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Do Job Seekers (Really) Procrastinate?

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Abstract

We elicited experimentally job seekers' short-run and long-run time preferences over money and effort. We found that long-run impatience affects search effort and the reservation wage, but only when elicited in the effort domain. Both procrastination and present bias over money decrease job search effort, with negative effects on early search outcomes for the former and on the exit of unemployment for the later. Both preferences over financial trade-offs and arbitrages over leisure affect job search. However, this is only observed when eliciting time preferences with the Double Multiple Price List method but not with 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 to compensate people for unemployment was equivalent to 0.58% of the GDP on average in the OECD countries in 2021 and it even exceeded 1.5% in countries such as France, Spain, and Finland (*source: OECD*).[1] While public support to unemployed people constitutes a powerful safety net for its beneficiaries, public debates about the funding of the unemployment benefit system are full of arguments accusing job seekers of abusing the system. Such claims fail to account for the complexity of job search processes and the unvoluntary behavioral biases of job seekers.

In reaction to the limitations of standard theories to explain job search anomalies,[2] economists have explored various behavioral biases that could increase the 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, a fraction of 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 be reaped only in the future (like when seeking a job), present-biased individuals may have trouble to stick to their plans and 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 provide less search

[1] https://data.oecd.org/socialexp/public-unemployment-spending.htm. Accessed on March 1, 2023. In 2017, expenditures on unemployment-related benefits in the EU-27 also represented 4.7% of total expenditures on social benefits. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Social_protection_statistics_-_unemployment_benefits. Accessed on August 29, 2023.

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

[3] Other behavioral factors influencing search and the 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).

[4] Interestingly, while economists have little explored the effects of procrastination on job search, one can find plenty of applications and blogs on the Internet that pretend 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 March 1, 2023.

effort than they would like to. Their estimations supported hyperbolic discounting, showing that impatience correlates with longer unemployment but not with the reservation wage. Since this early contribution, there have been very few attempts to document the effects of time inconsistencies on 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 a life insurance) from survey data on everyday life choices (PSID and NLSY in the US). However, these proxies constitute indirect and noisy measures of time preferences that do not permit to disentangle between short-run and long-run discounting, only enabling to estimate 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. (2021) 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 approach lies in the relatively low number of assumptions on which the inference of the parameters relies, as compared to the structural approach, and in the use of data directly collected in the purpose of inferring preferences.

Our research objectives are to explore experimentally how time preferences impact job search effort and its outcomes by means of an incentivized elicitation of time preferences, and investigate the nature of the mechanism: if present bias affects job search effort negatively, is it because of financial trade-offs that put an excessive weight on sooner financial streams, or because of a tendency to procrastinate in terms of effort over leisure? To that aim, we designed a longitudinal online experiment that allowed us to measure a French sample of job seekers' 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 students

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

[6] The 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. A higher present bias was found for the individuals who had 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.

[7] Meyer (2018) elicited experimentally the time preferences of low-skill workers in Ethiopia and correlated these measures with survey data, showing that present bias decreased by 57% the time spent on job search. His study includes on-the-job search and time-dated monetary allocations, whereas we consider unemployed individuals and measure time preferences both over money and effort, which is also a difference with Belot et al. (2021).

subject-pools usually studied, and combining experimental measures of these parameters with survey and administrative data from the French Public Employment Service ("Pole Emploi" and "Unédic") database. These data allow us to test DellaVigna and Paserman (2005)'s model predictions in terms of 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 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 they 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 more job search and its outcomes.

Second, we varied between-subjects the method used to elicit time preferences. Although the measurement of time preferences has been on the economists' agenda for long (see, *e.g.*, Frederick et al., 2002), there is still no consensus on which method provides the most accurate estimates. Several methods emerged (Laury et al., 2012; Attema et al., 2016; Belot et al., 2021), but those 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 first one, 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 second method introduces a convex choice environment and let individuals 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 the 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. With the CTB method, utility curvature and time preferences are recovered at the same time from a set of riskless choices.

Our third contribution is that, by using two types of rewards (money and leisure) and two elicitation methods (DMPL and CTB), we are able to test which type of reward

[8] In 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.

and which method have a higher explanatory power of job search behavior and success.

250 job seekers who recently registered in the French Public Employment Service (PES) participated in three experimental sessions that took place over seven weeks. They took their decisions at different points in time. 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, we asked participants to perform a task that consisted of entering the references of articles published in economic journals in their computer. The allocation of effort, in terms of a number of entries, was made in both the first and second sessions, and effort could be realized in the second and third sessions.

We found that regardless of the method used, job seekers discount effort more than they discount money, which is consistent with Augenblick et al. (2015). Controlling for prospects on the labor market did not reduce the gap between the two domains. However, we observed substantial differences in the estimates between the DMPL and the CTB methods.[9] The sample in the CTB treatment exhibited on average a long-run discount factor equal to one and a short-run factor greater than one, reflecting unexpected *future* bias for monetary payoffs. In contrast, both estimates of discounting for effort did not differ from one, showing neither present nor future bias for effort. In the DMPL treatment, consistently with the previous literature, the estimates of short-run and long-run discounting for money did not differ from one. In contrast, on average participants exhibited present bias for effort allocation in the experimental task, that is, they procrastinated, whereas the long-run discounting parameter did not differ from one.

We then tested the effects of time preferences for money and effort on job search and its outcomes, guided by the predictions of DellaVigna and Paserman (2005). Their model predicts that, with exponential time preferences, more impatient individuals (those with a higher long-run discount rate) search less than more patient individuals because they value less the present value of the future wages they could obtain. Meanwhile, because they value present gains and the immediate consumption they permit more than future ones, they tend to decrease their reservation wage and are more likely to accept a lower wage offer. 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 and thus, more impatient job seekers are expected to exit unemployment faster. Hyperbolic discounting (*i.e.*, high short-run and low long-run discounting) changes this prediction by strengthening the effect of short-run impatience on search. Present bias induces less search in response to the current disutility of search efforts for payoffs accruing in the future. Since the wage only involves future utility streams, present bias should be

[9] Cheung et al. (2021)'s meta-analysis showed that the CTB method is more likely to reject present bias compared to choice lists, but the difference is no longer significant when covariates are taken into account. In our study, they persist even after controlling for individual characteristics.

unrelated to the reservation wage. Thus, with hyperbolic discounting impatience should be negatively correlated with exit from unemployment.

We observed an effect of long-run impatience on both search effort and the reservation wage when time preferences were elicited in the effort domain: impatient job seekers search less and report a lower reservation wage. As predicted by DellaVigna and Paserman (2005)'s model with hyperbolic discounting, present bias over money reduced the number of hours searched and had no effect on the reservation wage. Similarly, procrastination in the effort domain decreased the number of direct actions undertook to find a new job but did not affect the reservation wage. However, all these effects were identified only when using the DMPL method. The time preferences elicited with the CTB method do not impact job search, except for a surprising positive effect of present bias for money on the time spent searching, driven by the middle of the distribution of short-run discounting. An interpretation could be that impatience for money makes the return to work more urgent, suggesting another mechanism than in DellaVigna and Paserman.

Regarding search outcomes 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 never reached significance. However, when elicited with the DMPL method, short-run impatience over money impacted negatively the hazard rate measured approximately a year after the experiment. Procrastinators identified with the DMPL method received less job interviews during their early unemployment spells. In line with DellaVigna and Paserman (2005), an interpretation is that procrastinators postpone their search effort, which subsequently provides them with less job opportunities. However, the pure effect of procrastination seems to only hit at the beginning of the spell, while present bias over money seems to affect longer-run perspectives in the labor market.

This analysis leads to three final remarks. First, present bias over money and procrastination describe different individuals. Second, in the long run job search is more affected by impatience in terms of financial trade-offs than by arbitrages over leisure, which tends to contradict populist arguments on job seekers' supposed laziness. Our findings suggest to target policy interventions on job seekers with hyperbolic time preferences in two directions: in the monetary dimension, helping them to focus on the current value of the future financial streams attached to the exit from unemployment, and in the real dimension, providing them with commitment devices to engage in concrete and planned job search actions. Finally, the link between time preferences and job search effort is very sensitive to the method used to elicit such preferences. The discrepancies observed in our results according to the method used call for a more systematic investigation of the ability of the two most popular methods to predict behavior in real settings.

The remainder of the paper is organized as follows. Section 2 presents our theoretical background. Section 3 describes our empirical strategy. Section 4 develops our results. Section 5 discusses these results and concludes.

2 Theoretical background

The model of DellaVigna and Paserman (2005) (DVP, hereafter) adds to the classical framework of Lippman and McCall (1976) an hypothesis on how future utility streams are discounted. If job search models usually rely on intertemporal trade-offs, job seekers are assumed to be time-consistent. A given future wage utility obtained at time t is given a weight δ^t, where δ represents the discount factor. This exponential discounting assumption has the elegant property that the weight given to future utility only depends on the length of the time horizon t, and any utility unit at time t is worth δ times as much as a utility unit at time $t-1$. A decision should stay unchanged if the option was left to modify later on. However, it has been observed that decision time does matter: when a decision is taken ahead of its actual application, some people change it when this date comes closer (Thaler, 1980). The novelty of their model was to introduce present bias in job search.

A notable finding of the recent empirical literature is that individuals tend to be present biased when allocating effort units, but much less so when allocating monetary units (Augenblick et al., 2015; Cheung et al., 2021). Therefore, we conjecture that in our sample, because of present bias, effort should be disproportionately postponed to a later date when decisions are made the day where the task should be performed, whereas we expect monetary units to be allocated consistently, that is, independently from the moment when the decisions are taken. This leads to 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 may anticipate heterogeneity in job seekers' available time and financial state over time, depending on their subjective prospects in the market. If job seekers believe they will exit unemployment quickly, they may prefer a positive income stream in the present to smooth background consumption, and performing the task early because they have more time available now (Belot et al., 2021). Controlling for such prospects could reduce the difference between patience over time and over money.

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

The following hypotheses derive from the model of DVP that uses a $\beta-\delta$ quasi-hyperbolic utility discounting à la Laibson (1997). This model augments the exponential discount factor δ by a parameter β when the decision timing matches the present date. This implies that future values are discounted β times more when the decision date

[9] These hypotheses, the experimental design, and the data analysis plan were preregistered at AsPredicted (#68035). The order of presentation of the hypotheses has slightly changed.

matches the present, while the model goes back to exponential discounting when planning is ahead of the present. At time t, a job seeker chooses a search effort, s_t, and a stopping condition for the wage to maximize the following program:

$$\underset{s_t \in [0,1]}{Max}\ b - c(s_t) + \beta\delta[s_t E\{max(V^E_{t+1}(w), V^U_{t+1})\} + (1 - s_t)V^U_{t+1}] \tag{1}$$

where b is the unemployment benefit, c the cost of search with $c(.)$ an exponential function, and w the wage level. The job seeker first 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, the job seeker receives a job offer at wage w, accepts it and gets the future value of employment at that wage, $V^E_{t+1}(w)$, or rejects it and gets the utility of staying unemployed in the next period, V^U_{t+1}. Second, with probability $(1 - s_t)$, she stays unemployed and receives the continuation payoff of staying unemployed, V^U_{t+1}. A reservation wage strategy maximizes this program with:

$$w^\star = (1 - \delta)V^U \tag{2}$$

and the first order condition of the program yields:

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

The reservation wage setting does not directly involve short-run discounting, which explains why present bias does not (or only marginally) affect the reservation wage. Regarding search, at the equilibrium the marginal cost of search equalizes its marginal expected benefit that directly depends on both discounting factors. Thus, whether sophisticated or naive, present biased job seekers search less than they would like to.

In a standard model in which job seekers simultaneously set their reservation wage and their search effort level, search costs are supported in the present, whereas the values of future potential incomes, conditional on receiving an offer and accepting a given wage, happen in the future and are discounted accordingly. Since only δ matters, two effects take place at the equilibrium. On the one hand, impatient individuals (with a lower δ) discount the future heavily, which leads to a lower valuation of what a future potential wage would bring to them, and thus, they lower their search effort. On the other hand, impatient individuals tend to accept lower wages than more patient individuals because they value the present more than patient individuals who prefer to wait in the hope of receiving a potential better offer. The first effect leads to a negative correlation between unemployment duration and the discount factor δ, through the search effort, whereas the second one implies a positive correlation, through the reservation wage.

DVP show that heterogeneity matters. For high values of δ, individuals wait too long in order to get higher wages, which delays exit. Overall, the effect of δ on exit is hump-shaped: the exit rate increases in δ up to a certain level above which it decreases in δ because search becomes more selective. We thus posit the following hypotheses:

Hypothesis 3: *Job seekers with a higher discount factor δ provide more job search effort and have higher reservation wages. This holds for both monetary and effort dimensions, as the decisions regarding job search effort provision and the reservation wage setting imply both real effort and financial trade-offs.*

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

Since the short-run discount factor, β, increases the discounting of future values, the job search model with hyperbolic discounting predicts a stronger effect of discounting on search effort. Indeed, the effort level is set at the beginning of the spell, whereas effort is realized all along the spell. In the case of naive agents unaware of their self-control issue, this creates a discrepancy between planned and realized effort. They fail to anticipate that when time to search arrives, they will both overestimate their future effort provision and undervalue the future return of their search. With procrastination, the combination of these two effects leads job seekers to provide less effort than planned. In contrast, the reservation wage is not affected by short-run impatience. 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, because what determines the reservation wage only depends on long-run considerations.[10] Hyperbolic discounters ($\beta < 1$) search less but have the same reservation wage as exponential discounters ($\beta = 1$) and thus, short-run impatience (lower β) delays exit. Following this argument, and given its strong reliance on effort allocation inconsistencies, we introduce our last hypothesis:

Hypothesis 5: *Present-biased job seekers in the effort domain provide lower search effort, which delays their exit of unemployment. Present bias does not affect the reservation wage that implies trade-offs made in the distant future.*

3 Empirical strategy

Our data come from three sources: an online experiment that aimed at measuring the time preferences of a sample of job seekers in France, a pre-experimental survey, and an

[10] Sophisticated present biased agents foresee their future low search level and marginally lower their reservation wage. However, DVP show that this effect is relatively small.

administrative dataset that both inform on the same job seekers' individual labor market history. In this section, we first introduce our sampling procedures and the administrative data. Then, we present the pre-experimental survey and detail the experimental design.

3.1 Sampling and administrative data

We sampled the participants to our study from the French Public Employment Service (PES) database.[11] In France, any individual can register at Pôle Emploi to receive support for job search. For the eligible unemployed persons, registering is a mandatory requirement to receive unemployment benefits from UNEDIC. Those who receive unemployment benefits are legally requested to update their job search information every month until they find a job.[12] The PES database records the job seekers' socio-demographic information (*e.g.*, age, education, gender), work history (*e.g.*, total number of unemployment spells in the career, previous wage, previous type of contract, motive of the end of the previous labor contract), and job search (*e.g.*, type of job sought and duration of the unemployment spell). This dataset enabled us to select our sample, trace each participant's history in the labor market since their first registration, and follow the updating of their situation with the PES about a year after the end of the experiment.[13]

A statistical power analysis conducted on G*Power 3 (Faul et al., 2007) indicated that we needed 210 participants to be able to detect a medium-size effect (d=0.5) with a power of 95% and a critical rejection value of 5%. We targeted a sample of 300 participants completing the three sessions of the experiment to account for the heterogeneity of job seekers' decisions which may lead to greater variance and thus reduce our power.[14]

Based on our expectations regarding the response and attrition rates during the experiment, we selected a sample of 40,000 individuals among all the unemployed job seekers eligible for the unemployment benefits. Since our predictions are derived from an environment without on-the-job search, we excluded employed job seekers from the sample. Because of the specific characteristics of their job market, we also excluded job seekers over 55 years old and below 18. To measure time preferences without any potential bias coming from the time spent unemployed, we only selected job seekers who registered to the PES at most four months before our invitation. The choice of this time frame was guided by operational considerations, as it may take up to four months for

[11]This database administered by Pôle Emploi is called the "Fichier National des Allocataires (FNA)".

[12]Once 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.

[13]A limitation is that the dataset allows us to know whether the participants continue their job search at that date, but if they stopped registering, we cannot be certain that this is because they found a job. The PES estimates that over 80% of the unemployed job seekers who stop registering before their unemployment benefit dried up do so because they accepted a job, a training or an internship.

[14]These numbers were pre-registered (AsPredicted #68035). The pre-registration also mentioned a pilot study with 20 data points that was conducted to test the experimental platform. These data are not used in the study.

the database to be updated with the relevant information needed to select our sample. We conducted the experiment with the agreement of the PES but the study was framed as an academic research to avoid a desirability bias in the response to questions on job search effort. The counterpart of this strategy is having to invite a larger sample since the expected response rate was lower than for an official survey by the PES.[15]

We sent an email to each participant in the sample with a link to register to our online experiment. Before registering, participants were invited to answer a pre-experimental survey (see next section). From the 40,000 individuals sample, 38,000 had valid emails 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 between registration and the first session reached 51%, leaving us with 304 participants. 235 participants completed the three sessions. The final sample used in the data analysis consists of the 250 participants who completed sessions 1 and 2, those 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 PES population, our final sample over-represents job seekers older than 25 years, those holding at least a Master degree, and those working in communication and firm support occupations; it under-represents those with at most a high-school degree, new entrants, and those in transport, bank, and commerce occupations.

3.2 Pre-experimental survey

Before registering to the experiment, the invited job seekers had to answer a survey. 750 fully completed questionnaires out of 937 could be exploited. 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. For the sub-sample who completed the experiment, this also allowed us to compare the predictive value of these unincentivized measures in terms of search effort and outcomes with that of the incentivized measures from the experiment.

These measures consisted in a weighted average of the answers to two types of questions (see Appendix A). In a first set of questions, job seekers reported the degree to which they agreed with three statements relative to risk, patience, and the tendency to procras-

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

[16]As pre-registered, we excluded participants who filled inconsistent values for the reservation wage. A valid value had to lie in a range equal to 0.5 and 1.5 the previous wage, recovered from individual administrative data. For the 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 that did not participate in session 3 since participants had no decision to make in the last session.

tinate, using 0-10 Likert scales.[17] The second set of questions are 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, 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, 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 in the past four weeks that we planned to correlate with the individuals' time preferences: the number of weekly hours spent searching, the frequency of use of eight search channels (online search engines, PES, local newspapers, friends, previous co-workers, interim agencies, social networks, direct contact with employers), the number of actions undertaken to find a job (training, sending resumes, attending job speed dating meetings), and the tendency to set a search target in terms of hours searched or number of resumes sent and its time horizon (not used). We asked questions about the reservation wage, and the minimum and maximum wages expected for the position sought. For the return to search, 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 these measures for the 250 job seekers who completed the experiment, the 50 job seekers who started the experiment but did not complete it, and the 450 job seekers who completed the survey but did not register to the experiment. It reveals no significant differences between those who started the experiment but quit before the end and those who completed it. In contrast, compared to our final sample, those who completed the survey but did not register spent significantly more hours searching for a job, had a higher search intensity and developed a more active search; they reported a significantly lower reservation wage and they received a higher number of offers; they also reported significantly less patience. This suggests that our experiment may over-represent job seekers that felt less time pressure to get back to work (and thus, took time to participate in our study) and had higher job requirements.

[17] For 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 in order 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 to our experiment, the job seekers committed to participate three times over a seven week horizon, with each participation scheduled exactly three weeks after the previous one. After answering the survey, they were invited to register and choose a day and time for their participation in session 1, knowing that the following two sessions would be scheduled 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 the instructions on their screen and they could ask questions through a chat platform. Since instructions were almost identical across sessions, for sessions 2 and 3 the chat was replaced by an email contact. Participants could log in to our online platform whenever they wanted the day chosen for sessions 2 and 3, between 8:30am and midnight. Reminders were sent two days before a session. In each session, we reminded the nature of the tasks, the decisions to make, and the timeline.

Treatments – The experiment used a 2x2 factorial design. One dimension manipulated between subjects the method used to elicit time preferences. 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] In order to create a common experimental assessment of risk attitude, we added for both treatments the Bomb Risk Elicitation Task (Crosetto and Filippin, 2013) (BRET) at the very end of session 1.[19]

The other dimension manipulated within subjects 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 different dates, with six gross interest rates, two time horizons, and two front-end delays. In the other condition, participants made 12 allocation decisions regarding a number of tasks to perform at a sooner or a later date, with 12 exchange rates. They made such decisions twice, once in session 1 and once in session 2; thus, in total they also made 24 decisions. They had to actually perform the task in sessions 2 and/or 3, according to one of their choices, randomly selected.[20] Figure 1 summarizes the timeline of the experiment.

[18] Participants were presented 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.

[19] A 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.

[20] The allocation of effort was made in two steps, while the allocation of money was made in a single session. The objective was to preserve the independence of these decisions and avoid that monetary decisions were made to compensate for effort choices. Imposing that the first effort allocation decisions were made in session 1 also

Figure 1: Timeline of the experiment

Monetary Allocations – All the intertemporal decisions relative to the 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, and 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 3 weeks after session 3 (6 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:

$$Pc_t + c_{t+k} = y \tag{4}$$

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=€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 €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 that was initially positioned

avoided asking participants to come back in a fourth session to perform the tasks assigned to the later date.

in the middle of the slider bar. Validating a decision was not possible without moving the slider. The gross interest rate was displayed on the left of the slider and as the participant moved the slider, the amounts 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] whereas in the DMPL treatment only choices at the extremes were allowed.

Effort allocations – Participants made 12 allocation decisions to 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. In session 2, they were not reminded which choices they made in session 1. They were informed that only one of these 24 decisions would be selected randomly and implemented, and that decisions made in session 2 had a 90% chance to be selected compared to 10% for those made in session 1, with equal chance for each decision in a given session to be selected. As in Augenblick et al. (2015), this was done to allow participants to keep flexibility while experiencing their possible present bias tendency when reallocating their 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 the sessions. Thus, decisions were only about when to perform the tasks.

The tasks consisted in entering in the computer the references of scientific articles published in economic journals. By clicking on the links provided, participants got access to the table of contents of one issue of a given journal. 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 by 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

[21] In 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 gave directly the resulting net payments in €at each of the two dates.

later dates. For each decision, the exchange rate of sooner *vs.* later tasks was visually indicated on the left of the bar. As the participant moved the slider, the number of pages to realize in each session was displayed on top of the bar (see Figure B3 in Appendix B). To proceed to the next decision, the participant had to move the slider. In the CTB treatment, inner allocations on the slider could be chosen, while in the DMPL treatment, only allocations at its extremes were allowed.[22] To guarantee that all the participants had the same transaction costs, independently from their choices, and to discard the show-up cost from the decisions, a minimum work requirement of five pages was imposed in each of the three sessions. This number did not count toward the allocation decisions.

Payment procedures – Previous research has revealed the importance of the credibility of payments in the measure of time preferences (Andreoni and Sprenger, 2012). To equalize the transaction costs between time-dated payments, participants' earnings were wired to their bank account by the National Center for Scientific Research (CNRS). CNRS is the main public research institution in France since 1939. Because of its historical presence in the French public debate, most citizens in France know and recognize the institution, which ensures a strong credibility in the payment of the earnings. Credibility was reinforced by the mention of the support of the PES to our study. However, paying through bank transfers means that the money was actually made available during the week following a session. This is a limitation since it has been found that present bias is very sensitive to same-day immediate payment (*e.g.*, Balakrishnan et al., 2020). We likely underestimate short-run impatience in the monetary dimension. In contrast, effort was performed in the hour. On average, participants earned €70.36 (S.D.=3.77) in total for their decisions, including the total show-up fees of €18 (€6 per session).

4 Results

In this section, we start by exposing our estimation strategies. Then, we present our estimations of time preferences over money and effort. Finally, we examine to what extent 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 preferences estimates were sensitive to changes in the assumptions. We adopted the framework of the quasi-hyperbolic discounting model (Laibson, 1997;

[22] Because the number of pages was discrete, a restricted set of decisions within the ranges defined by the constraints could be selected. Thus, the highest levels of R had a lower number of inner choices than lower levels. This constraint led to a greater variance in the decisions made with those rates and consequently led to weaker statistical power for effects driven by differences in choices made with these rates.

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:

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

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 in which monetary and effort units could 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:

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

For effort, the maximization yields the tangency condition:

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

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

[23]Estimating these parameters requires that participants change their allocations in response to the exchange rate. Only 6 participants in the CTB treatment never changed their allocations of tasks but 78 never changed their allocation of payments. Including or excluding them from the aggregate estimates does not affect the results.

The estimated equations take the form:

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

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 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 by means of the delta method.

Double Multiple Price List estimation – The approach followed to recover our parameters from the DMPL choices differs from that used for the CTB choices, using two different tasks. Indeed, the task used to identify discounting parameters relies on choices in which effort and money have to be allocated either to the sooner or to the 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 take into account the utility function curvature, using the choices made in the Holt and Laury (2002) risk elicitation task, which, in the presence of risk aversion, results in higher discounting rates.

Although we could strictly follow this method, using risk preferences and the allocation task simultaneously for the monetary dimension, the use of a separate task in the effort dimension represents a challenge because the curvature comes from effort aversion, which cannot be estimated through an adaptation of a Holt and Laury (2002) task to the effort domain. We thus estimated discounting and curvature in two steps. We first estimated effort aversion and discounting in the CTB sample and then, we incorporated the estimated average effort aversion level in the likelihood function to evaluate the discounting parameters in the DMPL sample. Following a similar strategy for the two dimensions, we also estimated risk aversion and time discounting in two steps in the monetary dimension. We first estimated risk aversion through the Holt and Laury (2002)

[24] Corner 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.

task, and subsequently estimated the 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:

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

$$PV_L = (\omega_1)^\theta + \beta^{\mathbb{1}_{t=0}} \delta^k (u_{t+k} + \omega_2)^\theta \tag{11}$$

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):

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

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

We assumed that a given option is chosen whenever its choice probability index gets larger than $\frac{1}{2}$. To allow for the positive probability of errors with respect to 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 gets large, this probability becomes random, while it goes back to a perfectly deterministic model when $\mu \to 0$. As in Holt and Laury (2002), we exploited the fact that the index is already in the form of a cdf function to define our log-likelihood functions, allowing us to estimate our parameters of interest through Maximum Likelihood:

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

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

4.2 Short- and long-run time discounting

We first present time preferences over money and then, 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

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

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 than the DMPL treatment because job seekers took advantage of the possibility to distribute their monetary units at two dates.

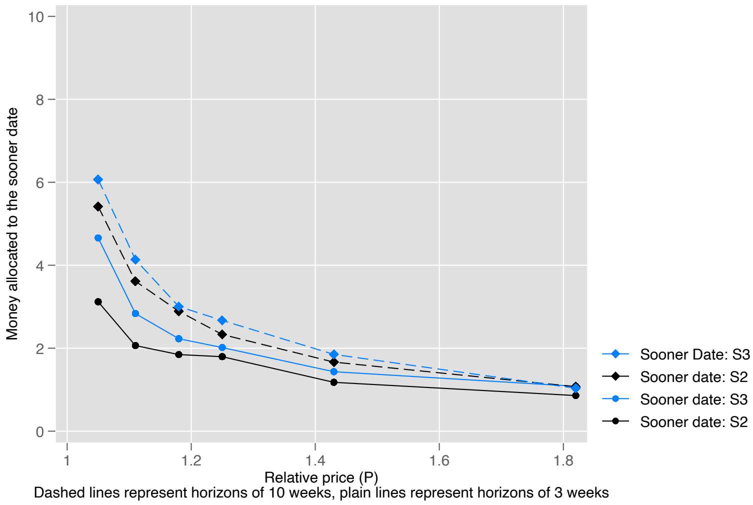

Figure 2: Monetary allocations in the CTB treatment

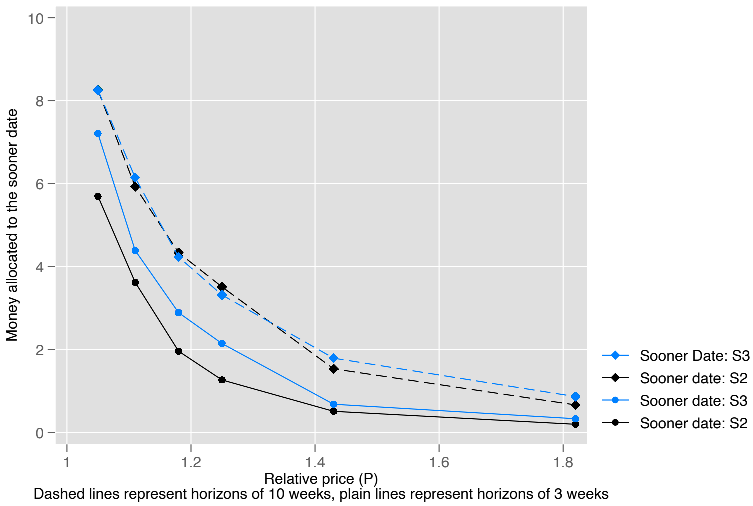

Figure 3: Monetary allocations in the DMPL treatment

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 for a ten-week horizon. S2 is for session 2 and S3 for session 3.

The figures reveal that in both treatments, participants became more impatient, that is, they allocated more units to the sooner date when the time horizon was getting

[26]At the individual level, 12 participants out of 128 had non-monotonically decreasing amounts 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 (sooner or later) regardless of the gross interest rate; the corresponding number is 46 in the DMPL treatment. It is impossible to estimate individual parameters for these individuals. We kept them in the aggregate analysis but removing them in the estimates does not change the results. We report in Appendix G the same estimates excluding these participants.

longer: in both figures, the dashed curves ($k = 10$ weeks) always lie above the plain 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 than when it was three weeks in the CTB ($p < 0.001$), and €1.5 (s.e.=0.2) more in the DMPL treatment ($p < 0.001$). In the short run, however, they exhibited future bias on average in both treatments, that is, 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 the curves 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 ($t = 0$) than 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 within[27] and between[28] 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 show that individuals were on average patient: the daily discount factor δ is very close to 1 in all estimates (and close to the 0.998 estimated in Augenblick et al. (2015) with a Two-Limit Tobit).[29] Regarding short-run discounting, both the linear and Tobit estimates reveal a strong future bias in the CTB treatment ($\beta = 1.187$ and 1.162, respectively), indicating that individuals preferred to shift payment to the future. When taking into account non-linearities in the way that the parameters enter the objective function, the level of future bias drops to 1.050 but it remains significantly higher 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

[27] Two-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.

[28] Two-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.

[29] The high number of decisions allows us to identify small effects up to three digits after the decimal point. However, since our horizons are relatively short we are limited in our inference for very long horizons over which such degree of precision may matter. Although the χ^2 test is significant in 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.

[30] A 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), but it also reveals heterogeneity across studies with few of them observing $\beta > 1$ (Andreoni and Sprenger, 2012; Aycinena et al., 2015; Aycinena and Lucas, 2018; Brocas et al., 2018). Present bias is less frequent in field studies than in the lab, and present biasedness is higher when the sooner reward is paid in the hours following the experiment, as already shown by (Balakrishnan et al., 2020).

comparing the choices made between €15 at a sooner date and a free amount three weeks later, individuals would be willing to pay approximately €0.9 to receive earnings in the future, that is, when the sooner date is in the future rather than in the present.

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***	0.862***	0.902***	0.732***	-
	(0.031)	(0.027)	(0.011)	(0.041)	
δ	1.002***	1.001***	1.000***	-	0.999***
	(0.0007)	(0.0006)	(0.0002)		(0.0003)
β	1.187***	1.162***	1.050***	-	1.043***
	(0.019)	(0.019)	(0.008)		(0.012)
Ho: $\delta = 1$, p	0.000	0.024	0.141	-	0.000
Ho: $\beta = 1$, 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Regarding risk preferences, the low OLS estimate of α (0.392) is attributable 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). 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 to 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 date of the decision (session 1 or 2) in the CTB and the 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 show some concavity for the most advantageous rates, signalling effort aversion. This global pattern is close to that observed in Augenblick et al. (2015).[31]

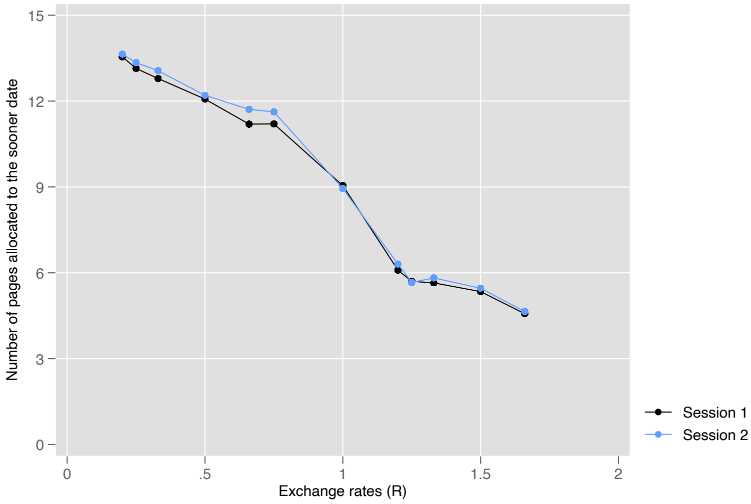

Figure 4: Effort allocations in the CTB treatment

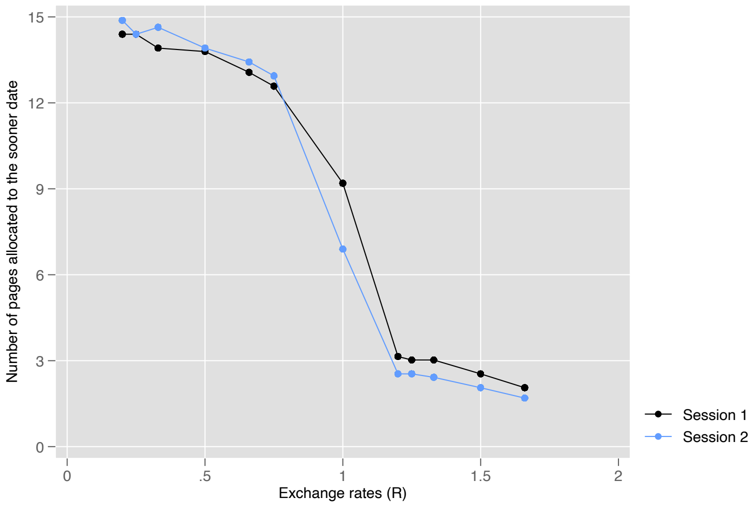

Figure 5: Effort allocations in the DMPL treatment

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).

Regarding the discounting patterns, there is no evidence of present bias in the CTB treatment: the two curves in Figure 4 largely overlap. When participants had to allocate all their effort to a single date, in Figure 5 the curve corresponding to the sooner date allocations of effort made in session 2 lies below the curve corresponding to the decisions made in session 1 when $R = 1$ and when sooner tasks become relatively more expensive to

[31] At the individual level, the total number of inconsistent patterns is in line with the monetary analysis: 12 participants out of 128 expressed preference reversals in the CTB treatment and 9 out of 124 had non monotonic choices in the DMPL treatment. 6 participants in the CTB treatment always allocated all their effort at the early date or at the late date, without any variation; this is the case for 3 participants in the DMPL treatment. They are thus excluded from the analysis.

perform ($R > 1$). While this suggests a tendency to postpone effort more when the sooner date for performing the task was today, the difference is not significant.[32] Controlling for the gross interest rates, participants allocated on average the same number of pages to the sooner date when it was in the present ($t = 0$) than when it was in the future in both the CTB and DMPL treatments (respectively the mean differences are 0.10 and -0.07, and the tests of equality of means indicate $p = 0.44$ and $p = 0.69$).

Table 2 reports the aggregate estimates of the 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 reveal a 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), capturing effort aversion, is the smallest using the Two-Limit Tobit estimation and the highest with NLS. Overall, the rates are quite close to each other and of the same magnitude of the rate of 1.589 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^{***}	1.171^{***}	1.750^{***}	-
	(0.030)	(0.025)	(0.117)	
δ	1.003^{***}	1.003^{***}	1.006^{***}	0.997^{***}
	(0.004)	(0.003)	(0.003)	(0.001)
β	1.018^{***}	1.009^{***}	1.045^{***}	0.969^{***}
	(0.067)	(0.067)	(0.066)	(0.015)
Ho: $\delta = 1$, p	0.372	0.402	0.038	0.065
Ho: $\beta = 1$, 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, supporting Hypothesis 1, job seekers in the DMPL treatment displayed a close to exponential behavior in the monetary dimension but exhibited present biasedness in the effort dimension. In contrast, job seekers in the CTB treatment exhibited a large future bias in the monetary dimension, whereas their behavior in the effort

[32] Two-tailed t-tests indicate that the average effort allocation to the sooner date was significantly different when decisions were made in session 1 or in session 2 neither in the CTB, nor in the DMPL treatment ($p = 0.554$ and $p = 0.776$, respectively).

dimension did not significantly differ from exponential discounting. This future bias is unusual although, consistently with the literature, participants exhibited lower short-run discounting (β) over effort than over money, which is again consistent with Hypothesis 1. 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 – First, we report in Table 3 summary statistics on the estimated percentage of job seekers whose behavior exhibited present bias, for each dimension.[33] In fact, it shows that at the individual level, a non-negligible proportion of job seekers exhibited present bias, especially in the effort dimension, notwithstanding substantial differences according to the elicitation method.

Table 3: Summary statistics on Iindividual estimates of time preferences

	CTB-Money (1)	CTB-Effort (2)	DMPL-Money	DMPL-Effort
% present-biased ($\beta < 1$)	15%	55%	53%	31%
N observations	55	110	77	123

Notes: The table displays the percentages of job seekers, based on the individual estimates using OLS for the CTB treatment and MLE for the DMPL treatment.

Next, we report estimates of the correlation between individual time and risk preferences, controlling for the elicitation method and individual characteristics. We had two objectives: i) to explore whether the elicitation method has a significant effect on the estimated value of the parameters, and ii) to test Hypothesis 2 regarding individual heterogeneity, in particular the possible role of job seekers' expectations in the labor market. The expectation of a quick exit might indeed lead them both to prefer a positive income stream in the present to smooth background consumption and to exhibit less procrastination since they may have more time available in the present 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 categorical subjective probabilities ("very low", "low", "neither high nor low", "high", "very high") of finding a job in the next four weeks, [1-3] months,]3-6] months, and after six months.

First, controlling for individual characteristics, with the CTB method we estimated a significantly (at the 5% level) lower tendency to smooth consumption, a 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. This indicates that the

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

analysis of the role of time preferences on job search and outcomes should control for the elicitation method. Second, we found no whatsoever significant correlation between any of the estimated parameters and job seekers' subjective prospects in the labor market and, more generally, with their individual characteristics. Thus, we reject Hypothesis 2 and its prediction that accounting for job prospects would reduce the difference between patience over time and over 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 in the labor market. We built three measures of search, based on the respondents' answers in the pre-experimental survey. The "Hours searched" variable is the number of hours spent each week on searching in the past four weeks. The "Search channel index" is an index equal to the sum of the ordinal frequencies of use of each of eight search channels weighted by the number of channels used. The "Active search" variable is the number of search actions undertook 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 4 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 that were estimated by OLS in the CTB treatment and by Maximum Likelihood in the DMPL treatment.[35] To control for risk, we used the BRET measure to have an estimate inferred from a common method between all participants.[36] In all models, each preference parameter was interacted with a dummy for the DMPL treatment because Table F1 in Appendix F has shown 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 to the PES and motive of the last registration) (Table H1 in Appendix H

[34]The variable contains four levels: "less than 5" to " 15 and more" using increasing steps of 5 actions per level. We report estimates using OLS but obtain similar results using an ordered logit model.

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

[36]We alternatively considered using our 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 $p = 0.034$).

displays the detailed coefficients of these controls).[37], [38]

Table 4 shows that the preference to smooth consumption had no significant impact on the intensity of job search or the reservation wage: the risk measure is significant in no 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 4 provides mixed support to this hypothesis. On the one hand, the long-run patience over money had no significant effect in any model. On the other hand, the 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, the participants in the upper quartile of the distribution of δ over effort set significantly (at the 5% level) higher reservation wages (this is the case for all quartiles compared to the first one in the DMPL sample, see Table I2). We interpret this as a reflection of the estimated value added that high δ job seekers may attribute to their ability to consistently plan effort.

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 has a negative effect on 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; surprisingly, 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 effort. In the monetary domain, assuming a non-linear effect of δ unveiled 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 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 the search effort and -with more contrasted evidence- the reservation wage, whereas long-run impatience over money has no significant impact on the intensity of search or the reservation wage.

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[37]For 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.

[38]The 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 led by the fact that those estimates provide the highest correlation to the choices made in the experiment. Indeed, when participants made their choices, they were more likely to take into account 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 together.

Table 4: Time preferences and job search effort

	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	0.005	-0.002	-0.00002	0.002	0.003	-0.002	0.0007
	(0.042)	(0.004)	(0.006)	(0.001)	(0.032)	(0.003)	(0.004)	(0.001)
δ (money)	0.013	-0.007	-0.011	-0.0003	-	-	-	-
	(0.055)	(0.006)	(0.008)	(0.002)				
DMPL $\times$ δ (money)	-0.011	0.006	0.010	0.0007	-	-	-	-
	(0.054)	(0.006)	(0.008)	(0.002)				-
β (money)	-3.943***	-0.170	-0.267	0.060	-	-	-	-
	(1.370)	(0.148)	(0.205)	(0.065)				
DMPL $\times$ β (money)	6.591***	0.242	0.276	-0.013	-	-	-	-
	(1.889)	(0.163)	(0.245)	(0.077)				
δ (effort)	-	-	-	-	0.001	0.0003	-0.0003	0.0005
					(0.006)	(0.001)	(0.001)	(0.0005)
DMPL $\times$ δ (effort)	-	-	-	-	-0.011	0.017	0.106***	0.0318**
					(0.381)	(0.030)	(0.039)	(0.012)
β (effort)	-	-	-	-	-1.186*	-0.160*	-0.176	-0.048
					(0.683)	(0.095)	(0.109)	(0.034)
DMPL $\times$ β (effort)	-	-	-	-	0.382	0.228*	0.651***	0.112*
					(1.381)	(0.135)	(0.169)	(0.067)
DMPL treatment	2.046	0.032	-0.117	-0.034	2.586	0.511	1.769***	0.514**
	(2.260)	(0.220)	(0.322)	(0.080)	(6.180)	(0.487)	(0.662)	(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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Regarding short-run impatience, Hypothesis 5 states that present bias over effort (procrastination) should lead to postpone the search effort without changing the reservation wage because the latter implies trade-offs made in the distant future. Table 4 gives some support to this hypothesis but again only in the DMPL treatment. Consistently with DVP, active search rised significantly (at the 1% level, see model (7)) with the value of β in this treatment. An increase of 0.1 in the value of β in the DMPL estimates increased the chances of sending at least 15 applications in the past four weeks by 10.6%.[39] Table I2 in Appendix I shows that this positive effect was driven by the job seekers belonging to the top quartile of the distribution of β. In contrast, in the CTB treatment the coefficients did not reach a standard level of significance (and Table I1 in Appendix I shows no difference across quartiles). As expected, the effect of short-run impatience on the reservation wage did not reach a standard level of significance in any treatment.

In an exploratory analysis, we also examined the effect of short-run impatience in the monetary domain on search effort. While no effect was observed on the reservation wage, we found that an increase of 0.1 in the value of β over money increased the weekly time spent searching for a job by 27 minutes in the DMPL treatment (significant at the 1% level in model (1)). In contrast, we found in the CTB treatment that the value of β over money decreased search effort significantly by 39 minutes. We reject that this was driven by the strong future bias for money observed in this treatment. Indeed, we found no significant effect of β over money on search effort 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 in fact an effect of financial and time prospects, as suggested by Belot et al. (2021)? We can discard this interpretation. Recall that we asked participants about their perceived likelihood to find a job in one, two, three, and six months. We regressed the stated likelihood to find a job in each time horizon on the discounting parameters over money and effort. The regression Table I6 in Appendix I shows that the values of β over money and over effort do not correlate with the subjective probability of finding a job in any time horizon (models (1) to (4), and (5) to (8), respectively). This means that those who exhibited more short-run impatience did not display a particular optimism about their short-run perspectives in the labor market.

Overall, our analysis leads to Result 4:

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

[39] The marginal effect on applications was estimated using an ordered logit model.

4.4 Time preferences and job search outcomes

4.4.1 Early outcomes

Hypotheses 4 and 5 predicted a negative effect of both long-run impatience and procrastination on exit out of unemployment, whereas more patient job seekers were expected to find a job faster, thanks to their higher search effort; an exception was for individuals with a very high level of δ whose extreme patience would make them too selective in their search, delaying their return to work. We tested these hypotheses with the responses to the pre-experimental questionnaire about the number of interviews and job offers obtained by the respondent since the beginning of their unemployment spell. We acknowledge that these measures constitute an imperfect proxy of search outcomes since the participants only experienced two to four months of unemployment at the time of the experiment and we could not observe job finding yet; therefore, the search effort reported at the time of the survey was more likely to have produced its effect only later on in the unemployment spell.[40] Although imperfect, these responses should nevertheless be correlated to unemployment exit and inform us about the return to search.

Table 5 reports Logit regressions in which the dependent variable is the probability to have got at least one job interview (models (1) and (3)) or to have received at least one job offer since the beginning of the unemployment spell (models (2) and (4)).[41] We regressed the same set of preferences variables, interaction terms, and controls as those in Table 4 on both outcomes. The first two models account for time preferences over money, and the last two models for preferences over effort (see Table H2 in Appendix F for the coefficients of the control variables).

Although long-run impatience over effort decreased active search and the reservation wage (see Table 4), Table 5 shows no significant effect of δ on the likelihood to get an interview or job offer in either dimension. To test more directly Hypothesis 4 that predicts a non-linear effect of discounting on search outcomes, we 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. The effects seemed to be convex in the CTB treatment, with individuals in the second quartile of the distribution displaying a smaller probability to get 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 than those who were closer to indifference between the

[40] The mean unemployment spell lasted 329 days in France in 2021 - *source : Pôle-Emploi* - "https://www.pole-emploi.org/statistiques-analyses/demandeurs-demploi/trajectoires-et-retour-a-lemploi/duree-de-chomage-4e-trimestre-2021.html?type=article" Accessed on March 3, 2023.

[41] We also regressed the raw number of interviews and offers obtained using Tobit models to account for the proportion of null answers. Respectively 47% and 73% of our sample had received no interview or no job offer since the beginning of their unemployment spell. The results were qualitatively similar to those in Table 5.

Table 5: 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 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 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 on the probability to get an interview (model (3)). Overall, we can reject Hypothesis 4.

Short-run impatience over money had no significant effect either on search outcomes in any treatment in our preferred specification. Note, however, that using NLS and Two-Limit Tobit models rather than OLS to estimate β revealed that the effects of short-run impatience over money on search outcomes were consistent with the effect on search effort. Indeed, job seekers displaying low levels of short-run impatience in the CTB treatment appeared to search less and consistently, had worse outcomes, whereas the opposite was true for those with low levels of impatience in the DMPL treatment. Here again, the negative effect observed with the CTB method seems to be 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 5). Consistent with DVP's prediction, this finding is not surprising because of procrastinators' lower level of search (Table 4). We only found this effect with DMPL.

4.4.2 Late outcomes

To investigate further the outcomes of job search, we took advantage of our administrative dataset. We tracked the participants of our experiment through their unemployment spell until they actually found a job.[42] Table J3 in Appendix J reports the estimates of three Cox proportional models ((1), (3), and (5)), analyzing the hazard rate based on the duration of unemployment spells, and three logit models ((2), (4), and (6)), analyzing the probability of finding a job. The first two regressions consider time preferences over money and the following two consider time preferences over effort, as elicited in the experiment. The last two regressions use the unincentivized measures of risk and time preferences from the pre-experimental survey, and include all the survey participants.

Table J3 shows that long-run impatience over both effort and money cannot explain long-run outcomes in any specification and treatment, as was the case for short-run outcomes. We also found no hump-shaped effect of long-run impatience on the hazard rate, rejecting once again Hypothesis 4. Regarding short-term preferences, the pattern is consistent with the search effect found in the previous section. Impatient individuals over money in the short run (who also tend to have a lower search effort) display a lower hazard rate (significant at the 5% level). This effect is only found in model (1) when preferences are estimated using the DMPL method while the preferences elicited using CTB tend to point to the opposite direction. Regardless of whether it is measured in the experiment or self-reported in the survey, we detected no effect of procrastination on the hazard rate or the probability to find a job, despite its negative effects on active job search and the probability to get interviews in the short run (in the DMPL treatment).

We thus conclude that biases affecting the ability to plan effort over time only affects job market outcomes in the short run, while biases affecting the perceived value of income streams in the future affect outcomes in the long run. This suggests that effort and monetary decisions capture two very different dimensions of time preferences. Overall, our analysis of outcomes rejects Hypothesis 4 and leads 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 to exit unemployment. Both short-run impatience effects only hold when using the DMPL method.

[42]In the administrative database, a job seeker record ends when he or she reports finding a job or when he or she stops registering to the PES. In the latter case, the reason for stopping the registration is not always supplied by the job seeker. Several motives can explain this decision, for example in case of pregnancy a female job seeker no longer depends on the employment system but on the health insurance one. This feature renders our long term outcome measure noisy. To reduce the noise, we report results using only known cases of job finding.

4.5 Robustness test

How would estimates based on different methods to measure time preferences compare with these results? Recall that in our pre-experimental survey we elicited risk attitudes, patience in the monetary domain, and procrastination (measured as a general tendency to postpone one's tasks in an abstract setting), using the unincentivized measures of Falk et al. (2018). Table 6 displays the same regressions as those presented in Tables 4 and 5, except that time and risk preferences are those from the pre-experimental survey.

Table 6: Search effort and outcomes - Parameters from the pre-experimental survey

	Search effort				Search outcomes	
	Hours searched	Search channel index	Active search	Reservation wage	Got interviews	Got offers
	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion	0.589	0.102**	0.172*	0.073**	0.165*	0.225**
	(0.508)	(0.050)	(0.100)	(0.034)	(0.085)	(0.095)
Patience	0.163	-0.017	-0.089	-0.022	-0.113	-0.050
	(0.477)	(0.045)	(0.094)	(0.024)	(0.085)	(0.090)
Procrastination	-1.046**	-0.094**	-0.316***	-0.054*	-0.169**	-0.202**
	(0.458)	(0.041)	(0.086)	(0.029)	(0.079)	(0.087)
Individual controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Unemployment controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 6, consistently with our previous findings showing no effect of long-run impatience over money on search effort and outcome, the survey measure of patience had no significant effect in any model. This holds even if we estimate these regressions on the sub-sample of job seekers who completed the experiment. In contrast, Table 6 reveals a significant negative effect of the self-reported tendency to procrastinate on search effort and thus, on search outcomes, as predicted by DVP. This finding on search effort is consistent with those based on procrastination elicited with the DMPL method, whereas it contradicts those using the CTB method. The effect of the self-reported procrastination remains significant when we restrict the sample to the job seekers who completed the experiment (who on average exhibited the same level of procrastination than the full survey sample). Thus, the difference with the results from the CTB treatment cannot be driven by attrition. Overall, using the survey measures of time preferences tends to support more the conclusions drawn from the use of the DMPL than the CTB method.

5 Conclusion

In the public debate, the ever-going argument of job seekers' lack of search effort is most of the time pushed by anecdotal evidence suggesting that not searching enough results from a selfish exploitation of the insurance system. In this study we tested whether the level of search effort could in fact be influenced by unintentional time inconsistencies that we elicited both in the monetary and effort dimensions, using two popular experimental methods, the Double Multiple Price List and the Convex Time Budget methods.

Eliciting time preferences in the monetary domain with the DMPL method showed that on average job seekers are not present biased when making monetary trade-offs. This result follows most of the previous literature. In contrast, using the CTB method gave evidence of future bias. This result, at odds with the literature and non-intuitive, would suggest that individuals are willing to pay to get money later in the future rather than now. In the effort domain, we also found differences depending on the elicitation method. The DMPL estimates revealed the presence of procrastination, whereas the CTB estimates indicated time consistency on average. Overall, despite these differences across methods, we found that job seekers discount utility more when it relates to effort than when it relates to money, which is globally in line with similar time preference studies with different populations (*e.g.*, Augenblick et al., 2015).

Estimates at the individual level show that time preferences matter substantially to explain how job search is organized, at least when using the DMPL method. In line with the model of DellaVigna and Paserman (2005), in the DMPL treatment we found that both long-run and short-run impatience over effort correlates negatively with active search effort. They also correlate negatively with the reservation wage (this was only predicted for long-run discounting by DVP). For job seekers with long-run impatience over effort, the future utility provided by a potential wage offer may represent a weaker source of motivation, as compared to more patient individuals. This is even more the case for present-biased individuals who tend to discount future utilities more heavily when they actually have to provide the effort or when they can get money immediately, leading them to search less than an exponential job search model would predict. In contrast to DVP, we found no effect of long-run impatience over money on job search effort or the reservation wage. The policy implications of such findings are a support to policies helping job seekers to plan a regular search effort program since the beginning of their unemployment spell. Since short-run impatience over money also decreases the number of hours spent searching for a job significantly, another policy implication could be to help job seekers to manage their streams of income over time.

Using the CTB method revealed almost no significant effects of time preferences on job search effort and the reservation wage. The only exception was an unexpected positive effect of short-run impatience over money on the number of hours searched (whereas the opposite was found when using the DMPL method), as if driven by a feeling of emergency.

Regarding job search outcomes, long-run impatience over money or effort does not explain the early or later actual outcomes of job search in the labor market. In contrast, procrastinators have a lower likelihood of receiving a job interview early in the unemployment spell and present-biased job seekers in the monetary domain have a lower probability to exit unemployment. Both effects were only identified when using the DMPL method.

Overall, our study reveals discrepancies in our findings depending on the method used to elicit time preferences. Using the DMPL method gave aggregate estimates of long-run and short-run impatience consistent with those obtained in the previous literature on time preferences. In contrast, using the CTB method concluded to average future bias over money, which was rarely observed in the literature and even more unexpected for job seekers. Moreover, when using the DMPL method, our findings linking impatience over effort and money and job search effort and outcomes were in line with the model of DellaVigna and Paserman (2005). This was not the case when using the CTB method.

The samples who received these two treatments did not differ substantially in terms of individual characteristics; thus, this should not drive the observed differences in preferences. We acknowledge that the delay in the actual payment of the early rewards due to administrative constraints may have led us to underestimate short-run impatience over money. However, this should have affected the measures regardless of the elicitation method. This lets us envision that it is the method itself that explains these discrepancies. A possibility could be that having more freedom in the allocation of units of effort or money over time created a more complex environment in the CTB treatment, and thus, a more noisy decision-making process. An implication would be to increase the sample size to estimate more precisely the patience parameters with this method. More systematic methodological comparisons between these two elicitation methods are needed to understand better the sources of their differences and which one is more reliable than the other when investigating how time preferences influence actual behavior.

More generally, we believe that more research on the mechanisms through which time preferences influence behavior in the labor market should be encouraged to measure to what extent the results are influenced by the nature of the elicited preferences. In our experiment, time preferences were elicited in a setting where the realization of the payments was certain; the task performance could also be considered as certain because payment was conditional to it. However, when looking for a job, individuals are placed in an intrinsically uncertain situation where the return of their effort may never be observed. This calls for further experimental investigations of time preferences in situations of uncertainty. Doing so should provide a better fit to the preferences at play in reality.

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6 Appendices

Appendix A: Instructions

Appendix B: Additional figures

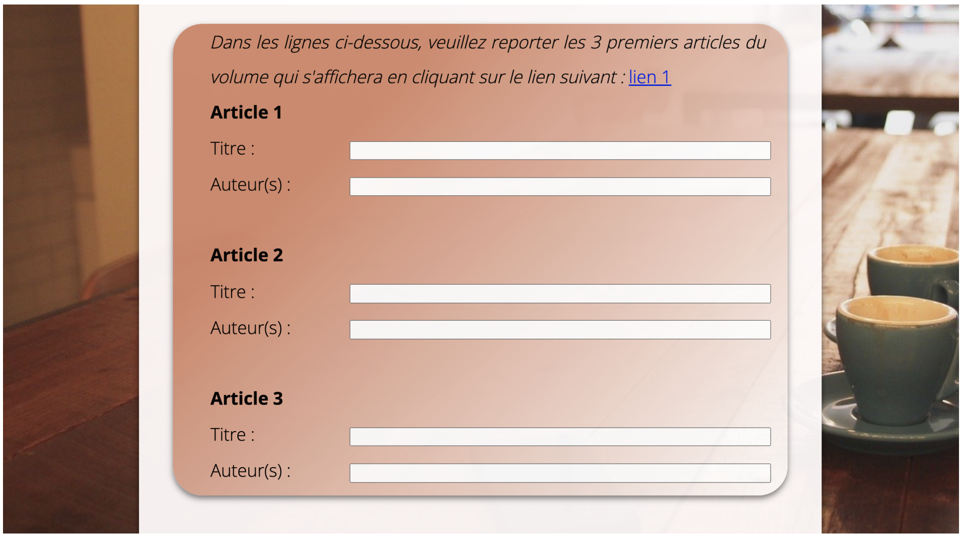


Figure B1: Screenshot of the real effort task

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)."

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."

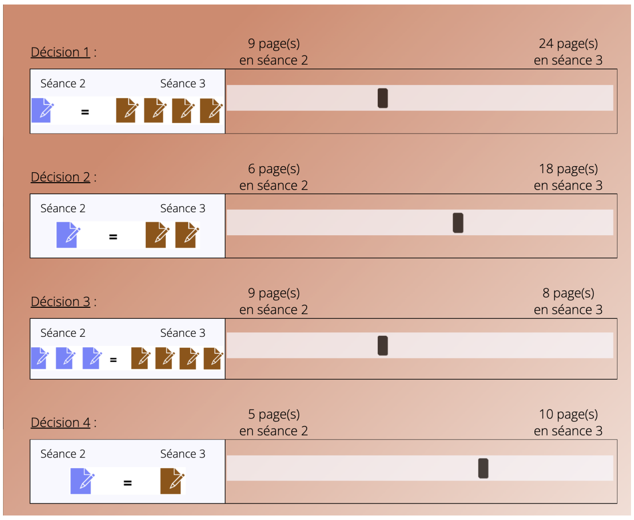
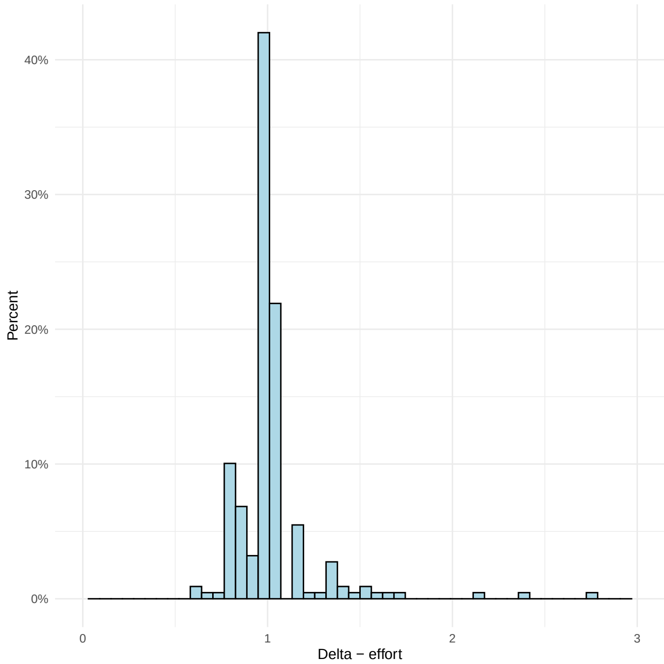


Figure B3: Screenshot of the effort allocation decisions

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."



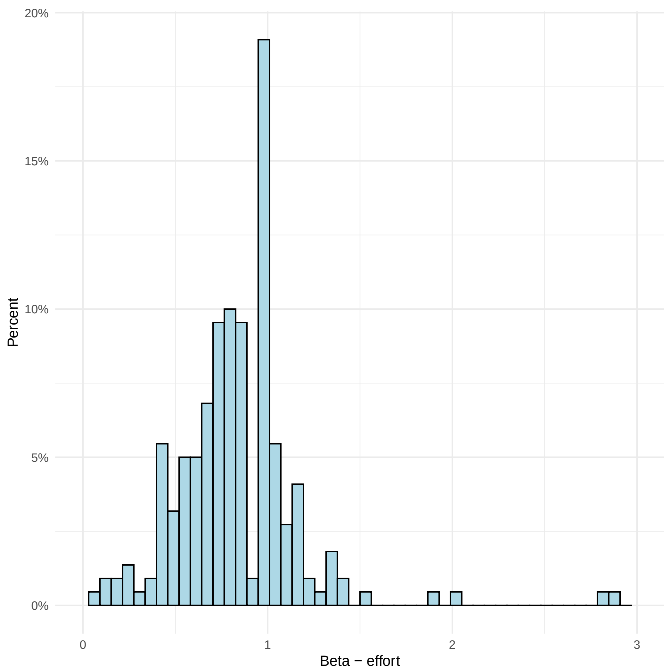


Figure B4: Distribution of the individual estimates of time preferences over effort

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.

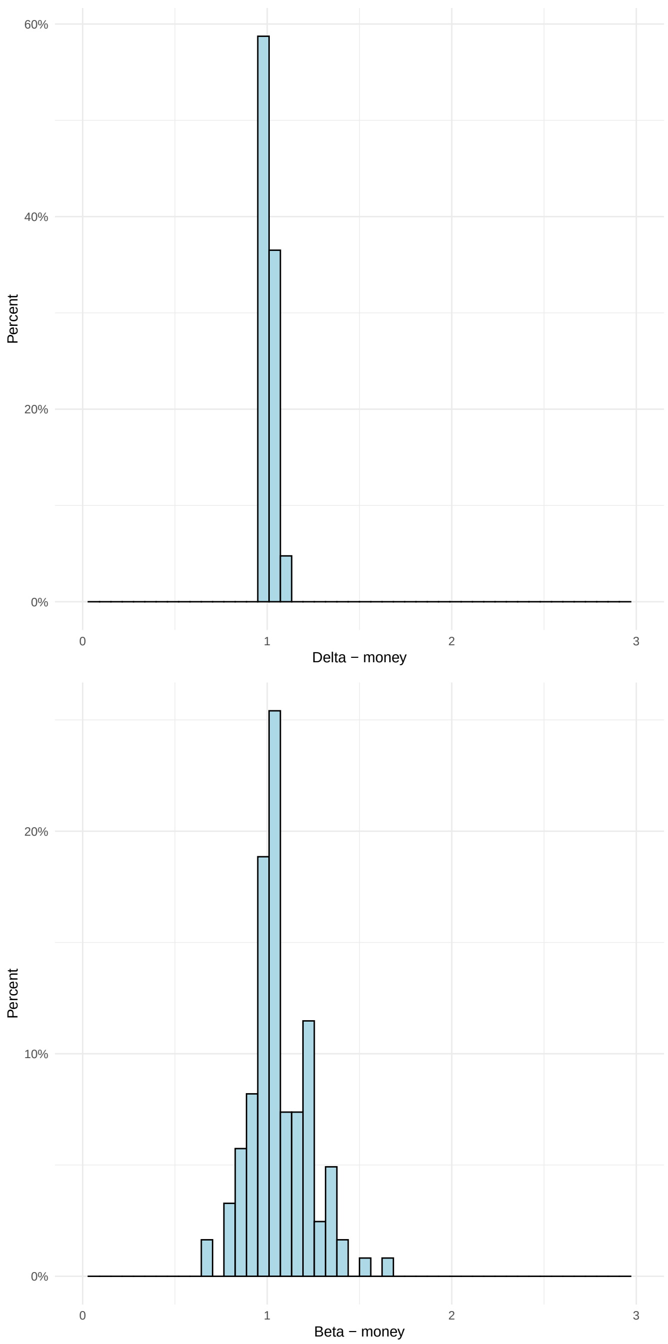


Figure B5: Distribution of the individual estimates of time preferences over money

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.

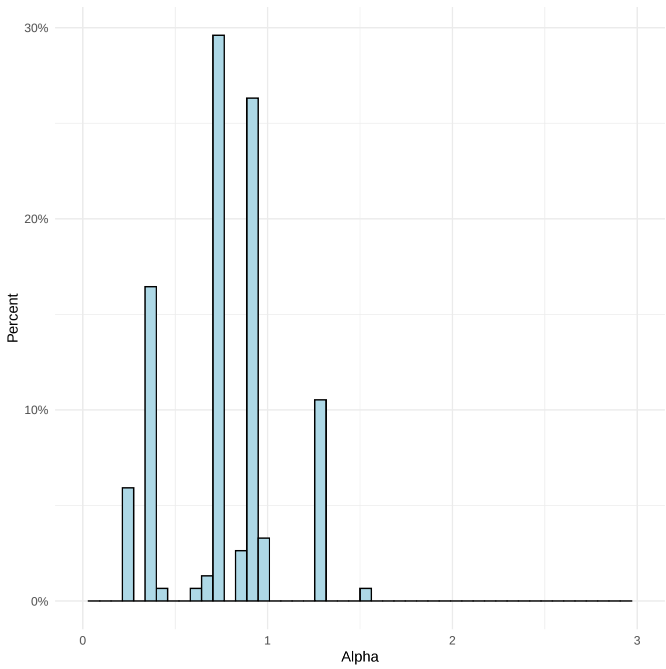


Figure B6: Distribution of the individual estimates of risk preferences

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
Gender			
Proportion of females	0.52	0.48	0.149
Age categories			
18/24	0.54	0.33	0.000
25/49	0.38	0.56	0.000
50+	0.08	0.11	0.023
Education			
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
Previous daily wage	76.62	81.55	0.578
Motive of the last registration to the PES			
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
Number of past registrations to the PES	1.05	1.02	0.089
Occupation			
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)
Search effort			
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)
Expected wage			
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)
Search outcomes			
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)
Preferences			
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)
Gender			
Females	0.52	0.62 (0.214)	0.49 (0.410)
Age			
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)
Education			
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

Rates																
1.05																
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
1.11																
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
1.18																
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
1.25																
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
1.43																
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
1.82																
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

Rates																
0.2																
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
0.25																
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
0.33																
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
0.5																
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
0.66																
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
0.75																
Pages attributed to the sooner date	15	-	-	12	-	-	9	-	-	6	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	4	-	-	8	-	-	12	-	-	16	-	-	20
1																
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
1.2																
Pages attributed to the sooner date	15	-	-	-	-	-	9	-	-	-	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	-	-	-	5	-	-	-	-	-	10	-	-	13
1.25																
Pages attributed to the sooner date	15	-	-	-	-	10	-	-	-	-	5	-	-	-	-	0
Pages attributed to the late date	0	-	-	-	-	4	-	-	-	-	8	-	-	-	-	12
1.33																
Pages attributed to the sooner date	15	-	-	-	11	-	-	-	7	-	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	-	3	-	-	-	6	-	-	-	9	-	-	12
1.5																
Pages attributed to the sooner date	15	-	-	12	-	-	9	-	-	6	-	-	3	-	-	0
Pages attributed to the late date	0	-	-	2	-	-	4	-	-	6	-	-	8	-	-	10
1.66																
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**	-0.941***	0.092	0.139	0.445***
	(0.165)	(0.139)	(0.209)	(0.139)	(0.150)
Female	0.279*	-0.078	0.195	-0.117	0.097
	(0.152)	(0.159)	(0.203)	(0.169)	(0.161)
Age: 25/49	-0.083	0.006	-0.089	-0.105	0.040
	(0.194)	(0.193)	(0.134)	(0.149)	(0.177)
Age: 50+	0.161	0.586	-0.253	0.393	-0.401
	(0.300)	(0.409)	(0.261)	(0.386)	(0.339)
Educ: Less than HS	0.920*	0.678	-0.879	-0.0003	-0.533
(High School)	(0.511)	(0.695)	(0.621)	(0.221)	(0.532)
Educ: HS+2	0.751**	-0.046	-0.769	0.638	-0.340
	(0.375)	(0.171)	(0.634)	(0.563)	(0.299)
Educ: HS+3/4	0.374*	0.205	-0.664	0.077	-0.380*
	(0.221)	(0.266)	(0.595)	(0.117)	(0.214)
Educ: HS+5 and more	0.434**	-0.022	-0.513	0.084	-0.130
	(0.193)	(0.148)	(0.523)	(0.105)	(0.196)
Educ: Professional training	1.644	0.066	-1.053	0.385	0.322
	(1.042)	(0.594)	(0.688)	(0.244)	(0.715)
Nb past registrations PES	-0.007	-0.193	0.131	0.120	-0.062
	(0.163)	(0.323)	(0.098)	(0.147)	(0.181)
Contract end, layoff	0.016	0.133	-0.066	-0.227	-0.400
	(0.227)	(0.163)	(0.127)	(0.215)	(0.405)
New entrants, career change	-0.182	0.377	-0.259	-0.075	-0.601*
	(0.265)	(0.255)	(0.199)	(0.168)	(0.331)
Other	-0.203	0.156	0.073	-0.322	-0.617**
	(0.254)	(0.192)	(0.189)	(0.327)	(0.282)
Job Prospect: [1-3] months	0.157	0.318	-0.585	0.060	-0.266
	(0.243)	(0.211)	(0.434)	(0.138)	(0.193)
Job Prospect:]3-6] months	-0.017	-0.052	-0.256	0.165	-0.092
	(0.204)	(0.155)	(0.297)	(0.248)	(0.313)
Job Prospect: $>$ 6 months	0.329	-0.059	-0.348	-0.035	-0.335
	(0.210)	(0.169)	(0.353)	(0.100)	(0.208)
Singe-use goods	0.016	-0.011	0.009	0.074	-0.050
	(0.109)	(0.167)	(0.072)	(0.128)	(0.105)
Average-life goods	0.015	-0.094	0.039	-0.001	0.098
	(0.099)	(0.088)	(0.048)	(0.045)	(0.099)
Durable goods	0.016	0.256**	-0.073	-0.079*	0.017
	(0.081)	(0.127)	(0.053)	(0.048)	(0.064)
Expenditures Index	0.078	0.049	-0.139	-0.146	-0.088
	(0.159)	(0.137)	(0.214)	(0.114)	(0.116)
Constant	-0.936*	0.419	1.035	0.163	0.945
	(0.526)	(0.517)	(1.355)	(0.459)	(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. "Expenditures Index" is defined as dep_indx= XXXXX. 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; finding 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***	0.807***	0.868***	0.732***	-
	(0.037)	(0.039)	(0.018)	(0.041)	
δ	0.999***	0.998***	0.998***	-	0.997***
	(0.0006)	(0.0006)	(0.0003)		(0.0004)
β	1.131***	1.126***	1.055***	-	1.017***
	(0.023)	(0.024)	(0.013)		(0.015)
Ho: $\delta = 1$, p	0.018	0.001	0.000	-	0.000
Ho: $\beta = 1$, 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***	1.172***	1.661***	-
	(0.027)	(0.025)	(0.096)	
δ	1.000***	0.999***	1.004***	0.996***
	(0.003)	(0.002)	(0.002)	(0.001)
β	1.018***	1.009***	1.042***	0.969***
	(0.067)	(0.067)	(0.062)	(0.002)
Ho: $\delta = 1$, p	0.865	0.825	0.099	0.011
Ho: $\beta = 1$, 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 (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)	-0.024	0.005	-0.002	-0.00002	0.002	0.003	-0.002	0.0007
	(0.042)	(0.004)	(0.006)	(0.001)	(0.032)	(0.003)	(0.004)	(0.001)
δ (money)	0.013	-0.007	-0.011	-0.0003	-	-	-	-
	(0.054)	(0.006)	(0.008)	(0.002)				
DMPL × δ (money)	-0.011	0.006	0.010	0.0007	-	-	-	-
	(0.054)	(0.006)	(0.008)	(0.002)				-
β (money)	-3.943***	-0.170	-0.267	0.060	-	-	-	-
	(1.370)	(0.148)	(0.205)	(0.065)				
DMPL × β (money)	6.591***	0.242	0.276	-0.013	-	-	-	-
	(1.889)	(0.163)	(0.245)	(0.078)				
δ (effort)	-	-	-	-	0.001	0.0003	-0.0003	0.0005
					(0.006)	(0.001)	(0.001)	(0.0005)
DMPL × δ (effort)	-	-	-	-	-0.011	0.017	0.106***	0.032**
					(0.381)	(0.030)	(0.039)	(0.012)
β (effort)	-	-	-	-	-1.186*	-0.160*	-0.176	-0.048
					(0.683)	(0.095)	(0.109)	(0.034)
DMPL × β (effort)	-	-	-	-	0.382	0.228*	0.651***	0.112*
					(1.381)	(0.135)	(0.169)	(0.067)
DMPL treatment	2.046	0.032	-0.117	-0.034	2.586	0.511	1.769***	0.514**
	(2.260)	(0.220)	(0.322)	(0.080)	(6.180)	(0.487)	(0.662)	(0.209)
Female	0.937	-0.031	-0.219	-0.230***	0.129	-0.141	-0.312*	-0.217***
	(1.876)	(0.154)	(0.243)	(0.062)	(1.458)	(0.130)	(0.173)	(0.049)
25/49 years old	1.166	0.295	-0.085	0.200***	2.028	0.216	-0.102	0.119**
	(2.292)	(0.192)	(0.277)	(0.070)	(1.958)	(0.145)	(0.224)	(0.058)
50+	8.979**	0.882**	0.097	0.394***	6.034**	0.534**	-0.125	0.449***
	(3.835)	(0.370)	(0.418)	(0.136)	(2.776)	(0.265)	(0.330)	(0.112)
Less than HS	-5.644	-1.090*	-0.299	0.132	-2.255	-0.960***	-0.302	-0.062
(High School)	(4.599)	(0.565)	(0.720)	(0.141)	(3.741)	(0.292)	(0.472)	(0.148)
HS+2	-3.327	-0.232	0.087	0.274*	-0.056	-0.166	0.235	0.143
	(4.225)	(0.411)	(0.584)	(0.145)	(2.499)	(0.260)	(0.403)	(0.111)
HS+3/4	-0.914	-0.291	0.374	0.168*	0.851	-0.345	-0.209	0.109
	(4.307)	(0.387)	(0.585)	(0.096)	(3.066)	(0.255)	(0.375)	(0.091)
HS+5 and more	-2.675	-0.482	0.038	0.353***	1.009	-0.520**	-0.207	0.284***
	(3.912)	(0.359)	(0.517)	(0.092)	(2.521)	(0.221)	(0.322)	(0.075)
Professional training	-7.714	-0.411	-0.839	0.027	-6.497**	-0.342	-1.180***	0.107
	(5.327)	(0.860)	(0.524)	(0.133)	(2.623)	(0.609)	(0.358)	(0.164)
Number of registrations (PES)	6.647	-0.413	-0.634*	0.413***	3.656	-0.366	-0.848***	0.326***
	(9.047)	(0.762)	(0.334)	(0.077)	(5.750)	(0.353)	(0.182)	(0.096)
Contract end and econ layoff	5.646**	0.494**	0.581*	-0.0541	3.110	0.364*	0.294	-0.149**
	(2.670)	(0.242)	(0.329)	(0.106)	(1.916)	(0.190)	(0.249)	(0.0716)
New entrants and career change	4.568	0.256	0.343	-0.099	5.131**	0.455**	0.403	-0.189**
	(3.034)	(0.269)	(0.359)	(0.109)	(2.456)	(0.202)	(0.290)	(0.0751)
Other	3.103	0.298	0.278	-0.114	2.625	0.227	0.093	-0.075
	(2.591)	(0.265)	(0.323)	(0.127)	(2.035)	(0.193)	(0.249)	(0.085)
Constant	0.945	-0.146	1.715*	7.005***	-0.186	-0.292	2.119***	7.153***
	(10.59)	(0.942)	(0.869)	(0.215)	(6.314)	(0.479)	(0.465)	(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 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 H2: Time preferences and job search outcomes - Full regressions

	Time preferences over money		Time preferences over effort	
	Got interviews	Got offers	Got interviews	Got offers
	(1)	(2)	(3)	(4)
Risk (BRET)	-0.002	0.00002	-0.003	0.002
	(0.010)	(0.011)	(0.007)	(0.007)
δ (money)	-0.009	-0.017	-	-
	(0.014)	(0.017)		
DMPL $\times$ δ (money)	0.006	0.030	-	-
	(0.014)	(0.033)		
β (money)	-0.366	-0.066	-	-
	(0.367)	(0.422)		
DMPL $\times$ β (money)	0.743	-0.008	-	-
	(0.483)	(0.676)		
δ (effort)	-	-	-0.002	-0.004
			(0.002)	(0.003)
DMPL $\times$ δ (effort)	-	-	0.105	0.054
			(0.077)	(0.079)
β (effort)	-	-	-0.388	-0.482
			(0.315)	(0.363)
DMPL $\times$ β (effort)	-	-	0.878**	0.396
			(0.419)	(0.466)
DMPL treatment	0.058	-0.330	1.649	1.118
	(0.573)	(0.622)	(1.255)	(1.295)
Female	-0.478	-0.572	-0.448	-0.129
	(0.419)	(0.490)	(0.307)	(0.333)
25/49 years old	0.342	0.544	0.186	-0.176
	(0.459)	(0.626)	(0.373)	(0.429)
50+	0.918	0.375	0.294	-0.237
	(0.882)	(1.097)	(0.579)	(0.612)
Less than HS	-2.927*	-1.804	-1.014	0.109
(High School)	(1.577)	(1.541)	(0.983)	(0.968)
HS+2	-2.559**	-2.005*	-0.885	-0.881
	(1.006)	(1.104)	(0.700)	(0.669)
HS+3/4	-0.506	-1.937*	-0.877	-1.197*
	(0.843)	(1.042)	(0.652)	(0.651)
HS+5 and more	-1.032	-2.882***	-0.824	-1.120**
	(0.754)	(0.933)	(0.580)	(0.531)
Professional training	-1.958	0	-2.203*	0
	(1.732)	(.)	(1.278)	(.)
Number of registrations (PES)	-0.587	1.267	-0.597	1.084
	(1.202)	(1.251)	(0.878)	(1.023)
Contract end and econ layoff	1.103*	1.488*	0.574	-0.130
	(0.653)	(0.767)	(0.422)	(0.491)
New entrants and career change	0.213	0.888	0.530	-0.415
	(0.696)	(0.909)	(0.502)	(0.583)
Other	0.341	0.960	0.382	0.008
	(0.691)	(0.764)	(0.433)	(0.489)
Constant	1.597	-0.707	1.419	-1.148
	(1.799)	(2.060)	(1.198)	(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.he 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 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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	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)	-0.001	0.005	-0.012*	0.002	0.026	0.009**	0.006	0.002
	(0.043)	(0.005)	(0.006)	(0.003)	(0.037)	(0.004)	(0.006)	(0.002)
δ (money)								
25% < δ (money) < 50%	3.720	-0.166	-0.923**	0.056	-	-	-	-
	(3.161)	(0.358)	(0.443)	(0.181)				
50% < δ (money) < 75%	6.347**	0.459	-0.158	-0.132	-	-	-	-
	(2.863)	(0.329)	(0.451)	(0.170)				
75% < δ (money)	2.443	-0.0161	-0.0821	0.0698	-	-	-	-
	(4.245)	(0.400)	(0.595)	(0.150)				
β (money)								
25% < β (money) < 50%	-6.905**	-1.083***	-1.550***	0.069	-	-	-	-
	(3.025)	(0.377)	(0.405)	(0.152)				
50% < β (money) < 75%	-8.890***	-1.152***	-0.836	0.0257	-	-	-	-
	(3.263)	(0.360)	(0.539)	(0.152)				
75% < β (money)	-5.833	-0.298	-0.543	0.199	-	-	-	-
	(4.365)	(0.369)	(0.425)	(0.200)				
δ (effort)								
25% < δ (effort) < 50%	-	-	-	-	-0.400	0.038	0.187	0.045
					(2.640)	(0.273)	(0.364)	(0.086)
50% < δ (effort) < 75%	-	-	-	-	-0.252	-0.186	-0.339	0.064
					(2.677)	(0.284)	(0.395)	(0.127)
75% < δ (effort)	-	-	-	-	-0.016	0.445	0.150	0.333**
					(3.033)	(0.329)	(0.437)	(0.129)
β (effort)								
25% < β (effort) < 50%	-	-	-	-	1.778	0.356	0.467	0.0629
					(2.442)	(0.256)	(0.341)	(0.122)
50% < β (effort) < 75%	-	-	-	-	1.500	0.166	0.599	-0.029
					(3.158)	(0.339)	(0.402)	(0.115)
75% < β (effort)	-	-	-	-	-1.190	-0.051	-0.391	0.006
					(2.674)	(0.309)	(0.320)	(0.111)
Female	3.615	0.459	-0.282	-0.113	2.225	0.092	-0.561**	-0.154*
	(3.415)	(0.289)	(0.408)	(0.136)	(1.809)	(0.223)	(0.281)	(0.080)
25/49 years old	3.779	0.293	0.095	0.225*	4.330	-0.074	0.053	0.023
	(2.554)	(0.331)	(0.415)	(0.117)	(2.813)	(0.238)	(0.368)	(0.096)
50+	7.691	1.154**	-0.304	0.261	8.019**	0.484	0.493	0.324*
	(4.938)	(0.566)	(0.575)	(0.173)	(3.651)	(0.394)	(0.427)	(0.167)
Less than HS	10.59	-1.429	3.214***	0.128	5.354	-1.158***	-0.004	-0.357
(High School)	(7.246)	(0.868)	(0.875)	(0.347)	(5.172)	(0.424)	(0.726)	(0.330)
HS+2	-0.097	-0.988*	-0.333	0.240	0.676	-0.394	-0.069	0.150
	(7.163)	(0.494)	(0.583)	(0.278)	(3.016)	(0.395)	(0.582)	(0.196)
HS+3/4	6.215	-0.732	1.025*	0.020	6.025	-0.506	-0.044	0.088
	(5.984)	(0.490)	(0.569)	(0.225)	(4.573)	(0.381)	(0.528)	(0.134)
HS+5 and more	-0.978	-0.885*	-0.194	0.362	0.609	-0.631**	-0.477	0.338***
	(4.935)	(0.437)	(0.516)	(0.239)	(2.710)	(0.297)	(0.468)	(0.125)
Professional training	-1.187	-0.681	-0.330	-0.225	-2.427	-0.903	-1.613***	-0.160
	(4.835)	(0.789)	(0.500)	(0.243)	(3.561)	(1.111)	(0.590)	(0.208)
Number of registrations (PES)	0	0	0	0	-0.819	-0.427	-1.008*	0.106
	(.)	(.)	(.)	(.)	(7.532)	(0.456)	(0.575)	(0.119)
Contract end and econ layoff	2.790	0.364	-0.154	0.030	3.232	0.441	0.165	0.002
	(3.322)	(0.427)	(0.506)	(0.194)	(2.549)	(0.309)	(0.329)	(0.102)
New entrants and career change	4.792	0.374	-0.218	0.095	7.098**	0.429	0.748	-0.091
	(3.492)	(0.472)	(0.481)	(0.199)	(3.177)	(0.285)	(0.459)	(0.114)
Other	2.404	0.970**	0.004	0.242	3.831	0.615*	-0.126	0.115
	(3.787)	(0.473)	(0.405)	(0.246)	(2.510)	(0.323)	(0.358)	(0.146)
Constant	2.538	-0.310	2.619***	7.080***	-2.175	-0.623	1.828**	7.099***
	(6.805)	(0.703)	(0.901)	(0.400)	(8.496)	(0.653)	(0.840)	(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	0.002	0.002	0.00007	-0.006	0.001	-0.007	0.0002
	(0.072)	(0.006)	(0.009)	(0.001)	(0.049)	(0.004)	(0.005)	(0.001)
δ (money)								
25% < δ (money) < 50%	3.573	-0.519	-0.095	0.227*	-	-	-	-
	(3.812)	(0.357)	(0.510)	(0.132)				
50% < δ (money) < 75%	-6.510*	-0.806***	-0.717	-0.063	-	-	-	-
	(3.293)	(0.277)	(0.446)	(0.085)				
75% < δ (money)	4.286	-0.525	-0.437	0.243	-	-	-	-
	(6.187)	(0.487)	(0.819)	(0.150)				
β (money)								
25% < β (money) < 50%	1.184	-0.065	0.372	0.194	-	-	-	-
	(5.750)	(0.447)	(0.695)	(0.130)				
50% < β (money) < 75%	3.011	-0.101	0.885	0.346***	-	-	-	-
	(4.433)	(0.402)	(0.552)	(0.115)				
75% < β (money)	9.082	-0.150	0.405	0.452***	-	-	-	-
	(5.867)	(0.478)	(0.658)	(0.146)				
δ (effort)								
25% < δ (effort) < 50%	-	-	-	-	-7.976*	-0.657*	-0.688	0.475***
					(4.503)	(0.353)	(0.604)	(0.109)
50% < δ (effort) < 75%	-	-	-	-	5.532*	0.231	0.708*	0.402***
					(3.108)	(0.229)	(0.382)	(0.120)
75% < δ (effort)	-	-	-	-	1.783	-0.024	0.964**	0.345**
					(4.760)	(0.355)	(0.433)	(0.143)
β (effort)								
25% < β (effort) < 50%	-	-	-	-	-1.656	-0.132	0.151	0.053
					(4.430)	(0.299)	(0.344)	(0.109)
50% < β (effort) < 75%	-	-	-	-	5.882	0.626	1.250*	-0.135
					(6.056)	(0.497)	(0.746)	(0.180)
75% < β (effort)	-	-	-	-	1.054	0.286	1.222***	0.237
					(4.557)	(0.332)	(0.455)	(0.148)
Female	-0.025	-0.047	0.116	-0.188***	-0.729	-0.174	-0.040	-0.194***
	(2.514)	(0.205)	(0.337)	(0.063)	(2.255)	(0.177)	(0.223)	(0.063)
25/49 years old	2.147	0.359	-0.354	0.140	1.148	0.233	-0.244	0.062
	(4.208)	(0.329)	(0.529)	(0.105)	(3.075)	(0.197)	(0.309)	(0.074)
50+	7.789	0.670	-0.326	0.407**	2.338	0.277	-0.852*	0.534***
	(6.313)	(0.555)	(0.652)	(0.187)	(4.653)	(0.430)	(0.454)	(0.140)
Less than HS	-12.85*	-0.511	-0.792	0.0369	-8.254	-1.074**	-0.439	0.040
(High School)	(6.416)	(0.654)	(0.966)	(0.105)	(5.484)	(0.482)	(0.733)	(0.133)
HS+2	-7.249	0.072	0.609	0.229	-2.087	-0.365	0.228	0.024
	(6.883)	(0.579)	(1.064)	(0.192)	(4.792)	(0.387)	(0.612)	(0.128)
HS+3/4	-3.846	0.143	0.434	0.277**	-3.440	-0.198	-0.180	0.095
	(6.927)	(0.587)	(0.973)	(0.108)	(5.188)	(0.389)	(0.545)	(0.124)
HS+5 and more	-4.128	-0.170	0.397	0.378***	-0.814	-0.421	0.110	0.191*
	(6.335)	(0.523)	(0.924)	(0.108)	(4.717)	(0.330)	(0.487)	(0.102)
Professional training	-9.492	-0.146	-0.249	0.528***	-7.345	-0.126	-1.211	0.271*
	(7.030)	(0.703)	(0.905)	(0.134)	(6.348)	(0.549)	(0.747)	(0.140)
Number of registrations (PES)	3.783	-0.847	-0.809	0.363**	4.456	-0.605	-0.746**	0.551***
	(7.772)	(1.031)	(0.625)	(0.142)	(10.18)	(0.644)	(0.327)	(0.142)
Contract end and econ layoff	8.349*	0.545	0.624	-0.049	1.490	0.405	0.304	-0.164
	(4.888)	(0.392)	(0.578)	(0.142)	(3.246)	(0.277)	(0.377)	(0.115)
New entrants and career change	6.508	0.202	0.239	-0.241*	3.531	0.403	0.394	-0.281***
	(5.155)	(0.389)	(0.600)	(0.135)	(4.023)	(0.298)	(0.424)	(0.103)
Other	1.842	-0.054	-0.058	-0.457***	0.117	-0.094	0.170	-0.127
	(4.700)	(0.395)	(0.557)	(0.134)	(3.398)	(0.280)	(0.353)	(0.109)
Constant	4.242	0.740	1.372	6.765***	5.767	0.287	1.376*	6.723***
	(10.40)	(1.292)	(1.249)	(0.257)	(12.49)	(0.857)	(0.774)	(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	0.003	-0.002	-0.0002	0.00006	0.002	-0.003	0.0006
	(0.0423)	(0.003)	(0.006)	(0.001)	(0.033)	(0.003)	(0.004)	(0.001)
δ (money)	0.041	-0.008	0.001	-0.001	-	-	-	-
	(0.059)	(0.005)	(0.007)	(0.002)				
DMPL × δ (money)	-0.039	0.007	-0.002	0.001	-	-	-	-
	(0.060)	(0.005)	(0.007)	(0.002)				
β (money)	-1.297	-0.243**	-0.273**	0.031	-	-	-	-
	(0.965)	(0.106)	(0.128)	(0.043)				
DMPL × β (money)	4.275**	0.329**	0.285	0.020	-	-	-	-
	(1.812)	(0.130)	(0.191)	(0.063)				
δ (effort)	-	-	-	-	-0.0291***	-0.001	0.001	0.0005
					(0.009)	(0.001)	(0.002)	(0.0004)
DMPL × δ (effort)	-	-	-	-	0.043	0.002	0.009**	0.002*
					(0.036)	(0.003)	(0.004)	(0.001)
β (effort)	-	-	-	-	-1.079	-0.117	-0.180*	0.0271
					(0.719)	(0.083)	(0.095)	(0.028)
DMPL × β (effort)	-	-	-	-	-0.397	0.245	0.820***	0.060
					(1.780)	(0.167)	(0.205)	(0.093)
DMPL treatment	3.408	0.055	0.298	-0.098	2.985**	0.306**	0.179	0.019
	(2.095)	(0.195)	(0.284)	(0.082)	(1.333)	(0.131)	(0.172)	(0.054)
Female	1.661	0.008	-0.170	-0.241***	0.107	-0.131	-0.287	-0.217***
	(1.877)	(0.148)	(0.245)	(0.062)	(1.490)	(0.133)	(0.175)	(0.050)
25/49 years old	1.025	0.288	-0.116	0.205***	1.715	0.191	-0.170	0.137**
	(2.386)	(0.187)	(0.278)	(0.073)	(1.958)	(0.148)	(0.221)	(0.056)
50+	9.766**	0.958**	0.166	0.382***	4.910*	0.518*	-0.133	0.430***
	(4.072)	(0.381)	(0.426)	(0.136)	(2.626)	(0.263)	(0.316)	(0.111)
Less than HS	-4.408	-1.007*	-0.273	0.122	-1.143	-0.917***	-0.323	-0.070
(High School)	(4.908)	(0.547)	(0.731)	(0.143)	(3.869)	(0.302)	(0.485)	(0.159)
HS+2	-2.153	-0.156	0.087	0.271*	0.151	-0.306	0.112	0.102
	(4.245)	(0.410)	(0.602)	(0.148)	(2.431)	(0.270)	(0.387)	(0.108)
HS+3/4	1.029	-0.286	0.387	0.147	0.351	-0.377	-0.295	0.124
	(4.289)	(0.384)	(0.572)	(0.095)	(2.950)	(0.257)	(0.368)	(0.087)
HS+5 and more	-1.599	-0.425	0.054	0.347***	0.961	-0.551**	-0.249	0.285***
	(3.942)	(0.351)	(0.518)	(0.092)	(2.519)	(0.222)	(0.319)	(0.075)
Professional training	-7.696*	-0.830*	-1.172*	0.028	-3.960	-0.160	-1.030***	0.117
	(4.027)	(0.461)	(0.621)	(0.144)	(3.727)	(0.604)	(0.394)	(0.155)
Number of registrations (PES)	7.189	-0.401	-0.592*	0.403***	4.414	-0.224	-0.751***	0.345***
	(9.272)	(0.706)	(0.323)	(0.077)	(7.164)	(0.420)	(0.201)	(0.113)
Contract end and econ layoff	5.646*	0.591**	0.634*	-0.051	3.122	0.315	0.244	-0.171**
	(2.859)	(0.246)	(0.336)	(0.106)	(1.991)	(0.200)	(0.260)	(0.078)
New entrants and career change	4.509	0.332	0.398	-0.093	4.447*	0.346	0.303	-0.193**
	(3.135)	(0.274)	(0.360)	(0.108)	(2.434)	(0.216)	(0.288)	(0.078)
Other	2.702	0.278	0.258	-0.107	3.145	0.109	0.118	-0.087
	(2.607)	(0.271)	(0.332)	(0.130)	(2.040)	(0.207)	(0.256)	(0.090)
Constant	-3.909	-0.271	1.224	7.080***	-0.788	-0.332	2.122***	7.144***
	(10.54)	(0.854)	(0.781)	(0.189)	(7.656)	(0.526)	(0.478)	(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 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	0.005	0.0003	-0.0003	0.014	0.002	-0.001	0.0003
	(0.045)	(0.004)	(0.006)	(0.001)	(0.034)	(0.003)	(0.004)	(0.001)
δ (money)	-0.048***	-0.004*	-0.006*	0.0007	-	-	-	-
	(0.018)	(0.002)	(0.004)	(0.0008)				
DMPL × δ (money)	0.049***	0.003	0.005	-0.0003	-	-	-	-
	(0.018)	(0.003)	(0.004)	(0.001)				
β (money)	-2.947***	-0.033	-0.177	0.024	-	-	-	-
	(0.610)	(0.117)	(0.155)	(0.029)				
DMPL × β (money)	6.820***	0.148	0.209	0.043	-	-	-	-
	(2.099)	(0.153)	(0.243)	(0.067)				
δ (effort)	-	-	-	-	0.011**	0.001***	-0.0007	0.00007
					(0.004)	(0.0005)	(0.0005)	(0.0002)
DMPL × δ (effort)	-	-	-	-	-0.010	0.001	0.005***	-0.001**
					(0.021)	(0.001)	(0.002)	(0.0005)
β (effort)	-	-	-	-	0.402	0.032	0.010	0.024
					(0.913)	(0.069)	(0.125)	(0.036)
DMPL × β (effort)	-	-	-	-	-2.221	0.056	0.308	-0.023
					(1.521)	(0.129)	(0.193)	(0.074)
DMPL treatment	0.972	0.136	0.151	-0.056	3.792***	0.345***	0.289*	-0.056
	(1.726)	(0.170)	(0.259)	(0.073)	(1.330)	(0.127)	(0.174)	(0.057)
Female	1.200	-0.037	-0.131	-0.246***	0.230	-0.126	-0.288	-0.239***
	(1.903)	(0.157)	(0.249)	(0.066)	(1.463)	(0.129)	(0.176)	(0.053)
25/49 years old	1.309	0.218	-0.110	0.182**	1.637	0.203	-0.114	0.177***
	(2.445)	(0.190)	(0.286)	(0.074)	(2.088)	(0.150)	(0.238)	(0.064)
50+	12.83***	1.019**	0.285	0.397***	4.744	0.410	-0.113	0.482***
	(4.014)	(0.425)	(0.475)	(0.141)	(3.019)	(0.271)	(0.341)	(0.124)
Less than HS	-6.370	-1.123*	-0.386	0.145	-3.414	-0.958***	-0.124	-0.015
(High School)	(4.498)	(0.600)	(0.723)	(0.137)	(3.817)	(0.273)	(0.459)	(0.136)
HS+2	-3.261	-0.193	0.150	0.281*	-1.540	-0.394	0.211	0.157
	(4.241)	(0.422)	(0.605)	(0.142)	(2.577)	(0.280)	(0.401)	(0.122)
HS+3/4	-0.015	-0.218	0.382	0.199**	-1.715	-0.373	-0.084	0.226**
	(4.481)	(0.415)	(0.610)	(0.091)	(2.977)	(0.241)	(0.384)	(0.097)
HS+5 and more	-3.036	-0.476	-0.037	0.391***	0.527	-0.527**	-0.019	0.343***
	(4.133)	(0.381)	(0.556)	(0.078)	(2.622)	(0.221)	(0.320)	(0.079)
Professional training	-13.34***	-0.336	-1.249*	0.280**	-7.950**	0.118	-0.874**	0.196
	(4.627)	(0.458)	(0.659)	(0.126)	(3.063)	(0.333)	(0.394)	(0.145)
Number of registrations (PES)	7.192	-0.380	-0.534	0.407***	4.846	-0.239	-0.804***	0.277***
	(8.601)	(0.752)	(0.341)	(0.079)	(6.988)	(0.406)	(0.179)	(0.094)
Contract end and econ layoff	7.778***	0.561**	0.677*	-0.068	4.166**	0.410**	0.301	-0.177**
	(2.822)	(0.256)	(0.369)	(0.110)	(1.974)	(0.198)	(0.254)	(0.082)
New entrants and career change	5.362*	0.231	0.394	-0.110	5.594**	0.434**	0.492*	-0.176**
	(3.116)	(0.271)	(0.376)	(0.110)	(2.574)	(0.217)	(0.294)	(0.084)
other	3.136	0.230	0.201	-0.113	3.843*	0.170	0.329	-0.083
	(2.700)	(0.278)	(0.339)	(0.134)	(2.271)	(0.214)	(0.259)	(0.098)
Constant	-0.942	-0.304	1.237	7.028***	-2.623	-0.415	1.646***	7.182***
	(9.912)	(0.903)	(0.823)	(0.191)	(7.658)	(0.532)	(0.499)	(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 I5: Time preferences and job search effort: Square specification

	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)	-0.025	0.004	-0.002	-0.00002	0.003	0.003	-0.002	0.0006
	(0.042)	(0.003)	(0.005)	(0.001)	(0.032)	(0.003)	(0.004)	(0.001)
δ (money)	0.015	-0.006	-0.011	-0.0003	-	-	-	-
	(0.054)	(0.006)	(0.008)	(0.002)				
DMPL $\times$ δ (money)	-0.040	-0.020**	0.002	0.0008	-	-	-	-
	(0.077)	(0.008)	(0.015)	(0.002)				
δ (money) $\times$ δ (money)	-0.442	-0.404***	-0.125	0.001	-	-	-	-
	(0.862)	(0.070)	(0.190)	(0.023)				
β(money)	-3.944***	-0.172	-0.268	0.060	-	-	-	-
	(1.372)	(0.145)	(0.206)	(0.066)				
DMPL $\times$ β (money)	6.190***	-0.125	0.163	-0.011	-	-	-	-
	(1.918)	(0.177)	(0.299)	(0.081)				
δ (effort)	-	-	-	-	-0.025	0.005	-0.003	0.005***
					(0.029)	(0.003)	(0.005)	(0.001)
DMPL $\times$ δ (effort)	-	-	-	-	-0.002	0.015	0.107***	0.030**
					(0.382)	(0.030)	(0.039)	(0.012)
δ (effort) $\times$ δ (effort)	-	-	-	-	2.212	-0.374	0.223	-0.358***
					(2.307)	(0.236)	(0.446)	(0.097)
β (effort)	-	-	-	-	-1.248*	-0.150	-0.182*	-0.038
					(0.685)	(0.098)	(0.109)	(0.029)
DMPL $\times$ β (effort)	-	-	-	-	0.436	0.219	0.656***	0.104
					(1.386)	(0.138)	(0.169)	(0.064)
DMPL treatment	2.154	0.131	-0.086	-0.034	2.817	0.472	1.792***	0.476**
	(2.277)	(0.218)	(0.326)	(0.081)	(6.186)	(0.489)	(0.662)	(0.207)
Female	0.913	-0.053	-0.226	-0.230***	0.185	-0.150	-0.307*	-0.227***
	(1.895)	(0.148)	(0.242)	(0.063)	(1.462)	(0.129)	(0.173)	(0.048)
25/49 years old	1.101	0.236	-0.104	0.200***	2.036	0.215	-0.102	0.118**
	(2.339)	(0.187)	(0.277)	(0.071)	(1.963)	(0.145)	(0.224)	(0.056)
50+	8.925**	0.833**	0.082	0.394***	5.982**	0.543**	-0.130	0.457***
	(3.883)	(0.342)	(0.422)	(0.137)	(2.778)	(0.266)	(0.335)	(0.109)
Less than HS	-5.453	-0.916**	-0.245	0.131	-2.311	-0.951***	-0.307	-0.0526
(High School)	(4.775)	(0.435)	(0.747)	(0.143)	(3.776)	(0.301)	(0.477)	(0.138)
HS+2	-3.227	-0.140	0.115	0.274*	0.0518	-0.184	0.246	0.126
	(4.317)	(0.384)	(0.587)	(0.146)	(2.484)	(0.264)	(0.403)	(0.107)
HS+3/4	-0.885	-0.264	0.383	0.168*	0.919	-0.356	-0.202	0.0984
	(4.358)	(0.369)	(0.589)	(0.097)	(3.061)	(0.260)	(0.375)	(0.087)
HS+5 and more	-2.663	-0.471	0.041	0.353***	1.095	-0.535**	-0.198	0.270***
	(3.951)	(0.340)	(0.521)	(0.092)	(2.504)	(0.226)	(0.321)	(0.070)
Professional training	-7.618	-0.323	-0.812	0.027	-6.310**	-0.373	-1.161***	0.077
	(5.364)	(0.844)	(0.520)	(0.134)	(2.657)	(0.577)	(0.361)	(0.177)
Number of registrations (PES)	6.476	-0.568	-0.682*	0.413***	3.866	-0.402	-0.827***	0.292***
	(9.258)	(0.913)	(0.375)	(0.077)	(5.743)	(0.345)	(0.177)	(0.112)
Contract end and econ layoff	5.576**	0.431*	0.561*	-0.055	2.950	0.392**	0.278	-0.123*
	(2.677)	(0.232)	(0.325)	(0.106)	(1.925)	(0.190)	(0.250)	(0.071)
New entrants and career change	4.664	0.343	0.370	-0.099	5.188**	0.445**	0.409	-0.198***
	(3.012)	(0.252)	(0.350)	(0.110)	(2.458)	(0.204)	(0.291)	(0.074)
Other	3.146	0.338	0.291	-0.114	2.536	0.242	0.084	-0.061
	(2.584)	(0.255)	(0.317)	(0.128)	(2.050)	(0.195)	(0.248)	(0.084)
Constant	1.143	0.035	1.770**	7.005***	-3.206	0.219	1.814**	7.642***
	(10.77)	(1.048)	(0.877)	(0.215)	(6.823)	(0.565)	(0.741)	(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 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 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	0.004	0.004	0.002	0.003	0.001	0.002	0.002
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
δ (money)	-0.009	-0.010	-0.010	-0.004	-	-	-	-
	(0.006)	(0.008)	(0.009)	(0.008)				
DMPL × δ (money)	0.009	0.010	0.011	0.004	-	-	-	-
	(0.006)	(0.008)	(0.009)	(0.008)				
β (money)	-0.090	-0.065	0.019	0.012	-	-	-	-
	(0.183)	(0.168)	(0.189)	(0.183)				
DMPL × β (money)	0.049	0.167	0.168	0.137	-	-	-	-
	(0.223)	(0.186)	(0.206)	(0.193)				
δ (effort)	-	-	-	-	-0.002*	-0.002***	-0.001	-0.00007
					(0.001)	(0.001)	(0.001)	(0.0009)
DMPL × δ (effort)	-	-	-	-	-0.005	0.043	0.0329	0.016
					(0.043)	(0.043)	(0.040)	(0.037)
β (effort)	-	-	-	-	-0.165	-0.173	-0.219	-0.074
					(0.175)	(0.171)	(0.156)	(0.133)
DMPL × β (effort)	-	-	-	-	0.128	0.401*	0.293	0.071
					(0.217)	(0.211)	(0.210)	(0.182)
DMPL treatment	0.002	0.203	0.451	0.425*	0.077	0.903	0.833	0.581
	(0.279)	(0.315)	(0.294)	(0.256)	(0.703)	(0.696)	(0.663)	(0.599)
Female	-0.146	-0.174	-0.155	-0.125	-0.207	-0.101	-0.150	-0.091
	(0.224)	(0.193)	(0.185)	(0.171)	(0.170)	(0.167)	(0.170)	(0.153)
25/49 years old	0.006	-0.137	-0.150	0.076	-0.073	-0.174	-0.220	-0.009
	(0.275)	(0.252)	(0.243)	(0.221)	(0.210)	(0.211)	(0.206)	(0.182)
50+	0.438	-0.019	0.099	0.201	-0.115	-0.404	-0.453	-0.125
	(0.443)	(0.511)	(0.493)	(0.406)	(0.285)	(0.340)	(0.357)	(0.293)
Less than HS	-1.489**	-0.698	0.458	0.523	-1.225***	-0.912***	-0.224	-0.153
(High School)	(0.598)	(0.560)	(0.523)	(0.448)	(0.393)	(0.329)	(0.407)	(0.537)
HS+2	-0.537	0.275	1.129**	0.695	-0.283	0.255	0.931**	0.593*
	(0.591)	(0.569)	(0.549)	(0.494)	(0.436)	(0.423)	(0.406)	(0.339)
HS+3/4	0.045	0.453	1.203**	0.878*	-0.010	0.095	0.730*	0.752**
	(0.539)	(0.531)	(0.502)	(0.467)	(0.397)	(0.383)	(0.372)	(0.321)
HS+5 and more	-0.743	0.045	0.778*	0.675	-0.644**	-0.259	0.356	0.464
	(0.470)	(0.480)	(0.468)	(0.444)	(0.314)	(0.310)	(0.330)	(0.291)
Professional training	0.741	0.867	1.441*	1.011	0.148	0.265	0.685	0.354
	(1.018)	(0.922)	(0.738)	(0.716)	(0.923)	(0.828)	(0.604)	(0.639)
Number of registrations (PES)	1.026***	0.434	-0.0715	-0.883***	0.0395	-0.230	-0.751	-0.559**
	(0.337)	(0.277)	(0.260)	(0.336)	(0.457)	(0.478)	(0.469)	(0.279)
Contract end and econ layoff	0.765**	0.803**	0.772**	0.346	0.162	0.249	0.306	0.246
	(0.310)	(0.308)	(0.299)	(0.249)	(0.247)	(0.245)	(0.261)	(0.217)
New entrants and career change	0.510	0.288	0.410	-0.021	0.204	0.0769	0.133	-0.064
	(0.355)	(0.365)	(0.339)	(0.296)	(0.281)	(0.278)	(0.285)	(0.254)
Other	0.301	0.194	0.367	-0.115	-0.121	-0.027	0.132	0.020
	(0.303)	(0.353)	(0.344)	(0.299)	(0.243)	(0.266)	(0.281)	(0.237)
Constant	1.024	2.032***	2.145***	3.928***	2.403***	3.137***	3.534***	3.816***
	(0.770)	(0.765)	(0.727)	(0.682)	(0.595)	(0.611)	(0.634)	(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	0.012	0.031**	0.015
	(0.018)	(0.034)	(0.015)	(0.014)
δ (money)				
25% < δ (money) < 50%	-3.303**	-3.274**	-	-
	(1.535)	(1.356)		
50% < δ (money) < 75%	-1.327	-3.041	-	-
	(1.286)	(2.520)		
75% < δ (money)	-1.183	-0.674	-	-
	(1.195)	(1.596)		
β (money)				
25% < β (money) < 50%	-1.714	0.633	-	-
	(1.386)	(2.403)		
50% < β (money) < 75%	0.732	1.312	-	-
	(1.160)	(1.720)		
75% < β (money)	-0.449	-0.248	-	-
	(1.569)	(1.639)		
δ (effort)				
25% < δ (effort) < 50%	-	-	0.245	-1.255
			(0.689)	(0.801)
50% < δ (effort) < 75%	-	-	0.008	-1.460*
			(0.877)	(0.864)
75% < δ (effort)	-	-	0.236	-1.285
			(0.899)	(1.032)
β (money)				
25% < β (money) < 50%	-	-	1.210	-1.378*
			(0.867)	(0.718)
50% < β (money) < 75%	-	-	0.461	-0.432
			(0.804)	(0.880)
75% < β (money)	-	-	-0.160	-0.869
			(0.856)	(0.954)
Individual controls	*Yes*	*Yes*	*Yes*	*Yes*
Unemployment controls	*Yes*	*Yes*	*Yes*	*Yes*
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	-0.007	-0.022**	0.0001
	(0.016)	(0.015)	(0.009)	(0.009)
δ (money)				
25% < δ (money) < 50%	-0.863	-1.020	-	-
	(1.032)	(1.063)		
50% < δ (money) < 75%	-1.640*	0.195	-	-
	(0.990)	(1.102)		
75% < δ (money)	-1.412	0.188	-	-
	(1.114)	(1.469)		
β (money)				
25% < β (money) < 50%	-0.598	-0.541	-	-
	(1.086)	(1.067)		
50% < β (money) < 75%	0.752	-2.198*	-	-
	(1.108)	(1.133)		
75% < β (money)	-0.244	-1.582	-	-
	(1.198)	(1.557)		
δ (effort)				
25% < δ (effort) < 50%	-	-	14.58***	1.473
			(1.194)	(1.448)
50% < δ (effort) < 75%	-	-	0.276	1.051
			(0.676)	(0.683)
75% < δ (effort)	-	-	0.807	-0.077
			(0.994)	(1.071)
β (money)				
25% < β (money) < 50%	-	-	-0.363	-1.131
			(0.845)	(0.806)
50% < β (money) < 75%	-	-	-15.14***	-1.519
			(1.469)	(1.711)
75% < β (money)	-	-	0.284	-0.538
			(0.948)	(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	0.003	-0.005	-0.003	-	-
	(0.008)	(0.008)	(0.006)	(0.006)		
δ (money)	0.004	-0.0002	-	-	-	-
	(0.012)	(0.014)				
DMPL $\times$ δ (money)	0.002	0.005	-	-	-	-
	(0.014)	(0.014)				
β (money)	-2.949*	-3.476*	-	-	-	-
	(1.530)	(2.039)				
DMPL $\times$ β (money)	3.782**	3.724	-	-	-	-
	(1.817)	(2.298)				
δ (effort)	-	-	0.0006	0.0004	-	-
			(0.002)	(0.002)		
DMPL $\times$ δ (effort)	-	-	0.004	0.021	-	-
			(0.055)	(0.077)		
β (effort)	-	-	0.528	-0.377	-	-
			(0.862)	(0.783)		
DMPL $\times$ β (effort)	-	-	-0.084	0.727	-	-
			(0.989)	(0.980)		
Risk : Above median	-	-	-	-	0.097	0.039
					(0.126)	(0.153)
Patience : Above median	-	-	-	-	-0.093	0.042
					(0.133)	(0.156)
Procrastination : Above median	-	-	-	-	0.243*	0.208
					(0.126)	(0.154)
DMPL treatment	-3.875*	-4.057	0.380	-0.305	-	-
	(2.057)	(2.687)	(1.081)	(1.296)		
Female	-0.247	-0.570	0.140	-0.260	-0.0678	-0.292*
	(0.315)	(0.433)	(0.242)	(0.316)	(0.127)	(0.154)
25/49 years old	-0.159	-0.756	0.0506	-0.222	-0.227	-0.252
	(0.365)	(0.511)	(0.324)	(0.399)	(0.152)	(0.182)
50+	-0.785	-0.987	-0.138	-0.150	-0.604**	-0.487
	(0.673)	(0.920)	(0.527)	(0.631)	(0.279)	(0.333)
Less than HS and pro training	-2.233**	-1.875	-1.228	-1.192	-0.248	-0.268
(High School)	(1.113)	(1.564)	(0.812)	(0.894)	(0.230)	(0.267)
HS+2	-0.724	-0.925	-0.245	-0.427	-0.00231	0.210
	(0.637)	(0.850)	(0.489)	(0.611)	(0.241)	(0.288)
HS+3/4	-1.406**	-0.875	-0.761	-1.084*	0.0820	0.284
	(0.617)	(0.871)	(0.503)	(0.590)	(0.221)	(0.269)
HS+5 and more	-1.319***	-1.248**	-0.828**	-0.814*	0.0692	0.518**
	(0.455)	(0.636)	(0.379)	(0.478)	(0.196)	(0.238)
Contract end and economic layoff	0.353	0.0303	0.743**	0.605	0.039	-0.004
	(0.534)	(0.693)	(0.357)	(0.452)	(0.193)	(0.247)
New entrants and career change	0.007	-0.841	0.680	-0.289	-0.135	-0.542**
	(0.555)	(0.773)	(0.424)	(0.525)	(0.219)	(0.262)
Other	-0.076	-0.769	-0.341	-0.757	-0.008	-0.295
	(0.570)	(0.701)	(0.423)	(0.507)	(0.188)	(0.233)
Constant	-	5.456*	-	0.844	-	-0.578*
		(2.902)		(1.071)		(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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.