0.243)	0.043 (0.067)	-	-	-	-
δ (effort)	-	-	-	-	0.011** (0.004)	0.001*** (0.0005)	-0.0007 (0.0005)	0.00007 (0.0002)
DMPL $\times \delta$ (effort)	-	-	-	-	-0.010 (0.021)	0.001 (0.001)	0.005*** (0.002)	-0.001** (0.0005)
β (effort)	-	-	-	-	0.402 (0.913)	0.032 (0.069)	0.010 (0.125)	0.024 (0.036)
DMPL $\times \beta$ (effort)	-	-	-	-	-2.221 (1.521)	0.056 (0.129)	0.308 (0.193)	-0.023 (0.074)
DMPL treatment	0.972 (1.726)	0.136 (0.170)	0.151 (0.259)	-0.056 (0.073)	3.792*** (1.330)	0.345*** (0.127)	0.289* (0.174)	-0.056 (0.057)
Female	1.200 (1.903)	-0.037 (0.157)	-0.131 (0.249)	-0.246*** (0.066)	0.230 (1.463)	-0.126 (0.129)	-0.288 (0.176)	-0.239*** (0.053)
25/49 years old	1.309 (2.445)	0.218 (0.190)	-0.110 (0.286)	0.182** (0.074)	1.637 (2.088)	0.203 (0.150)	-0.114 (0.238)	0.177*** (0.064)
50+	12.83*** (4.014)	1.019** (0.425)	0.285 (0.475)	0.397*** (0.141)	4.744 (3.019)	0.410 (0.271)	-0.113 (0.341)	0.482*** (0.124)
Less than HS (High School)	-6.370 (4.498)	-1.123* (0.600)	-0.386 (0.723)	0.145 (0.137)	-3.414 (3.817)	-0.958*** (0.273)	-0.124 (0.459)	-0.015 (0.136)
HS+2	-3.261 (4.241)	-0.193 (0.422)	0.150 (0.605)	0.281* (0.142)	-1.540 (2.577)	-0.394 (0.280)	0.211 (0.401)	0.157 (0.122)
HS+3/4	-0.015 (4.481)	-0.218 (0.415)	0.382 (0.610)	0.199** (0.091)	-1.715 (2.977)	-0.373 (0.241)	-0.084 (0.384)	0.226** (0.097)
HS+5 and more	-3.036 (4.133)	-0.476 (0.381)	-0.037 (0.556)	0.391*** (0.078)	0.527 (2.622)	-0.527** (0.221)	-0.019 (0.320)	0.343*** (0.079)
Professional training	-13.34*** (4.627)	-0.336 (0.458)	-1.249* (0.659)	0.280** (0.126)	-7.950** (3.063)	0.118 (0.333)	-0.874** (0.394)	0.196 (0.145)
Number of registrations (PES)	7.192 (8.601)	-0.380 (0.752)	-0.534 (0.341)	0.407*** (0.079)	4.846 (6.988)	-0.239 (0.406)	-0.804*** (0.179)	0.277*** (0.094)
Contract end and econ layoff	7.778*** (2.822)	0.561** (0.256)	0.677* (0.369)	-0.068 (0.110)	4.166** (1.974)	0.410** (0.198)	0.301 (0.254)	-0.177** (0.082)
New entrants and career change	5.362* (3.116)	0.231 (0.271)	0.394 (0.376)	-0.110 (0.110)	5.594** (2.574)	0.434** (0.217)	0.492* (0.294)	-0.176** (0.084)
other	3.136 (2.700)	0.230 (0.278)	0.201 (0.339)	-0.113 (0.134)	3.843* (2.271)	0.170 (0.214)	0.329 (0.259)	-0.083 (0.098)
Constant	-0.942 (9.912)	-0.304 (0.903)	1.237 (0.823)	7.028*** (0.191)	-2.623 (7.658)	-0.415 (0.532)	1.646*** (0.499)	7.182*** (0.155)
Observations	119	119	119	119	187	187	187	187
R^2	0.221	0.186	0.106	0.394	0.104	0.144	0.111	0.378
Adjusted R^2	0.081	0.040	-0.055	0.285	0.008	0.053	0.015	0.311

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by NLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the motive of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Time preferences and job search effort: Square specification

	Search and time preferences over money				Search and time preferences over effort			
	Hours searched	Search channel index	Active search	Reservation wage	Hours searched	Search channel index	Active search	Reservation wage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk (BRET)	-0.025 (0.042)	0.004 (0.003)	-0.002 (0.005)	-0.00002 (0.001)	0.003 (0.032)	0.003 (0.003)	-0.002 (0.004)	0.0006 (0.001)
δ (money)	0.015 (0.054)	-0.006 (0.006)	-0.011 (0.008)	-0.0003 (0.002)	-	-	-	-
D MPL \times δ (money)	-0.040 (0.077)	-0.020** (0.008)	0.002 (0.015)	0.0008 (0.002)	-	-	-	-
δ (money) \times δ (money)	-0.442 (0.862)	-0.404*** (0.070)	-0.125 (0.190)	0.001 (0.023)	-	-	-	-
β (money)	-3.944*** (1.372)	-0.172 (0.145)	-0.268 (0.206)	0.060 (0.066)	-	-	-	-
D MPL \times β (money)	6.190*** (1.918)	-0.125 (0.177)	0.163 (0.299)	-0.011 (0.081)	-	-	-	-
δ (effort)	-	-	-	-	-0.025 (0.029)	0.005 (0.003)	-0.003 (0.005)	0.005*** (0.001)
D MPL \times δ (effort)	-	-	-	-	-0.002 (0.382)	0.015 (0.030)	0.107*** (0.039)	0.030** (0.012)
δ (effort) \times δ (effort)	-	-	-	-	2.212 (2.307)	-0.374 (0.236)	0.223 (0.446)	-0.358*** (0.097)
β (effort)	-	-	-	-	-1.248* (0.685)	-0.150 (0.098)	-0.182* (0.109)	-0.038 (0.029)
D MPL \times β (effort)	-	-	-	-	0.436 (1.386)	0.219 (0.138)	0.656*** (0.169)	0.104 (0.064)
D MPL treatment	2.154 (2.277)	0.131 (0.218)	-0.086 (0.326)	-0.034 (0.081)	2.817 (6.186)	0.472 (0.489)	1.792*** (0.662)	0.476** (0.207)
Female	0.913 (1.895)	-0.053 (0.148)	-0.226 (0.242)	-0.230*** (0.063)	0.185 (1.462)	-0.150 (0.129)	-0.307* (0.173)	-0.227*** (0.048)
25/49 years old	1.101 (2.339)	0.236 (0.187)	-0.104 (0.277)	0.200*** (0.071)	2.036 (1.963)	0.215 (0.145)	-0.102 (0.224)	0.118** (0.056)
50+	8.925** (3.883)	0.833** (0.342)	0.082 (0.422)	0.394*** (0.137)	5.982** (2.778)	0.543** (0.266)	-0.130 (0.335)	0.457*** (0.109)
Less than HS (High School)	-5.453 (4.775)	-0.916** (0.435)	-0.245 (0.747)	0.131 (0.143)	-2.311 (3.776)	-0.951*** (0.301)	-0.307 (0.477)	-0.0526 (0.138)
HS+2	-3.227 (4.317)	-0.140 (0.384)	0.115 (0.587)	0.274* (0.146)	0.0518 (2.484)	-0.184 (0.264)	0.246 (0.403)	0.126 (0.107)
HS+3/4	-0.885 (4.358)	-0.264 (0.369)	0.383 (0.589)	0.168* (0.097)	0.919 (3.061)	-0.356 (0.260)	-0.202 (0.375)	0.0984 (0.087)
HS+5 and more	-2.663 (3.951)	-0.471 (0.340)	0.041 (0.521)	0.353*** (0.092)	1.095 (2.504)	-0.535** (0.226)	-0.198 (0.321)	0.270*** (0.070)
Professional training	-7.618 (5.364)	-0.323 (0.844)	-0.812 (0.520)	0.027 (0.134)	-6.310** (2.657)	-0.373 (0.577)	-1.161*** (0.361)	0.077 (0.177)
Number of registrations (PES)	6.476 (9.258)	-0.568 (0.913)	-0.682* (0.375)	0.413*** (0.077)	3.866 (5.743)	-0.402 (0.345)	-0.827*** (0.177)	0.292*** (0.112)
Contract end and econ layoff	5.576** (2.677)	0.431* (0.232)	0.561* (0.325)	-0.055 (0.106)	2.950 (1.925)	0.392** (0.190)	0.278 (0.250)	-0.123* (0.071)
New entrants and career change	4.664 (3.012)	0.343 (0.252)	0.370 (0.350)	-0.099 (0.110)	5.188** (2.458)	0.445** (0.204)	0.409 (0.291)	-0.198*** (0.074)
Other	3.146 (2.584)	0.338 (0.255)	0.291 (0.317)	-0.114 (0.128)	2.536 (2.050)	0.242 (0.195)	0.084 (0.248)	-0.061 (0.084)
Constant	1.143 (10.77)	0.035 (1.048)	1.770** (0.877)	7.005*** (0.215)	-3.206 (6.823)	0.219 (0.565)	1.814** (0.741)	7.642*** (0.189)
Observations	125	125	125	125	202	202	202	202
R^2	0.217	0.272	0.130	0.379	0.083	0.141	0.137	0.425
Adjusted R^2	0.076	0.140	-0.028	0.267	-0.013	0.051	0.047	0.365

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the D MPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table I6: Time preferences, job search effort and subjective prospects in the labor market

	Subjective probability of finding a job in the							
	Next 4 weeks	Next 2 months	Next 3 months	Next 6 months	Next 4 weeks	Next 2 months	Next 3 months	Next 6 months
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Risk (BRET)	0.006 (0.005)	0.004 (0.004)	0.004 (0.005)	0.002 (0.004)	0.003 (0.004)	0.001 (0.004)	0.002 (0.004)	0.002 (0.003)
δ (money)	-0.009 (0.006)	-0.010 (0.008)	-0.010 (0.009)	-0.004 (0.008)	-	-	-	-
DMPL \times δ (money)	0.009 (0.006)	0.010 (0.008)	0.011 (0.009)	0.004 (0.008)	-	-	-	-
β (money)	-0.090 (0.183)	-0.065 (0.168)	0.019 (0.189)	0.012 (0.183)	-	-	-	-
DMPL \times β (money)	0.049 (0.223)	0.167 (0.186)	0.168 (0.206)	0.137 (0.193)	-	-	-	-
δ (effort)	-	-	-	-	-0.002* (0.001)	-0.002*** (0.001)	-0.001 (0.001)	-0.00007 (0.0009)
DMPL \times δ (effort)	-	-	-	-	-0.005 (0.043)	0.043 (0.043)	0.0329 (0.040)	0.016 (0.037)
β (effort)	-	-	-	-	-0.165 (0.175)	-0.173 (0.171)	-0.219 (0.156)	-0.074 (0.133)
DMPL \times β (effort)	-	-	-	-	0.128 (0.217)	0.401* (0.211)	0.293 (0.210)	0.071 (0.182)
DMPL treatment	0.002 (0.279)	0.203 (0.315)	0.451 (0.294)	0.425* (0.256)	0.077 (0.703)	0.903 (0.696)	0.833 (0.663)	0.581 (0.599)
Female	-0.146 (0.224)	-0.174 (0.193)	-0.155 (0.185)	-0.125 (0.171)	-0.207 (0.170)	-0.101 (0.167)	-0.150 (0.170)	-0.091 (0.153)
25/49 years old	0.006 (0.275)	-0.137 (0.252)	-0.150 (0.243)	0.076 (0.221)	-0.073 (0.210)	-0.174 (0.211)	-0.220 (0.206)	-0.009 (0.182)
50+	0.438 (0.443)	-0.019 (0.511)	0.099 (0.493)	0.201 (0.406)	-0.115 (0.285)	-0.404 (0.340)	-0.453 (0.357)	-0.125 (0.293)
Less than HS (High School)	-1.489** (0.598)	-0.698 (0.560)	0.458 (0.523)	0.523 (0.448)	-1.225*** (0.393)	-0.912*** (0.329)	-0.224 (0.407)	-0.153 (0.537)
HS+2	-0.537 (0.591)	0.275 (0.569)	1.129** (0.549)	0.695 (0.494)	-0.283 (0.436)	0.255 (0.423)	0.931** (0.406)	0.593* (0.339)
HS+3/4	0.045 (0.539)	0.453 (0.531)	1.203** (0.502)	0.878* (0.467)	-0.010 (0.397)	0.095 (0.383)	0.730* (0.372)	0.752** (0.321)
HS+5 and more	-0.743 (0.470)	0.045 (0.480)	0.778* (0.468)	0.675 (0.444)	-0.644** (0.314)	-0.259 (0.310)	0.356 (0.330)	0.464 (0.291)
Professional training	0.741 (1.018)	0.867 (0.922)	1.441* (0.738)	1.011 (0.716)	0.148 (0.923)	0.265 (0.828)	0.685 (0.604)	0.354 (0.639)
Number of registrations (PES)	1.026*** (0.337)	0.434 (0.277)	-0.0715 (0.260)	-0.883*** (0.336)	0.0395 (0.457)	-0.230 (0.478)	-0.751 (0.469)	-0.559** (0.279)
Contract end and econ layoff	0.765** (0.310)	0.803** (0.308)	0.772** (0.299)	0.346 (0.249)	0.162 (0.247)	0.249 (0.245)	0.306 (0.261)	0.246 (0.217)
New entrants and career change	0.510 (0.355)	0.288 (0.365)	0.410 (0.339)	-0.021 (0.296)	0.204 (0.281)	0.0769 (0.278)	0.133 (0.285)	-0.064 (0.254)
Other	0.301 (0.303)	0.194 (0.353)	0.367 (0.344)	-0.115 (0.299)	-0.121 (0.243)	-0.027 (0.266)	0.132 (0.281)	0.020 (0.237)
Constant	1.024 (0.770)	2.032*** (0.765)	2.145*** (0.727)	3.928*** (0.682)	2.403*** (0.595)	3.137*** (0.611)	3.534*** (0.634)	3.816*** (0.480)
Observations	125	125	125	125	202	202	202	202
R^2	0.192	0.169	0.213	0.164	0.109	0.103	0.112	0.099
Adjusted R^2	0.055	0.028	0.080	0.022	0.021	0.015	0.024	0.011

Notes: The regressions are OLS models. The dependent variable is the response of the participant to the questions “Please tell us what is, in your opinion, your likelihood of finding a job in the next 4 weeks/2/3/6 months”. Robust standard errors are in parentheses. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix J: Regression tables on job search outcomes with alternative specifications

Table J1: Time preferences and job search outcomes: Quartile specification, CTB treatment

	Search outcomes and time preferences over money		Search outcomes and time preferences over effort	
	Got interviews (1)	Got offers (2)	Got interviews (3)	Got offers (4)
Risk (BRET)	0.007 (0.018)	0.012 (0.034)	0.031** (0.015)	0.015 (0.014)
<u>δ (money)</u>				
25% < δ (money) < 50%	-3.303** (1.535)	-3.274** (1.356)	-	-
50% < δ (money) < 75%	-1.327 (1.286)	-3.041 (2.520)	-	-
75% < δ (money)	-1.183 (1.195)	-0.674 (1.596)	-	-
<u>β (money)</u>				
25% < β (money) < 50%	-1.714 (1.386)	0.633 (2.403)	-	-
50% < β (money) < 75%	0.732 (1.160)	1.312 (1.720)	-	-
75% < β (money)	-0.449 (1.569)	-0.248 (1.639)	-	-
<u>δ (effort)</u>				
25% < δ (effort) < 50%	-	-	0.245 (0.689)	-1.255 (0.801)
50% < δ (effort) < 75%	-	-	0.008 (0.877)	-1.460* (0.864)
75% < δ (effort)	-	-	0.236 (0.899)	-1.285 (1.032)
<u>β (money)</u>				
25% < β (money) < 50%	-	-	1.210 (0.867)	-1.378* (0.718)
50% < β (money) < 75%	-	-	0.461 (0.804)	-0.432 (0.880)
75% < β (money)	-	-	-0.160 (0.856)	-0.869 (0.954)
Individual controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Unemployment controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	54	44	95	93

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table J2: Time preferences and job search outcomes: Quartile specification with DMPL method

	Search outcomes and time preferences over money		Search outcomes and time preferences over effort	
	Got interviews (1)	Got offers (2)	Got interviews (3)	Got offers (4)
Risk (BRET)	-0.020 (0.016)	-0.007 (0.015)	-0.022** (0.009)	0.0001 (0.009)
<u>δ (money)</u>				
25% < δ (money) < 50%	-0.863 (1.032)	-1.020 (1.063)	-	-
50% < δ (money) < 75%	-1.640* (0.990)	0.195 (1.102)	-	-
75% < δ (money)	-1.412 (1.114)	0.188 (1.469)	-	-
<u>β (money)</u>				
25% < β (money) < 50%	-0.598 (1.086)	-0.541 (1.067)	-	-
50% < β (money) < 75%	0.752 (1.108)	-2.198* (1.133)	-	-
75% < β (money)	-0.244 (1.198)	-1.582 (1.557)	-	-
<u>δ (effort)</u>				
25% < δ (effort) < 50%	-	-	14.58*** (1.194)	1.473 (1.448)
50% < δ (effort) < 75%	-	-	0.276 (0.676)	1.051 (0.683)
75% < δ (effort)	-	-	0.807 (0.994)	-0.077 (1.071)
<u>β (money)</u>				
25% < β (money) < 50%	-	-	-0.363 (0.845)	-1.131 (0.806)
50% < β (money) < 75%	-	-	-15.14*** (1.469)	-1.519 (1.711)
75% < β (money)	-	-	0.284 (0.948)	-0.538 (0.846)
Individual controls	Yes	Yes	Yes	Yes
Unemployment controls	Yes	Yes	Yes	Yes
Observations	68	68	114	114

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table J3: Long term employment outcomes

	Hazard rate	Finding a job	Hazard rate	Finding a job	Hazard rate	Finding a job
Risk (BRET)	-0.0006 (0.008)	0.003 (0.008)	-0.005 (0.006)	-0.003 (0.006)	-	-
δ (money)	0.004 (0.012)	-0.0002 (0.014)	-	-	-	-
DMPL \times δ (money)	0.002 (0.014)	0.005 (0.014)	-	-	-	-
β (money)	-2.949* (1.530)	-3.476* (2.039)	-	-	-	-
DMPL \times β (money)	3.782** (1.817)	3.724 (2.298)	-	-	-	-
δ (effort)	-	-	0.0006 (0.002)	0.0004 (0.002)	-	-
DMPL \times δ (effort)	-	-	0.004 (0.055)	0.021 (0.077)	-	-
β (effort)	-	-	0.528 (0.862)	-0.377 (0.783)	-	-
DMPL \times β (effort)	-	-	-0.084 (0.989)	0.727 (0.980)	-	-
Risk : Above median	-	-	-	-	0.097 (0.126)	0.039 (0.153)
Patience : Above median	-	-	-	-	-0.093 (0.133)	0.042 (0.156)
Procrastination : Above median	-	-	-	-	0.243* (0.126)	0.208 (0.154)
DMPL treatment	-3.875* (2.057)	-4.057 (2.687)	0.380 (1.081)	-0.305 (1.296)	-	-
Female	-0.247 (0.315)	-0.570 (0.433)	0.140 (0.242)	-0.260 (0.316)	-0.0678 (0.127)	-0.292* (0.154)
25/49 years old	-0.159 (0.365)	-0.756 (0.511)	0.0506 (0.324)	-0.222 (0.399)	-0.227 (0.152)	-0.252 (0.182)
50+	-0.785 (0.673)	-0.987 (0.920)	-0.138 (0.527)	-0.150 (0.631)	-0.604** (0.279)	-0.487 (0.333)
Less than HS and pro training (High School)	-2.233** (1.113)	-1.875 (1.564)	-1.228 (0.812)	-1.192 (0.894)	-0.248 (0.230)	-0.268 (0.267)
HS+2	-0.724 (0.637)	-0.925 (0.850)	-0.245 (0.489)	-0.427 (0.611)	-0.00231 (0.241)	0.210 (0.288)
HS+3/4	-1.406** (0.617)	-0.875 (0.871)	-0.761 (0.503)	-1.084* (0.590)	0.0820 (0.221)	0.284 (0.269)
HS+5 and more	-1.319*** (0.455)	-1.248** (0.636)	-0.828** (0.379)	-0.814* (0.478)	0.0692 (0.196)	0.518** (0.238)
Contract end and economic layoff	0.353 (0.534)	0.0303 (0.693)	0.743** (0.357)	0.605 (0.452)	0.039 (0.193)	-0.004 (0.247)
New entrants and career change	0.007 (0.555)	-0.841 (0.773)	0.680 (0.424)	-0.289 (0.525)	-0.135 (0.219)	-0.542** (0.262)
Other	-0.076 (0.570)	-0.769 (0.701)	-0.341 (0.423)	-0.757 (0.507)	-0.008 (0.188)	-0.295 (0.233)
Constant	-	5.456* (2.902)	-	0.844 (1.071)	-	-0.578* (0.316)
Observations	130	130	217	217	836	836

Notes: Models (1), (3) and (5) are Cox proportional models of the hazard rate, based on the duration of unemployment spells until the record ends. Models (2), (4) and (6) are logit models of the probability of finding a job. Robust standard errors are in parentheses. The risk measure is the number of boxes opened in the BRET in models (1) to (4), and the survey measure based on the Falk et al. staircase method in models (5)-(6). The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). Patience and procrastination in models (5)-(6) are the measures from the survey. The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the cause of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.