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Maxime Le Bihan

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A behavioral and experimental approach.

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Université Lumière Lyon 2

Ecole doctorale : ED 486

Unemployment and job search: a behavioral and experimental approach
Chômage et recherche d'emploi : une approche expérimentale et
comportementale

Maxime LE BIHAN

Sous la direction de Marie Claire VILLEVAL et Pierre CAHUC

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Introduction

The economic models used to design unemployment compensation policies today dates back to the 70s. They were developed to understand why the unemployment rate remained high in periods of economic growth, particularly when the market provided enough vacancies to take in the labor supply (Stigler, 1961, 1962; McCall, 1970; Mortensen, 1970). The main assumption of the models is that job seekers' information about available wages and job offers is imperfect. To find a job, job seekers have to search for this information which incurs a cost. The existence of a search cost has two important implications. The first is that during unemployment, people may not have the financial capabilities to bear the cost of search which explains why some individual can involuntarily and durably stay unemployed. Second, since searching is costly and happens at a moment where the financial state is weakened, people may want to insure against the risks of unemployment while employed which justifies the development of an unemployment insurance.

Although the model justifies unemployment insurance, it gives no practical guidance regarding the level and duration of unemployment compensation and their ability to provide the right level of incentive. If search costs are too high, the search might be inefficient, yet if the overall amount of benefits is too high, job seekers might be tempted to delay their job finding. This problem is still at the core of unemployment policies today. During the period going from 2019 to 2023, the unemployment policies in France give a perfect illustration of this tendency. The successive reforms decreased the level of compensation by 16% for half of the unemployment insurance beneficiaries, while its duration was reduced by 25%. This kind of compensation policy is mainly supported by the population that internalized the moral hazard problem. In December 2022, the Unédic (the institution in charge of the unemployment insurance system in France) ran a survey on the french population and asked the respondents to select from a list all the reasons why they believed unemployment was high in France. One-third believes unemployment to be caused by job seekers' unwillingness to work, 24% also pointed at the generosity of the unemployment compensation and 25% believe that unemployment is high because the monitoring of job search effort is too low.¹

¹source : *Unédic* - "https://www.unedic.org/publications/barometre-unedic-volet-4-quel-regard-les-francais-portent-ils-sur-le-chomage-et" Accessed on March 19, 2023.

According to the model, decreasing the benefits received by job seekers provides an incentive to search. Empirically, there is no doubt that such constraint, coming with the menace of financial hardship, leads households to mobilize all channels possible to bring their finance back to their prior level. This effect is now widely documented in the literature (Cahuc et al., 2014; Holmlund, 2014; Lopes, 2022). The positive effect of a reduction in benefits amount and duration on the exit of unemployment was found over different periods both in the US (Krueger and Mueller, 2010, 2011) and in Europe (Lalive et al., 2006; DellaVigna et al., 2016).

Yet, some "anomalies" (Kuhn, 1970; Thaler, 2015), at odds with the model predictions, are starting to pile up (see Dohmen (2014), Villeval (2016) or Cooper and Kuhn (2020a) for a review). These anomalies show that beyond the moral hazard problem, job seekers face behavioral and psychological barriers. The current framework is strongly relying on assumptions of the expected utility theory (Von Neumann and Morgenstern, 1947). It assumes job seekers to be perfectly rational, able to make perfect inter-temporal trade-offs, and to update their beliefs accurately regarding their wage distribution and job opportunities prospects when provided with the right amount of information (Babcock et al., 2012). Following DellaVigna (2009), people deviated from these assumptions in at least three regards that led to three different strands of literature. *Non-standard preferences* constitute deviations from the standard model caused by individual valuation for specific elements of the economic environment, that either is not supposed to enter the utility function or that enter in a different way than that hypothesized by standard models. This is notably the case of time preferences. In the mainstream theory individuals are supposed to make similar decisions when asked to plan their search effort, no matter when the decision is taken. However, when facing inter-temporal decisions, they end up planning differently when asked to plan for dates involving the present one, and when asked to plan exclusively for the future (DellaVigna and Paserman, 2005). This is also the case for loss aversion and reference points. Although individuals are supposed to form their reservation wages² using available offers on the market and individual characteristics only, they end up optimizing their search efforts based on previous consumption (DellaVigna et al., 2016). The second type of deviation is the *non-standard beliefs* which consist of errors in beliefs about the job search prospects, leading to a non-optimal search. Among this type of deviations, overconfidence drew the most attention in the job search literature. Recent empirical findings showed that unemployed job seekers start searching with overly optimistic beliefs about their return to search which can lead to a delayed return to employment. Lastly, *non-standard decision making* is represented by systematic errors due to the simplification of the optimization problem, and to the rules of thumbs

²In the job search models, individuals decide to accept or reject an offer by comparing the costs of continuing to search and the gains of accepting the job offer given its wage. The wage that makes the job seeker indifferent between both is called the reservation wage. The job seeker's optimal strategy to maximise his utility consist in accepting all wage offers superior or equal to the reservation wage and reject all offers below.

used to choose. For instance, job seekers have been shown to apply to job offers depending on the number of people applying at the same time although it should theoretically not affect this decision (Gee, 2019). Facing a large number of offers on the market can also lead to non-optimal decisions due to heuristics used by job seekers to simplify their decision. These heuristics called "menu effects" may lead job seekers to stick to the jobs they used to do in the past or to choose the options that require less search effort (e.g., the first offer received), which consequently close the door for potentially better offers (Belot et al., 2019).

With the development of this behavioral literature came new methods of study. While labor economics mainly relied on administrative and survey data (Cahuc et al., 2014), the use of experiments in economics initiated by Smith (1976) and Kahneman and Tversky (1979) gave birth to a new type of data in economics.

Although labor economists were not particularly enthusiastic about experiments (Dohmen, 2014), pointing at the difficulty of exporting experimental results outside of the lab (external validity - see Levitt and List (2009) for a review of these concerns and the response by Camerer (2015)), their field belongs to those that could benefit the most from its use. Theoretical models have the elegant properties to be universal - their conclusions should be valid in the conditions in which they apply, irrespective of the subject pool - testable and reproducible. Experimental methods consist in using these properties to build computerized, artificial situations, reproducing the settings of the models. In theory, to conclude that a relation between two elements is causal, the researcher needs to observe the change of the first one (the cause) and its effect on the second one (the consequence). Unlike most real-life situations where we only observe the outcome of a model and eventually some parameters leading to it, experiments allow to reproduce, watch and change models in their entirety. It is thus possible to duplicate several experimental situations (treatments) that differ in a perfectly controlled manner. This level of control gives the ability to draw causal relationships in experiments (internal validity, Falk and Heckman (2009)).

In some (rare) instances, administrative and survey data allow observing both the cause and the consequence of a phenomenon without any confounding effect that could lead to errors in the effect interpretation. By observing an exogenous shock on an element, we can infer how and in which proportions it affected the outcome. Experiments are particularly valuable when this is not the case. For this reason, in spite of the low enthusiasm towards the method, experiments were used relatively early in labor economics and job search analysis. The core assumptions of job search models are mainly untestable using survey and administrative data since job search and how job seekers decide to accept or reject offers are unobserved. For instance, to state that a job seeker use a reservation wage strategy, the researcher needs to observe both the accepted wage

and all the offers that were proposed but rejected. Most of the time, administrative and survey data only allow to observe accurately the first one. The seminal approach used to test the job search models in the literature ([Schotter and Braunstein, 1981](#); [Cox and Oaxaca, 1989a](#); [Sonnemans, 1998](#)) was to create a simple experimental search task mimicking the model. Subjects had to sell an object or offer their workforce to realize a real-effort task. They received price/wage offers that arrived following a distribution set by the researchers. Subjects had to decide whether to accept or reject offers knowing that waiting for each new one was costly. Using this method allowed to confirm some important implications of the model (e.g., the use of reservation wage strategies) and revealed that accepted wages were coherent with the model's equilibrium. However, anomalies were also spotted early on by experimenters. When placed in these situations, subjects searched less than predicted and could use search heuristics rather than reservation wage strategies. Their participants also set reservation wages that were initially elevated and declined over time.

Still today, this seminal experimental framework is used to find explanations for the anomalies found at the time. An example is [Schunk \(2009\)](#) who links the search strategies adopted by subjects in the search task to risk attitudes and loss aversion. He finds that subjects use heuristics to accept offers unrelated to risk attitudes but connected to loss aversion. Consistently with the effects described earlier from [DellaVigna et al. \(2017\)](#), loss aversion-based heuristics are a potential explanation for the empirical anomaly that individuals set higher reservation wages and stop searching earlier than predicted by the original models. Instead of basing their reservation wage solely on the wage distribution they face and the future wealth stream it may offer, job seekers subject to loss aversion base their desired salary on their previous level of wealth, irrespective of the current reality of the market. Another example is [Brown et al. \(2011\)](#) who find that individuals' subjective costs of search explain why the reservation wage declines over time. In their search experiment, they designed treatments where the search cost materializes in various ways. In some treatments, the cost of an offer is strictly monetary - subjects pay (from their final gains) a fee for each received one - and in others, it is represented by the real-time waited before finding one. These treatments allow isolating how the reservation wage varies over time while measuring its sensitivity to different search costs and their accumulation.

To sum up, as was the case in the 70s when the current mainstream models of job search were developed, we are once more facing behaviors - inconsistent with the theory in its current build - in need of an explanation. Not accounting for those behaviors fatally leads to building distorted incentive systems. This calls for a new framework to study job search, or an enhancement of the former one, accounting for the psychological and behavioral aspects of job search. This thesis, and the literature it builds on, humbly

contribute to the efforts made in this direction.

Following the classification of [DellaVigna \(2009\)](#) and [Dohmen \(2014\)](#), Chapter 1 investigates how non-standard time preferences can shape job search. In situations where efforts are required in the present but only yield benefits in the future, people have been shown to procrastinate by postponing their efforts in the future. although job search satisfies all the conditions for procrastination to happen, current main models expect that job seekers will consistently plan their effort over time. For that reason investigations of how job seekers plan and realize effort over time are still scarce. In this chapter, we test how procrastination occurs in the context of job search. Specifically, we test experimentally whether procrastination occurs through monetary reasoning - job seekers prefer immediate monetary streams over long-term ones when they are in the present, leading them to undervalue the future gains of returning to employment- or through effort reasoning that would lead them to prefer leisure over costly search effort.

Chapter 2 investigates one type of non-standard beliefs. Recent papers show that job seekers started their unemployment spells with over-optimistic beliefs that they fail to adjust over time which directly contradicts the assumption of job search models ([Spinnewijn, 2015](#); [Mueller and Spinnewijn, 2023](#)). However, the reason for the emergence of optimistic beliefs and the way their updating affects job search remains poorly understood. In this chapter, we contribute to the literature investigating this question by studying the extent to which overconfidence and updating biases arise through a simple self-protecting mechanism. We hypothesize that to protect their self-image, overconfident job seekers start with a generally positive view of themselves that they try to maintain over time, which backfires by delaying their return to employment.

While Chapters 1 and 2 use online experiments to test job search model assumptions using behavioral theories, chapter 3 uses the experimental methodology to enlighten a long-known puzzle where natural data only brought limited insights. In this chapter, we use a vignette experiment to study matching in the elders' labor market. In France, the question of senior unemployment is a major policy issue as the number of seniors is expected to grow, which puts at peril the retirement system. Maintaining workers at work at an old age is thus key, yet when losing their jobs, the probability of seniors going back to work is particularly low. We investigate the extent to which this low level of job finding can be partly attributed to the preferences of senior job seekers for specific job attributes that the market would be unable to provide. Using the compensating wage differential model of [Rosen \(1986a\)](#), a large literature used cross-sectional and administrative data to study matching in the labor market. However approaches using these data only brought limited results that were unstable and often inconsistent with the theory ([Mas and Pallais, 2017a](#); [Bonhomme and Jolivet, 2009](#)). We contribute to this literature by considering a new angle of analysis. We identify the amenities over which senior job seekers' search differ from the rest of the French job seekers, and provide a willingness-

to-pay estimate for each amenity.

The following sections will give an overview of the literature on the effects of non-standard preferences, non-standard beliefs, and describe my contributions to the use of experimental methods to improve the understanding of job search behavior.

Non-standard preferences

By far, deviations from the standard model coming from non-well-behaved and initially unaccounted-for preferences have concentrated the highest interest among all types of behavioral deviations in labor economics. Yet, studies reflecting how such deviations may affect job search are relatively scant.

A first type of non-standard preference that was introduced in economics earlier than most preferences is risk aversion ([Arrow, 1951](#); [Pratt, 1978](#)). Early in the development of job search models, extensions involving how the perception of risk could affect reservation wages and job search were developed to have a more realistic model. Because unemployment is risky in nature (e.g., uncertainty on the unemployment spell length, on the reachable job offers, on the future separation rate ...) the literature shows that risk averse job seekers set lower reservation wage to have shorter unemployment spells ([Pissarides, 1974](#); [Feinberg, 1977](#)). Another well known implication of risk aversion on unemployment is the theory of implicit contracts ([Baily, 1974](#); [Azariadis, 1975](#); [Azariadis and Stiglitz, 1983](#)). Since job seekers are risk averse and want to avoid fluctuations of their wages depending on the market situation, firms accept to set wages at a fixed price in exchange of the possibility to adjust costs by setting lower average wages and displacing workers if needed. In this situation, the lower wages and the probability to be displaced plays the role of a risk premium that workers are willing to pay to have a stable wage.

Although economists evoked the lack of realism of the job search theory to introduce risk aversion into the job search model, the argument was only recently extended to include other types of preferences. In their seminal work, [Kahneman and Tversky \(1979\)](#) showed how individual utility functions are likely to depend on a reference point, which is a relevant anchor from which individual compare their outcome, and from which any negative deviation bears more stigma than a positive variation of the same valence brings satisfaction. During the job search, this is of particular relevance as job seekers face many negative income changes during their unemployment which may constitute reference points. Indeed, empirical evidence showed that contrary to what standard job search models suggest, the instant probability to exit unemployment is high at the beginning of unemployment, declines first but then surges back when the benefit exhaustion arrives, and goes back down thereafter ([Schmieder et al., 2012](#); [Card et al., 2012](#); [Barbanchon, 2012](#)). [DellaVigna et al. \(2022\)](#) showed that the most suited model to explain such behavior is one taking the previous consumption level as a reference point. Around each income

changes from job loss to benefit exhaustion, the prospect of a downward reassessment of the consumption level creates a positive incentive to search, explaining the unemployment exit pattern described earlier. However, between each income change, job seekers adapt to the consumption level allowed by their financial state, which subsequently decreases their incentives to search. Reference points were also shown to affect reservation wage. While the standard assumption suggests that reservation wages are formed based on the reachable wage distribution, several work (Charness and Kuhn, 2007; Böheim et al., 2011; Fu et al., 2019) show instead that reservation wages may be based on other job seekers reached wages or on the own past wages which serve as reference points.

Another line of labor research studying *non-standard preferences* focuses mainly on social comparisons, reciprocity, and fairness. While the standard framework expects individuals to care only about their welfare, people were long shown to compare to others and view their gains and losses relative to a relevant comparison individual or group (Veblen, 1899; Duesenberry, 1949). For the labor market, the implications are vast as these comparisons affect how people perceive their level of job satisfaction regarding the relative wage they get (Clark and Oswald, 1996; Abeler et al., 2010; Gächter and Thöni, 2010; Card et al., 2012), or how they decide to work and provide efforts (Hamermesh, 1975; Neumark and Postlewaite, 1998; Angelova et al., 2012; Cohn et al., 2014). During the job search, competitiveness on the labor market leads job seekers to constantly face and compare to others, which subsequently changes their search behavior as was shown by (Gee, 2019). People also form reference points based on the behavior of their peers that end up shaping their job search (Clark, 2003; Fu et al., 2019).

A second type of other-regarding preferences that penetrated the labor economics literature focuses on how one takes into account how others treated them. Such preferences mainly affect the workplace relationships where fair treatments and reciprocity are determinants of the job satisfaction, efforts, and wages (Akerlof and Yellen, 1990; Falk et al., 2006a; Agell and Lundborg, 2003; Dohmen et al., 2006; Abeler et al., 2010). For job search, the effects are largely guided by how job seekers expect to be treated when they find a job. The standard job search literature usually studies the matching between employers and employees while other strands of literature focus on the tacit agreement that shapes the relation between job seekers and their future employers. This is the case of the literature on relational contracts which shows that the set of expectations both from job seekers and their future employers impacts the job search and the future relation between both parties. One compelling example is that of Altmann et al. (2014) who find, using an experimental job market, that employer-employee relationships last longer when both behave collaboratively. Employers in this experiment reciprocate the efforts of employees by re-hiring them for subsequent periods. Other examples are Eriksson and Villeval (2012), Board (2011) and Board and Meyer-ter Vehn (2015), who find that

loyalty, recognition and respect of workers are important factor in the development of durable professional relationships. Because those factors belong to the set of expectations that job seekers may have for their future job, they play an important role in the decision to accept or reject offers. Yet, they are not accounted for in standard job search theories.

The first chapter of the thesis contributes to this literature by studying present bias, one of the most prominent *non-standard preferences* that affects time discounting. It consists of an individual systematically adding extra weight to the future utility when asked to plan the reception of a gain or the exertion of effort between the present and a date in the future. Such overweighting does not occur when the same individual is asked to do this choice between two dates in the future while the standard time consistency assumption would predict both settings to be the same. A typical example of such bias is procrastination: individuals planning to, for instance, go to the gym in the future postpone their effort when the time comes to exert it (DellaVigna and Malmendier, 2006). Although it represents one of the most regarded biases touching time preferences (O'Donoghue and Rabin, 1999; Frederick et al., 2008), we only know little about job seekers' present bias. The seminal theoretical model of DellaVigna and Paserman (2005) describes how time preferences and procrastination should affect job search. The model's main conclusion is that present-biased individuals planning ahead of the start of their search set an effort level that their future selves will be unable to provide. This distortion subsequently leads them to search less than what they initially planned, which delays their job finding. The second conclusion of the model is that discounting the future more (i.e., being impatient in the long run) should lead one to search less and set lower reservation wages. This is due to individuals' lower perceived future returns of accepting an offer now, which gives lower incentives to search but in the meantime decreases the value of continuing the search for greater offers.

In spite of these clear predictions, evidences supporting them are rare because measuring time preferences on job seekers is challenging. First, there is no consensus on a single method to measure time preferences and the mainstream methods in the literature are time demanding (e.g., some experiments on time preference imply that subjects will show up for two to three experimental sessions several months apart) and are not robust to income changes during the period of the experiment (e.g., the decision to receive money now or in the future is likely to depend on the subject's employment). Second, job seekers are not a population that can be reached easily by researchers and most of the empirical evidence so far rely on administrative and survey data using proxies weakly related to time preference. Using this type of data, both DellaVigna and Paserman (2005) and van Huizen and Plantenga (2014) were able to provide evidences consistent with the model. However, in both papers, the use of imprecise proxies and unincentivized self reported

measures restrain the precision and validity of the results.

In this chapter, our main research question consists in testing [DellaVigna and Paserman \(2005\)](#) model's predictions on present bias and discounting. Using an online experiment with French job seekers, we face the challenge of measuring their time preferences and testing both predictions on discounting and present bias. We measure both over two dimensions, money and effort. First, the central position of monetary reasoning in the model and the prominent use of financial incentives in experiments on time preferences led us to measure time preferences in the monetary domain. Second, because of the specific characteristics of our population of job seekers mentioned earlier, solely measuring time preferences in this domain would not be sufficient. It led us to add measures of time preferences on the effort domain. Although effort planning is less robust to changes in the quantity of free time people have at their disposal over time, it is more robust to income changes over the unemployment spell than monetary decisions. Moreover, the model invokes reasoning over both money and effort while people were shown to be more present-biased when distributing effort over time than when allocating monetary streams over time ([Augenblick et al., 2015](#)). Measuring both allows us to have two complementary measures and to identify whether procrastination mainly occurs through monetary or effort reasoning.

In our experiment, we used the two main experimental metrics of time discounting used in the literature, the Convex Time Budget method (CTB) ([Andreoni and Sprenger, 2012](#)) and the Double Multiple Price List method (DMPL) ([Andersen et al., 2008](#)) that both involve the allocation of units over time. We used allocations of both real effort and money over present and future periods, alternating whether the first period was the present one or whether all allocation dates were in the future. We then related the discounting behavior in the experiment to the actual reservation wage and job search effort and outcomes of our job seeker sample, which were collected using a survey administered before the experiment and administrative data.

Our first finding is that job seekers discount in general in a consistent way, but in the present, they discount effort more than they discount money. We find that they are not present biased when it comes to monetary allocations, they rather seem to be future biased: they favor the reception of monetary rewards early in the future rather than in the present. Turning to the effort domain, we find that job seekers, depending on the measure used, are either time consistent or present-biased, preferring to postpone effort when deciding whether to do it in the present or the future.

We then related discounting and present bias over both effort and money to job search efforts and outcomes. Our first result is that, using the DMPL method over effort we are able to replicate most of the model's predictions. We find that individuals who displayed

a present bias over effort didn't have particularly different reservation wages but they exerted a lower effort in their job search. This result implies that present biased job seekers search less hard for a job (procrastination) as suggested by the model but search for the same jobs than similar unbiased individuals. Regarding impatient individuals (in the long run) over effort, they had both lower levels of job search effort and lower reservation wages. This second result suggests that, compared to similar patient individuals, impatient ones search less for new jobs but accept jobs with lower salaries. Turning to time preferences elicited over money, we find similarly that present bias correlates negatively to search effort without affecting the reservation wage. However, we are unable to detect any effect of long-run impatience over both the search effort and the reservation wage. Our second result is that present bias elicited over both money and effort correlates to job search outcomes. While present bias over effort seems to affect short run outcomes, present bias over money correlates to return to employment one year after the survey. This result is a first evidence that in the long run job search may be 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. Finally, our paper confirms that the elicitation method to measure time preference should be chosen with care as our results are sensitive to the method used. Using the CTB method, our metrics of time preferences never reach significance when used to explain job search effort and outcomes except for a surprising positive effect of present bias over money on the time spent searching. This result calls for a more systematic test of the ability of the two main method used to measure time preferences to predict real-settings behavior.

Non-standard beliefs

In theory, using all the available information in their possession, job seekers are supposed to form a correct view of their perspectives on the job market, wage offers included. If their information set is incomplete, they are supposed to adjust in Bayesian way their search strategy in light of the new pieces of information they receive (e.g., feedback from interviews and offer rejections). However, the job search environment makes such rational behavior particularly challenging. Job seekers mostly face rejections in the labor market with poor feedback on their chances to attain a job similar to the one they applied to, which leads them to rely on their initial beliefs. Behavioral economics studies showed that biased beliefs and updating appear almost systematically when feedback is noisy, and when people wrongly believe in controlling a situation (DellaVigna, 2009). Recent studies showed that job seekers are overconfident about their search prospects and update very little on their search strategy (Marinescu and Rathelot, 2016; DellaVigna et al., 2022) and reservation wage (Barbanchon, 2012; Krueger and Mueller, 2016). Despite the

identification of such biases as early as [McCall \(1970\)](#), the interest in *non-standard beliefs* is relatively recent, with the first modelization of confidence effects made by [Spinnewijn \(2015\)](#).

In this literature, job seekers' maintained overconfidence over time still represents a puzzle. Following negative feedback, a logical response, at odds with the empirical observation so far, would be a decrease in confidence, job search effort and reservation wage. In the behavioral economics literature, potential candidates to explain why we observe the opposite are motivated beliefs and reasoning - the set of beliefs, reasoning, and behaviors affected by the currently held beliefs or emotions (see [Bénabou \(2015\)](#) for a review). [Eil and Rao \(2011\)](#) and [Möbius et al. \(2022\)](#) showed in their papers that when people update their current level of knowledge in light of new information, they overweight positive feedback and underweight negative feedback when it is ego-relevant (e.g., information about one's intelligence or beauty). Job seekers' initial high confidence about their job finding may similarly reflect a protective mechanism against the expected negative feedback on the labor market that could thrust their self esteem and motivation. To preserve this good vision of their abilities, job seekers may additionally underweight the information provided by job applications turned down. The objective of Chapter 2 is to test the extent to which this explanation holds.

As in Chapter 1, we combined two datasets to investigate our research question. First, using the public employment services data, we sampled a set of recently unemployed job seekers that we followed up to a year after the beginning of their unemployment spell. Second, we designed an online experiment and a post-experiment survey to measure beliefs, updating, and job search behavior. We measured general confidence and belief updating using a real-effort task designed to be engaging. Through their engagement in the assignment, we expected participants to form an ego-relevant interest in its outcome. Before and after the task, we asked them their beliefs about their performance and being above the median performance, constituting a general measure of confidence. We then provided subjects with two rounds of noisy information with an accuracy of 75% about their ranking. Following each signal reception, they had to report their probability of being above the median performance. Their ability to adjust beliefs in a Bayesian way constituted our measure of self-relevant updating. Finally, we had subjects perform a similar neutral updating task to control for their general updating errors. Unlike the previous real-effort task, the neutral one did not involve the subject's abilities. Because abilities and outcomes were disconnected, we expected participants to attach fewer feelings to their results. The post-experimental survey included questions on job search habits (effort, search channels used, number of applications made), reservation wages, and early results.

Consistently with the literature investigating motivated beliefs and updating ([Bénabou,](#)

2015), we find that subjects didn't behave in a Bayesian way and updated too little when faced with new information. This conservatism followed a clear pattern. When facing ego-relevant information regarding their performance, our participants overweighted (underweighted) positive (negative) signals. This pattern was robust to using Bayes' rule or the neutral task outcome as a benchmark. Second, we find that job seekers are overconfident about their job search prospects and mainly believe that they would find a job faster than what happened in reality. Moreover, relating job search behavior to updating, we show that job seekers who fail to adjust their beliefs correctly due to self-serving motivated beliefs had longer unemployment spells. While this may seem a bad outcome, we also find that individuals who have the opposite behavior and overweight negative signals and underweight positive ones show significant signs of demotivation, illustrating that self-serving motivated beliefs may arise as a coping mechanism.

The role of caseworkers in helping and advising job seekers may be essential for adjusting their prospects, provided their efforts reach the right target. Our results suggest that, by giving relevant advice to overconfident job seekers to adjust their views and maintain their motivation by coaching them during their unemployment spell, caseworkers may significantly improve their job seekers' outcomes and reduce their unemployment spells.

Using vignettes to understand the role of job amenities in job search

In addition to the novel theories, behavioral economics also exported its methods to other fields. While mainstream methods and data are useful in most cases, experiments allow us to draw conclusions in settings where they are less efficient. The third chapter of the thesis illustrates this case by studying elder matching in the labor market. Working on matching usually involves both survey and administrative data. Using these types of data, we observe only the realized match, leaving aside the process leading to it. However, the process is determinant since the rejected options are as important as the selected one to infer individual preferences.

In France, despite their low unemployment rate seniors suffer from a low re-employment probability. Their unemployment spells appear as a bridge before retirement supported by unemployment insurance, especially in places where unemployment compensations are generous as in Europe. In the meantime, the possibility that they may stay unemployed longer can be due to either discrimination in favor of juniors or senior-specific job preferences due to the deterioration of their health condition while aging. The problem is critical with the aging of populations, especially in Europe, where maintaining the retirement regimes in their current states may be particularly challenging. Although it may not solve the problem entirely, finding a way to have elders return to employment may alleviate the burden of social security regimes by reducing costs and expanding the contributors' pool. Chapter 3 investigates the extent to which the low re-employment

probability is due to senior preferences and willingness to work in providing an accurate measure of their valuation for common and health-related job characteristics.

We designed a nationally representative survey using the vignette method. This method consist in offering job seekers the opportunity to select a job from a hypothetical but realistic menu of job offers (Eriksson and Kristensen, 2014a; Mas and Pallais, 2017a, 2019). Our sample from the public employment service database comprised senior and non-senior job seekers at the beginning of their spell. First, the participants had to fill out our online vignette study. Each job seeker realized six different choices between two fictive job proposals. The offers included seven job attributes. The five first attributes were directly relevant for all contracts: the worktime, whether the contract was a short or long-term one, the commuting distance to the workplace, the flexibility of the work planning, and the possibility to work from home. The two remaining attributes targeted health-related characteristics of the job: the work posture (standing or seated) and the exposition to transmittable diseases such as covid 19. Each offer also included a wage tailored to each job seeker's prospects based on his characteristics, which varied randomly. Using controlled variations of job characteristics, we computed willingness-to-pay estimates by measuring how the decision to accept a job depended on the combined variations of the wage and job characteristics.

This survey shows that elders undoubtedly have distinctive preferences for jobs. Compared to non-seniors, elders are more selective and frequently reject job offers. Our results indicate that seniors value significantly the possibility to adjust their planning as they will and are willing to avoid long commuting times. They value shorter contracts and care above all for health-related job characteristics two to three times more than non-senior respondents. These findings point out that by providing jobs to elders that fit their needs in terms of schedule flexibility and health preservation, it would be possible to have them return to employment. Using elders' experience to supervise and play the mentor figure for younger workers would be an interesting way to achieve this goal. However, matching involves two parties. Our results only reveal what seniors would be willing to do, irrespective of firms' preferences. Investigating the firm's willingness to provide these job amenities is of the utmost importance to answer whether discrimination occurs on the market and to design incentive policies accordingly.

"Is a hammer a better tool than a screwdriver (or vice versa)?" (Charness and Kuhn, 2011a, p. 236)

Despite experiments' clear benefits, their use in economics in general, and specifically in labor economics, was restrained because of economists' concerns regarding the external validity of the method. Yet, theories are - again - universal and should neither depend on the subject pool nor the artificial aspect of the task used. Accordingly, there is no reason to doubt that results should qualitatively be the same inside and outside the lab. As shown by Falk and Heckman (2009) and Charness and Kuhn (2011a), to convince that it was the case, there were tremendous efforts engaged in testing the robustness of experimental results on various subject pools, using less invasive environments to avoid concerns regarding Hawthorne effects, and using tasks that involve real efforts rather than hypothetical ones. These efforts were mostly successful. While economists used to oppose experiments to other methods, the paradigm is starting to change. Researchers now mostly consider them complementary. On the one hand, some theories' parts are irrefutable using real-life data: experiments provide a unique way to test them. On the other hand, if novel results come from lab behavior, they can, and in my opinion should, be challenged and tested using less controlled environments (real-life occurring behavior such as those observable using field experiments or survey and administrative data).

In addition to the literature contributing to bringing behavioral economics consideration into job search analysis, it is possible to read this thesis through its methodological contribution to the debate exporting lab methods to explain real-life behaviors. In the two first chapters, I use experimental methods to test anomalies originating from the standard job search models. By taking advantage of the development of web methods to design online experiments I related lab metrics to job seekers' search and their outcomes. In Chapter 3, I adopt a different approach that illustrates a case where experimental methods provide a novel angle of analysis to a long-known puzzle of the literature.

Chapter 1

Do Job Seekers (really) procrastinate?

1

1.1 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*).² 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 involuntary behavioral biases of job seekers.

In reaction to the limitations of standard theories to explain job search anomalies,³ 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, 2011b](#); [Cooper and Kuhn, 2020b](#)). 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](#)).⁴ In addition to exponential discounting of future consumption, a fraction of individuals exhibit present bias: while many prefer immediate smaller rewards to larger but

¹This chapter is joint with Marie Claire Villeval

²<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 March 1, 2023.

³For early experimental evidence, see [Braunstein and Schotter \(1982\)](#); [Cox and Oaxaca \(1989b, 1992\)](#).

⁴Other 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 Rathelot, 2016](#)), 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., 2006b](#); [Spinnewijn, 2015](#); [Golman et al., 2017](#); [Gee, 2018](#); [Belot et al., 2018](#); [Mueller et al., 2018](#)), and an external locus of control (*e.g.*, [Caliendo et al., 2015](#); [McGee and McGee, 2016](#); [Preuss and Hennecke, 2018](#)).

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.⁵ 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 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.⁶ 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.⁷ 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

⁵Interestingly, 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.

⁶Several 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.

⁷The 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.

received.⁸ 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 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](#)).⁹ 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.,](#)

⁸[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. \(2021\)](#).

⁹In 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.

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 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.¹⁰ 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

¹⁰Cheung 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.

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 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 undertaken 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 pro-

crastination 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.

1.2 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:

¹⁰These hypotheses, the experimental design, and the data analysis plan were preregistered at AsPredicted (#68035). The order of presentation of the hypotheses has slightly changed.

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 β - δ 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 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:

$$\underset{s_t \in [0,1]}{\text{Max}} \quad b - c(s_t) + \beta\delta[s_t E\{\max(V_{t+1}^E(w), V_{t+1}^U)\} + (1 - s_t)V_{t+1}^U] \quad (1.1)$$

where b is the unemployment benefit, c the cost of search with $c(\cdot)$ an exponential function, and w the wage level. The job seeker 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, $V_{t+1}^E(w)$, or rejects it and gets the utility of staying unemployed in the next period, V_{t+1}^U . Second, with probability $(1 - s_t)$, she stays unemployed and receives the continuation payoff of staying unemployed, V_{t+1}^U . A reservation wage strategy maximizes this program with:

$$w^* = (1 - \delta)V^U \quad (1.2)$$

and the first order condition of the program yields:

$$c'(s_t) = \frac{\beta\delta}{1 - \delta(1 - q)} \left[\int_{w^*}^{\bar{x}} (u - w^*) dF(u) \right] \quad (1.3)$$

The reservation wage setting does not directly involve short-run discounting, which ex-

plains 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.¹¹ 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.*

1.3 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 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.

1.3.1 Sampling and administrative data

We sampled the participants to our study from the French Public Employment Service (PES) database.¹² 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.¹³ 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.¹⁴

¹¹Sophisticated present biased agents foresee their future low search level and marginally lower their reservation wage. However, DVP show that this effect is relatively small.

¹²This database administered by Pôle Emploi is called the "Fichier National des Allocataires (FNA)".

¹³Once 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.

¹⁴A 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.

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.¹⁵

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 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.¹⁶

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.¹⁷

Table 2.1 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 communica-

¹⁵These 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.

¹⁶In 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.

¹⁷As 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.

tion 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.

1.3.2 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 procrastinate, using 0-10 Likert scales.¹⁸ 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

¹⁸For 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."

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.

1.3.3 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.¹⁹ In order to create a common experimental assessment of risk attitude, we added for both treatments the Bomb Risk Elicitation Task

¹⁹Participants 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.



Figure 1.1: Timeline of the experiment

(Crosetto and Filippin, 2013) (BRET) at the very end of session 1.²⁰

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.²¹ Figure 1.1 summarizes the 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

²⁰A 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.

²¹The 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 avoided asking participants to come back in a fourth session to perform the tasks assigned to the later date.

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:

$$Pc_t + c_{t+k} = y \tag{1.4}$$

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

The allocation decisions were made by moving a slider that was initially positioned 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,²² 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 $\text{€}27$ 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

²²In [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 $\text{€}1$ at the early date, and moving the slider gave directly the resulting net payments in € at each of the two dates.

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:

$$e_t + Re_{t+k} = m \tag{1.5}$$

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 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.²³ 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

²³Because 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.

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).

1.4 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.

1.4.1 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; O'Donoghue and Rabin, 2001) in a situation in which agents have to make intertemporal choices, and define an individual's objective function at date t as:

$$T(u_t, u_{t+k}) = (u_t + \omega_1)^\theta + \beta^{1_{t=0}} \delta^k (u_{t+k} + \omega_2)^\theta \quad (1.6)$$

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.²⁴ An agent maximizes (6) under the constraints (4) for money and (5) for effort. For money, the maximization yields the tangency condition:

$$\frac{c_t + \omega_1}{c_{t+k} + \omega_2} = (P\beta^{\mathbb{1}_{t=0}}\delta^k)^{\left(\frac{1}{\alpha-1}\right)} \quad (1.7)$$

For effort, the maximization yields the tangency condition:

$$\frac{e_t + \omega_1}{e_{t+k} + \omega_2} = \left(\frac{1}{R}\beta^{\mathbb{1}_{t=0}}\delta^k\right)^{\left(\frac{1}{\gamma-1}\right)} \quad (1.8)$$

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. The estimated equations take the form:

$$\ln\left(\frac{u_t + \omega_1}{u_{t+k} + \omega_2}\right) = \left(\frac{\ln\beta}{\theta - 1}\right)\mathbb{1}_{t=0} + \left(\frac{\ln\delta}{\theta - 1}\right)k + \left(\frac{1}{\theta - 1}\right)\ln(Rate) \quad (1.9)$$

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 $\ln\left(\frac{u_t + \omega_1}{u_{t+k} + \omega_2}\right)$ 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.²⁵ 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,

²⁴Estimating 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.

²⁵Corner choices represent the situations in which either c_t or c_{t+k} are null. These cases represent the bounds $\left[\frac{0+\omega_1}{u_{t+k}+\omega_2}, \frac{u_{t+k}+\omega_1}{0+\omega_2}\right]$ that change for each exchange rate and decision made by each participant.

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 \(2002\)](#) task, and subsequently estimated the discounting levels.²⁶

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

$$PV_S = (u_t + \omega_1)^\theta + \beta^{1-t=0} \delta^k (\omega_2)^\theta \quad (1.10)$$

$$PV_L = (\omega_1)^\theta + \beta^{1-t=0} \delta^k (u_{t+k} + \omega_2)^\theta \quad (1.11)$$

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

$$P(\text{choice} = S) = \frac{PV_S^{\frac{1}{\mu}}}{PV_S^{\frac{1}{\mu}} + PV_L^{\frac{1}{\mu}}} \quad (1.12)$$

$$P(\text{choice} = L) = 1 - P(\text{choice} = S) \quad (1.13)$$

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 $\mu \rightarrow 0$. 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

²⁶Estimating 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.

our parameters of interest through Maximum Likelihood:

$$\ln(L(\theta, \beta, \delta, \mu, \omega_1, \omega_2)) = \sum_i [(\ln(P(\text{choice} = S)) | \text{choice} = S) + (\ln(P(\text{choice} = L)) | \text{choice} = L)] \quad (1.14)$$

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.

1.4.2 Short- and long-run time discounting

We first present time preferences over money and then, time preferences over effort.

Discounting money over time – Figures 1.2 and 1.3 display the average amount of money allocated to the sooner date for each gross interest rate (P) and time horizon in the CTB and the DMPL treatments, respectively (see values in Tables E1 and E2 in Appendix E). All curves are downward sloping, consistently with the law of demand.²⁷ 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.

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 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 within²⁸ and between²⁹ time horizons are highly significant.

²⁷At 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.

²⁸Two-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.

²⁹Two-tailed t -tests conducted on the average allocations to the sooner date in the CTB and DMPL treatments

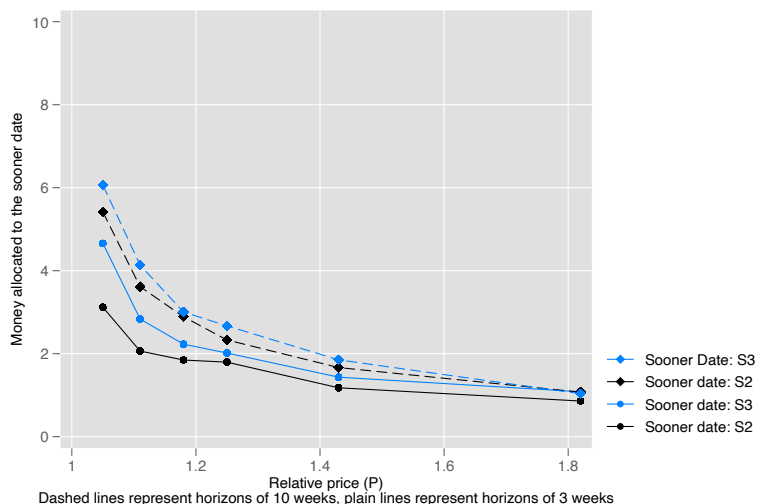


Figure 1.2: Monetary allocations in the CTB treatment

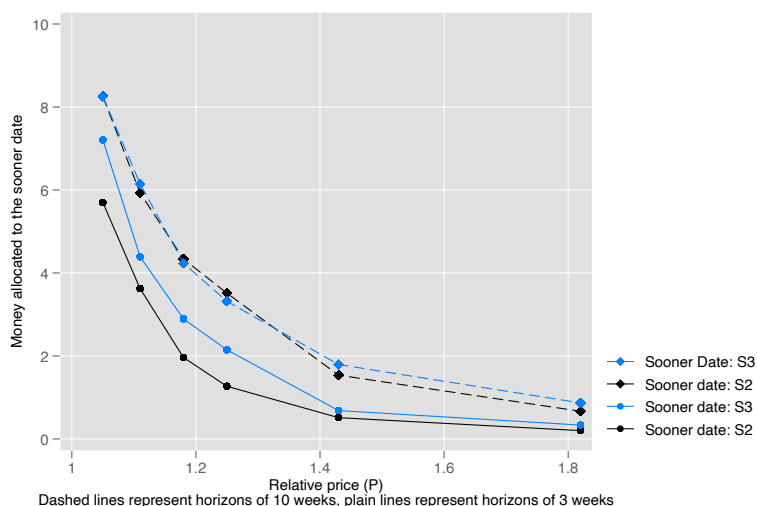


Figure 1.3: Monetary allocations in the DMPL treatment

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.

Pooling the data from all the participants (excluding only those with inconsistent –non-monotonic– choices, Table 1.1 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

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.

estimated in [Augenblick et al. \(2015\)](#) with a Two-Limit Tobit).³⁰ 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.³¹ The DMPL estimate of β is closer to the CTB estimate using NLS (1.043). Overall, the average level of future bias implies that when comparing 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 1.1: Average estimates of time preferences over money

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

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

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

³⁰The 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.

³¹A 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](#)).

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 1.4 and 1.5 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).³²

Regarding the discounting patterns, there is no evidence of present bias in the CTB treatment: the two curves in Figure 1.4 largely overlap. When participants had to allocate all their effort to a single date, in Figure 1.5 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 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.³³ 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 1.2 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

³²At 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.

³³Two-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).

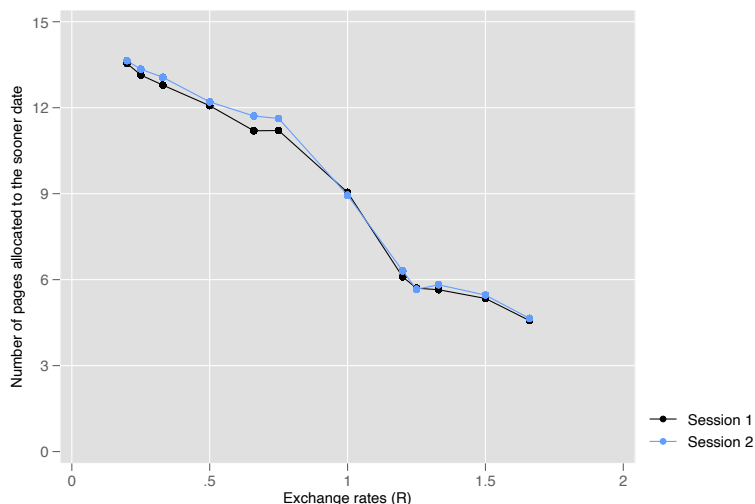


Figure 1.4: Effort allocations in the CTB treatment

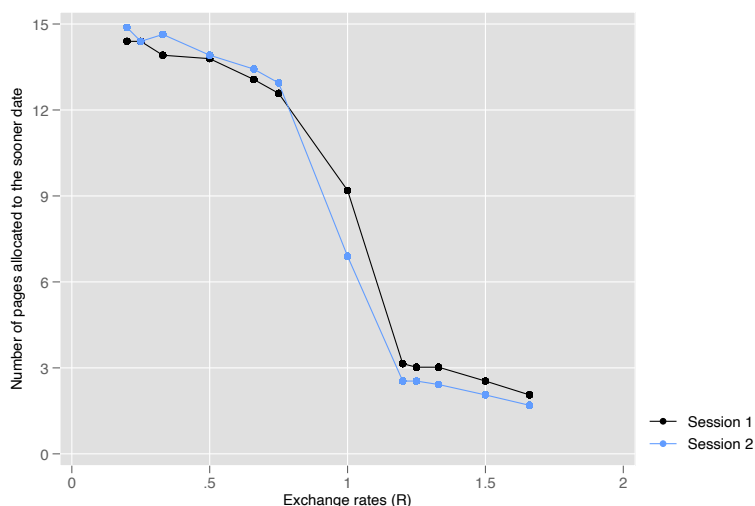


Figure 1.5: Effort allocations in the DMPL treatment

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).

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).

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

Table 1.2: Average estimates of time preferences over effort

	CTB			DMPL
	OLS (1)	Two-Limit Tobit (2)	NLS (3)	MLE (4)
γ	1.308*** (0.030)	1.171*** (0.025)	1.750*** (0.117)	-
δ	1.003*** (0.004)	1.003*** (0.003)	1.006*** (0.003)	0.997*** (0.001)
β	1.018*** (0.067)	1.009*** (0.067)	1.045*** (0.066)	0.969*** (0.015)
<i>Ho</i> : $\delta = 1$, p	0.372	0.402	0.038	0.065
<i>Ho</i> : $\beta = 1$, 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 1.3 summary statistics on the estimated percentage of job seekers whose behavior exhibited present bias, for each dimension.³⁴ 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 1.3: Summary statistics on Individual 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

³⁴Figures 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.

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 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.

1.4.3 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 undertaken to exit unemployment (*e.g.*, sending a CV, contacting a firm directly).³⁵ We also analyzed how time preferences impacted the log of the reservation wage reported by the participants in the survey.

Table 1.4 presents the estimates of OLS regressions on the pooled sample of partic-

³⁵The 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.

ipants 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.³⁶ To control for risk, we used the BRET measure to have an estimate inferred from a common method between all participants.³⁷ 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 displays the detailed coefficients of these controls).^{38, 39}

Table 1.4 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 1.4 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

³⁶Because the discrepancy in variance between the Maximum Likelihood and OLS methods is large, the standardized δ parameters were multiplied by 100 to ease interpretation.

³⁷We 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 $p = 0.034$).

³⁸For 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.

³⁹The 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.

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.

Table 1.4: Time preferences and job search effort

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

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

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 1.4

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%.⁴⁰ 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.

⁴⁰The marginal effect on applications was estimated using an ordered logit model.

1.4.4 Time preferences and job search outcomes

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.⁴¹ Although imperfect, these responses should nevertheless be correlated to unemployment exit and inform us about the return to search.

Table 1.5 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)).⁴² We regressed the same set of preferences variables, interaction terms, and controls as those in Table 1.4 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 1.4), Table 1.5 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

⁴¹The mean unemployment spell lasted 329 days in France in 2021 - *source* : *Pôle-Emploi* - "<https://www.pole-emploi.org/statistiques-analyses/demandeurs-demploi/trajecitoires-et-retour-a-lemploi/duree-de-chomage-4e-trimestre-2021.html?type=article>" Accessed on March 3, 2023.

⁴²We 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 1.5.

Table 1.5: 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 get job interviews (models (1) and (3)) and the probability to get a job offer (models (2) and (4)). Robust standard errors are in parentheses. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). The reference categories are: 18/24 years for age; high school (HS) degree for education; contractual terminations and resignations for the motive of registration to the PES. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

indifference between the future and the present. For long-run impatience over effort, the only significant (at the 1% level) and positive effect of δ was found for the second quartile in the DMPL treatment 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 1.5). Consistent with DVP's prediction, this finding is not surprising because of procrastinators' lower level of search (Table 1.4). We only found this effect

with DMPL.

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.⁴³ 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.

⁴³In 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.

1.4.5 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 1.6 displays the same regressions as those presented in Tables 1.4 and 1.5, except that time and risk preferences are those from the pre-experimental survey.

Table 1.6: Search effort and outcomes - Parameters from the pre-experimental survey

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

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

In Table 1.6, 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 1.6 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.

1.5 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.

1.6 Appendices

Appendix A: Instructions Instructions are available at : <https://nuage.gate.cnrs.fr/index.php/s/PE>

Appendix B: Additional figures

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

Article 1
Titre :
Auteur(s) :

Article 2
Titre :
Auteur(s) :

Article 3
Titre :
Auteur(s) :

Figure B1: Screenshot of the real effort task

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

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

cette semaine : 14.3 € dans 3 semaines : 0 €

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

cette semaine : € dans 3 semaines : €

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

cette semaine : € dans 3 semaines : €

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

cette semaine : € dans 3 semaines : €

Figure B2: Screenshot of the monetary allocation decisions

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

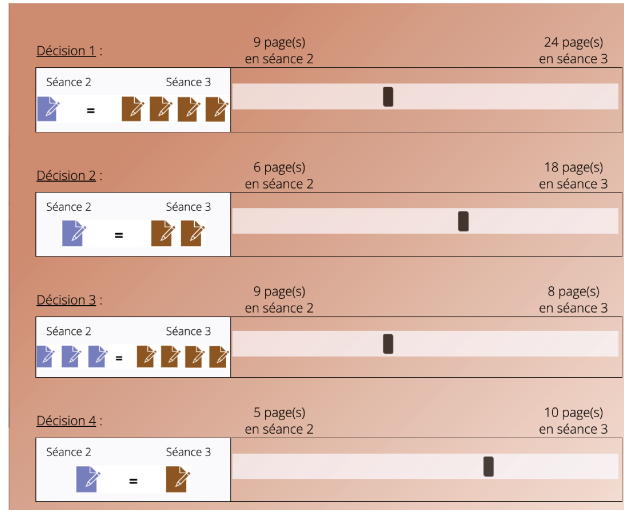


Figure B3: Screenshot of the effort allocation decisions

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

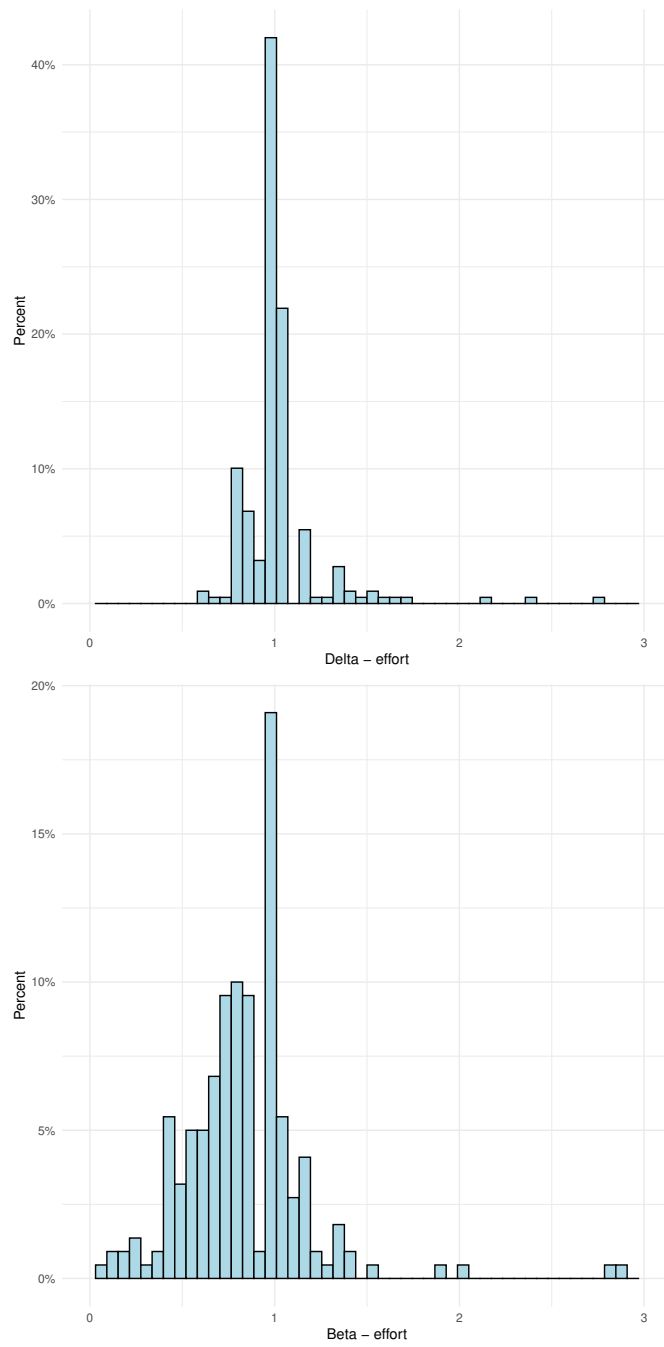


Figure B4: Distribution of the individual estimates of time preferences over effort

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

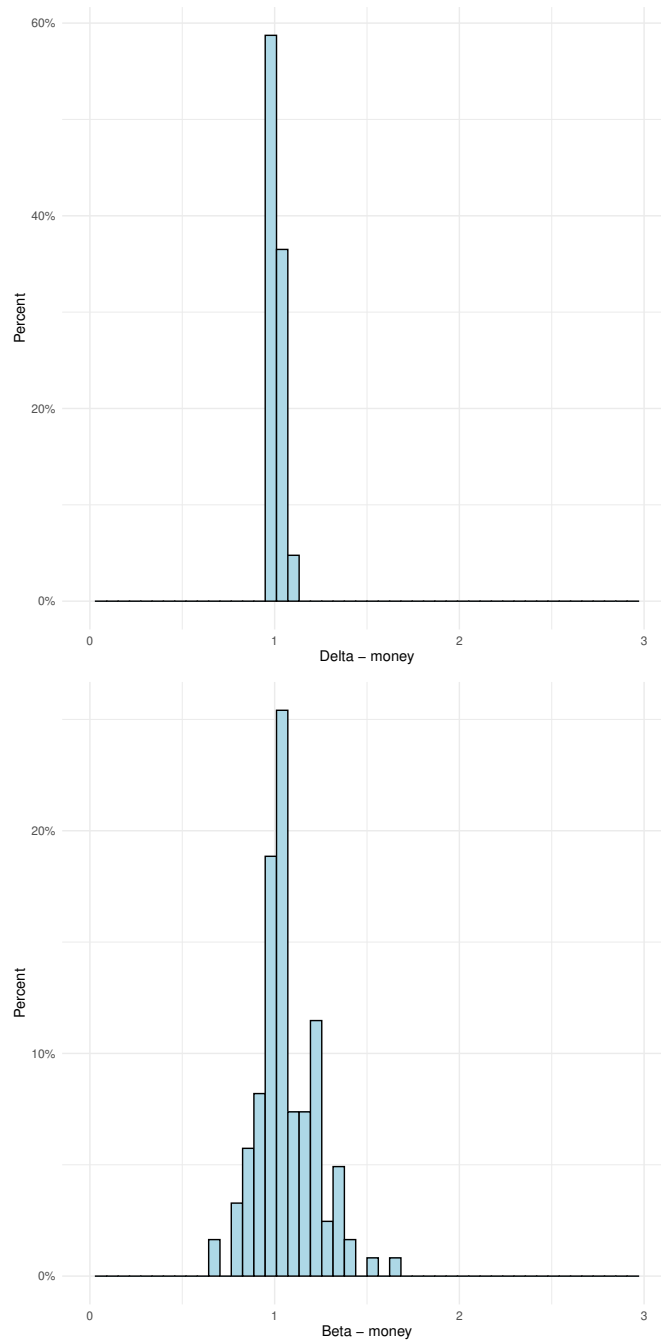


Figure B5: Distribution of the individual estimates of time preferences over money

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

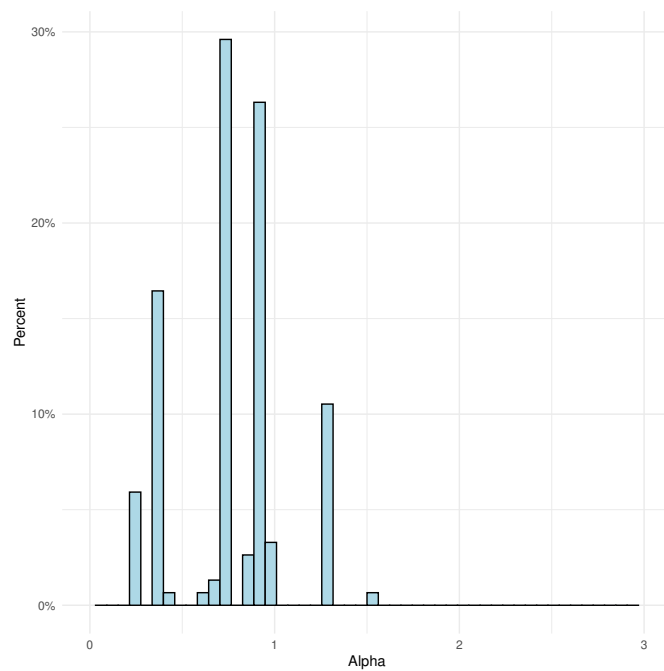


Figure B6: Distribution of the individual estimates of risk preferences

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

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

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

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

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

Table C2: Job search characteristics of the participants and attrition

Variables	In experiment until the end (1)	Started experiment but did not finish (2)	In survey but not in experiment (3)
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

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

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

Table D2: Effort choice sets

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix F: Individual determinants of risk and time preferences

Table F1: Individual determinants of risk and time preferences

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

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The value of α is directly recovered from the individual choices in the CTB treatment or estimated from choices in the Holt and Laury lotteries in the DMPL treatment. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the DMPL treatment (estimated by Maximum Likelihood). “Single-use goods” (food, oil, medicines, ...), “Average-life goods” (shoes, clothes, toys, leather goods, ...), and “Durable goods” (domestic appliances, furniture, cars, ...) correspond to recent purchases since they became unemployed. “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*** (0.037)	0.807*** (0.039)	0.868*** (0.018)	0.732*** (0.041)	-
δ	0.999*** (0.0006)	0.998*** (0.0006)	0.998*** (0.0003)	-	0.997*** (0.0004)
β	1.131*** (0.023)	1.126*** (0.024)	1.055*** (0.013)	-	1.017*** (0.015)
<i>Ho</i> : $\delta = 1$, p	0.018	0.001	0.000	-	0.000
<i>Ho</i> : $\beta = 1$, p	0.000	0.000	0.000	-	0.257
N	1584	1584	1584	1350	1656

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

Table G2: Preferences parameters for effort excluding non-switchers

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

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

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

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

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

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

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

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

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

Appendix I: Regression tables on search effort with alternative specifications

Table 11: Time preferences and job search effort: Quartile specification, CTB treatment

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

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

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

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

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

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

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

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

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

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

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

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

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

Notes: The regressions are OLS models. Robust standard errors are in parentheses. The reservation wage is expressed in log. The value of the Stone Geary parameter is 0.01 for individual monetary patience estimates and 5 for effort estimates. The risk measure is the number of boxes opened in the BRET. The values of δ and β are the individual estimates from either the CTB treatment (estimated by OLS) or the 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 (0.005)	0.004 (0.004)	0.004 (0.005)	0.002 (0.004)	0.003 (0.004)	0.001 (0.004)	0.002 (0.004)	0.002 (0.003)
δ (money)	-0.009 (0.006)	-0.010 (0.008)	-0.010 (0.009)	-0.004 (0.008)	-	-	-	-
DMPL \times δ (money)	0.009 (0.006)	0.010 (0.008)	0.011 (0.009)	0.004 (0.008)	-	-	-	-
β (money)	-0.090 (0.183)	-0.065 (0.168)	0.019 (0.189)	0.012 (0.183)	-	-	-	-
DMPL \times β (money)	0.049 (0.223)	0.167 (0.186)	0.168 (0.206)	0.137 (0.193)	-	-	-	-
δ (effort)	-	-	-	-	-0.002* (0.001)	-0.002*** (0.001)	-0.001 (0.001)	-0.00007 (0.0009)
DMPL \times δ (effort)	-	-	-	-	-0.005 (0.043)	0.043 (0.043)	0.0329 (0.040)	0.016 (0.037)
β (effort)	-	-	-	-	-0.165 (0.175)	-0.173 (0.171)	-0.219 (0.156)	-0.074 (0.133)
DMPL \times β (effort)	-	-	-	-	0.128 (0.217)	0.401* (0.211)	0.293 (0.210)	0.071 (0.182)
DMPL treatment	0.002 (0.279)	0.203 (0.315)	0.451 (0.294)	0.425* (0.256)	0.077 (0.703)	0.903 (0.696)	0.833 (0.663)	0.581 (0.599)
Female	-0.146 (0.224)	-0.174 (0.193)	-0.155 (0.185)	-0.125 (0.171)	-0.207 (0.170)	-0.101 (0.167)	-0.150 (0.170)	-0.091 (0.153)
25/49 years old	0.006 (0.275)	-0.137 (0.252)	-0.150 (0.243)	0.076 (0.221)	-0.073 (0.210)	-0.174 (0.211)	-0.220 (0.206)	-0.009 (0.182)
50+	0.438 (0.443)	-0.019 (0.511)	0.099 (0.493)	0.201 (0.406)	-0.115 (0.285)	-0.404 (0.340)	-0.453 (0.357)	-0.125 (0.293)
Less than HS (High School)	-1.489** (0.598)	-0.698 (0.560)	0.458 (0.523)	0.523 (0.448)	-1.225*** (0.393)	-0.912*** (0.329)	-0.224 (0.407)	-0.153 (0.537)
HS+2	-0.537 (0.591)	0.275 (0.569)	1.129** (0.549)	0.695 (0.494)	-0.283 (0.436)	0.255 (0.423)	0.931** (0.406)	0.593* (0.339)
HS+3/4	0.045 (0.539)	0.453 (0.531)	1.203** (0.502)	0.878* (0.467)	-0.010 (0.397)	0.095 (0.383)	0.730* (0.372)	0.752** (0.321)
HS+5 and more	-0.743 (0.470)	0.045 (0.480)	0.778* (0.468)	0.675 (0.444)	-0.644** (0.314)	-0.259 (0.310)	0.356 (0.330)	0.464 (0.291)
Professional training	0.741 (1.018)	0.867 (0.922)	1.441* (0.738)	1.011 (0.716)	0.148 (0.923)	0.265 (0.828)	0.685 (0.604)	0.354 (0.639)
Number of registrations (PES)	1.026*** (0.337)	0.434 (0.277)	-0.0715 (0.260)	-0.883*** (0.336)	0.0395 (0.457)	-0.230 (0.478)	-0.751 (0.469)	-0.559** (0.279)
Contract end and econ layoff	0.765** (0.310)	0.803** (0.308)	0.772** (0.299)	0.346 (0.249)	0.162 (0.247)	0.249 (0.245)	0.306 (0.261)	0.246 (0.217)
New entrants and career change	0.510 (0.355)	0.288 (0.365)	0.410 (0.339)	-0.021 (0.296)	0.204 (0.281)	0.0769 (0.278)	0.133 (0.285)	-0.064 (0.254)
Other	0.301 (0.303)	0.194 (0.353)	0.367 (0.344)	-0.115 (0.299)	-0.121 (0.243)	-0.027 (0.266)	0.132 (0.281)	0.020 (0.237)
Constant	1.024 (0.770)	2.032*** (0.765)	2.145*** (0.727)	3.928*** (0.682)	2.403*** (0.595)	3.137*** (0.611)	3.534*** (0.634)	3.816*** (0.480)
Observations	125	125	125	125	202	202	202	202
R^2	0.192	0.169	0.213	0.164	0.109	0.103	0.112	0.099
Adjusted R^2	0.055	0.028	0.080	0.022	0.021	0.015	0.024	0.011

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

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

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

	Search outcomes and time preferences over money		Search outcomes and time preferences over effort	
	Got interviews (1)	Got offers (2)	Got interviews (3)	Got offers (4)
Risk (BRET)	0.007 (0.018)	0.012 (0.034)	0.031** (0.015)	0.015 (0.014)
<u>δ (money)</u>				
25% < δ (money) < 50%	-3.303** (1.535)	-3.274** (1.356)	-	-
50% < δ (money) < 75%	-1.327 (1.286)	-3.041 (2.520)	-	-
75% < δ (money)	-1.183 (1.195)	-0.674 (1.596)	-	-
<u>β (money)</u>				
25% < β (money) < 50%	-1.714 (1.386)	0.633 (2.403)	-	-
50% < β (money) < 75%	0.732 (1.160)	1.312 (1.720)	-	-
75% < β (money)	-0.449 (1.569)	-0.248 (1.639)	-	-
<u>δ (effort)</u>				
25% < δ (effort) < 50%	-	-	0.245 (0.689)	-1.255 (0.801)
50% < δ (effort) < 75%	-	-	0.008 (0.877)	-1.460* (0.864)
75% < δ (effort)	-	-	0.236 (0.899)	-1.285 (1.032)
<u>β (money)</u>				
25% < β (money) < 50%	-	-	1.210 (0.867)	-1.378* (0.718)
50% < β (money) < 75%	-	-	0.461 (0.804)	-0.432 (0.880)
75% < β (money)	-	-	-0.160 (0.856)	-0.869 (0.954)
Individual controls	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 (0.016)	-0.007 (0.015)	-0.022** (0.009)	0.0001 (0.009)
<u>δ (money)</u>				
25% < δ (money) < 50%	-0.863 (1.032)	-1.020 (1.063)	-	-
50% < δ (money) < 75%	-1.640* (0.990)	0.195 (1.102)	-	-
75% < δ (money)	-1.412 (1.114)	0.188 (1.469)	-	-
<u>β (money)</u>				
25% < β (money) < 50%	-0.598 (1.086)	-0.541 (1.067)	-	-
50% < β (money) < 75%	0.752 (1.108)	-2.198* (1.133)	-	-
75% < β (money)	-0.244 (1.198)	-1.582 (1.557)	-	-
<u>δ (effort)</u>				
25% < δ (effort) < 50%	-	-	14.58*** (1.194)	1.473 (1.448)
50% < δ (effort) < 75%	-	-	0.276 (0.676)	1.051 (0.683)
75% < δ (effort)	-	-	0.807 (0.994)	-0.077 (1.071)
<u>β (money)</u>				
25% < β (money) < 50%	-	-	-0.363 (0.845)	-1.131 (0.806)
50% < β (money) < 75%	-	-	-15.14*** (1.469)	-1.519 (1.711)
75% < β (money)	-	-	0.284 (0.948)	-0.538 (0.846)
Individual controls	Yes	Yes	Yes	Yes
Unemployment controls	Yes	Yes	Yes	Yes
Observations	68	68	114	114

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

Table J3: Long term employment outcomes

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

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

Chapter 2

Confident or discouraged? Experimental and survey evidence on job seekers confidence and belief updating biases

1

2.1 Introduction

A common assumption of classical job search models is that job seekers rationally form beliefs about their prospects on the job market, using all available information to set an optimal search strategy. When their information set is incomplete, or when new pieces of information arise, job seekers are assumed to update their beliefs using Bayes' rule and subsequently adjust their search strategy. However, these assumptions are challenged by a growing literature which shows that persistent behavioral biases affect both initial beliefs and the way they are revised (Bénabou, 2015). Labor economists have recently considered how these biases may affect labor markets and especially job search (Mueller and Spinnewijn, 2021; Santos-Pinto and de la Rosa, 2020).

Beliefs regarding oneself are often self-serving. In many different contexts, people have been shown to systematically overestimate their own abilities and probability of positive outcomes. These tendencies extend to the labor market: unemployed job seekers tend to predict their unemployment spells will be shorter than the true length, whether these beliefs were elicited in the short or long run (Spinnewijn, 2015; Santos-Pinto and de la Rosa, 2020; Mueller et al., 2021) and in various job markets (for instance see Abebe et al. (2020); Bandiera et al. (2021); Banerjee and Sequeira (2020) for very recent evidences in emerging countries).

While pervasive, initially overconfident beliefs would not represent such a large threat

¹This chapter is joint with Michael Cooper

to job finding if they were rationally updated. Throughout an unemployment spell, successive rejections should lead job seekers to adjust their beliefs in the right direction. However, the assumption of rational Bayesian updating has also recently been challenged by empirical evidences. In their work studying the decline of employment prospects with the unemployment length, [Mueller et al. \(2021\)](#) find that over the unemployment spell, job seekers optimistic beliefs remain constant. The reason for this lack of updating, out of the scope of their paper, remains to be clarified.

So far, the literature on job search has only scratched the surface of belief-related biases, leaving us with questions regarding their potential consequences. First, while overconfident beliefs about labor market prospects seem to affect search outcomes (), the channel through which they arise, and the behavioral mechanisms that they trigger are not clear. On the one hand, overconfident beliefs about one's own job prospects may lead one to set reservation wages too high or search effort too low. On the other hand, holding a positive vision of oneself could lead to greater long-term motivation due to the returns to search effort being perceived as higher. Identifying which mechanism prevails may help policymakers advise job seekers more effectively by adjusting beliefs and/or fostering motivation. Second, overconfidence is not only absolute, it may also be relative ([Moore and Healy, 2008](#)). In a competitive environment such as job search, beliefs about one's worth and prospects relative to similar individuals on the job market should affect search as well. Yet this aspect of overconfidence has not attracted as much attention in the literature as absolute aspects of overconfidence. Here again, advice to job seeker should substantially differ depending on the type of overconfident beliefs held. Third, once overconfident beliefs are formed on the job market, the mechanisms leading to a lack of updating are unknown. Still, in modern job search where rejections are the norm, a natural suspect for the lack of updating is motivated beliefs. To preserve their motivation and a positive view of themselves, job seekers may update beliefs too conservatively and/or by giving more weight to good news but not to bad news. Such motivated beliefs may lengthen the unemployment spell and would call for targeted advice to job seekers.

The objective of our paper is thus to test the effects of different types of overconfident beliefs and belief updating biases on job search behavior and related labor market outcomes. The traditional approach in the literature to study the beliefs of job seekers relies mainly on survey data. The novelty in our approach is to measure the relevant behavioral biases using an incentivized experiment with recently unemployed job seekers, and following up with linked administrative data on their labor market behaviors and outcomes. We measure the subjects' tendency to form overconfident beliefs by asking them to forecast their performance (both absolute score and performance relative to other subjects) in a real effort task. We then measured their belief updating behavior by presenting noisy signals about their performance ranking, eliciting new beliefs about their

performance after each signal. To disentangle ego-related motivated beliefs from general mathematical errors in Bayesian updating, we have each subject complete a theoretically identical belief updating task unrelated to their own performance. Finally, we included a post-experiment survey asking about their beliefs about employment prospects and job search effort, all linked to administrative data following the unemployment spells of our subjects up to a year after the initial experiment.

We contribute to the literature in several ways. First, we provide estimates of confidence-related biases among recently unemployed job seekers. The estimates are particularly credible due to being elicited in an incentive-compatible experiment design. [Mueller and Spinnewijn \(2021\)](#) show that beliefs about job finding should affect the search effort since a confident job seeker may believe that his return to search is higher and subsequently search more. But reverse causality may be at play if feedback from job search changes one's beliefs about job prospects. To circumvent this issue, we elicit job seekers' beliefs about the return to search at the very beginning of their spells. Using the French Public Employment Services database ("Unedic" and "Pole-Emploi") we are able to target individuals in the first few months of their spells where the individual prospects about the return to employment have not been heavily affected by the early results of search. Additionally, we provide measures of relative confidence (i.e., comparisons against other similar job seekers) while the literature typically focuses only on absolute measures.

Our second main contribution is to link our incentive-compatible measures of motivated beliefs to real job search effort and outcomes. Our experimental treatment creates a situation where updating biases are likely to show up due to motivated beliefs. We elicit subjects' initial beliefs about their performance in our task relative to that of a randomly selected group of participants and analyze how they update after receiving two noisy signals. This design closely follows that of [Möbius et al. \(2022\)](#); [Ertac \(2011\)](#) and [Eil and Rao \(2011\)](#) with the difference that we keep the design simpler to reduce the cognitive burden on our sample of job seekers. We chose a relatively entertaining real effort task, accessible to all irrespective of their education and abilities, and elicited beliefs about being above the median in terms of performance (as in [Möbius et al. \(2022\)](#)). This choice of real effort task reduces drop-outs and limits the noise in subject's answers. In a similar way as [Ertac \(2011\)](#) and [Eil and Rao \(2011\)](#), we expect subjects to engage sufficiently in our task so that they subsequently gain utility from the belief that they performed well. We then compare the behavior in this self-related updating task to predictions from Bayes' rule and to subject behavior in a neutral updating task unrelated to self-image. We expect that this tendency to behave in a self-protective way spreads over different contexts in life due to the similarity of the updating task to noisy feedback from real job search. If anything, beliefs about one's career prospects may have a greater impact on utility from ego than beliefs about performance in an entertaining real effort task. We then relate these ego-relevant and neutral belief updating biases to search effort,

reservation wages, and short- and long-run outcomes of search.

We report several key results. First, as suggested by the literature (Spinnewijn, 2015; Mueller and Spinnewijn, 2021), we find that job seekers largely underestimate their own unemployment duration. However, on average they do not believe their unemployment duration will be shorter than other job seekers in their same situation. We were unable to reproduce experimentally this pattern in our real effort task, as our subjects were rather pessimistic compared to their own absolute performance, but believed themselves to perform better than others. Second, certain confidence measures related to the job market are associated with job market outcomes. Job seekers who report high levels of absolute confidence in unemployment duration were less likely to obtain job interviews and offers and had longer unemployment spells. However, job seekers who reported high levels of *relative* confidence (i.e., their unemployment spell would be shorter than others in a similar situation) were more likely to have better search outcomes in the short and long run. We do not detect any effect of job-related confidence measures on traditional search effort metrics or reservation wages, implying the impacts operate through other channels. Third, we replicate typical results from the literature of conservatism and asymmetry in the updating tasks in our incentivized experiment (Clark and Friesen, 2009; Eil and Rao, 2011; Möbius et al., 2022). When relating the job search and the updating behavior in the experiment, we find that those making the bigger mistakes from Bayes in self-relevant contexts also tend to have longer unemployment spells. This effect seems to stem from the reduced search time of individuals who over-interpret good and/or bad news. Fourth, confidence measures from our incentivized experiment have only weak evidence of effects on search effort and outcomes. Relative underconfidence in the real effort task was associated with longer unemployment duration, while relative overconfidence in the real effort task was associated with a lower probability of obtaining a job offer early in the unemployment spell. None of our experimental measures of confidence were able to explain long term outcomes.

Overall our findings imply that active labor market policies should systematically investigate the confidence biases one suffer from on the job market. Doing so would allow to provide tailored advice that correctly calibrate individuals' beliefs while maintaining their motivation over time.

The rest of the paper will be organized as follows. Section 2 presents our hypotheses, Section 3 describes the experimental design and the data, Section 4 describes our results, and Section 5 concludes.

2.2 Hypotheses

The literature has only recently applied findings about overconfidence and bias in belief updating to the job market. For that reason, our hypotheses serve two main purposes.

First, we test whether the most recurrent findings from the behavioral economics and psychology literature extend to a general sample of job seekers' beliefs about their labor market prospects. Second, we test the effects of those biases on search behavior and outcomes.

Evidence from psychology shows that overconfident beliefs about one's own ability and situation are extremely common (Moore and Healy, 2008). Spinnewijn (2015) applies this to the job market, showing that job seekers in the USA tend to start their job search with overconfident beliefs about their unemployment duration, possibly leading them to provide too little search effort.

While it is clear that confidence should matter for job search, there are multiple types of confidence which may apply. Moore and Healy (2008) describe two types of confidence biases that may be at play in our case.² Overestimation refers to believing that one's absolute performance or ability is higher than one's actual performance or ability. This is the type of confidence found in Spinnewijn (2015), where individuals over-estimate their chances to find a job in the short-run. Overplacement (also referred to as the "better-than-average effect") refers to incorrectly believing that one's relative performance or ability is higher than others' performance or ability – in other words, incorrectly placing oneself too high in the distribution. Evidence that this bias matters for job search was found by Gee (2019). She shows that displaying the number of applicants on offers posted on the online job search platform LinkedIn increased the probability that a job seeker completes an application by 3.5%. This effect could result from inferring good news about the competition for the offer but also from the beliefs one has regarding his relative competence.

Given these results from the literature, we formulate the following general conjecture:

Hypothesis 1. Overconfidence: *Subject beliefs will show overconfidence (both overestimation and overplacement) regarding performance in our experimental real effort task and beliefs about job search prospects.*

In spite of the evidence we have on overconfidence in the job market, one caveat should be noted. Most of the results we have so far come from the USA. The labor market in France, where the unemployment rate is more than the double of that in the USA since 2014³, with an average time spent unemployed close to a whole year, may represent a particularly different context. There is evidence that job seekers facing adverse conditions may become underconfident, discouraged, and suffer mentally and possibly even physically due to unemployment (Wanberg, 2012). This demotivation effect could result from reactions to the information received on the market, which directly questions how one update beliefs when receiving new pieces of relevant information.

²A third confidence type called over-precision involves excessive precision in beliefs, but the typical incentive-compatible experimental measurement of this bias was too complicated and time-consuming to implement in our sample. A typical measurement method involves eliciting 90% confidence intervals from subjects, where a finding that the intervals only include the correct answer 50% of the time would be strong evidence of over-precision.

³source OECD data : <https://data.oecd.org/unemp/unemployment-rate.htm>

Our next hypotheses concern updating beliefs in the labor market. Overconfident initial beliefs about one’s job prospects may be less harmful if job seekers update beliefs optimally using Bayes’ Rule. However, recent evidence suggests that although people tend to follow the general principles of Bayesian updating well (i.e., updating beliefs in the correct direction), they make systematic errors in the magnitude of updating (Grether, 1980; McKelvey and Page, 1990). Specifically, the dominant behavior is to underweight (overweight) signals that were likely (unlikely) to occur (Massey and Wu, 2005). This behavior consisting in downplaying all signals’ strength is called conservatism. The literature has also shown that one of the main drivers of conservatism was the ego-relevance of the situation (Ertac (2011)). During job search, a common experience is to send many applications but receive few callbacks, interviews, and offers. This implies that job seekers mainly receive information that should lead them to revise downward their beliefs about their abilities and job finding prospects. For this reason, we formulate the following hypothesis about belief updating:

Hypothesis 2. Conservatism: *Subjects will on average update their beliefs too little after receiving informative signals. This tendency will be exacerbated when the information is ego-relevant.*

Recent research has also shown that positive and negative signals are interpreted differently when the signals involve self-image. In order to protect themselves, people often update asymmetrically: they overweight flattering signals and underweight painful ones. However, conflicting results have been found on asymmetry. Most papers show that subjects overweight positive feedback in order to maintain a positive self-image (Möbius et al. (2022); Eil and Rao (2011)). The method used usually involves comparing belief updating after self-relevant signals to belief updating after self-irrelevant signals. In contrast, one paper, using a very similar method, has found that subjects sometimes overweight negative feedback when it involves their self image (Ertac (2011)). Asymmetry also seems conditional on the extent to which the signal is informative about the self, which suggests that biased updating is self-serving in a protective way. However, the results in Ertac (2011) indicates that this bias can sometimes be self-harming. In light of this evidence, we formulate the following hypothesis:

Hypothesis 3. Asymmetry: *Subjects will update their beliefs more after receiving positive self-relevant signals than they do after receiving negative self-relevant signals.*

In classical job search models with endogenous search (i.e., Lippman and McCall (1976)), several effects may result from overconfident beliefs with biased belief updating. First, an individual starting unemployment overconfident about returning to work should stay unemployed longer because incorrect, slowly updating beliefs would lead to a suboptimal search strategy. Second, overconfidence about the unemployment length should lead to lower search effort, since holding correct beliefs about a potentially long unemployment spell would normally lead to higher search effort in order to compensate

for the utility loss of staying unemployed.⁴ Overconfidence about one’s own abilities and job prospects should also result in higher reservation wages. As stated by [Mueller and Spinnewijn \(2021\)](#), when deciding to accept a job offer, individuals compare the future value of accepting the offer to the future value of continuing to search for a better job offer. If one overestimates one’s value on the job market, the wage offer received should be in a relatively lower position in his subjective wage distribution, and/or will be evaluated against a lifetime value of accepting the job offer with an overestimated probability to draw higher offers from the wage distribution, leading in both cases to a higher probability of rejecting the offer. We expect both search and reservation wage effects to drive the probability to exit unemployment down over time. If indeed overconfidence is the predominant bias among job seekers, updating biases should reinforce both effects by slowing down the adjustments of beliefs to the true state of the market. This leads to the following hypotheses:

Hypothesis 4. Overconfidence and Search: *Overconfident subjects will exert too little search effort and set their reservation wages too high, leading to a delayed return to employment.*

Hypothesis 5. Updating Bias and Search: *Being prone to updating biases leads to longer unemployment spells, especially when initial beliefs are more overconfident.*

2.3 Experimental design and dataset

2.3.1 Data

Our participants were sampled from the french Public Employment Services (PES)⁵. In France, any individual seeking for a job can register to a local agency of the PES to require assistance in their job search. Registering to an agency also represents a mandatory condition for eligible job seekers willing to receive their unemployment benefits. The PES require its beneficiaries to update their job search information every month until they find a job. ⁶ 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 of potential participants, trace each participant’s history in the labor market since their first registration, and follow the

⁴This statement should hold given a relatively favorable market tension and a cost function that does not increase too steeply. Otherwise, the marginal cost of increased effort will not be compensated by its marginal benefits.

⁵This database administered by Pôle Emploi is called the "Fichier National des Allocataires (FNA)".

⁶Once the eligibility period for receiving unemployment benefits ends, a job seeker is no longer requested to update her information every month, except if she is willing to keep on receiving the assistance of a caseworker. Assistance remains accessible even to job seekers who no longer receive benefits.

updating of their situation with the PES about a year after the end of the experiment.⁷

We randomly selected 20 thousand newly registered job seekers from the PES database. Because no clear theoretical prediction link clearly job search, confidence and updating, we built a sample fitting the most simple job search situation with no on the job search. To maintain the situation simple, we also excluded job seekers over 55 years old and below 18 for the complexity of their job market specificities. To keep the updating situation as comparable as an experiment allows between our experimental situation and job search, we sampled individuals who registered to the PES in the four preceding months. Job seekers in this situation likely had not received a significant amount of feedback from their job search, but spent just enough time unemployed to get acquainted with the job search task. The choice of this time frame was also guided by operational consideration as it may take up to four months for the database to be updated with the information we required for our sampling.

To avoid any biases coming from job seekers' fear to be observed by the PES, we framed our study as an academic one even though we had the full agreement and support of the PES. Among our 20 000 selected job seekers, 19 000 had valid emails. An invitation email was sent to each individual. Once received, invited job seekers could click on a link to participate on our OTree (Chen et al., 2016) server and we closed registrations once we reached 350 completed questionnaires.

Table 2.1 shows how our participants differ from the 20 000 sampled job seekers using two-tailed t-tests. Our sample over-represents highly educated individuals with masters degrees and above, and under-represents job seekers with professional training and who have at most a high school degree. This bias can be attributed to the low provision/use of computer and tablets among the less educated job seekers. Our sample also over-represents individuals working in the banking sector and in communication and firm support occupations.

⁷A 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.

Table 2.1: Socio-Demographic Characteristics of the Initial and Final Samples of Job Seekers

	Invited sample	Final sample	p-values t-tests
<u>Age categories</u>			
18/24	0.58	0.54	0.127
25/49	0.36	0.40	0.076
50+	0.06	0.05	0.677
<u>Education</u>			
Less than HS (high school degree)	0.18	0.06	0.000
HS	0.24	0.21	0.160
HS+2	0.13	0.15	0.212
HS+3/4	0.13	0.17	0.020
HS+5+	0.13	0.31	0.000
Professional training	0.18	0.09	0.000
<u>Motive of the last registration to the PES</u>			
Voluntary unemployment (resignations)	0.16	0.18	0.537
Unvoluntary unemployment (contract end)	0.26	0.25	0.710
New entrants, reorientation	0.28	0.29	0.963
Other motives	0.29	0.29	0.849
<u>Occupation</u>			
Undefined	0.30	0.28	0.338
Agriculture	0.03	0.03	0.985
Art, entertainment, catering, hotels	0.08	0.06	0.315
Bank, commerce	0.12	0.08	0.011
Communication and firm support	0.14	0.24	0.000
Construction, maintenance, industry	0.13	0.11	0.179
Health and related	0.15	0.18	0.183
Transport	0.05	0.03	0.060
<u>Previous daily wage</u>	71.56	78.79	0.152
<u>Number of past registrations to the PES</u>	1.05	1.05	0.781
<u>proportion of females</u>	.49	.52	0.213
N observations	20,000	352	-

Notes: The initial sample includes the 20000 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 experiment. The previous daily wage is expressed in euro.

2.3.2 Experimental design

In our experimental design, we aim at studying confidence and belief updating using a real effort task. First we elicit beliefs about performance before and after the task to measure confidence. Second, we elicit beliefs about own performance ranking to observe updating patterns, and control, within subject, for general errors in updating using a control updating task. In this section, we detail the experiment course.

Once they clicked on our link, participants were sent to our online OTree experiment and were told about the course of the experiment. Participants could complete the experiment at any time of the day and were invited to email us in case they needed more information. The overall experiment was kept particularly simple to avoid drop-outs.

The online study was composed of the main experiment part followed by a post-experimental questionnaire asking about the participant's job search. The main experiment unfolds in three parts.

Part One : Real effort and confidence – Subjects were first asked to complete a

real effort task, without any real-time feedback about their own performance or of others. They were first introduced to the task with a detailed explanation and a visual display (Figure C1 in Appendix). Before completion, participants were asked to predict their own number of correct answers/task completed. They were then asked the same question about the performance of a sample of 20 job seekers randomly sampled from the same pool of individuals they were sampled from. This group was referred to as the *comparison group* and was composed of 21 individuals invited using the same invitation sample one week prior to the main experiment.

By comparing our participants' first predicted performance to their actual performance, we measured *Optimism* prior to any feedback, and by comparing their own prediction and the prediction they made about other's performance we constituted a first measure of *Placement*. After the task, subjects were again asked the exact same question about their own performance and that of others. Similarly to the measures before the task we built a measure of *Confidence* as the difference between own performance estimated after the task and realized one, and a measure of *Placement* as the difference between own performance and predicted performance of the comparison group.

Part Two : Performance feedback and updating – The second objective of our experiment consisted in observing information processing when information was self relevant. For that purpose we first asked our subjects to estimate their probability to be ranked in the top half of the respondents pool in terms of performance in the task. We then offered subjects to give them a feedback about their true rank. The feedback took the form of 2 binary (and noisy) signals about performance. The signals stated that performance was either "greater" or "lower" than half of the participants with 75% accuracy. To ease participants' understanding, and avoid biases linked to probability processing, we explained the signals reveal using an urn analogy. Subjects were told that there were two urns containing green balls labeled "higher performance" and orange balls labeled "lower performance". If they performed better than half of the comparison group, they would draw 2 balls from an urn containing 3 green balls and 1 orange ball, in case their performance was worse than half of the comparison group, they would draw 2 balls from an urn containing 3 orange balls and 1 green ball⁸. We asked them to update their probability after each signal, with a remainder of their initial estimate, and the color and label of the previously drawn signal if any. Once the updating task completed, participants were offered an opportunity to get their ranking. To elicit their willingness to pay or their willingness to accept to reveal their rank, we gave them 3€, and asked for each amount between 3 and 0 whether they were willing to pay that sum to know their ranking, and similarly we asked them for each amount whether they were willing to receive that sum to know their ranking.

⁸We insisted on the fact that the drawn ball would be put back in the urn for the next draw.

Part Three : belief updating control – Because we wanted to compare updating to a similar neutral task, we asked participants to complete a second task. Once the main updating task completed, participants were shown two urns; the blue urn with 3 blue balls and 1 red ball, and the red urn with the opposite distribution. Participants were explained that the red urn would be attributed to them with a probability equal to their initial estimate to be in the top half of the performers. They were not explicitly told that the probability was their estimate, only the value was displayed. Once an urn attributed, participants were successively shown two balls drawn from their urn. The task consisted in giving their own estimated probability that the urn they were attributed was the red one after seeing each drawn ball. Our methodology, based on [Ertac \(2011\)](#) and [Mobius et al. \(2011\)](#), holds prior beliefs constant while setting up an identical updating task; this will allow us to isolate self-image biases in updating from general cognitive errors in updating.

Real effort task – The real effort task we chose come from the psychology literature. The task is referred to as the overlapping figures task [Poppelreuter \(1917\)](#) (cf. screenshot in appendix C). It consists in a main image composed of several transparent overlapping figures, three in our task. The figures we chose were recognizable objects and animals, rotated to a random degree. Subjects were shown a set of 8 figures and had to report which of these could be recognized in the main image. A task was considered correct when all 3 images composing the main one were recognized. Subjects had 5 minutes to complete as many tasks as they could, without any real-time feedback. The task mainly required attention. Since attention is common to most occupations and since it is unlikely that our subjects would have encountered such tasks, all subjects are, ex-ante, expected to perform equally well. On average our participant completed 19.4 tasks in 5 minutes and the comparison group we used to rank them had an average of 21.8. Both means are not significantly different from each other using a U Mann-Whitney test ($p=0.33$) and the median score was, conveniently, equal to 20 in both groups. We chose this task for its simplicity and for its ability to be engaging. By engaging enough in the task, we expect subjects to consider their performance as a self-related information (e.g ego utility).

Payment procedure – We designed our payment procedure to have subjects make their most accurate possible predictions while giving their best in the task. The task was paid using a piece rate. Every correct answer given during the task was paid €0.5. Questions about own performance and average performance of the comparison group were paid €1 if the answer was in a range of $+/- 2$ around the correct answer. Finally, questions about estimates to be in the top-half were paid using an incentive

compatible BDM mechanism [Becker et al. \(1964\)](#). Two numbers between 0 and 100 were randomly drawn, if they were in the top (bottom) half, subjects were paid €1 if their stated probability was above (below) one of the drawn number. Due to the complexity of the mechanism, subjects were simply told that giving their most precise estimate was the best way to maximize their earnings. The detailed mechanism was displayed on a help box that participant could click on at the bottom of their screen.

To make sure subjects couldn't game the payment mechanism by predicting poor performance and then intentionally performing poorly, we randomly paid for their performance in the task, or for all questions about self and others performance before and after the task. Additionally we paid a participation fee equal to €6. Subjects earned on average €12 (S.D.=4.6) for their decisions including their show-up fees.

Post experiment survey – After they completed the second updating task, participants were asked to complete a questionnaire about their job search. Doing so we collected measures concerning their job search habits in the past month : the number of hours spent searching for a job each week, the frequency of use of eight search channels (on- line search engines, PES, local newspapers, friends, previous co-workers, interim agencies, social networks, and direct contact with employers) and the number of actions engaged to find a job (training, sending resumes, attending job speed dating meetings). We also asked them about their estimated wage distribution (reservation wage, minimum and maximum wages expected for the type of position sought). Respondents were then asked to estimate the probability that they, and the other participants in the survey would find a job in 3, 6 and 12 months. After this estimation, they had to report the time frame in which they thought they would be more likely to find a job in the future: 0-3 months, 3-6 months, 6-12 months and 12+ months. They also answered all four questions about the average of the comparison group members.

Finally, to obtain search outcome measures we asked about the number of interviews and job offers received. Since the time spent since the beginning of the unemployment spell is short for our respondents, those outcomes measures are only weak estimate about the true return to search. For that reason we also followed in the PES database our job seekers up to 11 months after their initial registration. Though an exit of the database cannot be systematically associated with a return to employment, it is the case for about 80% of them according to the PES. We thus collected the duration and number of unemployment spells during this 11 months period.

2.4 Results

2.4.1 Confidence and job search prospects

We start with the results from confidence behavior, we first look at individuals beliefs about performance before and after the task.

Optimism and Confidence- Figure 2.1 shows the distribution of both optimism and confidence among our respondents. Individuals predicting a higher (lower) number of correct answers than their realized performance before the task were categorized as optimistic (pessimistic). Similarly, we classified job seekers as overconfident (underconfident) when they estimated a higher (lower) number of correct tasks than what they were truly able to realize. In both case we allowed an error range of ± 2 around the right answer and considered that subjects guessed correctly when they were in that range⁹. Our alluvial 2.1 allows to follow the stream of individuals before and after the task. On average, our participants were pessimistic and underconfident about their performance with 75% of the sample predicting a lower number of realized task before the task and 66% after the task. The information obtained by individuals when doing the task allowed them to update in the right direction as the proportion of individuals correctly guessing their performance doubled. However only half of those who initially guessed correctly remained right in their post task estimations. Overall, the uncertainty about performance was high, most of those who were pessimistic remained pessimistic while most optimistic updated their estimate downward. These evidences enter in direct contradiction with Conjecture 3.

Over/Underplacement- As we can see in the literature (e.g Moore and Healy (2008)) confidence cannot be reduced to simple subjective beliefs about performance. Confidence is also experience through the beliefs about relative performance and ranking. We thus asked our participants to provide estimates of their own performance but also that of others. Comparing estimates we categorized subjects as overplaced (underplaced) when they hypothesized a greater (lower) performance than that of the average of the *comparison group*. As showed in figure 2.2, we find that on average people mainly place themselves above the others in terms of performance. Before the task, subjects expected mainly to perform as the average of the group (37%) or above the average (38%). However, once the task completed, beliefs were mainly overconfident with subjects placing themselves above the others 48% of the time whereas the proportion of those placing themselves at the average collapsed to 23%. The second alluvial 2.3 shows subjects' reaction by performance rank (subjects had no feedback on their actual number of realized tasks). The graph puts into light that people were unable to infer the relative quality of their performance by performing the task. Most individuals kept their initial belief which represents a first hint of conservatism in updating. The greatest changes come from uncertain individuals who initially predicted an average performance. Those individuals

⁹Only a couple of individuals successfully estimated their exact number of correct tasks. 3% of them did so before the task and 7% after. Our results stay unchanged when taking the exact values.

massively adjusted upward their beliefs irrespective of their actual rank which suggests self-serving updating.

Even though we are able to describe well the initial beliefs using the previous placement measure, it is not adjusted for the correctness of the belief. We thus create a second measure of placement adjusted using their actual rank. Participants are now considered overplaced (underplaced) if they place their performance above (below) that of the median of the *comparison group* while not being above (below). Categorizing subjects in this way shows that half of the subjects held correct beliefs about their placement (49%), 30% placed their performance at a higher rank than the true one and 20% placed it below its true position. This confirms that the main biased belief that individuals hold is overplacement.

Given our result we are unable to conclude in favor or against Conjecture 1 since subjects confidence level differ depending on the type of confidence considered.

Confidence and search- To measure overconfidence in job search, we asked subjects the most likely time frame in which they believe they, and the average participant in the experiment, would find a job among 4 (0-3 month, 3-6 month, 6-12 month, more than 12). using the PES database we followed our subjects over time and compared their predicted time to their actual exit time. Second, we compared their predicted time frame to the time frame they predicted for the average of the other participants to the experiment to build a placement measure.

On average subjects were optimistic about their return to employment. 49% of the individuals found a job later than what they predicted and only 15% were overestimating this timing. This confirms the literature findings that overconfidence is the norm regarding job search, confirming Conjecture 1. Regarding placement, for 50% of the subjects the time frame in which they expect to find a job was the same that they predicted for others. They believed finding faster than the others 30% of the time and later in 20% of the time. These beliefs were driven by individuals already having an offer. Subjects who accepted an offer represented 2/3 of those reporting they would find a job earlier (chi square test significant at the 1% level). Finally, we find no correlation between confidence in the experiment and confidence regarding job search. This finding is not surprising, even though we could expect that general confidence biases spread to specific domains, the situation of unemployment should be sufficiently specific for job search confidence to operate through its own channels (Spinnewijn, 2015; Mueller et al., 2021).

Although the pattern we found between relative and absolute confidence seems unusual, it can be explained by the uncertainty of the task. Moore and Healy (2008) show that in situations where there is a high level of uncertainty about performance, people underes-

estimate themselves. Meanwhile, because they know even less about other's performance, they tend to underestimate them more. This behavior naturally leads people to place themselves above others which explains our results.

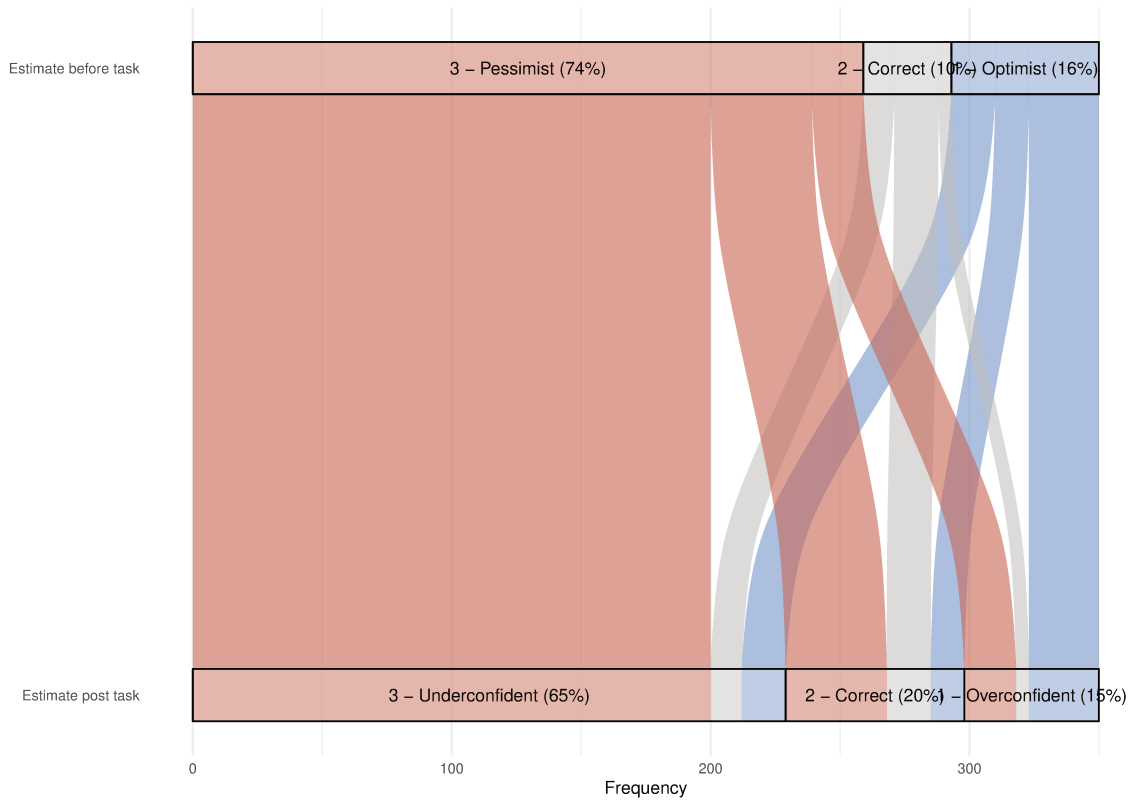


Figure 2.1: Distribution of confidence before and after effort task

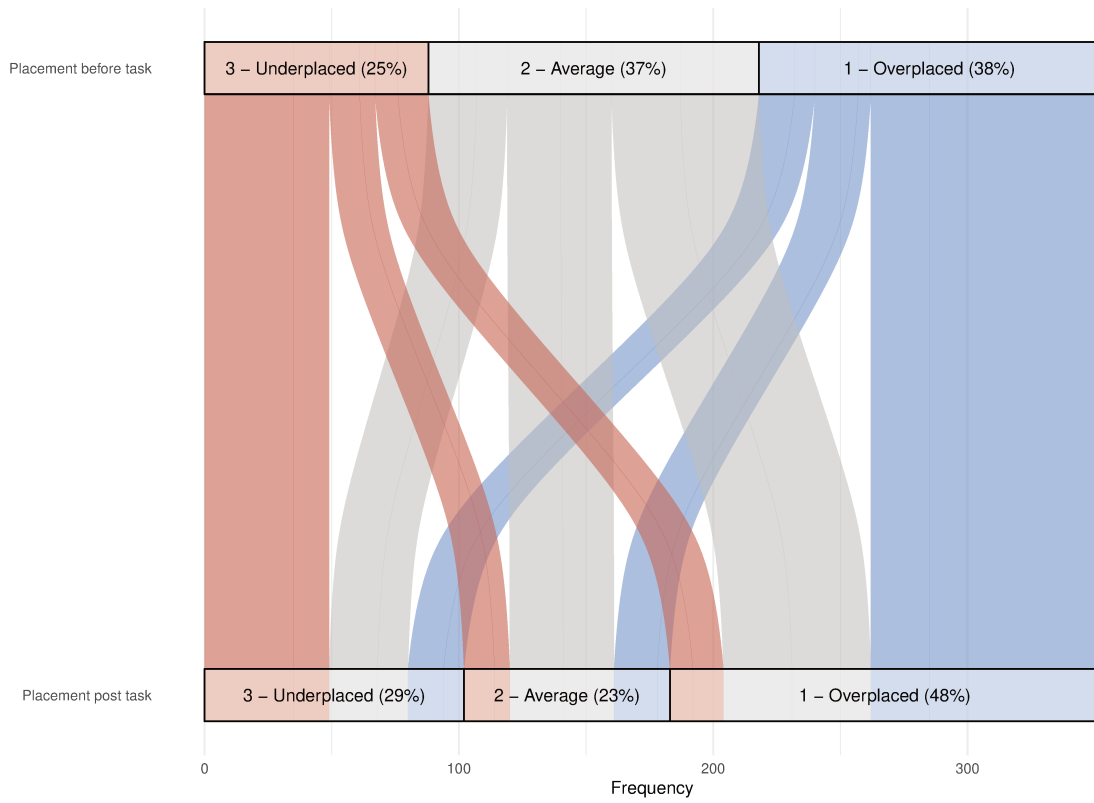


Figure 2.2: Distribution of self placement before and after effort task

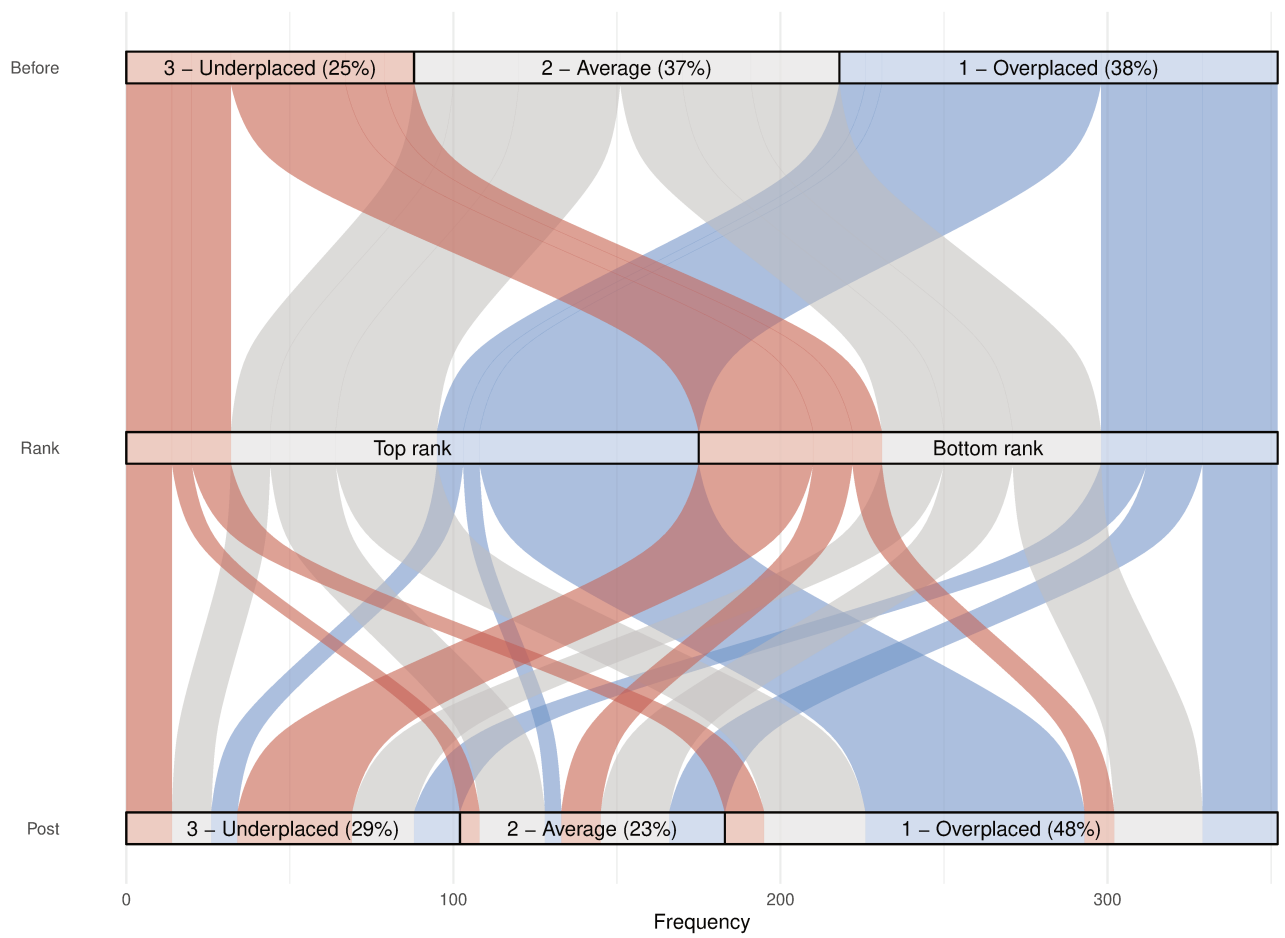


Figure 2.3: Distribution of self placement before and after effort task

2.4.2 Asymmetry and conservatism

We start by testing Conjectures 2 and 3 by comparing updating patterns after the two rounds of signals post task.

The initial estimate to be above the median of the group performance was equal to 66.46% (S.D = 22.87), and was positively correlated to subjects number of task successfully completed (correlation equal to 22.6% with $p = 0.001$). We interpret the correlation as the result of engaging in the task : engaging in the task raises the beliefs about being one of the top performers. We thus expect subject to derive some ego utility related to the belief to have an honorable performance.

Turning to how subjects update beliefs after the signal rounds of both updating tasks (relative to performance and neutral one), we first compute the Bayes posterior beliefs given subjects initial estimate to be in top half. Overall we have a set of 1408 updated estimates after signals with 704 per updating task (note that in both tasks subjects start with the same prior but the valence of the signals received are random and depend on the subject state). Additionally, we removed from the analysis all wrong updating patterns (posterior estimate superior to the prior after a negative signal and conversely), leaving us with 1197 estimates (574 after negative signals and 619 after positive signals).

Comparing subjects posterior beliefs to the correct Bayes posterior probability, we find that, on average subjects update their beliefs in a conservative manner. Comparing all individual error from Bayes, computed as the individual posterior probability minus the Bayes posterior, we find that the error from Bayes after a negative signal irrespective of the signal timing and the type of updating task is equal to -7.14 and equal to 2.18 after a negative signal (both significantly different from zero with t-test p-values equal respectively to $p < 0.001$ and $p = 0.0413$). This indicates that irrespective of the signal, subjects stayed too close to their initial beliefs, but more so after positive signals.

While being an instructive evidence, this result may be biased by the timing of the signal as individuals may react differently depending on the previously received signals. We also know from the literature that this effect may be driven by the self relevance of the signal, people may only exert conservatism when the signal is self relevant. We address both issues in turn.

In order to correct for the signal valence bias, we recompute the differences using individual estimates after the first signal, and after the second signal when the second signal was the same as the first one. This allows to correct for the difference in behavior depending on the signal valence (positive or negative) and for the confusion created by two opposed signals but restrict the sample¹⁰. Doing so, we find that the mean error from

¹⁰For the rest of the results we keep the restriction we applied here on the sample to correct for the signal valence bias. An alternative correction for this bias would be to keep only the update from the first signal. However, doing so prevents us from using the ability to of subjects to learn from their first update and restrict

Bayes for positive signals and negative signals is respectively -8 (S.D = 16.59, test for equality of means between Bayes and subjective estimate gives $p < 0.01$) and 6.23 (S.D = 24, test for equality of means between Bayes and subjective estimate gives $p < 0.001$). Here again we find a consistent conservatism when comparing estimates updating to Bayes posteriors.

We then turn to the reaction heterogeneity depending on the self relatedness of the information. The conservatism we find so far could simply be driven by the fact that individuals derive a utility from holding certain beliefs regarding their performance even though they behave in a Bayesian way in general. Figure 2.4 shows the differences from Bayes by task and signal direction. What clearly stands out is that subjects behaved in a divergent manner depending on the self relevance of the signal.

First we observe that in the neutral updating task, subjects update their belief consistently with Bayes rules (Test for the equality of means gives $p < 0.01$). In the meantime, negative signals relative to performance were strongly under-weighted, the difference in errors from Bayes by task is strongly significant (Mann-Whitney test gives $p = 0.0016$). We thus conclude that updating errors from Bayes rules after negative signals can be attributed to the signal self-relevance. Updates following positive signals on the other hand were consistently conservative no matter the task. However, we find a significant difference between self relevant updates and neutral ones (Mann-Whitney test gives $p = 0.0008$) showing that subjects were less conservative when the signals were self relevant than they were in the neutral task.

In addition we find that the difference in errors from Bayes between the neutral and effort task is greater for negative signals than for positive ones (Mann-Whitney test gives $p = 0.003$). This difference in reaction confirm Conjecture 3 by showing an asymmetry in updating.

Finally, we look at updating by job search relative and absolute confidence. We expect to find that overconfidence bias leads to more protective updates reinforcing the good news bad news effect. we find no evidence supporting this claim. Graph B1 in appendix shows the updating patterns by confidence type. As can be seen from the confidence intervals, we are unable to reveal a clear pattern.¹¹

To summarize, we find that subjects on average behave conservatively no matter the context contrary to what Conjecture 2 suggests. Still, we find that conservatism is self serving and follows an asymmetric pattern as stated in Conjecture 3. Subjects behave conservatively and do not update as much as they should when receiving negative signals

the sample further. Nonetheless, we performed the test using this method and obtained similar results.

¹¹Because of the high number of categories involved we are underpowered to discard the existence of such pattern.

and update more in reaction to positive signals than what they usually do in a neutral context. This pattern is commonly found in the literature and referred to as the good news/Bad news effect (Bénabou, 2015). In order to maintain a positive belief, subjects are more likely to update in a self serving way. This shows both that performance was indeed considered as self relevant by individuals, but also that they derived some utility in believing that performance was high. Importantly Bénabou (2015) shows that such pattern is commonly associated with overconfident beliefs regarding how people evaluate their situation as compared to that of others.

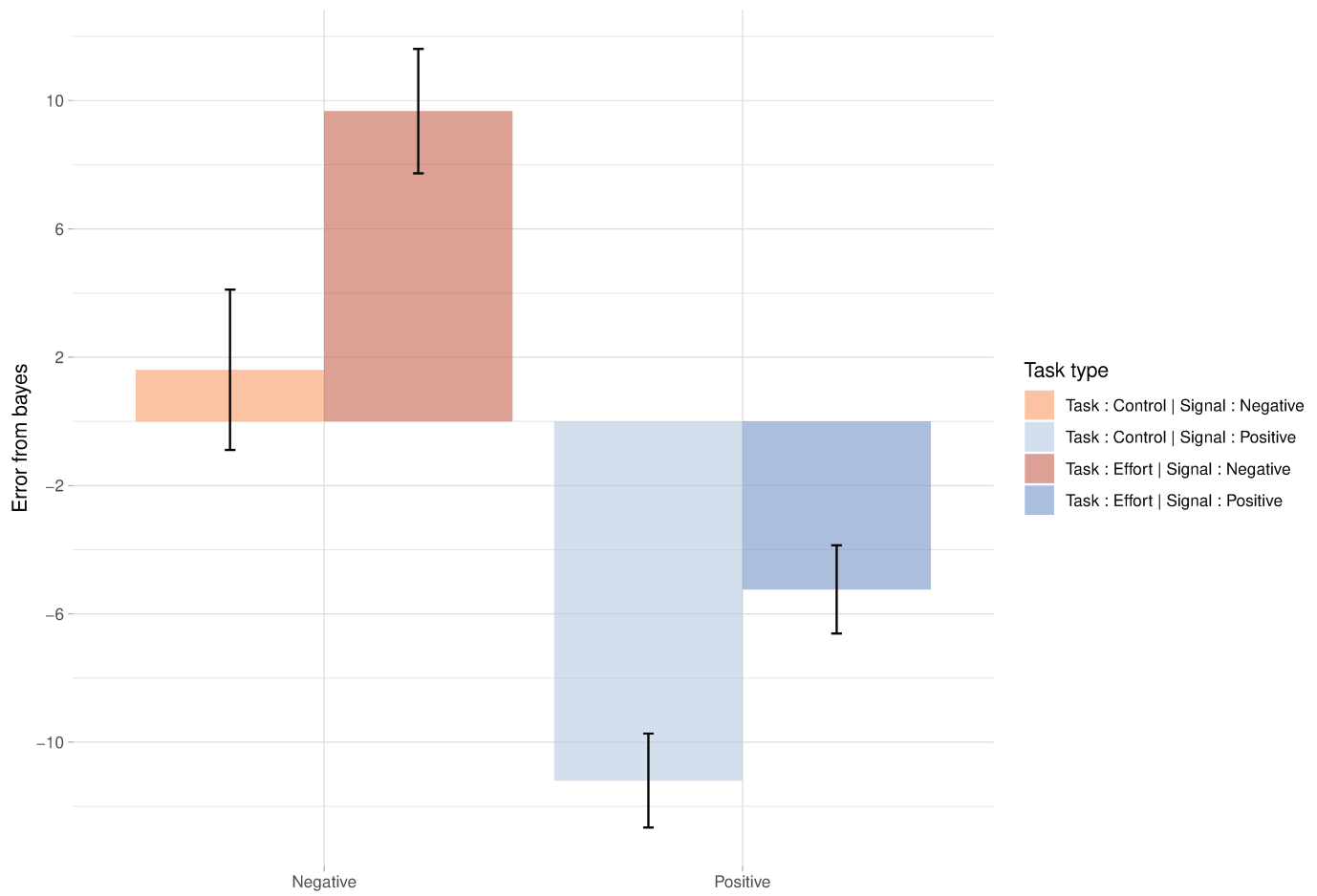


Figure 2.4: Updating behavior after signal

2.4.3 Job search and biased beliefs

Conjectures 4 and 5 predicted that both confidence biases and updating have negative effects on job search and its outcomes. In decreasing search and raising reservation wage, overconfidence affects search outcomes in a detrimental way. Still, if job seekers were able to update in the correct direction over time, negative effects of confidence would not last. Our previous results suggests the opposite. For that reason, Conjecture 5 implies that updating biases, especially in ego relevant domain such as job search, are likely to delay unemployment exit.

To test our claims, we first use questions about job search effort and outcomes present in the post-experimental questionnaire. Table 2.2 presents the results from regression on four search effort determinants and two early search outcomes. "Hours search" represent the number of weekly hours spent searching during the past month, the "search channel index" represents an index composed of the sum of the frequencies of 8 different search channels, and "Active search" is an ordinal measure of the number of search actions carried out by the job seekers to exit unemployment (e.g. sending resume, contacting employers directly). We also use the log of the reservation wage as a dependent variable. For the outcomes we use both the interviews and job offers received by the job seekers. Because our job seekers are at the beginning of their spell, we acknowledge that those outcomes are early ones and the true results of the search effort engaged are likely to materialize in the future. For that reason we use the duration of the spell recovered from the administrative database to study later search outcomes.¹²

In Table 2.2, models (1) to (4) represents OLS regressions on the search effort variables while models (5) and (6) are logit models on whether or not subjects received an interview or a job offer.

We use as regressor in Table 2.2 both confidence types (placement and estimation) measured using beliefs about performance in the experiment and about return to employment¹³. While the former may reveal a general bias in confidence, the latter should be more acquainted to explain job search.

In Table 2.2 we find that our over/under-estimation measure in the task is unable to explain search effort and outcomes. However, placement biases seems to affect significantly search effort. Those who under-place themselves in terms of performance in our

¹²All individuals having reported an unlikely high levels of search and/or reservation wages were discarded from the analysis. Also the job over-Estimation measure was not available for all subjects as 4% of them changed of identification number in the PES database which prevented us from tracking them.

¹³We use estimates made by job seekers after doing the task. For our placement measure, we use the version adjusted for the correctness of beliefs. Those who are considered over-placed here estimated a higher performance for themselves than for the others but failed to achieve such a performance. Regarding the job search domain we have no way to check for actual correctness of belief, we thus keep the simple measure described in the previous section.

task spend 2.6 hours less looking for a job each week as compared to the two other types (Overplaced and correctly calibrated individuals search with the same intensity irrespective of the search effort measure). This finding is consistent with [Wanberg \(2012\)](#) and could indicate a lower motivation of those suffering from under-placement bias. Yet, we also find that placement biases have no effect on outcomes of search neither in the short nor the long run.

In contrast to the experimental one, our measure of job over/under-estimation allows us to conclude in favor of a negative impact of over-estimation on exit out of unemployment. Model (6) in [Table 2.2](#) shows that those over-estimating their chances to go back to work have a significantly lower probability to get a job offer (effect significant at the 5% level). Consistently with this finding, the same group of individuals also have significantly lower unemployment spells as shown by [Table 2.4](#) whereas those over-estimating that chance had significantly shorter spells.

Placement biases relative to the time frame in which people believe to find a job as compared to others affect significantly search outcomes. We find that people who are under-placed along this measure obtain a lower number of interviews and job offers. Looking at the Cox regression, they also have longer unemployment spells whereas over-placed individuals have shorter ones. Even controlling for subjects individual prospects to find a job in the 3 month following the experiment, which should control for the probability that job seekers already have an offer at the time of the experiment, we continue to find a significant effect of job placement on search outcomes. To be sure, we cannot totally discard that these effects are not coming from subjects good calibration, that is we cannot verify that individuals have good reasons or justification for believing they will actually find a job sooner or later than the rest of the population. For that reason our estimate is likely an upper bound estimate of the true effect of job placement. Still, it suggests that there is a pure effect of placement biases that affect unemployment spells' length especially in the long run.

To sum-up, we find that experimental measures of confidence correlate weakly to search effort and are unable to explain coherently outcomes in the long run. Irrespective of the type, job related measures of confidence affects neither search effort nor the reservation wage. Both findings enter in contradiction with [Conjecture 4](#). In the meantime, job related confidence give two opposed results on search outcomes. Overestimation seems to worsen outcomes of search whereas overplacement improves them. This result suggests that both confidence types measure different behavior that seems to act through different channels than the traditional search effort and reservation wage channels. One potential explanation is a demand side selection effect. If overestimation comes with a pretentious behavior, employers may reject such candidates. Similarly overplacement may be asso-

ciated to self-confidence which may represent a positive soft-skill favored by employers. Another explanation is search quality as an individual believing his spell to be short when providing a given level of effort may not be tempted to improve its quality which may not be the case for a job seeker believing his spell to be shorter than others.

This effect is not led by the beliefs about the marginal effect of effort as suggested for instance by [Spinnewijn \(2015\)](#). We asked subjects about how an additional hour of search would increase their stated probability to find a job in the next 0-3 month time frame. Adding this stated probability as a variable in our regressions is significantly correlated to the probability to get a job offer and to shorter unemployment spells. Still it leaves unchanged our previous findings showing that they are not driven by beliefs about the control one has over own search outcomes.

To study the effects of updating we used the sum of errors made as compared to Bayes in both rounds of the updating tasks, irrespective of the signal valence. We find only weak evidence that errors in updating affect search and outcomes. The only effect is a positive one of errors made on self-relevant task on the search index, yet the effect is only significant at the 10% level. This measure of errors in updating is rather weak as updating errors made by our participants are not removed here to maintain the sample's power. However, we decided to dig deeper and investigate in [Table 2.3](#) how each type of updating errors, by task and signal valence, could affect search. In these regressions we use the individual responses to signal as a determinant of search and clustered our standard errors at the individual levels. We categorized responses to signals to ease their interpretation. When subjects updated their estimates above that suggested by Bayes rule after receiving a signal, we considered that subject over-weighted the signal. Conversely, when subjects updated too little after a signal we considered that the signal was under-weighted. In both cases we allowed for a range of ± 5 around Bayes and categorized individuals in that range as Bayesian. Finally we removed individuals who made errors in updating as we did in the previous section. Proceeding in that way, we confirm that self-relevant signals have the greatest effect on search.

We find that subjects under-weighting self-relevant positive signals engage in a significantly lower number of active search actions than the rest while it's not the case for those over-weighting neutral signals. Regarding negative signals, subjects over-weighting self-relevant negative signals devote on average 4 hours less to search than the others. We also find that subject under-weighting negative signals in the urn task tend to undertake a lower number of search actions. Finally Subject over-weighting neutral negative signals were also less likely to receive job offers. Taken together, those results indicate that self-relevant signals seem to affect search through incentive effects. Those who put more weight on self relevant negative signals and/or weight on positive self-relevant signals are likely to be discouraged more easily explaining their lower level of search. On the other hand it is not surprising that those who over-weight negative signals even in a

neutral context also tend to be discouraged and get less job offers. This effect can thus be attributed to a general errors in updating effect.

Finally, looking at long term outcomes from the Cox proportional model run on the unemployment spell duration in Table 2.4, we find that those making bigger mistakes from Bayes in a self-relevant context take more time to find a job. Overall those finding are consistent with Conjecture 5. It seems clear that the self relevant feedback that job seekers are prone to receive while searching for a job naturally leads to self protective behavior. As we saw, job seekers tend to be too conservative and prefer sticking to positive beliefs about themselves. This mechanism seems to affect both effort and outcomes of search negatively.

Table 2.2: Confidence bias effects on job search

	Search effort				Search outcomes	
	Hours searched	Search channel index	Active search	Reservation wage	Got interviews	Got offers
	(1)	(2)	(3)	(4)	(5)	(6)
Overestimation - Performance in real effort task						
Underconfident	-0.510 (1.186)	-0.0456 (0.176)	-3.647 (2.829)	0.0190 (0.0564)	0.321 (0.415)	0.124 (0.375)
Overconfident	1.985 (2.052)	-0.00661 (0.214)	-2.263 (3.114)	0.0256 (0.0836)	0.336 (0.504)	-0.238 (0.487)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Overestimation - Confidence in return to employment						
underconfident	-0.582 (1.596)	0.119 (0.192)	0.158 (2.374)	0.00390 (0.0658)	0.453 (0.475)	-0.589 (0.417)
Overconfident	1.086 (1.153)	0.166 (0.135)	0.570 (2.048)	-0.0238 (0.0447)	-0.489 (0.345)	-0.727** (0.303)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Errors from bayes						
Overplacement - Performance in real effort task						
Underplaced	-2.596** (1.139)	-0.150 (0.148)	-3.068 (1.920)	-0.0660 (0.0443)	-0.152 (0.393)	-0.147 (0.347)
Overplaced	1.381 (1.405)	0.132 (0.158)	-0.861 (1.934)	0.0136 (0.0519)	-0.444 (0.348)	-0.727** (0.326)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Overplacement - Confidence in return to employment						
Underplaced	0.350 (1.506)	-0.176 (0.168)	-0.853 (2.200)	0.0171 (0.0573)	-1.015*** (0.345)	-0.993*** (0.335)
Overplaced	-0.368 (1.367)	0.0311 (0.153)	-0.610 (2.333)	-0.00541 (0.0476)	0.436 (0.399)	0.525 (0.333)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Errors from bayes						
Errors from bayes in self-relevant updating task	0.0129 (0.0144)	0.00258* (0.00151)	0.0189 (0.0225)	0.000375 (0.000503)	-0.00399 (0.00393)	0.00290 (0.00358)
Errors from bayes in neutral updating task	0.00640 (0.0114)	-0.0000146 (0.00138)	-0.0169 (0.0154)	0.0000384 (0.000407)	0.00304 (0.00295)	0.00128 (0.00266)
Individual controls	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>	<i>Yes</i>
Observations	277	277	277	276	291	291
R^2	0.097	0.091	0.118	0.449		
Adjusted R^2	0.003	-0.004	0.026	0.391		

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. The individual controls include gender, age and education and the number of past registrations to the PES. The number of observations varies between 277 and 299 out of 352 respondents to the experiment, because of missing observations in some variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.3: Updating bias effects on job search

	search_hours	sint_idx	search_applications	logresw	gotinterview	gotoffer
	(1)	(2)	(3)	(4)	(5)	(6)
Sample : positive signals in control task						
Underweight	-0.350 (1.631)	0.0313 (0.210)	-1.903 (2.965)	0.0112 (0.0608)	-0.445 (0.480)	-0.582 (0.421)
Overweight	-2.870* (1.728)	-0.0328 (0.271)	-4.571 (4.001)	-0.0629 (0.0726)	-0.854* (0.510)	-0.405 (0.477)
Bayesian	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Observations	228	228	228	226	243	243
R^2	0.111	0.187	0.118	0.435		
Adjusted R^2	0.034	0.117	0.042	0.386		
Sample : positive signals in effort task						
Underweight	0.704 (1.167)	-0.0943 (0.133)	-5.278** (2.603)	0.0635 (0.0561)	-0.0647 (0.382)	-0.0948 (0.363)
Overweight	0.391 (1.264)	-0.215 (0.148)	-3.838 (2.828)	0.0424 (0.0595)	-0.0553 (0.436)	-0.237 (0.397)
Bayesian	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Observations	247	247	247	245	253	253
R^2	0.159	0.200	0.158	0.415		
Adjusted R^2	0.092	0.136	0.091	0.368		
Sample : Negative signals in control task						
Underweight	3.326* (1.742)	-0.207 (0.231)	-6.908** (3.249)	0.0195 (0.0773)	-0.935 (0.613)	-0.754 (0.569)
Overweight	1.781 (1.809)	-0.276 (0.205)	-2.651 (3.372)	0.0341 (0.0670)	-0.648 (0.599)	-1.582*** (0.540)
Bayesian	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Observations	186	186	186	186	178	193
R^2	0.207	0.103	0.145	0.442		
Adjusted R^2	0.121	0.007	0.053	0.381		
Sample : Negative signals in effort task						
Underweight	-1.695 (2.046)	-0.156 (0.238)	-0.381 (2.713)	-0.0200 (0.0631)	-0.512 (0.498)	-0.188 (0.411)
Overweight	-3.732** (1.838)	-0.0370 (0.251)	-2.436 (2.623)	-0.0275 (0.0641)	-0.287 (0.522)	-0.299 (0.444)
Bayesian	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Observations	240	240	240	240	255	255
R^2	0.129	0.087	0.186	0.454		
Adjusted R^2	0.058	0.012	0.120	0.410		
For all						
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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. The individual controls include gender, age and education and the number of past registrations to the PES. The number of observations varies between 277 and 299 out of 352 respondents to the experiment, because of missing observations in some variables. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.5 Conclusion

When starting their job search, unemployed individuals are generally assumed by job search theories to perfectly know their environment to formulate a coherent search strategy. In rare occurrences, they are assumed to start with an imperfect knowledge of the market but with a perfect ability to update in reaction to feedback.

Empirical evidences from the job market show in the meantime that job seekers are not likely to behave as predicted by the theories. They start with an over-optimistic view of their prospects on the job market and fail to update consistently in reaction to the feedback received from the labor market. In this paper, we investigated the extent to which those findings could be attributed to self-serving motivated beliefs by relating the results of an online experiment on job seekers to administrative data on job search .

We find, consistently with the literature on biased updating (Clark and Friesen, 2009; Eil and Rao, 2011; Möbius et al., 2022) that job seekers update feedback in a conservative way. They fail to update sufficiently in reaction to feedback. Besides we find that job seekers also process feedback in an asymmetric way when receiving self relevant information by being more conservative after the reception of negative information than after the reception of positive ones.

When it comes to initial beliefs, we confirm that job seekers start overconfident about the outcomes of their search but don't expect to find systematically faster than others in their situation indicating that they are overall biased in their view of the labor market. This confidence is very specific to the job market as our experimental measures of confidence on a neutral task were uncorrelated to labor market ones.

We then related updating biases to search and find that holding a self serving bias in updating delays job finding while general errors in updating don't. This effect seems mainly driven by the effect of updating failure on search. Finally we find, consistently with our findings on updating, that those holding a self-serving positive bias about return to employment had longer unemployment spells. While failing to update when starting under-confident or perfectly informed may reveal to be a minor issue for the unemployment length (i.e under-confident finding faster by underestimating their reservation wages), failing to update with a positive view of one's prospects should consistently delay job finding.

Overall our findings imply as suggested by the psychology literature that the feedback received by unemployed individuals during their search is likely self hurting (Wanberg, 2012). In this context, an indirect protective behavior consisting in downplaying negative signals appears as a nice coping behavior. Still, it implies a harmful effect both on individuals as it delays their job finding and overall can represent an increase in public spending. This effect is also not likely to be solved by classical monetary incentives,

Table 2.4: Updating bias effects on hazard rates

	Cox proportional model Analysis time when record ends
Overestimation - Performance in real effort task	
Underconfident	-0.166 (0.170)
Overconfident	-0.0479 (0.223)
Right	0 (.)
Overestimation - Confidence in return to employment	
Underconfident	0.700*** (0.175)
Overconfident	-1.852*** (0.173)
Average	0 (.)
Overplacement - Performance in real effort task	
Underplaced	0.117 (0.174)
Overplaced	0.179 (0.154)
Correct	0 (.)
Overplacement - Confidence in return to employment	
Underplaced	-0.690*** (0.170)
Overplaced	0.544*** (0.164)
Correct	0 (.)
Errors from bayes	
Errors from bayes in self-relevant updating task	-0.00341** (0.00173)
Errors from bayes in neutral updating task	0.000713 (0.00129)
Avoidance	
Doesn't want to learn rank for free	0 (.)
Wants to learn rank for free	-0.0524 (0.134)
Individual controls	Yes
Unemployment controls	Yes
Individuals	291
Individual spells	370

Notes: The duration of the spell is computed using the exit of the PES database. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

however accompanying program targeting overconfident individuals to help them adjust their job finding prospects over time could represent an interesting way to deal with the updating bias.

2.6 Appendices

Appendix A: Full tables

Table A1: Confidence bias effects on job search

	Search effort			Search outcomes		
	Hours searched (1)	Search channel index (2)	Active search (3)	Reservation wage (4)	Got interviews (5)	Got offers (6)
Overestimation - Performance in real effort task						
Underconfident	-0.510 (1.186)	-0.0456 (0.176)	-3.647 (2.829)	0.0190 (0.0564)	0.321 (0.415)	0.124 (0.375)
Overconfident	1.985 (2.052)	-0.00661 (0.214)	-2.263 (3.114)	0.0256 (0.0836)	0.336 (0.504)	-0.238 (0.487)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Overestimation - Confidence in return to employment						
Overconfident	1.086 (1.153)	0.166 (0.135)	0.570 (2.048)	-0.0238 (0.0447)	-0.489 (0.345)	-0.727** (0.303)
underconfident	-0.582 (1.596)	0.119 (0.192)	0.158 (2.374)	0.00390 (0.0658)	0.453 (0.475)	-0.589 (0.417)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Errors from bayes						
Overplacement - Performance in real effort task						
Underplaced	-2.596** (1.139)	-0.150 (0.148)	-3.068 (1.920)	-0.0660 (0.0443)	-0.152 (0.393)	-0.147 (0.347)
Overplaced	1.381 (1.405)	0.132 (0.158)	-0.861 (1.934)	0.0136 (0.0519)	-0.444 (0.348)	-0.727** (0.326)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Overplacement - Confidence in return to employment						
Underplaced	0.350 (1.506)	-0.176 (0.168)	-0.853 (2.200)	0.0171 (0.0573)	-1.015*** (0.345)	-0.993*** (0.335)
Overplaced	-0.368 (1.367)	0.0311 (0.153)	-0.610 (2.333)	-0.00541 (0.0476)	0.436 (0.399)	0.525 (0.333)
Correct	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Errors from bayes						
Errors from bayes in self-relevant updating task	0.0129 (0.0144)	0.00258* (0.00151)	0.0189 (0.0225)	0.000375 (0.000503)	-0.00399 (0.00393)	0.00290 (0.00358)
Errors from bayes in neutral updating task	0.00640 (0.0114)	-0.0000146 (0.00138)	-0.0169 (0.0154)	0.0000384 (0.000407)	0.00304 (0.00295)	0.00128 (0.00266)
Education						
HS	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
HS+2	-0.655 (1.997)	0.344 (0.216)	4.751 (3.036)	0.176** (0.0755)	0.158 (0.553)	0.523 (0.473)
HS+3/4	0.154 (1.922)	0.378* (0.193)	-2.169 (2.318)	0.351*** (0.0785)	0.619 (0.513)	0.375 (0.427)
HS+5+	0.567 (2.046)	0.313 (0.200)	3.425 (2.344)	0.468*** (0.0782)	0.624 (0.458)	0.183 (0.422)
less_than_HS	-0.242 (2.487)	0.417 (0.352)	-1.316 (2.106)	0.149* (0.0881)	-0.600 (0.581)	1.169** (0.581)
pro_train	-0.186 (2.217)	-0.0392 (0.278)	-1.578 (2.731)	0.0922 (0.0729)	0.124 (0.591)	1.312** (0.587)
Gender						
Male	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Female	2.112* (1.159)	0.0989 (0.126)	-2.778 (1.976)	-0.145*** (0.0430)	0.233 (0.317)	0.208 (0.286)
Age category						
18/24	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
25/49	-1.051 (1.220)	-0.217 (0.134)	-3.657** (1.675)	0.189*** (0.0476)	-0.489 (0.317)	-0.0835 (0.289)
50+	-2.748 (1.920)	-0.0913 (0.341)	-4.942* (2.641)	0.544*** (0.128)	-0.353 (0.733)	-1.688** (0.768)
Occupation						
Unknown	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
agriculture	-1.843 (2.941)	0.167 (0.422)	-1.302 (3.258)	0.0452 (0.0945)	-0.335 (0.851)	0.730 (0.858)
art_entertainment_catering_hotel	-3.617* (1.902)	-0.0316 (0.357)	-2.360 (2.081)	-0.119 (0.0935)	0.518 (0.739)	0.200 (0.636)
bank_commerce	0.326 (2.257)	0.239 (0.225)	6.966* (3.873)	0.218** (0.0999)	1.340* (0.687)	0.838 (0.534)
com_and_firm_support	0.759 (1.584)	0.000973 (0.164)	3.607* (1.970)	0.232*** (0.0580)	0.501 (0.404)	-0.218 (0.381)
construction_maintenance_industry	-1.109 (1.746)	0.187 (0.231)	4.514 (3.287)	0.0497 (0.0745)	0.158 (0.552)	-0.552 (0.493)
health_and_related	-0.516 (1.966)	-0.174 (0.203)	2.406 (2.686)	-0.0572 (0.0591)	0.0133 (0.469)	0.231 (0.450)
transport	-4.618*** (1.696)	-0.443 (0.361)	-6.418 (4.368)	-0.153 (0.112)	0.798 (1.256)	-0.335 (0.948)
Prospects : finding a job in next 3 months	0.0139 (0.0244)	0.00255 (0.00288)	0.0481 (0.0463)	0.00111 (0.000862)		
Constant	6.808*** (2.436)	-0.410 (0.338)	9.565*** (3.576)	6.958*** (0.110)	1.023* (0.614)	0.474 (0.550)
Observations	96	277	277	276	291	291
R ²	0.097	0.091	0.118	0.449		
Adjusted R ²	0.003	-0.004	0.026	0.391		

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A2: Updating bias effects on hazard rates

	Cox proportional model Analysis time when record ends
Overestimation - Performance in real effort task	
Underconfident	-0.166 (0.170)
Overconfident	-0.0479 (0.223)
Right	0 (.)
Overestimation - Confidence in return to employment	
Underconfident	0.700*** (0.175)
Overconfident	-1.852*** (0.173)
Average	0 (.)
Overplacement - Performance in real effort task	
Underplaced	0.117 (0.174)
Overplaced	0.179 (0.154)
Correct	0 (.)
Overplacement - Confidence in return to employment	
Underplaced	-0.690*** (0.170)
Overplaced	0.544*** (0.164)
Correct	0 (.)
Errors from bayes	
Errors from bayes in self-relevant updating task	-0.00341** (0.00173)
Errors from bayes in neutral updating task	0.000713 (0.00129)
Avoidance	
Doesn't want to learn rank for free	0 (.)
Wants to learn rank for free	-0.0524 (0.134)
Education	
HS (High school degree)	0 (.)
HS+2	-0.00705 (0.229)
HS+3/4	0.108 (0.221)
HS+5+	0.250 (0.194)
Less than HS	0.505* (0.283)
Education : professional training	0.257 (0.257)
Gender	
Male	0 (.)
Female	-0.112 (0.141)
Age category	
18/24	0 (.)
25/49	-0.549*** (0.154)
50+	-0.463 (0.342)
Occupation searched for :	
NA	0 (.)
Agriculture	0.200 (0.431)
Art, entertainment, catering, hotels	-0.0437 (0.278)
Bank, commerce	0.0652 (0.233)
Communication and firm support	0.266 (0.184)
Construction, maintenance, industry	-0.156 (0.262)
Health and related	-0.0458 (0.211)
Transport	-0.141 (0.536)
Observations	370

Notes: The duration of the spell is computed using the exit of the PES database. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Updating bias effects on job search positive signals effort task

	search_hours	sint_idx	search_applications	logresw	gotinterview	gotoffer
Underweight	-0.350 (1.631)	0.0313 (0.210)	-1.903 (2.965)	0.0112 (0.0608)	-0.445 (0.480)	-0.582 (0.421)
Overweight	-2.870* (1.728)	-0.0328 (0.271)	-4.571 (4.001)	-0.0629 (0.0726)	-0.854* (0.510)	-0.405 (0.477)
Bayesian	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Education						
HS	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
HS+2	-4.124* (2.485)	0.312 (0.347)	-1.776 (3.910)	0.190** (0.0821)	-0.475 (0.674)	-0.130 (0.611)
HS+3/4	1.959 (2.596)	0.663** (0.267)	1.840 (2.778)	0.340*** (0.0993)	0.603 (0.624)	-0.212 (0.552)
HS+5+	-0.911 (2.656)	0.418 (0.277)	3.616 (3.420)	0.387*** (0.0891)	1.705*** (0.659)	-0.225 (0.539)
Less than HS	-0.967 (4.051)	0.774 (0.541)	-4.070 (4.033)	0.00980 (0.236)	-2.165* (1.127)	1.209 (1.116)
Professional training	-0.531 (3.644)	-0.210 (0.401)	-3.796 (4.429)	-0.0101 (0.102)	-0.366 (0.810)	0.595 (0.904)
Gender						
Male	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Female	0.272 (1.570)	-0.164 (0.185)	-4.812* (2.797)	-0.0895* (0.0533)	0.0543 (0.448)	0.297 (0.378)
Occupation						
Unknown	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
agriculture	-1.063 (2.357)	-0.409 (0.307)	-3.141 (3.677)	0.0661 (0.127)	0.679 (1.765)	0.125 (1.033)
Art, entertainment, catering, hotels	1.736 (3.031)	-0.247 (0.642)	-5.851** (2.794)	-0.0513 (0.111)	-0.399 (0.874)	-0.873 (0.740)
Bank commerce	2.889 (2.810)	0.254 (0.306)	11.95* (7.142)	0.127 (0.0767)	0.778 (1.163)	0.0362 (0.776)
Communication and firm support	1.300 (2.326)	-0.243 (0.260)	-2.760 (3.260)	0.200** (0.0834)	-0.794 (0.562)	-0.783 (0.515)
Construction, maintenance, industry	0.574 (2.962)	0.259 (0.309)	5.014 (6.117)	0.118 (0.103)	-0.985 (0.791)	-1.658** (0.722)
Health and related	-0.695 (2.220)	-0.567** (0.265)	-0.990 (3.780)	-0.0548 (0.0874)	-1.474** (0.619)	-0.602 (0.557)
Transport	5.949 (7.012)	-0.600 (0.537)	0.275 (6.389)	0.0243 (0.128)	0.175 (1.408)	0.0579 (1.223)
Age category						
18/24	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
25/49	-0.275 (1.812)	-0.146 (0.186)	0.744 (2.176)	0.159*** (0.0592)	-0.490 (0.470)	0.348 (0.407)
50+	-3.524 (2.595)	0.189 (0.491)	-3.996 (3.145)	0.812*** (0.241)	-1.633 (1.060)	-2.098* (1.255)
Prospects : finding a job in next 3 month	0.0164 (0.0250)	0.00701** (0.00327)	0.0414 (0.0533)	0.000774 (0.000948)		
Constant	8.529** (3.628)	-0.436 (0.365)	12.21* (6.298)	7.002*** (0.122)	1.796*** (0.652)	0.918 (0.572)
Observations	227	227	227	225	242	242
R ²	0.086	0.189	0.136	0.462		
Adjusted R ²	0.007	0.119	0.061	0.415		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Updating bias effects on job search positive signals effort task

	search_hours	sint_idx	search_applications	logresw	gotinterview	gotoffer
Underweight	0.704 (1.167)	-0.0943 (0.133)	-5.278** (2.603)	0.0635 (0.0561)	-0.0647 (0.382)	-0.0948 (0.363)
Overweight	0.391 (1.264)	-0.215 (0.148)	-3.838 (2.828)	0.0424 (0.0595)	-0.0553 (0.436)	-0.237 (0.397)
Bayesian	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Education						
HS	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
HS+2	-1.435 (1.984)	0.378 (0.301)	7.008* (3.760)	0.253*** (0.0952)	0.426 (0.706)	0.874 (0.667)
HS+3/4	0.590 (1.892)	0.477* (0.283)	2.266 (2.992)	0.382*** (0.0996)	0.343 (0.696)	0.337 (0.649)
HS+5+	4.788** (2.168)	0.542* (0.308)	7.679** (3.331)	0.465*** (0.0966)	1.609** (0.641)	0.769 (0.658)
Less than HS	4.552 (3.576)	0.335 (0.454)	-0.222 (2.616)	0.0680 (0.164)	-0.835 (0.895)	1.405 (0.881)
Professional training	3.114 (2.893)	0.364 (0.341)	2.878 (4.327)	0.175 (0.113)	0.520 (0.808)	1.631* (0.890)
Gender						
Male	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Female	1.238 (1.246)	0.246 (0.158)	-1.968 (2.549)	-0.134** (0.0553)	-0.351 (0.482)	-0.227 (0.416)
Occupation						
Unknown	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Agriculture	-2.704 (2.625)	-0.190 (0.324)	-0.0900 (2.985)	-0.0810 (0.0839)	0.883 (1.392)	1.792 (1.210)
Art, entertainment, catering, hotels	-4.295* (2.202)	-0.0424 (0.316)	1.032 (3.088)	-0.192 (0.127)	1.614 (1.170)	0.827 (0.823)
Bank, commerce	2.068 (3.207)	0.0823 (0.357)	8.211 (5.273)	0.0669 (0.113)	1.045 (0.934)	1.456* (0.845)
Communication and firm support	-1.311 (2.071)	-0.178 (0.226)	0.422 (2.253)	0.139* (0.0720)	0.620 (0.571)	-0.0877 (0.509)
Construction, maintenance, industry	-0.960 (2.333)	0.198 (0.271)	8.345* (4.602)	-0.0497 (0.0846)	0.686 (0.826)	-0.373 (0.613)
Health and related	-5.766** (2.373)	-0.547** (0.239)	2.173 (3.799)	-0.162 (0.0988)	-0.671 (0.618)	-0.0969 (0.610)
Transport	1.155 (4.121)	-0.252 (0.675)	2.109 (7.923)	0.0789 (0.130)	-0.742 (1.384)	-0.145 (1.287)
Age category						
18/24	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
25/49	-0.876 (1.418)	-0.290 (0.176)	-3.867* (2.115)	0.178*** (0.0586)	-0.548 (0.480)	-0.0157 (0.411)
50+	-1.239 (3.530)	-0.393 (0.285)	-5.752* (3.363)	0.524*** (0.157)	-0.425 (0.942)	-1.672 (1.132)
Prospects: finding a job in next 3 months	0.00507 (0.0209)	0.00294 (0.00257)	-0.0113 (0.0420)	0.00142* (0.000816)		
Constant	6.149*** (2.246)	-0.458 (0.305)	10.12** (4.098)	6.928*** (0.0910)	0.747 (0.637)	-0.490 (0.577)
Observations	248	248	248	246	254	254
R^2	0.163	0.180	0.142	0.428		
Adjusted R^2	0.097	0.116	0.075	0.383		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Updating bias effects on job search positive signals effort task

	search_hours	sint_idx	search_applications	logresw	gotinterview	gotoffer
Underweight	3.326*	-0.207	-6.908**	0.0195	-0.935	-0.754
	(1.742)	(0.231)	(3.249)	(0.0773)	(0.613)	(0.569)
Overweight	1.781	-0.276	-2.651	0.0341	-0.648	-1.582***
	(1.809)	(0.205)	(3.372)	(0.0670)	(0.599)	(0.540)
Bayesian	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Education						
HS	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
HS+2	-2.250	0.182	4.919	0.269**	-0.0565	1.436*
	(3.408)	(0.283)	(3.820)	(0.124)	(0.826)	(0.781)
HS+3/4	-5.246	-0.0426	3.278	0.386***	0.653	0.975
	(3.562)	(0.294)	(5.015)	(0.117)	(0.706)	(0.718)
HS+5+	-1.216	0.0189	3.899	0.514***	0.867	0.699
	(4.107)	(0.358)	(3.780)	(0.144)	(0.747)	(0.813)
Less than HS	-2.596	-0.491	-2.538	0.280**	0.444	1.793**
	(3.613)	(0.319)	(2.548)	(0.133)	(1.005)	(0.833)
Professional training	2.858	0.0677	4.076	0.278**	0.217	2.430**
	(3.352)	(0.378)	(3.760)	(0.110)	(0.907)	(0.962)
Gender						
Male	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Female	2.670	0.0122	-0.235	-0.153*	0.0757	0.132
	(2.054)	(0.177)	(2.722)	(0.0812)	(0.499)	(0.460)
Occupation						
NA	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
Agriculture	-1.322	0.754*	-3.819	0.253***	0	0
	(3.798)	(0.398)	(4.244)	(0.0827)	(.)	(.)
Art, entertainment, catering, hotels	-7.367***	0.143	-2.101	-0.0611	-0.165	1.185
	(2.008)	(0.298)	(2.754)	(0.148)	(0.850)	(0.842)
Bank commerce	-2.267	0.275	2.323	0.159	1.233	1.756**
	(2.945)	(0.276)	(3.145)	(0.151)	(1.077)	(0.857)
Communication and firm support	0.359	0.270	8.915**	0.163*	1.217*	-0.733
	(2.489)	(0.216)	(3.967)	(0.0876)	(0.735)	(0.635)
Construction maintenance industry	-2.896	0.232	4.018	0.00672	-0.194	-0.325
	(2.277)	(0.284)	(4.360)	(0.0888)	(0.762)	(0.709)
Health and related	-1.221	0.302	5.042	0.101	-0.333	-0.909
	(2.989)	(0.350)	(3.496)	(0.0904)	(0.737)	(0.721)
transport	-2.543	0.500	-0.860	-0.491***	-0.819	0.474
	(3.155)	(1.127)	(4.158)	(0.124)	(1.981)	(1.151)
Age category						
18/24	0	0	0	0	0	0
	(.)	(.)	(.)	(.)	(.)	(.)
25/49	4.502*	0.115	-2.177	0.227***	-0.907*	-0.371
	(2.483)	(0.233)	(3.441)	(0.0781)	(0.504)	(0.512)
50+	-2.046	-0.347	-1.519	0.556***	1.057	-2.211**
	(2.087)	(0.429)	(3.857)	(0.123)	(0.948)	(1.032)
Prospects : finding a job in next three months	0.0510	0.000889	0.0480	0.000208		
	(0.0391)	(0.00315)	(0.0420)	(0.00114)		
Constant	3.831*	-0.0577	7.242*	6.895***	1.683**	0.141
	(2.266)	(0.362)	(4.031)	(0.115)	(0.830)	(0.808)
Observations	186	186	186	186	189	189
R^2	0.191	0.095	0.168	0.425		
Adjusted R^2	0.104	-0.003	0.079	0.363		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Updating bias effects on job search positive signals effort task

	search_hours	sint_idx	search_applications	logresw	gotinterview	gotoffer
Underweight	-1.695 (2.046)	-0.156 (0.238)	-0.381 (2.713)	-0.0200 (0.0631)	-0.512 (0.498)	-0.188 (0.411)
Overweight	-3.732** (1.838)	-0.0370 (0.251)	-2.436 (2.623)	-0.0275 (0.0641)	-0.287 (0.522)	-0.299 (0.444)
Bayesian	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Education						
HS	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
HS+2	-2.295 (2.961)	0.394 (0.320)	6.386 (4.354)	0.0748 (0.102)	-0.177 (0.682)	0.663 (0.622)
HS+3/4	-1.939 (2.993)	0.0813 (0.274)	3.663 (2.827)	0.333*** (0.108)	0.536 (0.647)	0.110 (0.532)
HS+5+	-5.241 (3.197)	0.147 (0.273)	1.691 (2.953)	0.464*** (0.108)	0.424 (0.594)	-0.00711 (0.531)
Less than HS	-2.668 (3.079)	-0.109 (0.401)	-1.528 (2.985)	0.124 (0.126)	-0.376 (0.861)	0.552 (0.723)
Professional training	-0.821 (3.305)	-0.132 (0.402)	0.103 (2.788)	0.118 (0.0904)	-0.489 (0.738)	0.494 (0.697)
Gender						
Male	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Female	-0.229 (1.858)	-0.463** (0.190)	-2.723 (2.027)	-0.195*** (0.0676)	0.143 (0.445)	0.354 (0.382)
Occupation						
Unknown	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
Agriculture	-4.462* (2.674)	-0.291 (0.474)	-2.794 (3.009)	0.0687 (0.105)	-0.440 (1.262)	0.680 (1.299)
Art, entertainment, catering, hotel	-1.293 (2.681)	0.0738 (0.427)	-3.330 (2.320)	0.0803 (0.109)	-0.827 (0.818)	-0.454 (0.673)
Bank, commerce	1.979 (4.199)	0.511* (0.288)	7.572 (5.380)	0.358* (0.202)	1.873* (1.106)	1.096 (0.770)
Communication and firm support	4.301* (2.464)	0.377 (0.255)	8.942*** (2.930)	0.270** (0.110)	-0.0764 (0.590)	-0.898* (0.518)
Construction, maintenance, industry	-2.900 (2.309)	0.149 (0.345)	-0.181 (3.585)	0.103 (0.0974)	-0.783 (0.700)	-0.621 (0.658)
Health and related	4.700* (2.615)	0.193 (0.293)	2.204 (3.315)	0.0537 (0.0898)	-0.0517 (0.656)	0.317 (0.555)
Transport	-1.298 (5.903)	-0.627 (0.513)	-1.881 (5.460)	-0.235* (0.140)	1.150 (1.035)	-0.0936 (1.080)
Age category						
18/24	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)	0 (.)
25/49	0.0758 (2.025)	0.0763 (0.213)	-3.444* (1.883)	0.186** (0.0860)	-0.321 (0.457)	0.407 (0.398)
50+	-4.159 (2.839)	-0.227 (0.455)	-3.264 (3.643)	0.605*** (0.169)	-1.666** (0.833)	-1.913* (1.054)
Prospects : finding a job in next 3 months	0.0527 (0.0329)	0.00430 (0.00334)	0.0975*** (0.0328)	0.000642 (0.00120)		
Constant	9.680*** (3.184)	-0.0872 (0.434)	3.609 (2.547)	7.000*** (0.134)	1.581** (0.633)	0.0660 (0.541)
Observations	237	237	237	237	250	250
R ²	0.128	0.108	0.188	0.426		
Adjusted R ²	0.055	0.034	0.121	0.379		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B: Overconfidence and biased updating

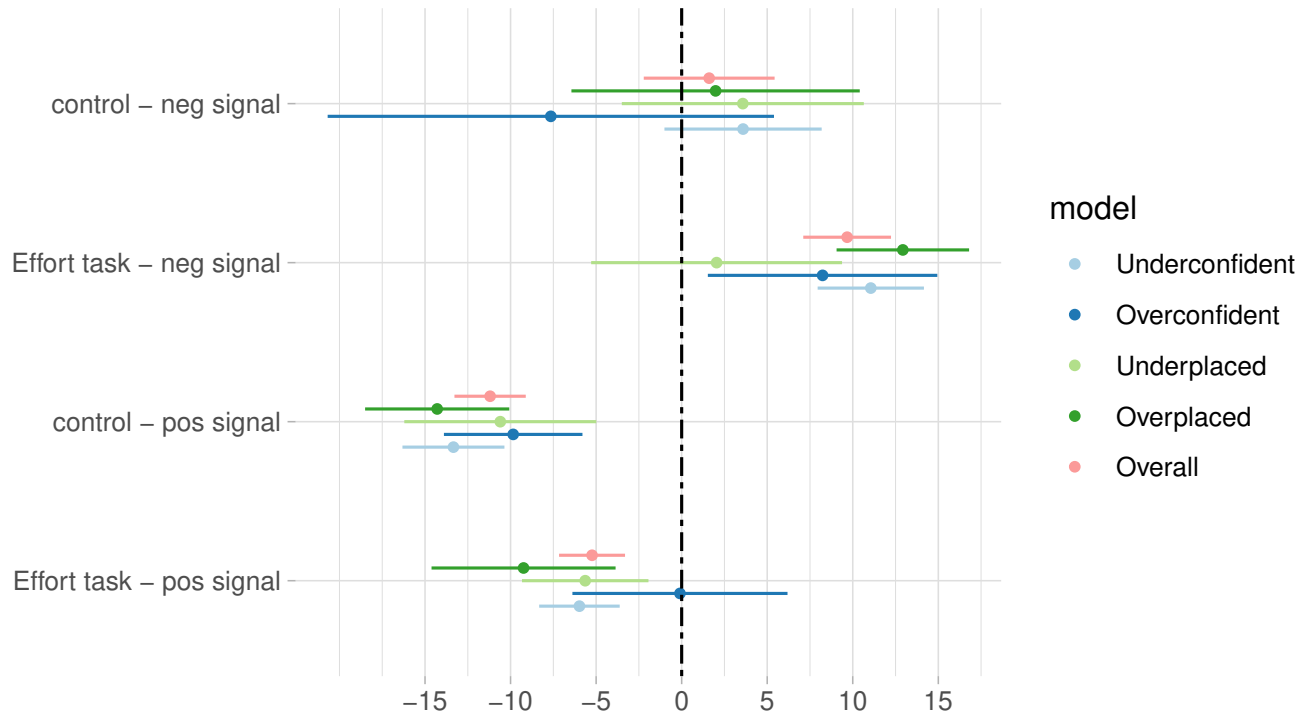


Figure B1: Updating bias by Job search confidence types

Notes: The figure represents the errors made from Bayes rule by signal, type of task, and type of confidence about the return to employment.

Appendix C: Real effort task

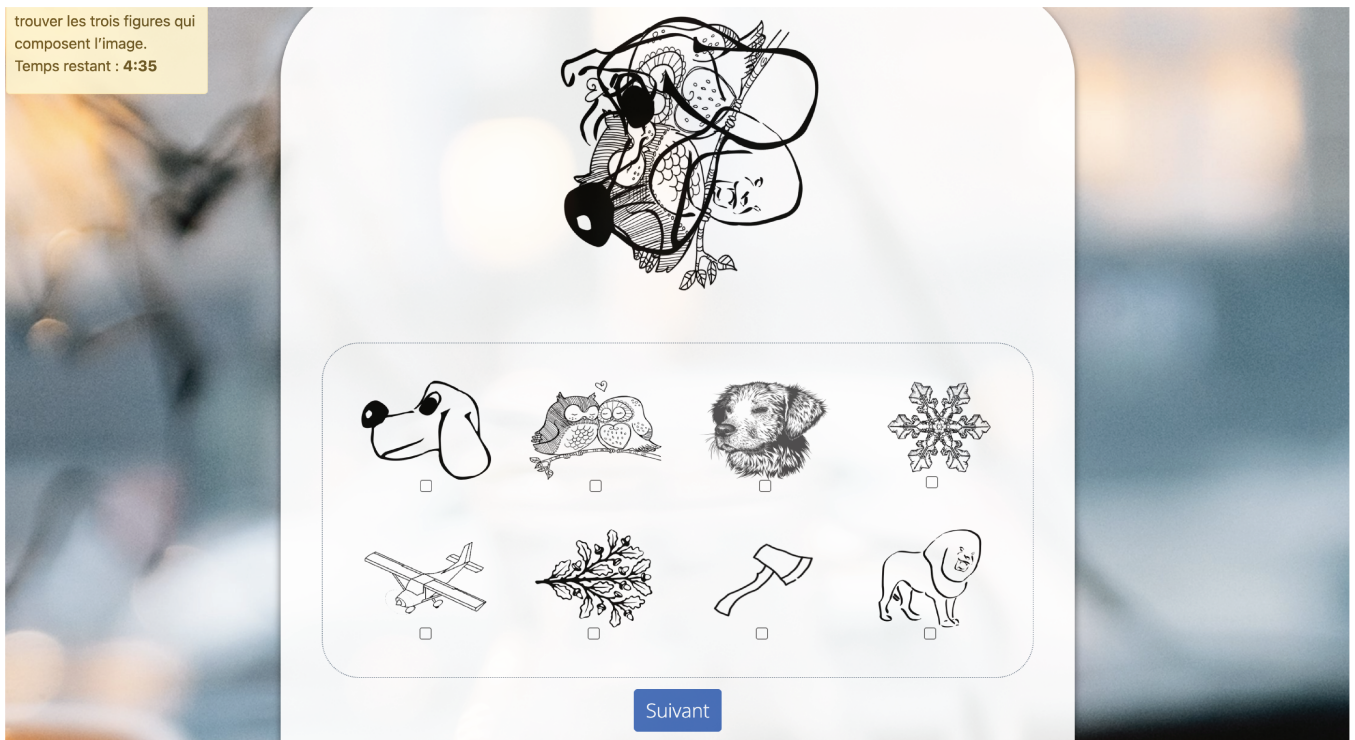


Figure C1: Screenshot of real effort task

Notes: The figure represent a screenshot of one of the real effort task

Instructions are available at : <https://nuage.gate.cnrs.fr/index.php/s/eAzELRIgMOdYOix>

Chapter 3

Older workers and the value of job amenities

1

¹This chapter is joint with Mathilde Godard

3.1 Introduction

This article connects two debates in labor economics: how to promote longer working lives, and whether and how government should encourage alternative work arrangements. While promoting longer working lives is a top priority on the policy agenda, there are multiple barriers that hinder the employment of older workers. On the demand side, these barriers include employer practices, such as age discrimination. On the supply side, barriers include disincentives for older individuals to continue working, but also low employability due to insufficient training and poor health (OCDE, 2019). Most policy responses address supply-side barriers, and take the form of pension reforms (OCDE, 2019). But pension reforms may run up against various forms of constraints – employer practices and the employability of workers – and fail to be fully effective. An related and overlooked barrier as people age has to do with work arrangements, defined both by working conditions and by worker’s relationship to their employers (Mas and Pallais, 2017b). Can alternative work arrangements influence workers’ decision to continue working into old age? Should alternative work arrangements be encouraged? Surprisingly, these questions have received limited attention so far. We lack credible evidence on the extent to which older workers value work arrangements. What job amenities older workers are looking for? How much wage are they willing to pay for these job amenities? What drives their preferences over job amenities near career end?

We sample job seekers from the *Fichier National des Allocataires*, an administrative database collected by the organization in charge of unemployment insurance in France, and invite them to take an online survey.² We ask them about the job amenities they look for, as well as the ones they had in their previous job. We implement a vignette experiment to elicit their willingness-to-pay over a wide range of job amenities, which we validate with actual job search. We consider a number of commonly-discussed arrangements, including contract type, part-time work, schedule flexibility, working from home, commuting time, on-the-job physical constraints, and on-the-job exposure to infectious diseases. Our results show that older job seekers (55+) differ from the prime-aged (18-54) both in the value they place on each job attribute, and in the ranking of job attributes they value most. Most notably, we find large differences in preferences to avoid health risks. Older job seekers value sitting at work at 16.36% of an average net wage, while the corresponding estimate for the prime-aged is negative. We find the highest mean willingness-to-pay for commuting time, both for senior and prime-age job seekers. Senior job seekers, however, are willing to forego twice as much of an average net wage to avoid a one-way commute over an hour. Schedule flexibility is one of the most valued attribute among senior job seekers : our estimates predict that on average, senior job seekers would

²The survey is specifically designed to study how older job seekers (55+) value job amenities relative to the prime-aged (18-54). We oversample senior job seekers and ask them specific questions at the end of the survey (see Section 3.3.2).

be willing to trade-off 4.96 €/hour (22.62% of an average net wage) to have a fully flexible schedule rather than a schedule fixed by the employer (the corresponding estimate for prime-aged individuals is equal to 5.70% of an average net wage). Senior job seekers seem to value permanent contracts *less* than prime-aged job seekers (4.15% vs. 12.16% of an average net wage, although the difference is not statistically different at conventional levels). On average, senior job seekers do not have specific preferences over remote work and part-time work. But if the mean willingness-to-pay is informative, it is also important to look at the distribution of willingness-to-pay for a given amenity. We find evidence of heterogeneity in valuations in all of the job attributes we consider, especially among senior job seekers. Even when mean willingness-to-pay estimates are close zero, there is substantial heterogeneity in how job seekers value job amenities. For instance, while most senior job seekers are not willing to pay for part-time work, a tail of job seekers with high valuations allows for a sizable compensating differential (and possibly sorting). We close the paper by looking at the drivers of heterogeneity in valuations over job amenities near career end, and find that retirement expectations and health status can be important factors.

Quantifying preferences over job amenities is challenging because of the great demands on the field data that are required. Building on the theoretical framework for hedonic pricing in Rosen (1986b), an enormous literature has sought to test for a negative trade-off between amenities and pay using cross-sectional and longitudinal data. The estimates from these approaches, however, are unstable to adding person or workplace controls, and are often wrong-signed (Bonhomme and Jolivet, 2009; Mas and Pallais, 2017b). Most recent papers use stated preferences approaches or field experiments to measure how much are workers are willing to pay for a given job amenity. These methods directly control for job opportunities in hypothetical scenarios, which is key to identify how individuals value job amenities independent from what they expect to find in the actual labor market. In this paper, we run a survey-based vignette experiment : respondents make a series of choices between two fictive jobs described in so-called vignettes. Survey-based choice experiments with vignettes, when designed properly, elicit trade-offs that are close to market choices elicited in field experiments (Mas and Pallais, 2017b). A survey has additional advantages that it has information on individual characteristics that are not always possible to obtain from applicants in field experiments, such as the presence of health problems, or the expected date of retirement.

Our analysis is set in France. France is an interesting laboratory to study whether and how individuals – and the 55+ in particular – trade off wage and nonwage characteristics. The employment of older workers has traditionally been low in France, and the effective labour force exit age is among the lowest in OCDE countries (60.4 years for men and 60.9 for women in 2020, compared with 63.8 and 62.4 years for the OECD as a whole). The estimated health capacity to work at older ages (a measure based on the

gap in employment rates across time for given mortality rates) is among the highest in ISS countries³ (Coile et al., 2022; Blanchet et al., 2016). There is, arguably, some room to foster employment after age 55 in France. While promoting the hiring and retention of older workers and improving workers' employability are crucial, pension reforms usually stir social tensions and immediate political backlash. In this context, the case for alternative work arrangements is worth considering, at least if senior individuals place some value on them.

Our article provides evidence that older workers have specific preferences over job amenities; it quantifies these preferences, and examines the sources of preferences heterogeneity. A small literature studies how workers value work arrangements using stated preferences approaches or field experiments (Eriksson and Kristensen (2014b); Mas and Pallais (2017b); Maestas et al. (2018); He et al. (2021)), but without a specific focus on older workers. Maestas et al. (2018) marginally addresses this question. Using data from the RAND American Life Panel, the authors estimate the value of the working conditions in the US and assess its implication on estimates of the wage structure. As a side analysis, they report that physical constraints and work autonomy are disproportionately important after age 62. The closest paper to ours is Ameriks et al. (2020). The authors use strategic survey questions (SSQs) in a panel of American Vanguard clients more than 55 years old, and focus on a single job amenity. They establish that older Americans, even those who are long retired, have strong willingness to work, especially in jobs with flexible schedules – in which they can choose the number of hours worked instead of having to work the same number of hours as in their last job.⁴ Their findings suggest that for many, labor force participation near or after normal retirement age is limited more by a lack of acceptable job opportunities or low expectations about finding them than by unwillingness to work longer.

We extend the existing literature in several directions. First, we quantify the average WtP for a job amenity, but also the WtP distribution, which is seldom done in existing papers. This allows us to investigate the heterogeneity in valuations over job amenities, but also, under restrictive assumptions, to derive the market compensating differential for a given amenity. Second, we focus on a sample of job seekers. We hypothesize that their responses to the vignette experiment are probably close to what their choices would have been on the labour-market given the same options. After all, the fictive scenarios they face in our survey are not too dissimilar from application choices they make on a day-by-

³The National Bureau of Economic Research (NBER)'s International Social Security (ISS) project was established in the mid-1990s, based on the experience of a dozen developed countries : Japan, Sweden, US, UK, Denmark, Canada, Spain, Germany, Netherlands, Belgium, Italy, France.

⁴More specifically, they find that about 40 percent of respondents that were not working at the time of the survey, mostly in their late 60s or 70s, were willing to work again if all the conditions were the same as their last job; this number rises to 60 percent with a flexible schedule. Furthermore, 20 percent of them would be willing to take more than a 20 percent hourly wage reduction to do so.

day basis. If this is true, hypothetical bias is low, and willingness to pay estimates will closely align with their true preferences.⁵ Fourth, we provide estimates of willingness-to-pay for a wide range of job amenities. Above and beyond schedule flexibility or working conditions, we study how job seekers value the relationship to one’s employer (type of contract, hours worked). Fourth, while most papers in the literature focus on the US, we provide WtP estimates for France, where social protection schemes (pension systems, unemployment and disability insurance) provide less incentives to continue working, and where the functioning of the labour-market is different.

The remainder of this paper is organized as follows. Section 3.2 provides information about the labour-market situation of older workers in France We describe our survey and the vignette experiment in Section 3.3. Section 3.4 presents our empirical strategy, Section 3.5 the results obtained and compares our findings with related evidence. Section 3.6 discusses the results and concludes.

Employment rates of people aged 55-64 have improved sharply since the start of the century in most OECD countries, from 43.8% in 2000 to 61.4% in 2020 on average.

3.2 The labour-market situation for older workers in France

3.2.1 Employment rate and pension reforms

France ranks near the low end among OECD countries in terms of employment rate in the 55-64 group. From 38.2% in 2003 to 55.2% in 2020, the employment rate has sharply increased, but remains low compared to the OECD average (61.4% in 2020). The sharp rise in employment rate can be attributed in large part to the policies implemented to strengthen incentives to continue working after the age of 50 (OCDE, 2014). The 2003 pension reform extended the duration for contributions necessary to qualify for a full pension (from 40 to 41 years and three quarters). The 2010 reform pushed back, between 2011 and 2017, the minimum age at which people are entitled to receive either reduced pensions or full pensions – conditional on a sufficient number of years of social security contributions – from 60 to 62 years; the qualifying age for full pension entitlement from 65 to 67 years. Mandatory retirement age in the private sector has been postponed to 70 years.

⁵Another advantage of focusing on job seekers is that we can link individual willingness-to-pay estimates to job seekers’ future outcomes (exit from unemployment, job amenities conditional on employment) and test for sorting (i.e. whether job seekers who value a given amenity end up in jobs providing that amenity). This analysis is not included in the paper yet. For implement it, we need to extract data from the FNA to obtain exit from unemployment and, conditional on employment, some of the amenities in the new job (type of contract, hours worked, and commuting time).

The transition from employment to retirement takes place early in France. Only 55% of older workers moved directly from employment to retirement; 11% moved directly from unemployment to retirement. Consequently, France ranks near the low end among OECD countries in terms of effective labour force exit age. In 2020, it was estimated at 60.4 years for men and 60.9 for women, compared with 63.8 and 62.4 years for the OECD as a whole.

3.2.2 Unemployment rules

The unemployment rate for workers aged 55-64 was 5.8% in France in 2020, placing the country close to the OECD average (5.3%). Even it is lower than the total unemployment rate (8%), it is marked by a greater frequency of unemployment exceeding one year. While older workers are much less likely to be unemployed than younger ones, if unemployed, they are much less likely to find a similarly paid new job, and would even find it difficult to re-enter the labour market.

The provision that exempts older unemployed persons from looking for work as well as the public funding of early retirement have been largely abandoned. In France, unemployment insurance is based on the rule that the recipient must actively look for a job, but for older workers the maximum time during which benefits may be claimed is the longest among OECD countries. The maximum duration is three years for persons over 55 years, and it rises to eight years after age 59, since the unemployment benefit is maintained until the person is eligible for a full pension. The potential monthly allowance is much higher than in other OECD countries (OCDE, 2014).

Older persons are overrepresented among unemployed workers who have voluntarily left their firms following a *rupture conventionnelle*, i.e. a negotiated termination of their work contract, which entails eligibility to unemployment insurance benefits. The number of *rupture conventionnelles* peaks about three years before the minimum age at which individuals are entitled to pension benefits (DARES, 2020). This form of termination seems particularly attractive for better-paid older workers and their employers, but it rarely involves a return to employment after 58 years.

3.2.3 Prevalent work arrangements

In France, as is the case on average in other countries, the vast majority of older workers are employed on a permanent basis and in full-time jobs. Among individuals in employment, part-time work is more prevalent among the 55-64 group than the 30-54 group (23% vs. 18%); after age 55, its prevalence increases with age – to reach 41% at age 64 (DARES, 2017). Self-employment is less common than in other countries, on average. Full-time workers aged 55-59 are earning, on average, a wage that is 1.5 times that of those aged 25-29, a ratio that is slightly above international average (1.4 in Europe

and 1.3 for the OECD average). Figure C1 presents the prevalence of job amenities in France among people in employment using data from the European Working Conditions Survey (EWCS). The prevalence of amenities does vary with age, especially after age 64. Employees who are working beyond age 64 have indeed more flexibility in their schedule, are more often in part-time jobs and fixed-term contracts (although this shift may reflect the changing composition of the workforce).

3.3 Data

3.3.1 The FNA

We use administrative data (*Fichier national des allocataires*, FNA) collected by the organization in charge of unemployment insurance in France, the *Union nationale interprofessionnelle pour l'emploi dans l'industrie et le commerce* (UNÉDIC). The FNA gathers the information needed to compute UI entitlements, as well as the characteristics of the unemployment spell, and some sociodemographic variables. From the FNA, we select the inflow of job seekers registering for a new UI claim from January 1, 2021 to April 15, 2021.⁶ We restrict the sample to claimants entitled to UI benefits, who were actively seeking for a job, and did not work in the month of registration. In order to maximize the number of senior potential respondents to the survey, we select all individuals aged 55 and over (16,003 individuals) as well as a $\tilde{25}\%$ random sample of individuals under the age of 55 (30,323 individuals). We obtain their email addresses from the Public Employment Service (PES).⁷

3.3.2 The survey

Launching the survey

An invitation to take an online survey was sent in May 2021⁸ to the 43,407 individuals sampled from the FNA for which we retrieved an email address and who consented to be contacted for surveys. The survey took place right after the third (and last) national lockdown.⁹ The survey was framed as purely research-oriented : potential respondents were explicitly told that the unemployment services did not initiate the survey, nor would

⁶There was no lockdown in France during this period, except for the last couple of weeks (March 31-April 15).

⁷The FNA and the PES registers can be linked using a unique identifier. We retrieved email addresses for 45,844 individuals out of 46,326 (a 99% match rate). We dropped 2,437 individuals who did not consent to be contacted for PES surveys.

⁸A pilot survey was launched in February 2021 among job seekers who registered for a new UI claim from October 1, 2020 to January 15, 2021. The goal was to estimate the response rate, to collect comments on survey items, and to run several checks on the vignette experiment responses.

⁹Lockdown measures – closure of non-essential shops, suspension of school attendance, a ban on domestic travel and a nationwide curfew from 7pm-6am – were lifted on May 11. We discuss in Section 3.5.4 how to interpret our results in light of that context.

have access to the data. Figure C2 shows a screenshot of the personalized survey invitation email. We added two features to increase the response rate : two reminders, and the use of an incentive (a prize draw with a chance to win the most recent iPad). Out of the 43,407 individuals to which we sent an invitation to participate, 5,185 individuals responded, of whom 3,112 completed it.

The response rate –12%– is not high.¹⁰ A low response rate may or may not introduce non-response bias, because answers to survey items may not differ substantially between respondents and non-respondents. Table D1 shows the socio-demographic characteristics of survey respondents relative to the FNA sample. The 51% female share in the sample is above the FNA share (53%). Survey respondents tend to be older in our survey than in the FNA (42 vs. 39 years old). The survey contains relatively many highly educated respondents – more than 44% have 3-4 years of higher education. The corresponding share in the FNA is equal to 25%. Consequently, the distribution of respondents across sectors does not fully match the one in the FNA.

Weights can markedly improve population estimates and reduce nonresponse bias. We employ a weighting scheme that accounts for both sampling design and non-response, both in the computation of descriptive statistics and when fitting regression models. Weight adjustments are determined by the probability-sampling weights¹¹ and auxiliary variables (sex, age (five categories), education (six categories), previous job’s sector (fifteen categories), and reason for enrolling into UI (four categories)). Reassuringly, once we control for age, sex, education, previous job’s sector, and reason for enrollment, the other variables available in the FNA (time into unemployment, total number of unemployment spells, maximum duration of unemployment benefits) are not predictive of survey response.

Contents of the survey

The survey first asks respondents about their current job search, including the reservation wage and the type of job arrangements mainly looked for. Specifically, we ask about the type of contract respondents look for (permanent/temporary); whether they look for a full/part-time job; their maximum (one-way) acceptable commute; whether they would accept a job where the schedule is set by the employer; whether they look for a job where they can work remotely at least one day per week; for a job requiring primarily sitting; for a job minimizing the exposure to Covid-19. This initial part of the survey allows

¹⁰According to Cook et al. (2000), the average response rate for online surveys in research is close to 40%. Several features of our survey may explain why we obtain a lower rate. First, the length of the survey (up to 50 questions). Second, the fact that job seekers are less educated than the overall population (see Wu et al. (2022)’s meta-analysis on the role of education as a determinant to survey response rates).

¹¹Probability-sampling weights account for the higher probability that senior job seekers have of being sampled in the FNA. These weights are equal to the inverse of the probability of inclusion to the FNA sample (i.e, 1 for individuals aged 55 and more, and 4.09 for individuals aged less than 55).

us to provide detailed explanations of the job amenities that we include later on in the vignette experiment. Following the vignette experiment – discussed in length below – we collect information on the job arrangements in the respondent’s previous job. Before closing the survey, we collect some background individual characteristics (age, sex and ability to make ends meet). To investigate the sources of heterogeneous valuations in work arrangements, we also ask a question on self-rated health. Respondents are asked to rate their health on a 5-point scale : very good, good, fair, bad or very bad. We dichotomize the responses into good (very good and good) and bad health (fair, bad or very bad).¹² For individuals aged 55 and plus, we collect additional information on the age at which they expect to retire, and whether they provided informal care in the twelve past months.¹³ Overall, respondents have to answer a maximum of 50 questions (including vignettes) and spent on average 15 minutes completing the survey.

The vignette experiment

Although the theory on the relationship between job characteristics and wages is clear (Rosen (1986b)), it is empirically difficult to document the existence and magnitude of a trade-off between work arrangements and wages. A key difficulty is that we do not necessarily observe the relevant attributes of work arrangements, and we rarely observe what an individual alternatively could have chosen, i.e. her/his choice set. Besides, the choice set is distorted by employer-level decisions to provide (or not) work arrangements that individuals desire.

To circumvent these problems, we set up a choice experiment with vignettes. We confront respondents to a series of fictive choices between two job offers, Job A and Job B, defined by a set of job attributes and monetary compensation. This exercise is repeated six times per respondent, each time with different values for the attributes that characterize the wage-work arrangement offer. The order of the vignettes is randomized during the experiment. We explicitly state each vignette should be considered independently. The advantage of the vignette approach is twofold : i) job attributes can be randomized in a manner that would be difficult to implement in the labor market, ii) we observe the full set of choices provided to each respondent. The vignette experiment takes advantage of the information contained in the acceptance and rejection of job offers to derive valuations over alternative work arrangements.

Consider the example given in Figure 3.1. The left column lists all attributes de-

¹²There is evidence in the literature that dichotomized self-rated health is a good indicator of individual overall health. It has been found to be a good predictor of mortality even after controlling for more objective measures of health (Idler and Kasl, 1991; Idler and Benyamini, 1997; Bath, 2003).

¹³Informal care giving is captured by two questions. The first asks : "In the past 12 months, have you personally provided any assistance to a family member (whether in your household or not e.g. spouse, parent, step-parent, children or grandchildren)?" If the answer is yes, the second question asks : "In the past 12 months, on average, how often did you provide this help?" (almost daily/almost every week/almost every month/less often).

scribing the job. These attributes do not change across vignettes, but their values do. We instruct respondents that all other job characteristics not explicitly described are constant across jobs, minimizing concerns that certain job amenities often predict other job characteristics. In order to induce a high degree of variation in the possible combinations, 98 different vignettes were applied. This yields variation in the data that allows us to identify parameter values. For further details on the introductory text, the attributes and attribute levels, see Appendix 3.7. Further details on the creation and randomization of vignettes are provided in Appendix 3.7.

In the example given in Figure 3.1, Job A offers a short commute (less than 30 minutes) while the alternative, Job B, implies a long commute (more than 60min). However, opting for the short commute comes at a cost, since Job B offers a lower wage (-15% less than Job A), and higher physical demands. In the example, five of the attributes, "Hours worked", "Type of contract", "Schedule flexibility", "Option to work remotely" and "Exposure to infectious diseases" are held constant across the two alternatives. In other vignettes, these could vary while, typically, some other attributes would then be held constant. The respondent may accept Job A, Job B or accept neither of them (the so-called 'opt-out' solution). That we allow for such an 'opt-out' solution is a specificity of our design, which has consequences on the model specification (see Section 3.4). Going back to our example in Figure 3.1, an individual could accept neither of the two jobs if, for instance, s/he's looking exclusively for a permanent contract.

There are several challenges that require addressing in such a vignette experiment. First, some respondents could not pay close attention to the job descriptions, which could affect the precision of our estimates.¹⁴ To estimate the inattention rate and account for it in our econometric models, we implement two placebo tests. First, we randomly chose a vignette to be repeated twice during the vignette experiment. The inattention measure is derived as the share of job seekers who give different answers to the same choice situation. Second, we add a vignette with a dominated job offer. This approach requires us to make to a priori judgments about which amenity levels are likely preferred within a job characteristic. We assume that respondents prefer higher wage, higher schedule flexibility, and less commuting, but we do not make a priori judgements on other job characteristics. The 'dominated' vignette presents respondents with two job offers that are identical, except that one of them is better on the wage dimension and on another (randomly-chosen) attribute : either schedule flexibility or commuting. The corresponding inattention measure is derived using the share of respondents picking the dominated

¹⁴DellaVigna (2009) finds that agents are prone to inattention in many contexts. In the labour-market context, Mas and Pallais (2017b) find evidence of inattention in a field experiment where job seekers chose between two jobs offers.

position.¹⁵ In Section 3.5.4, we re-estimate our models excluding inattentive individuals according to either definition, and verify that our results are virtually unchanged.

Second, even if respondents pay close attention to the description of choice situations, cognitive load could be an issue. If the number of choice situations and the number of job attributes varying within a choice situation are too high, the quality of the inferred preferences will be poor. To alleviate the choice burden, we chose to limit to eight the number of choice situations that the respondent face (including the two placebo vignettes); we also limit to three the number of job attributes varying within a choice situation. This has important consequences on the design of the vignette experiment, which we explain in detail in Appendix 3.7.¹⁶ The importance of cognitive load can be assessed with data on the time spent answering each vignette. Figure C3 shows that respondents spend on average 1.4 minutes to answer the first (randomly-ordered) vignette, and then answer the seven remaining vignettes quite rapidly (30sec). This striking pattern suggests learning : respondents first take the time to understand the hypothetical situation and to scroll over the job characteristics to see their definitions; once they've understood the experiment, they make choices without too much cognitive effort.

Finally, there might be some degree of "hypothetical bias", that is, that respondents "offer" to pay more in hypothetical choice situations compared to their true preferences revealed through choices in real action situations (List, 2001). A careful design of the experiment is needed to alleviate this problem. The hypothetical situation should not be too unrealistic; we should ask job seekers to make choices over realistic work arrangements. Several features of our experiment reduce hypothetical bias. First, in order not to force a choice and to infer realistic preferences, we designed choice situations where respondents could choose neither of the two offers. Second, our fictive job offers lists the characteristics usually available in real job-market offers : the wage, the type of contract, and the number of hours. To match closely what the respondent would face on the market, the wage offered is based on the average wage in the respondent's former sector*qualification level.¹⁷ We build discrete variations around this baseline wage (+/- 5%, +/- 10% , +/- 15%) so that the wage difference between the two jobs cannot exceed 30%. We report hourly wages, and also include the monthly wage in parentheses (using

¹⁵Even with perfect attention, inattention rates would not necessarily be equal to zero. Choosing a dominated option can reveal an extreme preference for an attribute, and choosing two different jobs in the same situation may reveal real indifference.

¹⁶The three attributes that can vary within a choice situation are the same during the whole experiment for a given respondent. The levels of the remaining four attributes may vary across choice situations but are constant within a choice situation. In practice, we implement a balanced incomplete block design – see Appendix 3.7 for further details.

¹⁷We do not have information on the respondent's past wage in the FNA. We use instead FNA information on the former sector and qualification level. We then use data from the 2017 *Déclarations administratives de données sociales* (DADS – built by the French Institute of Statistics (Insee) from firms' fiscal declarations) to compute the average wage at the sector*qualification level (225 levels corresponding to the "FAP" classification).

the hours associated with the hypothetical job). To match closely what is available in the labor market, we propose the two most common types of contracts in the market (permanent contracts and fixed-term contracts) and the two most common types of working hours (35h and 24h per week).¹⁸

3.3.3 Descriptive statistics

Table 3.1 shows the socio-demographic characteristics (sex, age, education, health status, informal care giving) for the full sample (column 1), individuals aged 55 and over (column 2) and individuals aged less than 55 (column 3). On average, respondents are aged 34 years; 53% are females, and almost 40% obtained a higher education degree. Senior job seekers are particular in a number of ways. Aged 59 years on average, they are more often female, lesser-educated, and in worse health than prime-aged individuals. They are also specific in terms of labour-market characteristics – see Table 3.2. The net wage at the former sector*qualification level is higher on average for senior (21.8 €/hour) than for prime-aged job seekers (18.2 €). Only 35% of senior job seekers declare it likely to find a job in the next six coming months, while this proportion is almost twice as large among prime-aged job seekers. Senior seem to search more narrowly than prime-aged job seekers : 61% declare that they look for a specific occupation, and only 30% are willing to change occupation/sector or to become self-employed (the corresponding shares for prime-aged job seekers are 53% and 36%, respectively). 51% of senior job seekers expects to retire within three years. Finally, Table 3.3 lists the sectors in which respondents are looking for a job. Business assistance, commerce, sales and retail, and care are the most represented sectors, for senior and prime-aged job seekers alike.

Figure 3.2 shows which amenities job seekers look for. Again, senior job seekers seem to differ from the prime-aged on a number of dimensions. They search less often for a full-time job, but equally often for a permanent contract. In contrast, they look more often for short commute times, flexible schedules, the option to work remotely; they look primarily for sitting jobs, and jobs with low Covid-19 exposure. All two-sample t-tests are significant at the 5% level (except for contract type).

Does current job search depend on amenities held in the previous job? Figure 3.4 shows the share of respondents looking for a particular amenity among those who had that amenity in their previous job, and those who did not. Two patterns are worth noting. First, there is some consistency in the type of jobs respondents look for and the type of jobs they had. Respondents who had a particular amenity look more often for

¹⁸Permanent and fixed-term contracts represent respectively 85% and 15% of waged employment in France (OECD, 2021). Standard working hours for a full-time job in France are 35h per week. All additional hours require a bonus pay. A part-time job may set the work load anywhere below 35h and the minimum bound of 24h. If the work load is not defined in the job offer, it is set to 24h per week by default and this case is the most common on the job market.

that amenity than those who did not, irrespective of age. Second, senior individuals tend to stick more to amenities they had. For instance, 55% of senior who had a primarily-sitting jobs look for one; this proportion falls to 37% for prime-aged individuals who had that amenity as well. The pattern is similar for short commute times, flexible schedules, the option to work remotely, and low Covid-19 exposure. For permanent contracts and full-time jobs, however, the pattern is reversed. Seventy-three percent of prime-aged individuals who had a permanent contract look for one, while this proportion falls to 57% for senior individuals.

3.4 Empirical strategy

The vignette experiment produces the key data for our analysis. It allows us to estimate willingness to pay for job attributes. The starting point to estimate willingness to pay for job attributes is a random utility model (RUM). Each decision maker n faces a series of choice situations. In each choice situation t , s/he faces a choice set with three alternatives (Job A, Job B, or neither of them). Each alternative j of choice situation t brings the (unobserved) utility U_{njt} , and s/he chooses the alternative providing her/him the greatest utility :

$$U_{njt} = V_{njt} + \mathcal{E}_{njt} \quad (3.1)$$

In this two part model, \mathcal{E}_{njt} is a random term and V_{njt} is the representative utility, which is composed of the set of attributes of alternative j of choice situation t and background individual variables interacted with these attributes.¹⁹

The mixed logit is a highly flexible model that can approximate any random utility model. By allowing for random taste variation, unrestricted substitution patterns, and correlation in unobserved factors over choice situations, it obviates the three limitations of the standard conditional logit (Train, 2009).²⁰ This model writes as follows :

$$U_{njt} = x_{njt}\beta_n + \mathcal{E}_{njt} \quad (3.2)$$

where x_{njt} is a matrix of job attributes of alternative j of choice situation t and back-

¹⁹Given the RUM choice probabilities specification, only variables generating variations in utility *between* alternatives can be estimated. This property constrains the individual characteristics to be interacted with the vignette specific variables to be estimated.

²⁰According to Train (2009), the three limitations of the standard conditional logit are "the inability to represent random taste variation (differences in tastes that cannot be linked to observed characteristics); the inability to capture more flexible forms of substitution than proportional substitution across alternatives (Independence of Irrelevant Alternatives (IIA)); the inability to handle situations where unobserved factors are correlated over time".

ground characteristic of individual n interacted with job attributes jt . The associated parameter β_n is specific to individual n , representing that person's tastes. In this model, the coefficients β are distributed with density $f(\beta|\theta)$, where θ refers to the mean and covariance of β .²¹ This allows us to estimate mean and standard deviation of the WtP for job attributes.²² The error term in Equation (3.1) is assumed to be i.i.d. extreme-value distributed.

Equation (3.2) can be rewritten as :

$$U_{njt} = x_{njt}b + z_{njt}\mu_n + \mathcal{E}_{njt} \quad (3.3)$$

where b is a vector of fixed coefficients (the population means), and μ_n is a vector of random terms with zero mean (the individual n 's stochastic deviation from the average in the population). The terms in z_{njt} are error components that, along with \mathcal{E}_{njt} define the stochastic portion of utility. Various correlation patterns, and hence substitution patterns, can be obtained by appropriate choice of variables to enter as error components in z_{njt} (Train, 2009). In our case, the presence of the "opt-out" solution implies a nested structure, and hence a specific substitution pattern. Formally, the set of alternatives faced by a decision maker can be partitioned into subsets, called nests. The decision maker first chooses whether or not to accept any job (nest 1), then chooses between Job A and Job B (nest 2). This nested structure can be specified by introducing a dummy variable for each nest that equals 1 for each alternative in the nest (Job A/Job B) and zero for alternatives outside the nest (opt-out).²³

By definition, an individual's willingness to pay for a given job attribute is the decrease in his/her wage that keeps his/her utility constant given his/her job features that attribute. An estimate of the WtP is obtained by dividing a parameter for a given attribute with the parameter of the net wage. As usual in the literature, the wage coefficient is fixed, so that the distribution of willingness to pay for each non-monetary attribute has the same distribution as the corresponding attribute's coefficient. The mean WtP for a given attribute writes as follows :

$$\overline{WtP}_{commuting} = \frac{b_{commuting}}{\beta_{wage}} \quad (3.4)$$

²¹We usually assume each of these coefficients to be independent and normally distributed. We test in the next section for different specifications for the distribution of the random coefficients. We also test a version of the model that allows for correlated random coefficients.

²²To ease the computational burden we only estimate mean effects of interaction terms between job attributes and individual observable characteristics. Although we can compare mean WtP across socio-demographic groups, we assume the same distribution around their means.

²³The random quantity μ_{nk} thus enters the utility of each alternative in nest k , inducing correlation among these alternatives (IIA holds within nest). It does not enter any of the alternatives in other nests, thereby not inducing correlation between alternatives in the nest with those outside the nest (IIA does not hold in general for alternatives in different nests).

Deriving willingness to pay for each job attribute allows us to answer such questions : how much wage are you willing to forego in order to have e.g. full flexibility in your job? How physically-demanding should your job be in order to be fully compensated for a wage decrease of a magnitude of 5%?

3.5 Results

3.5.1 Willingness-to-Pay for job amenities.

To test for the existence of a trade-off between the wage and the job attributes – and to evaluate its magnitude – we start by comparing three models.

Table 3.5 shows the results for the full sample (irrespective of age) from a standard conditional logit, a mixed logit assuming that random coefficients are i.i.d, and a mixed logit allowing for correlation across job attributes coefficients. In both mixed logit models (columns (2) and (3)), the coefficients on job attributes are assumed to be normally distributed. This specification choice implies to carefully interpret the coefficient distributions, as normal distributions have relatively long tails. This forces some individuals in our sample to have negative valuations of job attributes. This could reflect the diversity of preferences, however : after all, not everyone is willing to work seated, and some are even willing to avoid it at all costs.

Results in Table 3.5 illustrates four key points. First, coefficients on all job attributes are positive and significant across all models, except for remote work. Such positive values indicate that on average, individuals derive an intrinsic utility from job attributes that they would be willing to trade off for a monetary equivalent. Second, we observe a large difference in coefficients between conditional and mixed logit models. This large difference comes from the ability of the mixed logit models to explain a larger part of the unobserved portion of utility.²⁴ Third, the standard deviation of each random coefficient is highly significant, indicating that these coefficients do indeed vary in the population. The mixed models thus provide a significantly better representation of the choice situation than standard logit, which assumes that coefficients are the same for all respondents. Fourth, the opt-in constant in mixed logit models is negative and significant. This additional parameter captures the average effect of all factors that influence opt-in choices that are not included in the utility specification. It should be noted that this parameter includes various components (e.g. status-quo bias, unobserved attributes, complexity of the experiment). This means that its interpretation as a utility parameter can be unclear

²⁴Usually, any logit model is expressed in its scaled form : only the ratio $\beta = \frac{\beta^*}{\sigma}$ can be estimated. β^* (the effect of each observed variable) and the scale parameter σ (the variance of the unobserved portion of utility) are not separately identified. For that reason, a larger variance in unobserved factors σ lead to smaller coefficients, even if the observed factors have the same effect on utility. Note that willingness to pay, values of time, and other measures of marginal rates of substitution are not affected by the scale parameter, as the scale parameter does not affect the ratio of any two coefficients (Train, 2009).

(Campbell and Erdem, 2019). It is not necessarily the case that accepting a job offer reduces utility. In column (2), the coefficients are estimated under the assumption that they are i.i.d. One could reasonably expect that some of them are correlated. The model shown in column (3) allows for correlated random coefficients. A likelihood ratio test between models in the two mixed logit models shows that allowing correlation across coefficients significantly improves the model’s ability to explain the choices of our participants ($p < 0.001$).²⁵

We use the mixed correlated model as our main specification. We add two features to the model. To account for the fact that individuals with higher wage incomes are expected to have a stronger demand for positive job amenities due to decreasing marginal utility of money, we control for the respondent’s wage (more specifically : the wage offered in the vignette experiment). We follow Eriksson and Kristensen (2014b) and introduce an interaction term between each of the job attributes and an indicator for whether the respondent’s own wage is above the median wage in our sample. We also explicitly model the ”opt-in” behaviour. We do so by introducing interaction terms between the opt-in constant and several individual observable characteristics (age category, sex, wage above median, and education). The resulting model is shown in column (1) of Appendix Table D2. As expected, it is relevant to control for the respondent’s own wage : all job attributes are valued significantly higher among respondents in the upper half of the wage distribution. Our results also indicate that individual observable characteristics can significantly explain job acceptance behaviour. The increased log-likelihood also indicates a better fit to the data.

Based on the coefficients in Appendix Table D2 – column (1), we can compute WTP for the job attributes; these are shown in the first column of Table 3.6. Panel A shows the results for the full sample (irrespective of age). The highest mean WTP is found for commuting time, which is valued to 7.63€/hour (one-way commute less than 30 min) and 4.46€/hour (one-way commute between 30 and 60 minutes). These estimates correspond to, respectively, 40.9% and 23.9% of an average net wage (see column (3)). The mean WTP for a full-time job is also high : on average, job seekers are willing to forego 22.6% of their net wage to avoid a part-time job. Schedule flexibility comes next as the most valued job attribute. Job seekers are willing to trade off wage (1.78€/hour) against some flexibility (control over starting and ending hours, but no control over the number number of hours/day or hours/week). The mean WTP for full flexibility (control over starting and ending hours; control over the number of hours worked per day or per

²⁵We test different specifications for the distribution of the random coefficients. We exclude the use of non normal distributions (which do not allow correlation across coefficients) as our tests in Table 3.5 favor the correlated mixed model over the simple one (see bottom panel of columns (2) and (3)). We test a lognormal distribution, which is useful when the coefficient is known to have the same sign for every individual (since the lognormal distribution is defined over the positive range). Our likelihood ratio tests, however, all conclude in favor of the normal mixed logit models.

week) is even higher (3.5€/hour, corresponding to 18.7% of an average net wage). High WTP for low commuting time and schedule flexibility suggest that job seekers forego a substantial share of their wage to improve work-life balance. Our results, however, show that the average WTP for remote work is close to zero. Even the 10% in the high tail of the WTP distribution attributes quite a low value to remote work (7% of an average net wage, given the normal mixing distribution). A possible explanation is that while remote work can strike a good work-life balance, it can also imply isolation, increased needs for meetings, distractions at home, etc. In fact, remote work is the job attribute that has the highest variation in how it is valued relative to its mean WTP. This translates into a large share of job seekers (44%) who attribute a negative value to remote work (given the normal mixing distribution). While remote work became widely available at the time of the survey²⁶, our results suggest that on average, job seekers still prefer the pre-pandemic ideal, with on-site schedule flexibility and short commuting time. The mean WTP for a permanent contract is 2.7€/hour. This may not seem high given the obvious advantages a permanent contract gives in France (e.g. easier access to credit or the rental housing market, long-term financial stability), but still corresponds to 14.4% of an average net wage. Finally, the WTP for health-related job attributes is quite low on average. There is a large variation in the valuation of physical on-the-job demands; the associated mean WTP is close to zero (0.74€/hour). Almost fifty percent of job seekers attribute a negative value to being 'mainly seated' at the workplace (given the normal mixing distribution). On average, job seekers are willing to forego 11% of an average net wage to minimize exposure to infectious diseases (e.g. Covid-19) in the workplace.

Is the magnitude of these WtP reasonable? Overall, our estimates lie within the range of WtP estimated in the literature. In our sample, making one's own schedule (relative to a schedule set by the company with no possibility for changes) is equivalent to a 18.7% wage increase. For comparison, [Maestas et al. \(2018\)](#) find a 9% wage increase for US workers, and [Eriksson and Kristensen \(2014b\)](#) a 13% wage increase for Danish workers. [Mas and Pallais \(2017b\)](#) find that the average worker is not willing to pay to make one's own schedule, but find large heterogeneity in valuations, and a strong aversion to jobs that permit employer discretion in scheduling: the average worker is willing to take a 20% wage cut to avoid these jobs. Similarly, our mean estimated WtP for remote work (a 2.5% wage increase equivalent) is close to the estimates obtained by [Lewandowski et al. \(2023\)](#), [Eriksson and Kristensen \(2014b\)](#) and [Maestas et al. \(2018\)](#) – 2.9%, 3.8% and 4.1%, respectively – but lower than the 8% estimate obtained by [Mas and Pallais \(2017b\)](#). Regarding part-time work, [Maestas et al. \(2018\)](#) find that the average worker

²⁶With the Covid-19 crisis, successive lock-downs and restrictions, remote work in France reached its peak in 2020 affecting 41% of employees. This share went down the pre-crisis level (30%) in 2021, although the number of days worked remotely remained well above the pre-pandemic average (3.6 days per week vs. 1.6 days per week in late 2019) ([Humanis, 2021](#)).

is willing to accept a 40-hour week job which pays 17% less than an equivalent 20-hour per week job; the corresponding estimate in Mas and Pallais (2017b) is 40%. Although our estimates are not directly comparable to theirs, we also find that individuals are willing to forego an important share of the average net wage (22%) to have a 35-hour job rather than a 24-hour job. Finally, our WtP for commute time and on-the-job physical constraints seem reasonable in magnitude. Our estimates suggest that the average worker is willing to sacrifice about 24% of an average wage to have a medium commute (30-60 min) rather than a long commute (>60min). For comparison, Mas and Pallais (2017b) finds that the average worker is willing to sacrifice about 15% of an average wage to have a short commute (<40 min). We find that individuals in our sample value primarily sitting as equivalent to a 4% average wage; Maestas et al. (2018) find a mean WtP of 12% of an average wage.

3.5.2 Do senior job seekers value differently job attributes?

The first obvious difference between senior and prime-age job seekers relates to the willingness to accept an offer. When looking at raw data from the vignette experiment, we see that prime-aged job seekers accept a job offer four out of five times, while senior job seekers only do so half of the time. Results presented in Appendix Table D2 – column (1) confirm that conditional on gender, education and wage, senior job seekers are less likely to accept a job offer.²⁷ But the differences between senior and prime-age job seekers go beyond the mere decision to work.

To study whether senior job seekers have specific preferences over job amenities, we introduce an interaction term between an indicator for whether or not the job seeker is above age 55 and i) wage ii) each of the nonmonetary job attributes. We also include interaction terms between each of the nonmonetary job attributes and sex/education indicators to avoid composition effects. The results are presented in Appendix Table D2 – column (2). Corresponding WTP for senior and prime-aged job seekers are shown in Panel B and C of Table 3.6. Figure 3.3 presents the results graphically. Overall, senior job seekers differ from prime-aged individuals, both in the value they place on each job attribute, and in the ranking of job attributes they value most. Most notably, we find large differences in preferences to avoid health risks. Senior job seekers value primarily sitting at work at 16.4% of an average net wage, and low workplace exposure to infectious diseases at 27.9% of an average net wage. We estimate much smaller (or even negative) valuations for prime-aged job seekers. We find the highest mean willingness-

²⁷The coefficient on the opt-in indicator interacted with an indicator for whether or not the job seeker is above age 55 is negative and highly significant (coeff : -3.86***, s.e : 0.17). An interpretation could be that the derived utility from accepting a job is lower for senior job seekers. Alternatively, there are systematic differences in the average effects of factors not included in the utility expression between senior and prime-age job seekers.

to-pay for commuting time, both for senior and prime-age job seekers. But senior job seekers are willing to forego twice as much of their average net wage to avoid very long commuting time. Schedule flexibility is one of the most valued attribute among senior job seekers : our estimates predict that on average, senior job seekers would be willing to trade-off 4.96€/hour (22.6% of an average net wage) to have a fully flexible schedule (the corresponding estimate for prime-aged individuals is equal to 5.7% of an average net wage). While senior job seekers place some value on permanent contracts, they seem to value it *less* than prime-aged job seekers (4.2% vs. 12.2% of an average net wage, although the difference is not statistically different at conventional levels). On average, senior job seekers do not have specific preferences over remote work and part-time work.

While the mean willingness-to-pay is informative, it is also important to look at the distribution of willingness-to-pay for a given amenity. An appealing feature of the mixed logit is that the WtP can be given a graphical representation. In particular, we can derive individual-level parameters, which are indicative of where in the distribution of tastes does a particular job seeker lie.²⁸ Figure 3.4 shows the distribution of individual-level WtP for each nonmonetary job attribute, for senior and prime-aged workers separately. We find evidence of heterogeneity in valuations in all of the job attributes we consider, especially among senior job seekers (which suggest greater heterogeneity in preferences near career end). Even when mean willingness-to-pay estimates are close zero, individual willingness-to-pay can differ quite substantially. For instance, while most senior job seekers are not willing to pay for part-time work, a tail of workers with high valuations allows for sizable compensating differentials.

3.5.3 Heterogeneity in senior preferences

What drives preferences over job amenities near career end? Who values what, and how much? To answer these questions, we examine how the WtP for nonmonetary job attributes varies across individuals with different observable characteristics. We look at three individual features, which we hypothesize are the main drivers of preferences near career end : health status, informal care giving, and expected distance to retirement. We estimate the previous model for the subset of senior job seekers. We extend the model by interaction terms between nonmonetary job attributes and indicator variables for dichotomized self-reported health status, informal care giving, and expected retirement within a three-year horizon. Interaction terms between nonmonetary job attributes and age (as a continuous variable) are also included in the model.

The results are shown in Table 3.7. As a note of caution, they are not fully robust

²⁸The distribution of coefficients conditioned on the individual's observed choices can be obtained from the distribution of coefficients in the population Train (2009). The so-called "individual parameters" correspond to $\bar{\beta}_n$ for each individual n . Using the estimated model in Appendix Table D2 – column (2), we obtain for each respondent a vector of individual parameters, where each parameter corresponds to the individual's preference over an nonmonetary job attribute.

across alternative specifications, which is natural given the number of interactions we introduce in the model. The following results, however, hold across all specifications : individuals in poor health tend to value health-related amenities significantly more than individuals in good health; individuals who expect to retire within a three-year horizon value significantly less full-time jobs. From Table 3.7 it is possible to calculate the extra amount (in percent) job seekers with a particular characteristic are willing to pay for job attributes. As such, individuals in poor health are willing to pay an extra 116% WtP for mainly-seated jobs, and an extra 50.6% WtP for low Covid-19 exposure. Individuals close to retirement are willing to pay 67% less for full-time jobs.

3.5.4 Robustness checks

A key concern is whether respondent's choices in the vignette experiment reflect how they would respond in the labour-market given the same options. To test for this, we compare individual willingness-to-pay estimates to current job search. More specifically, we use information about current job search collected at the beginning of the survey, where we ask job seekers about the job arrangements they mainly look for. For a given job attribute k , we calculate the share currently looking for that attribute among job seekers with $WtP_k = x$. The results for the full sample are shown in Figure C4, with each panel of the Figure showing the results for a different job attribute. Overall, individuals who value a specific job attribute look more often for that attribute on the labour-market. This is important for the internal validity of our estimates : the valuations elicited in the vignette experiment are correlated with actual search behavior.

Another crucial point in vignette experiments is to account for potential inattention. In our experiment, 16.6% of respondents give a different answer to a same vignette, while 8.6% choose the dominated alternative in the placebo vignette. We re-estimate our models excluding inattentive individuals according to either definition. Results are virtually unchanged – see Table 3.8, columns (2)-(3).

Concerns may arise regarding the external validity of our estimates given the specific context in which the survey was conducted. As discussed in Section 3.3.2, the survey was launched right after the third (and last) national lockdown due to the Covid-19 pandemic. Many workers experienced remote work, no commute and high schedule flexibility during lockdowns. If they disproportionately value these job attributes in the immediate aftermath of the lockdown, but not under normal circumstances (e.g. because of loss aversion), our WtP estimates will be upward-biased. This does not appear to be the case, however, for at least two reasons. First, our WtP estimates fall within the range of WtP estimated in the existing literature. In particular, the estimated WtP for remote work is very close to the estimates obtained both before and after the Covid-19 pandemic

(Eriksson and Kristensen, 2014b; Maestas et al., 2018; Lewandowski et al., 2023). Second, our results are robust to the exclusion of respondents who declared that their answers in the vignette experiment would have differed in the absence of the Covid-19 crisis.²⁹ Results are virtually unchanged – see Table 3.8, column (4).

3.6 Conclusion

We employ a choice experiment with vignettes in a nationally representative survey of job seekers to estimate the willingness-to-pay distribution over a wide range of job amenities. Older job seekers (55+) differ both in the value they place on each job attribute, and in the ranking of job attributes they value most. Most notably, we find large differences in preferences to avoid health risks, long commuting times, and schedules fixed by the employer. We find evidence of heterogeneity in valuations in all of the job attributes we consider.

Overall, our results suggest that job seekers have specific preferences over work arrangements in the final stage of their working lives. The average ideal job is close from home, flexible³⁰, and features low health risks. When looking at the drivers of heterogeneity in WtP near career end, we find that the expected distance to retirement and health status are important factors, especially when considering on-the-job health risks and hours worked.

Now, if preferences over job amenities change as people age, what then explains the slow change in the incidence of job amenities late in life, as pictured in Figure C1? The answer to that question is complex. How many and which kind of amenities will eventually be observed on the market, and for whom, is the outcome of interaction of workers' preferences, the firm's cost structure, and the desire to attract specific types of labor (Eriksson and Kristensen, 2014b). Our results suggest that employers may not find it profitable to employ older workers on e.g. flexible schedules or less-physically demanding jobs, despite higher willingness to pay estimates. This may have to do with higher costs to firms of providing these amenities to older workers.³¹ Alternatively, it

²⁹Specifically, we ask "When reflecting on the various hypothetical scenarios presented to you earlier, would you say that your choices would have remained unchanged in the absence of the Covid-19 crisis?"

³⁰This result is in line with the results of Ameriks et al. (2020) who find that that flexibility is an important characteristic for US workers pursuing bridge jobs.

³¹Following Mas and Pallais (2017b), we can interpret WTP distributions to shed light on the cost to firms of alternative work arrangements. Under perfect sorting (no frictions, perfect information on both sides of the market), if p is the share of workers in the alternative arrangement, the marginal worker's valuation is the $1-p$ percentile of the WTP distribution. In our case, the market compensating differential for e.g. a fully flexible schedule is 2.12 euro/hour – implying a 11% discount. The fact that employers are not offering flexible schedules to these marginal workers suggests that flexible scheduling is quite costly for the marginal employer to implement

may have to do with the relative productivity of senior workers, or the limited ability of firms to distinguish higher-ability senior applicants with a high WTP for these amenities from lower-ability workers, since setting a lower wage would mean attracting more lower-ability applicants (Mas and Pallais, 2017b).

Our findings contribute to two strands of policy discussions. First, work arrangements are rarely included in the policy tools to foster older workers' employment. We have established that older workers have quite specific preferences over job amenities. If, however, older workers fail to sort into jobs that feature these amenities because sorting is imperfect³², which in turn leads to premature exit from employment, there is a case for policy intervention. Second, the question of older workers employment is seldom mentioned in the discussions on alternative work arrangements.³³ While gender differences in alternative work arrangements are largely discussed (see e.g. Le Barbanchon et al. (2021); Goldin and Katz (2016)), age differences are rarely touched upon.³⁴ Understanding how preferences over alternative work arrangements change with age is important. If providing desired amenities to older workers can help them re-enter or remain in the labor-market, such arrangements should be encouraged.

(coordination, monitoring). Age-specific p shares and WTP distributions would imply a +31% extra cost of providing flexible schedules to senior individuals, which seems quite extreme.

³²Sorting can be imperfect because of various frictions on the labour-market, or imperfect information on e.g. worker productivity.

³³In a recent and comprehensive literature review on alternative work arrangements, Mas and Pallais (2020) list a number of reasons why alternative work arrangements are of interest to economists and policymakers, but do not mention older workers' labor force participation.

³⁴In a very interesting paper, Jackson (2022) uses U.S tax return data to analyze the impact of the gig economy on the careers of unemployed workers. She finds that access to the gig economy does crowd out traditional employment in the long run but increases earnings in the short-run. For workers who are 55 and over when they lose their jobs, the gig economy prolongs their working life and decreases their reliance on Social Security Disability Insurance and Social Security retirement benefits, whereas for prime-age workers the gig economy leads to bigger crowdout of traditional employment and future earnings.

Figure 3.1: Screenshot of a vignette in survey

*As part of your job search, imagine you are offered the two jobs shown below. Except for the characteristics highlighted in red below, please assume the jobs are the strictly identical in all other ways, including on characteristics no listed in the table. Please review the jobs and indicate below whether you prefer Job A or Job B. If neither job is suitable for you, you may decide to accept neither of them (you prefer to continue your job search).

You may scroll over the characteristics to see their definitions. ⓘ

	Job A	Job B
Gross wage ⓘ	17,9€/hour => 1856€/month	15,3€/heure => 1591€/month
Hours worked ⓘ	Part-time	Part-time
Type of contract ⓘ	Fixed-term	Fixed-term
Schedule flexibility ⓘ	Partial	Partial
Option to telecommute ⓘ	No	No
Commuting time ⓘ	More than 60 min	Less than 30 min
Physical demands ⓘ	Mainly seated	Mainly standing
Exposure to infectious diseases (relative to the average risk in your sector) ⓘ	Low	Low

Which job do you prefer?

Figure 3.2: Job amenities looked for

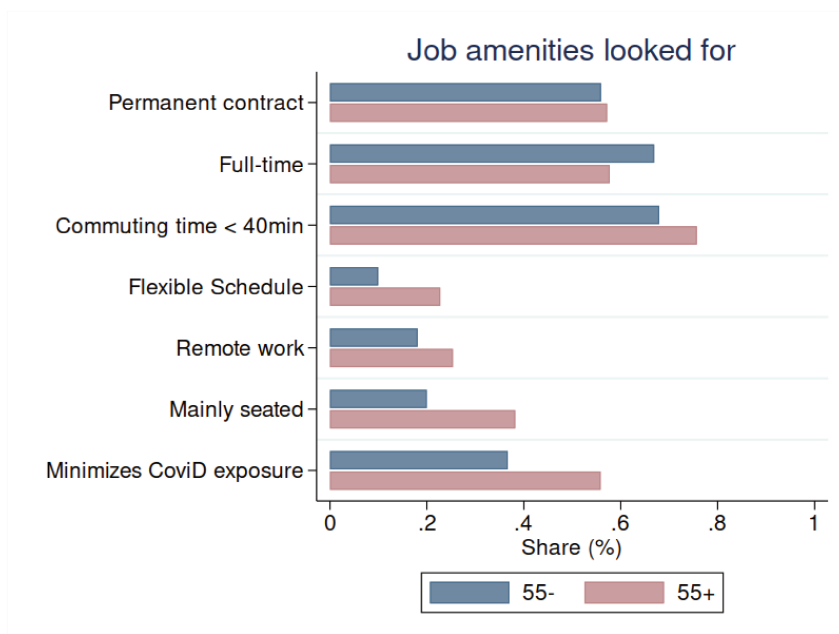


Figure 3.4: Distributions of Willingness to Pay for Job Attributes, by Age Group

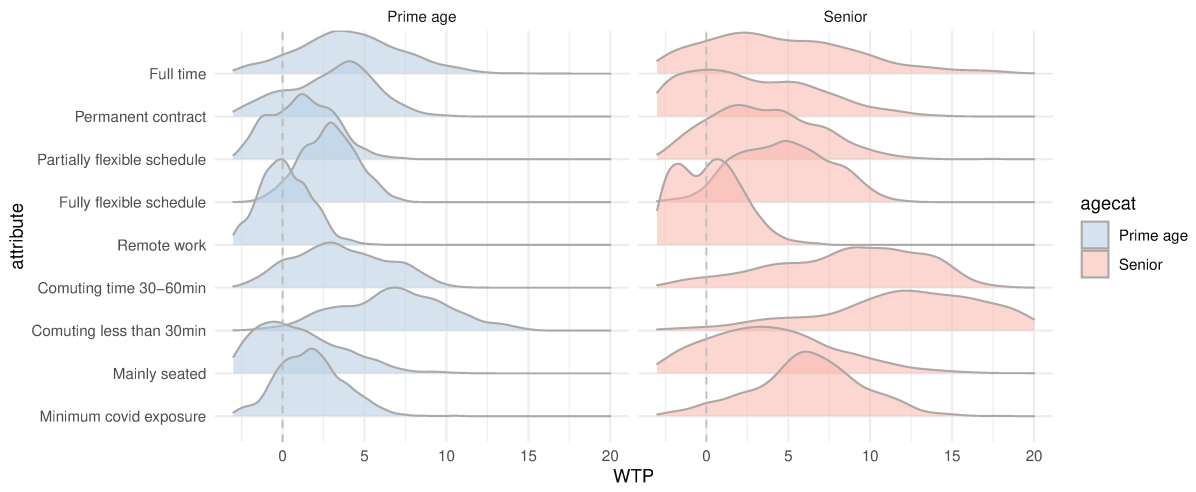


Figure 3.3: Willingness to pay by Age Group

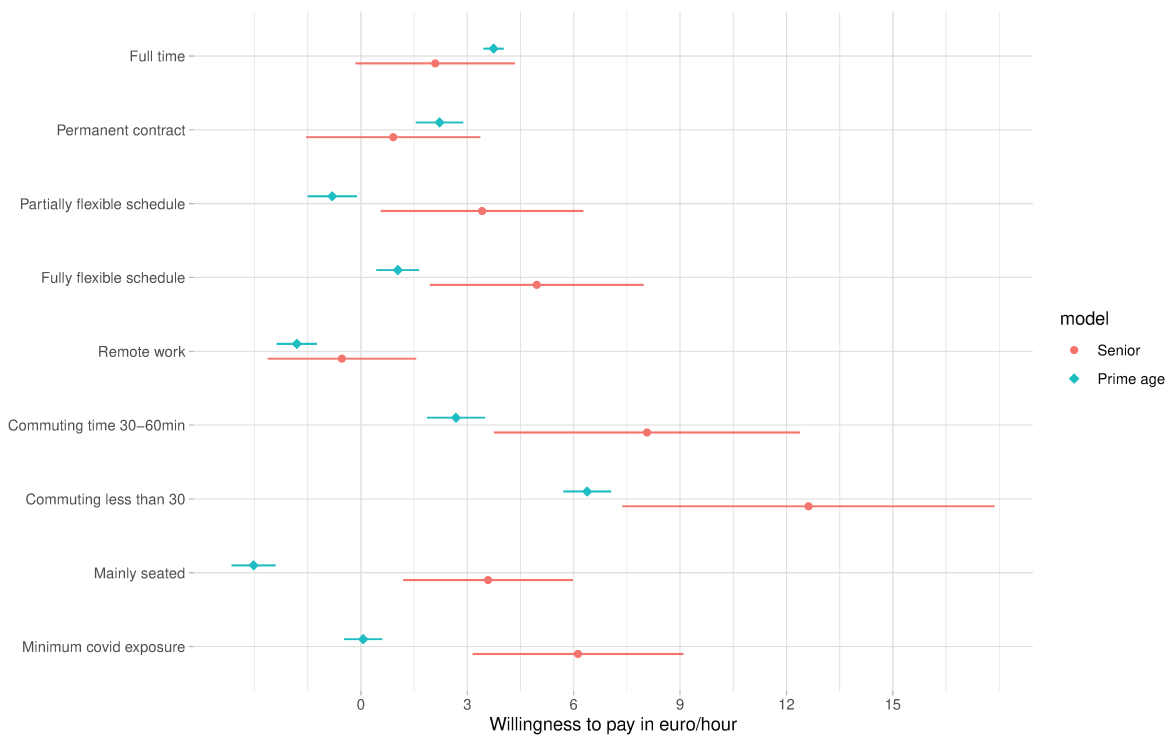


Table 3.1: Socio-demographic characteristics of the sample

	Full sample	Senior	Prime-aged
Age	31.97	58.00	28.53
Female	0.53	0.61	0.52
Highest education level			
Max BEPC	0.23	0.23	0.22
CAP,BEP	0.14	0.30	0.12
BAC	0.24	0.16	0.25
BAC+2	0.11	0.13	0.11
BAC+3/4	0.11	0.09	0.11
Bac+5	0.17	0.09	0.18
Good self-assessed health	0.77	0.51	0.80
Informal care giving (daily-weekly)	.	0.36	.
Nb observations	3112	1272	1840

Notes : Weighted estimates. Our weighting scheme accounts for both sampling design and non-response (see Section 3.3.2). The number of observations corresponds to the actual number of individual in our sample.

Table 3.2: Labour-market characteristics of the sample

	Full sample	Senior	Prime-aged
Hourly net wage ^(a)	18.66	21.81	18.24
High (subjective) probability of finding a job	0.66	0.35	0.70
Looks for a job in particular	0.53	0.61	0.52
Open to career change ^(b)	0.36	0.30	0.37
Expects to retire within 3 years	.	0.51	.
Nb observations	3112	1272	1840

^(a) We do not observe the hourly net wage at the individual level. We assign to each individual the hourly net wage in his/her former sector*qualification level. ^(b) Willing to change job/sector, or transit to self-employment. Note : Weighted estimates. Our weighting scheme accounts for both sampling design and non-response (see Section 3.3.2). The number of observations corresponds to the actual number of individual in our sample.

Table 3.3: Repartition of survey respondents by sectors

	Full sample	Senior	Prime-aged
Agriculture, forestry etc	0.03	0.01	0.04
Arts and craftsmanship	0.01	0.01	0.01
Banking, Insurance, Real Estate	0.02	0.04	0.01
Commerce, Sales and Retail	0.14	0.11	0.14
Communication, Media	0.03	0.03	0.03
Construction, Building etc	0.06	0.05	0.06
Hotels, Restaurants, Tourism etc	0.07	0.04	0.07
Industry	0.06	0.07	0.06
Installation and Maintenance	0.04	0.07	0.03
Health	0.03	0.02	0.03
Care	0.13	0.10	0.13
Show business	0.01	0.01	0.01
Business assistance	0.14	0.21	0.13
Transport and Logistics	0.07	0.08	0.07
Not specified	0.17	0.16	0.18
Nb observations	3112	1272	1840

Notes : Weighted estimates. Our weighting scheme accounts for both sampling design and non-response (see Section 3.3.2). The number of observations corresponds to the actual number of individual in our sample.

Table 3.4: Job amenities looked for, by previous situation

	Had amenity in previous job		Did not have that amenity in previous job	
	Senior	Prime-aged	Senior	Prime-aged
<u>Share looking for:</u>				
Permanent contract	0.57	0.73	0.41	0.48
Full-time	0.63	0.79	0.11	0.40
Commuting time < 40min	0.84	0.79	0.57	0.42
Flexible Schedule	0.16	0.08	0.28	0.20
Remote work	0.41	0.35	0.15	0.13
Mainly seated	0.55	0.37	0.19	0.09
Low CoviD exposure	0.56	0.32	0.49	0.32

Reading note : Among senior individuals who had a permanent contract in their previous job, 57% are looking for a permanent contract. The corresponding share for prime-aged individuals is equal to 73%. Notes : Weighted estimates. Our weighting scheme accounts for both sampling design and non-response (see Section 3.3.2).

Table 3.5: Results from standard conditional logit and mixed logit models

	Standard conditional logit (1)	Mixed normal (2)	Mixed normal correlated (3)
<u>Mean :</u>			
Wage	0.14*** (0.01)	0.30*** (0.01)	0.31*** (0.01)
Full time	0.53*** (0.03)	1.21*** (0.04)	1.23*** (0.04)
Permanent contract	0.25*** (0.03)	0.73*** (0.04)	0.77*** (0.04)
Partially flexible schedule	0.22*** (0.03)	0.37*** (0.04)	0.41*** (0.05)
Fully flexible schedule	0.50*** (0.03)	0.92*** (0.04)	0.98*** (0.04)
Remote work	0.07* (0.03)	0.05 (0.03)	0.02 (0.03)
Commute time 30-60min	0.65*** (0.04)	1.24*** (0.05)	1.43*** (0.06)
Commute time less than 30min	1.10*** (0.03)	2.13*** (0.05)	2.37*** (0.05)
Mainly seated	0.25*** (0.03)	0.19*** (0.03)	0.21*** (0.04)
Exposure to infectious diseases	0.42*** (0.03)	0.63*** (0.03)	0.71*** (0.04)
Opt-in	-1.59*** (0.05)	-0.88*** (0.06)	-0.97*** (0.07)
<u>Standard deviation :</u>			
Full time		1.69*** (0.05)	1.78*** (0.06)
Permanent contract		1.55*** (0.06)	1.61*** (0.07)
Partially flexible schedule		0.97*** (0.08)	1.30*** (0.08)
Fully flexible schedule		0.72*** (0.08)	0.79*** (0.08)
Remote work		0.69*** (0.06)	0.79*** (0.06)
Commute time 30-60min		-0.18 (0.11)	1.42*** (0.09)
Commute time less than 30min		1.10*** (0.07)	1.59*** (0.07)
Mainly seated		1.34*** (0.05)	1.68*** (0.06)
Exposure to infectious diseases		1.05*** (0.06)	1.22*** (0.06)
Opt-in		3.60*** (0.07)	4.01*** (0.08)
AIC	38163.90	31374.05	
Log Likelihood	-19070.95	-15666.03	-15467.25
Num. obs.	3, 101	3, 101	3, 101

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. (i) Standard errors are in parenthesis. (ii) Weighted estimates. The weighting scheme accounts for both sampling design and non-response (see Section 3.3.2). (iii) As there are repeated observations for the same individuals, the longitudinal dimension of the data is taken into account in the mixed logit models. The panel data version of the log-likelihood is used (assuming that the random parameters of individual n are the same for all his choice situations). (iv) The coefficient on the "opt-in variable" captures the nested nature of the choice set and is excluded from the correlations in the last model.

Table 3.6: Willingness to Pay for Job Attributes.

Attribute	WTP (€/hour)	Mean wage share (%)
	(1)	(2)
Panel A : Full sample		
Full time	4.21 ***	22.55%
Permanent contract	2.69 ***	14.42%
Partially flexible schedule	1.78 ***	9.53%
Fully flexible schedule	3.49 ***	18.68%
Remote work	0.47 ***	2.53%
Commuting time 30-60min	4.46 ***	23.9%
Commuting time less than 30 min	7.63 ***	40.86%
Mainly seated	0.74 ***	3.97%
Exposure to infectious diseases	2.05 ***	10.98%
Panel B : Senior (55+)		
Full time	2.1 *	9.57%
Permanent contract	0.91	4.15%
Partially flexible schedule	3.42 **	15.59%
Fully flexible schedule	4.96 ***	22.62%
Remote work	-0.54	-2.45%
Commuting time 30-60min	8.07 ***	36.8%
Commuting less than 30	12.62 ***	57.58%
Mainly seated	3.59 ***	16.36%
Exposure to infectious diseases	6.12 ***	27.92%
Panel C : Prime age (18-54)		
Full time	3.74 ***	20.51%
Permanent contract	2.22 ***	12.16%
Partially flexible schedule	-0.81	-4.44%
Fully flexible schedule	1.04 ***	5.7%
Remote work	-1.81	-9.91%
Commuting time 30-60min	2.68 ***	14.7%
Commuting less than 30	6.38 ***	34.97%
Mainly seated	-3.03	-16.58%
Exposure to infectious diseases	0.06	0.34%

Notes: (i) WTP are derived from the model shown in Appendix Table 3.7. (ii) Column (2) shows the percent share of the average net wage. The average net wage is equal to 18.9 €/hour in Panel A, 21.7 €/hour in Panel B, and 18.5 €/hour in Panel C.

Table 3.7: Parameter Estimates for Mixed Logit Model with Interactions – Senior sample

	(1)
<u>Mean :</u>	
Wage	0.26 (0.02)***
Full time	1.84(0.26)***
Permanent contract	0.46 (0.28)
Partially flexible schedule	0.53 (0.33)
Fully flexible schedule	1.07 (0.31)***
Remote work	0.23 (0.25)
Commute time 30-60min	1.39 (0.37)***
Commute time less than 30 min	2.17 (0.32)***
Mainly seated	-0.09 (0.26)
Exposure to infectious diseases	0.79 (0.24)**
Opt-in	-3.48(0.48)***
<u>Interaction terms with observables (mean) :</u>	
Less than three years before retirement by :	
Full time	-0.93 (0.24)***
Permanent contract	-0.29 (0.26)
Partially flexible schedule	0.38 (0.30)
Fully flexible schedule	0.00 (0.26)
Remote work	-0.39 (0.23)
Commute time 30-60min	-0.15 (0.33)
Commute time less than 30 min	0.20 (0.29)
Mainly seated	0.15 (0.23)
Exposure to infectious diseases	-0.11 (0.22)
Opt-in	-0.01 (0.39)
Poor Health by :	
Full time	-0.39 (0.19)*
Permanent contract	-0.11 (0.22)
Partially flexible schedule	-0.23 (0.26)
Fully flexible schedule	-0.55 (0.23)*
Remote work	-0.60 (0.19)**
Commute time 30-60min	0.39 (0.29)
Commute time less than 30 min	0.22 (0.25)
Mainly seated	0.64 (0.20)**
Exposure to infectious diseases	0.52 (0.19)**
Opt-in	-0.10 (0.32)
Informal care by :	
Full time	-0.28 (0.20)
Permanent contract	0.10 (0.23)
Partially flexible schedule	0.10 (0.27)
Fully flexible schedule	0.13 (0.24)
Remote work	0.42 (0.20)*
Commute time 30-60min	-0.28 (0.31)
Commute time less than 30 min	-0.13 (0.25)
Mainly seated	-0.13 (0.20)
Exposure to infectious diseases	0.21 (0.20)
Opt-in	-0.02 (0.35)
(Wage < median) by Job Amenities	✓
Sex by Job Amenities	✓
Education ^(a) by Job Amenities	✓
Age (continuous) by Job Amenities	✓
(Wage > median)*Opt-in	✓
Sex*Opt-in	✓
Education ^(a) *Opt-in	✓
Age (continuous)*Opt-in	✓
Log Likelihood	-4736.92
Nb. individuals	1,033

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Notes : (i) Standard errors are in parenthesis. (ii) Weighted estimates. The weighting scheme accounts for both sampling design and non-response (see Section 3.3.2). (iii) As there are repeated observations for the same individuals, the longitudinal dimension of the data is taken into account in the mixed logit models. The panel data version of the log-likelihood is used (assuming that the random parameters of individual n are the same for all his choice situations). (iv) The coefficient on the "opt-in variable" captures the nested nature of the choice set and is excluded from the correlations in the last model. (a) Education in six categories.

Table 3.8: Robustness checks

	Baseline	Without inattentive respondents (def.1)	Without inattentive respondents (def.2)	Without respondents affected by Covid
	(1)	(2)	(3)	(4)
Wage	0.356*** (0.008)	0.382*** (0.010)	0.391*** (0.009)	0.385*** (0.010)
Full time	1.192*** (0.042)	1.351*** (0.051)	1.358*** (0.046)	1.313*** (0.050)
Permanent contract	0.799*** (0.052)	0.808*** (0.060)	0.871*** (0.055)	0.959*** (0.059)
Partially flexible schedule	0.281*** (0.054)	0.294*** (0.062)	0.301*** (0.059)	0.349*** (0.062)
Fully flexible schedule	0.801*** (0.046)	0.890*** (0.052)	0.861*** (0.046)	0.896*** (0.051)
Remote work	-0.142*** (0.038)	-0.162*** (0.044)	-0.015 (0.041)	-0.188*** (0.045)
Commute time 30-60min	1.245*** (0.071)	1.384*** (0.089)	1.361*** (0.079)	1.258*** (0.087)
Commute time less than 30min	2.407*** (0.062)	2.641*** (0.076)	2.649*** (0.068)	2.677*** (0.075)
Mainly seated	-0.168*** (0.043)	-0.094* (0.052)	-0.099** (0.047)	-0.162*** (0.049)
Exposure to infectious diseases	0.584*** (0.041)	0.628*** (0.048)	0.678*** (0.043)	0.475*** (0.045)
(Wage > median) by Job Amenities	✓	✓	✓	✓
Opt-in	✓	✓	✓	✓
(Wage > median)*Opt-in	✓	✓	✓	✓
Sex*Opt-in	✓	✓	✓	✓
Education*Opt-in	✓	✓	✓	✓
Senior*Opt-in	✓	✓	✓	✓
Log Likelihood	-14,909.850	-11,997.300	-13,411.020	-11,595.430
Number of observations	3,068	2,560	2,803	2,430

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Standard errors are in parenthesis. In column (2), respondents who give a different answer to a same vignette are excluded (16.6% of respondents). In column (3), respondents who choose the dominated alternative in the placebo vignette are excluded (8.6% of respondents). In column (4), we exclude respondents who declared that their answers in the vignette experiment would have been different without the Covid crisis (see Section 3.5.4).

3.7 Appendices

Appendix A: Details on the vignettes

The introductory text reads as follows :

As part of your job search, imagine you are offered the two jobs shown below. Except for the characteristics highlighted in red below, please assume the jobs are the strictly identical in all other ways, including on characteristics no listed in the table. Please review the jobs and indicate below whether you prefer Job A or Job B. If neither job is suitable for you, you may decide to accept neither of them (you prefer to continue your job search). You may scroll over the characteristics to see their definitions.

Table 3.9: Possible Values of Vignette Attributes

Attributes	Possible levels of attributes
Hourly wage	Average hourly gross wage in former sector Average hourly gross wage in former sector +/- 5% Average hourly gross wage in former sector +/- 10% Average hourly gross wage in former sector +/- 15%
Hours worked	Full-time (35h) Part-time (24h)
Type of contract	Permanent Fixed-term
Schedule Flexibility	No Flexibility: schedule fixed by employer Partial Flexibility : control over starting (7am-10am) and ending (4pm-7pm) hours, but no control over the number of hours worked per day or per week. Full Flexibility : control over starting and ending hours + control over the number of hours worked per day or per week.
Option to work from home at least one day/week	Yes No
Commuting time (one-way trip, using the usual commuting mode)	<30min 30-60min >60min
Physical demands	Mainly seated Mainly standing
Exposure to infectious diseases	Above sector average Below sector average

Appendix B: Creation and randomization of the vignettes

Before running a vignette experiment, one needs a design matrix defining how the choice situations are displayed to the respondents, and how the attributes levels vary. A design matrix consist in the full description of the choice situations of the experiment where each column represents a job characteristic, each row represents a job offer and each pair of rows corresponds to a job choice situation. We designed the full set of choice situations with three main objectives in mind: reducing the cognitive load of the respondents, reducing inattention and limiting the hypothetical bias. To reach those objectives we modified the design matrix in three ways. We added an opt-out option to our design, and we chose to limit the number of choice situations per respondents as well as the number of job attributes varying at the same time.

While seemingly unimportant, those choices have important implications on the optimality of the final design matrix we could adopt. In order to have the best estimation of our model, the ideal statistical strategy would be to expose each participant to all potential combination of attributes (i.e a full factorial design). Though statistically optimal, this option is unpracticable and fails to achieve our three main goals.

As compared to the full factorial, our design choices constrain us to divide the overall matrix in blocs and show only one of the blocs to each respondent. It also implies a bigger number of potential job characteristics combinations in the matrix since we constrain to three the number of variable job attributes in each bloc, and additionnally imposes to find optimal values for the constant attributes. As is common in cases where a full factorial design is not feasible (Hensher et al., 2005), we adopted a procedure that optimize the design's D-efficiency. This optimization criterion takes advantage of the fact that, in a vignette experiment, a part of the data is readily available before running the survey since the design matrix defines the jobs participants are exposed to. By assuming a prior value for our main job characteristic effects θ it is possible to generate a design that maximizes the identification of parameters close to the assumed priors.

To build our matrix, we followed the litterature (Cuervo et al., 2016) by first reducing the hypothesized utility to:

$$U_{nj} = A_j\theta + \mathcal{E}_{nj} \quad (3.5)$$

Second we assumed a simple multinomial logit model instead of a mixed logit model, reducing the choice probabilities to:

$$P_{nj} = \frac{e^{(A_j\theta)}}{\sum_{i=1}^J e^{(A_i\theta)}} \quad (3.6)$$

Both reductions of the model allow to greatly simplify the computations of the

optimal matrix without altering the ability of the design to identify the right parameters when assuming more complex models such as the panel mixed logit model that we use (Bliemer and Rose, 2010). Because the value of θ is estimated by maximum likelihood, it is possible to build the Fisher information matrix and the associated asymptotic variance covariance matrix of the model by assuming a prior value for the parameters. The D-optimality criterion consists in finding the design with the greatest value of the log of the determinant of the information matrix, or equivalently the minimum value of the D-error which is a function of this determinant ³⁵. In our design generating process, we assumed that the prior values of our parameters were all equal to zero, implying that the probability P_{nj} is random and equal for all alternatives, which means that our respondents do not value any of the job characteristics levels. Our assumption is commonplace in cases where the true value of the parameters is unknown (Street and Burgess, 2007). It ensures that if the true effects are null, we have sufficient power to detect it efficiently, and partly prevents from biases due to a wrong specification of the parameters.

Our D-optimal matrix selection worked in two steps. In the first step, we used a Balanced Incomplete Bloc Design (BIBD) to select the varying attributes in each bloc of the matrix. The BIBD ensures that all attributes vary the same number of times, and that each couple of varying attributes are displayed the same number of times. In our selected BIBD, we use 14 blocs (14 different questionnaire versions) where 3 job characteristics vary in addition to the wage³⁶. Each job characteristic varies in 6 different blocs and each couple of characteristics varies twice in the same bloc. Having job attributes evenly balanced in the matrix avoid biased estimates due to a too low or too high presence of a given varying attribute in the blocs. Similarly, having pairs displayed a same number of times allows to properly estimate simple interaction effects (we assume that higher order interactions have null or negligible effects).

In the second step, we implemented the algorithm of (Cuervo et al., 2016) in the software R. This algorithm is based on a coordinate exchange algorithm (Meyer and Nachtsheim, 1995) that sequentially modifies the level of each varying attribute level per row according to the BIBD. At each step, the algorithm computes the D-optimal criterion and adopts a criterion improving level as soon as it is found. Our final design has 168 different job offers evenly distributed over the 14 versions of the questionnaires and a D-error equal to 0.0125.

We then added four additional lines per questionnaire for our attention checks as described in the design section, and a line with all attributes levels equal to zero per choice situation to represent the opt-out ³⁷. The duplicated choice situation was randomly chosen among

³⁵The D-error is equal to $|I^{-1}(A, \theta)|^{-\frac{1}{k}}$ where I is the Fisher information matrix and k the number of parameters of the model. As it clearly appears in the function, the D-error value depends on the vector θ .

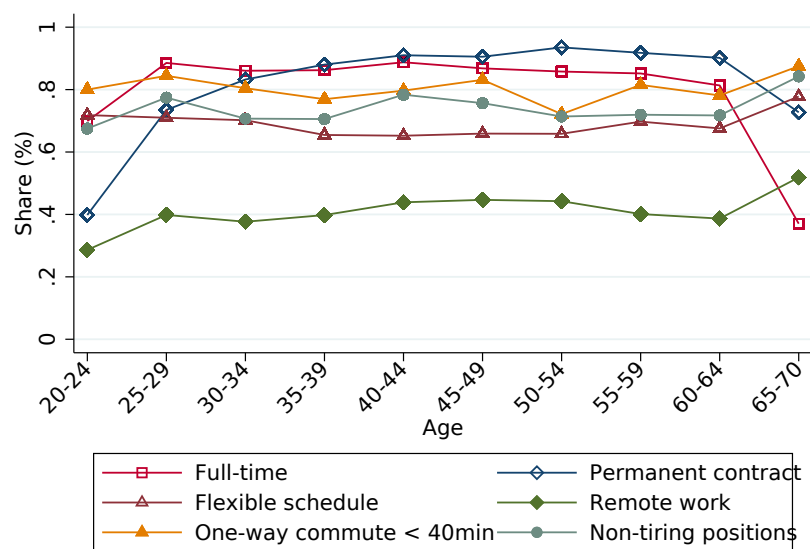
³⁶Because our aim is to estimate willingness to pay, we imposed the wage to vary in all blocs

³⁷Because the opt-out is not informative about the parameters, it is not included in the optimization procedure. Thus, we add ex-post the lines representing the opt-out choices.

the ones generated by the algorithm, and the dominated profile was created arbitrarily to have one of the two job offer dominated by the other.

Appendix C: Additional figures

Figure C1: Prevalence of job amenities in France, by age group



Source: EWCS 2021, EU

Figure C2: A screenshot of the (personalized) survey invitation email

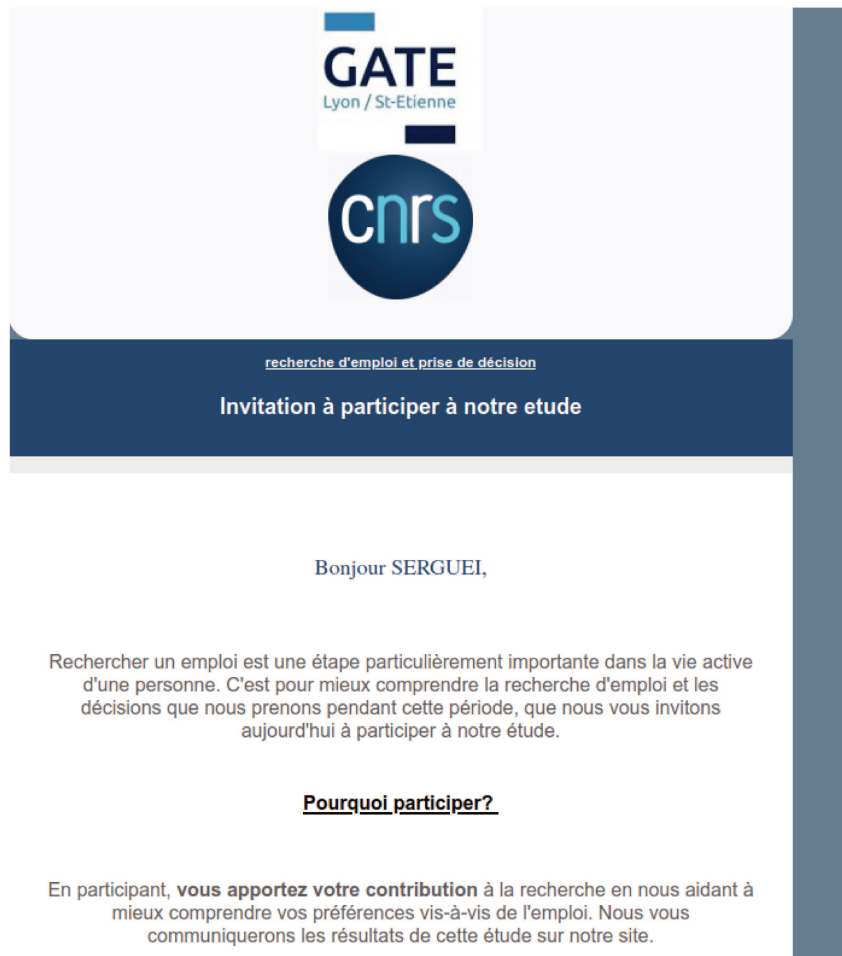


Figure C3: Average time answering a vignette

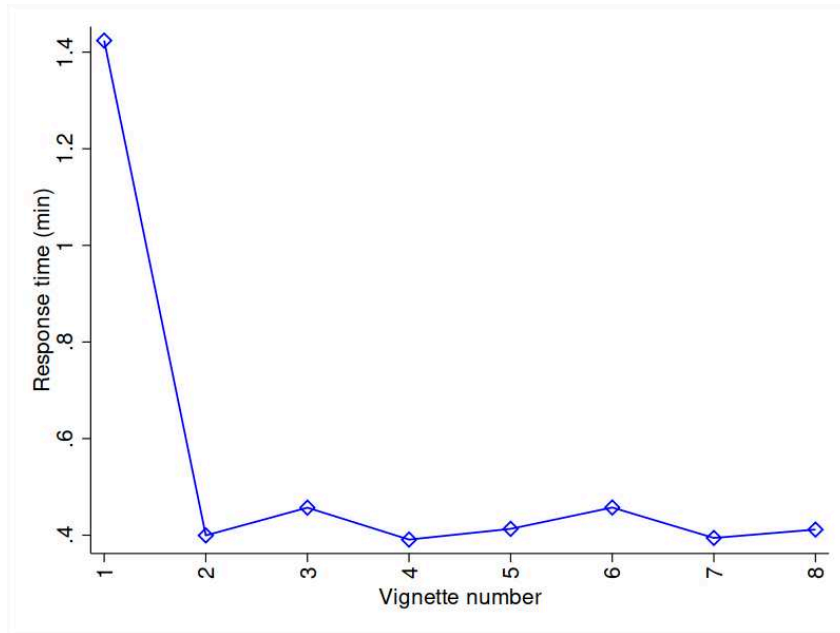
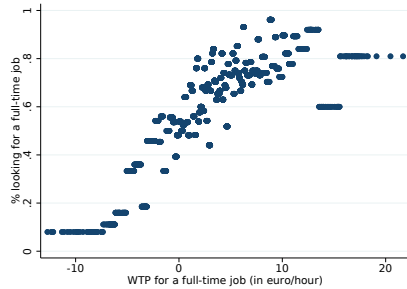
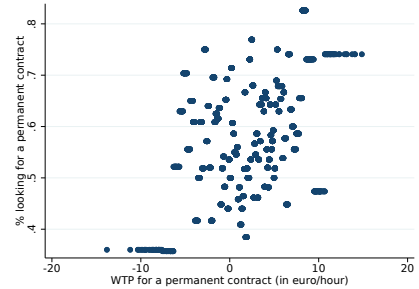


Figure C4: Validation of individual willingness-to-pay estimates with current job search.

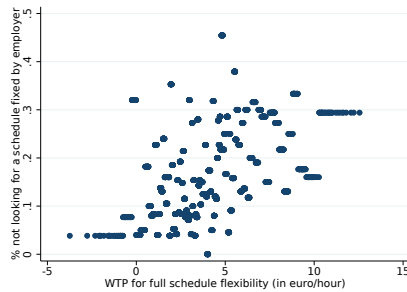
(a) Share of job seekers looking for a full-time job, by WTP



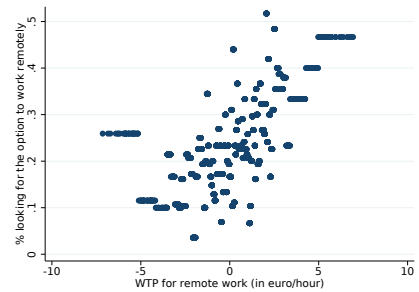
(b) Share of job seekers looking for a permanent contract, by WTP



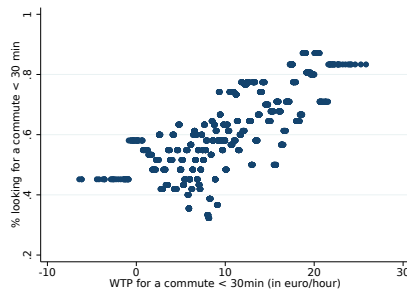
(c) Share of job seekers not looking for a schedule fixed by the employer, by WTP



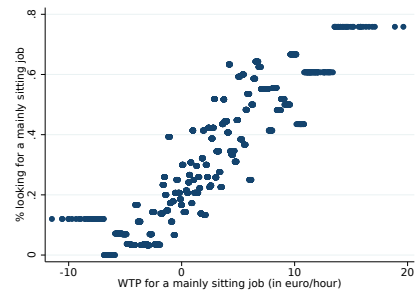
(d) Share of job seekers looking for the option to work remotely, by WTP



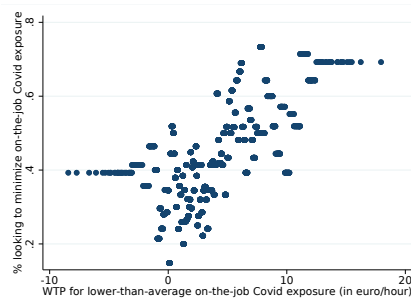
(e) Share of job seekers looking for a commute < 30 min, by WTP



(f) Share of job seekers looking for mostly sitting jobs, by WTP



(g) Share of job seekers looking to minimize on-the-job Covid-19 exposure, by WTP



Appendix D: Additional tables

Table D1: Socio-demographic characteristics of survey respondents relative to the FNA sample.

	Survey	FNA sample	Diff.	Std. Error	Obs.
Female	0.51	0.53	-0.02**	0.01	43407
Age	42.39	38.68	3.99***	0.31	43407
Age category					
18-24	0.21	0.32	-0.12***	0.01	43407
25-34	0.20	0.19	0.01	0.01	43407
35-44	0.08	0.08	0.00	0.01	43407
45-54	0.10	0.07	0.03***	0.00	43407
55+	0.41	0.34	0.08***	0.01	43407
Highest education level					
Max BEPC	0.14	0.23	-0.10***	0.01	42914
CAP,BEP	0.12	0.18	-0.06***	0.01	42914
BAC	0.16	0.21	-0.06***	0.01	42914
BAC+2	0.14	0.11	0.03***	0.01	42914
BAC+3/4	0.15	0.10	0.05***	0.01	42914
Bac+5	0.29	0.16	0.14***	0.01	42914
Sector in previous job					
Agriculture, forestry and fishing	0.02	0.03	-0.02***	0.00	43407
Arts and craftsmanship	0.00	0.01	-0.00**	0.00	43407
Banking, Insurance, Real Estate	0.02	0.02	0.00	0.00	43407
Commerce, Sales and Retail	0.11	0.13	-0.02***	0.01	43407
Communication, Media and Multimedia	0.04	0.03	0.01***	0.00	43407
Construction, Building and Public Works	0.04	0.06	-0.02***	0.00	43407
Hotels and Restaurants, Tourism, Leisure and Entertainment	0.04	0.06	-0.02***	0.00	43407
Industry	0.09	0.07	0.03***	0.00	43407
Installation and Maintenance	0.03	0.04	-0.01*	0.00	43407
Health	0.03	0.03	-0.00	0.00	43407
Care	0.15	0.13	0.02***	0.01	43407
Show business	0.01	0.01	0.00	0.00	43407
Business assistance	0.22	0.16	0.07***	0.01	43407
Transport and Logistics	0.05	0.07	-0.02***	0.00	43407
NA	0.14	0.17	-0.04***	0.01	43407

Table D2: Parameter Estimates for Mixed Logit Model with Interactions – Full sample

	(1)	(2)
<u>Mean :</u>		
Wage	0.34 (0.01)***	0.38 (0.01)***
Full time	1.12 (0.04)***	1.90 (0.08)***
Permanent contract	0.75 (0.05)***	1.29 (0.10)***
Partially flexible schedule	0.33 (0.05)***	0.12 (0.11)
Fully flexible schedule	0.78 (0.04)***	0.66 (0.09)***
Remote work	-0.16 (0.04)***	-0.31 (0.08)***
Commute time 30-60min	1.19 (0.07)***	1.64 (0.13)***
Commute time less than 30 min	2.30 (0.06)***	3.00 (0.11)***
Mainly seated	-0.17 (0.04)***	-0.75 (0.08)***
Exposure to infectious diseases	0.49 (0.04)***	0.55 (0.08)***
Opt-in	0.34 (0.09)***	0.15 (0.15)
<u>Interaction terms with observables (mean) :</u>		
(Wage ι median) by :		
Full time	0.60 (0.08)***	0.27 (0.10)**
Permanent contract	0.31 (0.10)**	0.34 (0.13)**
Partially flexible schedule	0.54 (0.11)***	0.41 (0.14)**
Fully flexible schedule	0.80 (0.10)***	0.72 (0.12)***
Remote work	0.64 (0.08)***	0.52 (0.10)***
Commute time 30-60min	0.62 (0.15)***	-0.00 (0.17)
Commute time less than 30 min	0.53 (0.11)***	0.06 (0.13)
Mainly seated	0.83 (0.09)***	0.47 (0.11)***
Exposure to infectious diseases	0.39 (0.09)***	0.19 (0.10)
Opt-in	-2.58 (0.16)***	-1.48 (0.18)***
Senior by :		
Wage		-0.15 (0.05)***
Full time		-0.70 (0.25)**
Permanent contract		-0.80 (0.29)**
Partially flexible schedule		0.32 (0.32)
Fully flexible schedule		-0.08 (0.29)
Remote work		-0.25 (0.24)
Commute time 30-60min		0.54 (0.37)
Commute time less than 30 min		0.40 (0.31)
Mainly seated		0.68 (0.25)**
Exposure to infectious diseases		0.74 (0.24)**
Opt-in	-3.86 (0.17)***	-4.76 (0.45)***
Sex by Job Amenities		✓
Education ^(a) by Job Amenities		✓
Sex*Opt-in	✓	✓
Education ^(a) *Opt-in	✓	✓
(Wage ι median)*Opt-in	✓	✓
Log Likelihood	-15000.84	-14745.64
Nb. individuals	3,069	3,069

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. Notes : (i) Standard errors are in parenthesis. (ii) Weighted estimates. The weighting scheme accounts for both sampling design and non-response (see Section 3.3.2). (iii) As there are repeated observations for the same individuals, the longitudinal dimension of the data is taken into account in the mixed logit models. The panel data version of the log-likelihood is used (assuming that the random parameters of individual n are the same for all his choice situations). (iv) The coefficient on the "opt-in variable" captures the nested nature of the choice set and is excluded from the correlations in the last model. ^(a) Education in six categories.

General conclusion

This thesis contributes to the integration of theories and methods of behavioral economics within the conventional framework of economic job search analysis.

Chapter 1 focuses on how time preferences and present bias could affect job search. Although a model describes how this bias could result in procrastination and affect negatively job search ([DellaVigna and Paserman, 2005](#)), its predictions have never been directly tested with conventional experimental measurements of time preferences. The chapter's main contribution is to provide a first test of the effect of present bias using an adapted online version of the most common methods of the literature - the Double Multiple Price List method ([Andersen et al., 2008](#)) and the Convex Time Budget method [Andreoni and Sprenger \(2012\)](#). - over two different domains. We elicited experimentally job seekers' short-run and long-run time preferences over money and effort to investigate how these preferences interfere with job search effort and its outcomes. As suggested by the model we found that long-run impatience affects search effort and the reservation wage, but only when it is elicited in the effort domain. Both procrastination and present bias over money tend to decrease the level of search effort, with negative effects on early search outcomes for the former and on the probability to leave unemployment for the latter. Overall, the job search is affected both by financial trade-offs and by arbitrage over leisure. However, these effects are only observed when eliciting time preferences with the Double Multiple Price List method but not with the Convex Time Budget method. This result calls for more research exploring the predictive power of the two methods.

The second chapter of the thesis emphasizes the persistence of excessive confidence in the period of unemployment. After facing job loss, empirical evidence from the literature suggests that job seekers tend to exhibit a significant level of optimism regarding their job prospects. This excessive confidence persists even when confronted with unfavorable outcomes. Chapter 2 explores this intriguing puzzle by investigating whether the sustained overconfidence observed among job seekers can be attributed to their motivation to safeguard their self-perception and perceived capabilities. The Chapter introduces a novel contribution by utilizing experimental measures of confidence and biased updating within a self-relevant context to explain job search efforts and outcomes. Consistent with

the literature, our results indicate that our participants are predominantly overconfident in both the experiment and their job search. Although overconfidence in the experiment fails to predict our subjects' job-seeking behaviors, we find that overconfidence in job-seeking delays the return to employment in both the short and long term. Our findings reveal that when it comes to the ability of job seekers to question their own beliefs, they tend to update them in a manner that protects their ego. During the experiment, we observed that new information holding personal relevance was systematically updated to a lesser extent (conservatism). This behavior became even more pronounced when the information was negative (asymmetry). Consistently with our initial hypothesis, when related to the job search, this self-serving information processing in the experiment adds to the effect of overconfidence and further lengthens the unemployment spell. Our findings indicate that providing job seekers with targeted advice aimed at fostering accurate beliefs and sustaining motivation could significantly enhance their outcomes in the labor market.

Chapter 3 uses a vignette experiment to study the labor market matching of seniors. Observing both the rejected options and the final match is necessary when studying matching to determine an individual's preferences. Usually, only the latter can be observed with administrative or survey data. To avoid this problem, the vignette method reproduces hypothetical but realistic choice situations, enabling an accurate preference profile to be identified. In France, senior's unemployment is becoming an important policy issue because, when unemployed, elders have a particularly low job-finding rate as compared to the rest of the active population. Both discrimination in the labor market and specific preferences of seniors for jobs and job amenities could explain this outcome. The main objective of Chapter 3 is to quantify the extent to which elders' low return to employment arises due to the latter reason. The main contribution of the chapter is that it provides evidence that older workers have specific preferences over job amenities; it quantifies these preferences and examines the sources of preferences heterogeneity. We find that older job seekers (55+) differ both in the value they place on each job attribute and in the ranking of job attributes they value most. Most notably, we find large differences in preferences to avoid health risks, long commuting times, and schedules fixed by the employer. We find evidence of heterogeneity in valuations in all of the job attributes we consider. When looking at the drivers of heterogeneity in preferences over job amenities near career end, we find that retirement expectations, health status, and informal care provision are important factors. Our results suggest that policies that promote longer working lives should not overlook the role of work arrangements.

Limitations and extensions

Using the theories and methods of behavioral economics to shed light on job-seeking

behavior is challenging. Behavioral economics is usually applied in the abstract setting of the laboratory. Over the course of the chapters, exporting these results to the more concrete context of job search has brought to light certain limitations that call for further study.

In Chapter 1, two main caveats arise from our study. First, as mentioned by [Belot et al. \(2021\)](#), using conventional experimental measures of time preference exposes our estimates to biases. Our estimates rely on the assumption that the decisions made by our participants in the experiment remain independent of shocks occurring outside of the experiment. While we used two complementary dimensions - money and effort - that are sensitive to different shocks, to circumvent this issue, we cannot fully ensure that exogenous variations on our participants' available free time or on their finances left unaffected our estimates. Second, due to the lack of consensus on a single method to use to measure time preferences, we used the two most conventional ones to do so. As a result, we observed that both methods provide different results even though they rely on comparable decisions. This difference in results could be due to several factors. Risk estimation in the two methods is based on different assumptions. The CTB method infers risk parameters in the convexity of choices, whereas the DMPL method uses a separate task involving only risky choices. This difference leads to risk estimates in CTB being closer to neutral than those in DMPL. Consequently, it could explain why the parameters we find in CTB for temporal preferences are higher ([Andersen et al., 2008](#); [Andreoni and Sprenger, 2012](#); [Harrison et al., 2013](#)). At the same time, the difference in the nature of the tasks in DMPL represents an additional element of divergence. The choices in the risk and time domains may not be related, which would imply that the risk estimated in DMPL is not appropriate for estimating the time parameters ([Andreoni and Sprenger, 2012](#); [Andreoni et al., 2015](#)). The estimation method is also a factor in the divergence of estimates. The need to estimate all the risk and time parameters of the same task in CTB makes the econometric task more complex. The econometric approach adopted to infer preferences seems to result in different estimates, even though the equality constraint represented by the subjects' decisions is the same. These differences stem in particular from the assumptions made about the value of the Stone-Geary parameters, the non-linearity of the relationship and the censored nature of the data. In comparison, the DMPL method, which is based on a probabilistic choice model, leaves less latitude as to the estimation method. Overall, these results highlight the need to understand the sources of difference between these two methods, and call for further research exploring their ability to predict behavior related to time preferences. A last limitation of this paper lies in the monetary payment method. In their meta-analysis, [Imai et al. \(2021\)](#) show that estimates of present bias are sensitive to the payment's timing used in the experiment. In our work, due to important administrative limitations, our payments were delivered

to participants a few days after their decisions which may have limited our ability to observe monetary present bias. This limitation calls for an extension to our experiment in an environment where payments could be delivered directly after participants' decisions (i.e. field experiments in public employment agencies).

Similarly to the first Chapter, one of the limitations of Chapter 2 findings comes from weaknesses in the experimental measurement method. In our experiment, general confidence measures relative to our real effort task were only weakly related to actual confidence in return to employment. Since our belief updating measure also relies on the confidence measures in the same task, it weakens the link we can draw between our experimental measurements and job search behavior. Yet, in spite of this weakened link, we were still able to find correlations between updating patterns in ego-relevant environments and job finding which reassures us in our intuition. To deepen and improve the conclusions of this article, a potential extension might be to develop a more direct method of measuring the update after job-relevant feedback. For instance, this would be possible in a longitudinal field experiment following job seekers over their unemployment spell. Another limitation of this Chapter lies in the absence of a theory to build explicit predictions about the effect of updating on the job search. So far, only the model of [Spinnewijn \(2015\)](#) describes how confidence interacts with job search, leaving aside the question of feedback. Although it may be particularly challenging, an avenue for future research on this topic would consist in building a theoretical model accounting both for the effects of confidence and belief updating.

In Chapter 3, both the most important contributions and limitations come from the vignette method design. The vignette method offers considerable freedom in the choice of job attributes. This freedom of choice is, however, limited by the relevance of the attributes chosen. Attributes that are too far removed from reality or inappropriate to describe the real concerns of individuals could lead to erroneous estimates. In our experiment, we offered participants wages based on the average for their sector of activity. In sectors where the distribution of wages is particularly dispersed, the average may be unrealistic with respect to the situations experienced by our participants in their job search. In particular, this makes our estimate for elders' willingness to work an upper bound as wages might have been irrelevant for those whose wages rose with experience. To circumvent this effect, a potential extension could use a self-reported optimal wage to set the wages of the vignettes. Regarding the rest of the vignette attributes, we chose to display attributes that were the most common in surveys. However, these attributes may not be relevant in some occupational sectors (e.g., some individuals looking for jobs that require changing workplace regularly may have found the distance to the workplace attribute irrelevant). Yet, in spite of these caveats, we are quite confident in our estimates that appear close to similar findings in the literature ([Eriksson and Kristensen, 2014a](#); [Lewandowski et al., 2023](#)). In the chapter, we mentioned that the low re-employment

probability of elders could come from either elders' preferences for some job attributes or from employer discrimination. One natural extension to this study would be to investigate the extent to which employers would be willing to offer senior job seekers job packages representing their preferences. Another direction would be to focus on elders' willingness to work depending on their retirement ages. Using an exogenous variation of the legal retirement age, we could compare the willingness to work and the exigence regarding the preferred attribute depending on the time before retirement.

To sum up, this thesis builds on a still recent, but growing literature aiming at bringing behavioral economic theories and methods to the analysis of job search. While the aging classic models of job search still allow us to predict the most basic behavior of job seekers in reaction to variations in the unemployment benefits, this literature reminds us that humans lie behind the *homo-economicus* theorized in the models. As humans, job seekers make errors in their judgments, they form wrong beliefs, and are subjects to various temptations. Failing to take into account this part of human reasoning when building policies can lead to inefficiencies and undesired side effects. Yet, we still know very little about how people look for their jobs, and the behavioral works so far are still short to provide important policy recommendations. Overall, this calls for the development of a more unified and efficient framework to study job search using behavioral economics. This analytical framework would provide an explanation for the behavior of job seekers when the unemployment rate is high and people who rarely experience tensed periods of unemployment find themselves out of work, but also when the unemployment rate is low and people who are most remote from employment are struggling to reconnect with the job market. As developed in this thesis, these situations lead to behaviors resulting from complex combinations of elements from classic and behavioral theories.

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