Unemployment Insurance and Job Search Behavior

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Abstract

Unemployment benefits provide workers with insurance at job loss and affect their behavior due to moral hazard. We shed new light on the moral hazard effect by using longitudinal data on job search behavior instead of the typical data on unemployment spells: we track applications on a major online search platform for 500,000 French unemployed workers eligible to various potential benefits durations. Workers increase their search intensity and decrease their target wages in the quarters before benefits exhaustion, and keep both roughly constant after. Using structural estimation, we show that the standard search model predicts the dynamics of search behavior better than the behavioral search model with reference-dependent preferences. Prior results apparently contradictory with the standard search model can be explained by dynamic selection and duration dependence. Overall, our results reject search-free models where unemployment insurance (UI) only subsidizes leisure and advocate for the standard search model, hence supporting the large body of literature on the welfare analysis of UI based on this model.

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1 Introduction

Unemployment benefits policy aims to provide workers with insurance when they lose their job while limiting moral hazard effects. If workers can find a new job immediately and at no cost – as in the static labor supply model (Moffitt and Nicholson, 1982) – unemployment insurance only serves to subsidize leisure and moral hazard effects are maximum. If instead workers need to invest time and effort to find a new job – as in search models (Mortensen, 1977) – unemployment benefits have an insurance value and a gradual moral hazard effect on job search. While the standard search model is the workhorse of contemporary welfare analyses of unemployment insurance (Baily, 1978; Chetty, 2008), there is limited empirical evidence about the effects of unemployment insurance on search behavior.

In this paper, we study the effect of unemployment insurance (UI) on individual-level search behavior using a novel longitudinal data on job applications. We estimate the effect of benefits exhaustion on search behavior in a panel model with individual and time of the spell fixed effects. Comparing workers eligible to different potential benefits durations allows us to isolate the impact of UI from the impact of elapsed unemployment duration. Our results contradict the predictions of search-free models and thus confirm that UI does not merely subsidize leisure. Moreover, we find that, among search models, the standard search model best predicts the time path of search behavior. We show that results from prior literature (Nekoei and Weber, 2017; DellaVigna et al., 2017) on the impact of UI on job finding and re-employment wages that appeared to contradict the standard search model can be explained by dynamic selection and negative duration dependence. Overall, we conclude that the standard search model can be used to explain the impact of UI and inform discussions of the optimal UI policy (e.g. Kolsrud et al., 2018).

We now describe our results in more detail. We measure job search over time at the individual level by tracking the applications made on the online search platform of the French public employment agency. The platform is used by about one fifth of French job seekers and, unlike data collected from private job search platforms, this dataset can be connected to other administrative data sources: unemployment register, data on unemployment benefits and on hires.[1] This allows us to document the timing of unemployment insurance, job finding and search behavior for about 500,000 individuals. We measure job seekers' selectivity using the information on the job openings that individuals apply to, in particular the posted wage. We track job seekers' search intensity or effort (number of job applications sent) and target wages (average wage applied to) as long as individuals remain unemployed.

To guide our empirical analysis, we start with presenting a standard search model with finite unemployment benefits and endogenous search intensity following Mortensen (1977) and van den Berg (1990). To capture workers' behavior on online search platforms,

[1]It is the same data as in Skandalis (2018).

we assume that search is directed (Nekoei and Weber, 2017): at each period, job seekers choose where in the wage distribution to target their search effort, their "target wage", knowing that higher wages are associated with a lower job finding probability. The model predicts that, as benefit expiration approaches, job search effort increases and target wages decrease. After exhaustion, both job search effort and target wages stay constant as job seekers then face a stationary environment. For workers without unemployment insurance, both search intensity and target wages are constant.

We estimate the impact of benefits exhaustion on individual search behavior in a panel model with spell and time of the spell fixed effects: specifically, we estimate a coefficient for each time to benefits exhaustion on a sample of unemployment spells balanced around benefits exhaustion to rule out dynamic selection. In order to isolate the impact of UI from the impact of elapsed unemployment duration, we leverage variation in potential benefits durations (PBD): some workers are not eligible to UI, and PBD ranges between 12 and 24 months among UI recipients in our analysis sample. We identify the impact of benefits exhaustion on search behavior under the assumption that different workers would have a similar *evolution* of search behavior if they were eligible to the same PBD. This assumption is consistent with our descriptive statistics: individuals with different PBD have a parallel time path of search behavior except for the periods around benefits exhaustion.

We explore the impact of UI on two dimensions of search behavior: search intensity and target wages. First, we highlight a large effect of UI on search intensity. Individual search effort increases progressively before benefits exhaustion and is 50% higher in the quarter of benefits exhaustion than one year before. For workers still unemployed after benefits exhaustion, search effort remains roughly constant. In contrast, when we estimate the model without cancelling out the effect of dynamic selection, we find that search intensity exhibits a steep decrease after benefits exhaustion. This highlights that dynamic selection, not individual search effort, is responsible for most of the decrease in aggregate search effort after benefits exhaustion. We then investigate the source of this dynamic selection and find that individuals with high unemployment benefits – who stand to lose the most money at exhaustion – are those who increase their search effort the most prior to exhaustion, and who are most likely to find a job in that period. With only data on job finding, one could have concluded that the predictions of the standard search model fail. Instead, we find that the evolution of individual search intensity is consistent with the standard search model.

Second, we show that UI also affects target wages. In anticipation of their benefits exhaustion date, workers progressively apply to job ads with lower and lower posted wages. After they exhaust their benefits, they keep their target wage roughly constant. This is consistent with the predictions of the standard search model. Quantitatively, unemployed workers decrease their hourly wage target by 0.8% during the year prior to benefits exhaustion, and also lower their targeted number of hours, so that their monthly wage target decreases by 3.5% during the same period. Most of the decrease in target wages comes from applying to *occupations* associated with lower wages on average, and hence seems to reflect a productivity decrease rather than a shift to employers who capture a larger share of the surplus.

To complement to our main empirical analysis of target wages where we study the impact of UI after controlling for elapsed unemployment durations, we also study the impact of elapsed unemployment duration itself. In a panel model with spell and time to benefits exhaustion fixed effects, we estimate that targeted monthly wages decrease by 1.2% each year, independently of unemployment insurance. This decrease in wages comes from unemployed workers applying to lower-paying *occupations* as their time in unemployment increases, suggesting a decrease in targeted productivity. It could be because job seekers experience a depreciation in their skills over time, or because they anticipate a stigma associated with long unemployment spells (Kroft et al., 2013). Put together, our results on target wages help explain the impact of unemployment insurance on re-employment wages. There are two offsetting forces: on the one hand, workers with longer benefit duration have higher target wages at each time of their unemployment spell; on the other hand, they are likely to stay unemployed longer and find a job at periods when target wages are lower due to negative duration dependence.

Finally, we turn to structural estimation in order to quantitatively assess which search model best fits our empirical results. Qualitatively, our results appear consistent with the predictions of the standard search model although we observe that individual search effort exhibits a small and temporary decrease after benefit exhaustion while this model predicts that it remains constant. The reference-dependence search model developed in DellaVigna et al. (2017) precisely departs from the standard model in predicting a decline in search effort after benefits exhaustion. We hence structurally estimate a generalized search model that nests the standard model and the reference-dependent model. We use a minimum-distance estimator, and target the empirical dynamic of individual search behavior estimated in our reduced-form analysis. We find an estimate for the reference-dependence discount parameter very close to zero, which shows that the model that best fits our empirical moments is the standard search model. As a robustness test, we replicate the structural estimation of the generalized model when we allow for negative duration dependence and obtain essentially the same results. Our structural estimation hence allows to establish that the standard search model best predicts the impact of UI on individual search behavior.

Our paper is related to several strands of literature. First, it offers new evidence on the impact of unemployment insurance on individual search behavior. Prior studies have documented the impact of unemployment benefit extensions on job search behavior based on aggregate or cross-sectional data on search behavior. In contrast with our analysis, they did not explore the impact of UI on the dynamics of search behavior over time. At the macro level, Marinescu (2017), Fradkin and Baker (2017) have established that PBD extensions have a negative impact on search intensity. At the micro level, Lichter (2017) shows that UI extensions decrease search intensity measured two months after the start of the unemployment spell while Barbanchon et al. (2017) show that PBD extensions do not affect the reservation wage that job seekers declare when they register as unemployed. We show that the impact of PBD extensions is smaller early in the unemployment spell, in line with the predictions of the standard search model, and therefore help reconcile these seemingly disparate results.

Second, we provide new evidence on the impact of elapsed unemployment duration on wages. Quantifying this impact is crucial to assess the cost of long term unemployment and explain the impact of UI on re-employment wages. Indeed, substantial negative duration dependence implies that UI extensions have two opposite effects on re-employment wages (Caliendo et al. (2013); Schmieder et al. (2016); Nekoei and Weber (2017)): workers have higher target wages at any given period, but tend to delay job finding to later periods when target wages are lower. Our finding of a negative impact of past unemployment duration on target wages hence helps reconcile the disparate estimates of the impact UI duration on re-employment wages in the prior literature (Card et al., 2007a; Lalive, 2007; van Ours and Vodopivec, 2008; Caliendo et al., 2013; Schmieder et al., 2016; Nekoei and Weber, 2017). Previous studies have documented that workers decrease their reservation wage over time (Krueger and Mueller (2011)) and apply to lower skilled jobs (Kudlyak et al. (2014)), but they did not isolate the effect of elapsed unemployment duration from the effect of unemployment benefits on these dynamics. Schmieder et al. (2016) estimate a negative impact of elapsed unemployment duration on re-employment wages using UI extensions as an instrument for unemployment duration. This strategy holds under the assumption that the effect of UI extensions on reservation wages is negligible, which is in contradiction with our findings.

Third, our new empirical findings on search behavior allow us to directly test the predictions of search models. Although these models provide the basic framework for the welfare analysis of UI (Baily (1978), Chetty (2008)), there is little direct evidence of their validity. Previous tests of search models came from data on unemployment spells but there is no direct mapping between these outcomes and search behavior because of dynamic selection and potential manipulation of re-employment timing. In contrast, we directly validate a large set of model predictions about search behavior: we show job seekers adjust their job search in reaction to UI not only through search intensity but also through target wages, and that they react to benefits exhaustion long in advance, consistent with low returns to search. Each of these findings contradicts the search-free static labor supply model (Moffitt and Nicholson, 1982) where new jobs can be started at any time at a fixed wage. In particular, our results show that the increase in job finding at benefit exhaustion cannot be explained away by an agreement between workers and firms on the timing of re-employment, as suggested in the literature on recalls (Katz and Meyer, 1990b) and storable job offers (Boone and van Ours, 2012). Overall, our findings provide micro-foundations to search models and emphasize the importance of an insurance during the process of job search.

Finally, we contribute to the active new debate on the role of behavioral mechanisms in job seekers' behavior.[2] Behavioral mechanisms should be taken into account in the welfare analysis of UI if they importantly determine job seekers' reaction to UI. Following DellaVigna et al. (2017), we estimate a search model with reference-dependent preferences based on insights from prospect theory.[3] In their structural estimation, DellaVigna et al. (2017) show that both the reference-dependent search model and the standard search model with heterogeneity in search cost convexity fit data on unemployment spells very well. These two models offer different predictions about job search behavior but similar predictions for unemployment spells. With only data on unemployment spells, the authors cannot implement further tests to distinguish between the two models and conclude in favor of the reference-dependence model because it requires fewer structural parameters. Our data allows us to test predictions about individual job search behavior and reject the reference-dependence model. While insights from behavioral economics might be very useful to explain other aspects of job search, we conclude that a standard search model appears to be the best tool to analyze job search behavior around benefits exhaustion.

The paper is organized as follows. Section 2 presents the predictions of a simple standard search model to offer a benchmark for our empirical analysis. Section 3 presents the institutional setting and our data. Section 4 describes the empirical strategy. In Section 5, we estimate the impact of unemployment insurance and elapsed unemployment duration on search behavior. In Section 6, we turn to structural estimation to compare alternative search models. Section 7 concludes.

2 Theoretical framework

To help interpret the empirical findings, we start by developing a simple directed search model with endogenous search intensity.

Model: Following Mortensen (1977), Mortensen (1986), van den Berg (1990), we introduce non stationarity in a job seeker's environment in the form of finite duration of unemployment benefits: when they get unemployed, workers are eligible to unemployment insurance for T periods. If they are still unemployed after that, they receive welfare transfers of a lower amount than the unemployment benefit. At each time t of their unemployment spell, workers choose both their search effort s_t and target wage w_t to maximize their discounted expected utility. Search costs are given by the function $c(s)$, which we assume to be time-separable, twice continuously differentiable, increasing, and convex, with $c(0) = 0$ and

[2] Paserman (2008), Spinnewijn (2015), Caliendo et al. (2015), DellaVigna et al. (2017). See Schmieder and von Watcher (2016) for a meta-analysis.

[3] Kahneman and Tversky (1979)

$c'(0) = 0$. The most notable difference we introduce in comparison to Mortensen (1977), Mortensen (1986), van den Berg (1990) is to assume that search is directed and not random: following Nekoei and Weber (2017), we assume that job seekers choose where in the wage distribution to target their search effort instead of choosing the minimum wage they are willing to accept and taking random draws from the job offer distribution. The job finding rate decreases in target wages. Thus, the target wage – like the reservation wage – is the result of a trade-off between the probability to transition to employment and the value of employment. We denote $\lambda(s_t, w_t)$ the job finding function which is increasing in s_t and decreasing in w_t. We choose this directed search hypothesis for two reasons. First, this assumption appears more realistic in the context of online applications: on online job platforms, job seekers enter search criteria and sort the job offers according to their characteristics. Second, this directed search model allows us to stay very close to random search models, which are commonly used in the literature on unemployment insurance. Indeed, Nekoei and Weber (2017) prove that for all a random search models, there exists a job finding function such that a directed search model yield the same optimal job search strategy.

For simplicity here, we consider that workers are hand-to-mouth and consume all their income at each period. The flow utility from consumption in period t is given by the function u. b is the unemployment benefit and m is the welfare payment with $m < b$. β represents the discount rate. At each period, the value function of an unemployed worker is given by the following equations:

$$\text{If } t < T\text{: } V_u(t) = u(b) + \max_{s_t, w_t}\{-c(s_t) + \beta[\lambda(s_t, w_t) \cdot V_e(w_t) + (1 - \lambda(s_t, w_t)) \cdot V_u(t+1)]\}$$

$$\text{If } t \geq T\text{: } V_u(t) = u(m) + \max_{s_t, w_t}\{-c(s_t) + \beta[\lambda(s_t, w_t) \cdot V_e(w_t) + (1 - \lambda(s_t, w_t)) \cdot V_u(T)]\}$$

An employed worker receives at each period a constant wage w and faces an exogenous risk of losing her job δ. In case of job loss, she is eligible to her full duration of unemployment insurance. The value function of an employed worker can be formulated as:

$$V_e(w) = u(w) + \beta[(1 - \delta) \cdot V_e(w) + \delta \cdot V_u(0)]$$

The optimization problem can be easily solved for all periods after benefit exhaustion as job seekers are then facing a stationary environment. We can then infer the optimal search strategy for each period before benefit exhaustion using backward induction.

Calibration: In order to illustrate the predictions of the standard directed search model with finite UI, we calibrate the model's parameters with realistic values. We calibrate the model at the monthly frequency, with a discount factor of 0.996 (about a 5 percent annual discount rate). Employed workers may lose their job with a monthly probability of 0.02.[4] Based on descriptive statistics (Table A.2), we set unemployment benefits to 6.3 euros/hour and welfare transfers to 3 euros/hour.

We choose a form of the job finding function λ that allows us to use the data on the job offer distribution as is typically done in random search models (Krueger and Mueller (2016)). For that purpose, we choose λ so that our model predict the same job finding hazard and the same expected job quality in each period as the random search model where the job offer distribution F is calibrated on our job vacancy data. Let's write first the expression of the job finding hazard and the expected job quality at each period in the two models. In a reservation wage model, we can express the expected wage conditional on finding a job at each period as a function of the reservation wage w^r and the job offer distribution F: $\phi(w^r, F) = \frac{1}{1-F(w^r)} \cdot \int_{w^r}^{\infty} udFu$. The probability of transitioning to a job can be written: $g(s) \cdot (1 - F(w^r))$. In the target wage model, the expected wage corresponds at each period to the target wage w^t. The probability of transitioning to a job is $\lambda(s, w^t)$. Hence, the two models yield equivalent optimal strategies if we have $\phi(w^r) = w^t$ and $g(s) \cdot (1 - F(w^r)) = \lambda(s, w^t)$. Combining these two equations, we can write an expression of the job finding function such that our directed search model is equivalent to the random search model with an offer distribution F: $\lambda(s, w^t) = g(s) \cdot (1 - F(\phi^{-1}(w^t))$. We do not have a closed-form expression of the function λ but we approximate it numerically based on F. We assume that the distribution of wages (in €) in job vacancies F is log-normal with the mean and standard deviation of the logged hourly posted wage in our data, i.e. a mean of 2.15 and a standard deviation of 0.36.[5] We assume that the returns of search effort are of the form $g(s) = \alpha_1 \cdot s$ and take $\alpha_1 = 0.2$, which implies that job seekers with a maximum search intensity have at most 20 % chances to find a job and hence captures the low search returns suggested by the very long unemployment spells in French data.

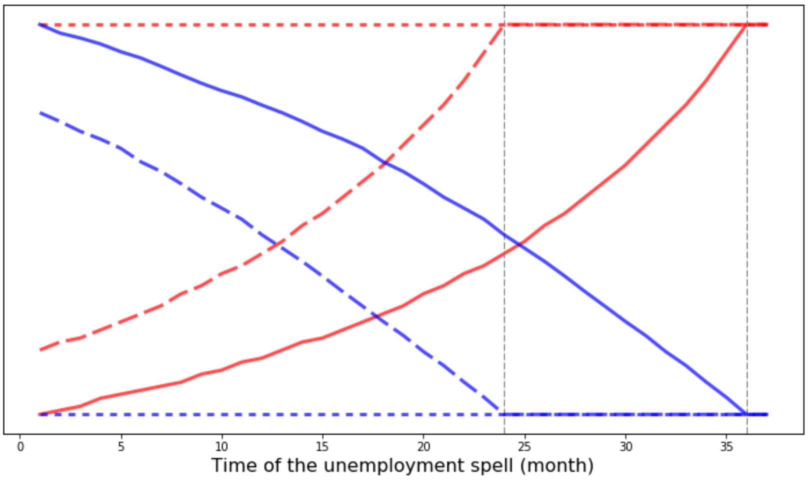
We assume a search cost function as in Paserman (2008), DellaVigna et al. (2017): $c(s) = \frac{\beta_1}{(1+\beta_2)} \cdot s^{1+\beta_2}$. We choose the proportional term $\beta_1 = 8.48$, while the curvature of search cost corresponds to $\beta_2 = 1.00$. We show in section 6 that this calibration of search cost parameters allows the model to best fit the empirical evolution of search behavior around benefits exhaustion. Our calibration for all parameters is summarized in Table A.1.

Predictions: Figure 1 shows the predicted behavior for three types of unemployed workers: workers ineligible to unemployment insurance, workers eligible to 24 months and 36 months of unemployment insurance. First, we see that the level of search effort and reservation wage after benefit exhaustion is not affected by PBD. But PBD affects the path

[4] A 2% monthly separation rate is commonly used for calibration (Krueger and Mueller (2016)) and Hobijn and Sahin (2009) have shown that there are little differences in separation rates across countries.

[5] We actually fit the mean and standard deviation of the predicted monthly posted wage, converted in hourly units, for more consistency with the rest of the analysis. We explain how we obtain this measure in the data section.

Figure 1: Search intensity and reservation wage over the unemployment spell, in the model



Notes: The graph displays the optimal search intensity (in red) and reservation wage (in blue) each month for an unemployed worker ineligible to UI (small dash), eligible to 24 months of benefits (large dash) and 36 months (continuous line). The vertical lines indicate the dates of benefit exhaustion, at 24 and 36 months.

of search intensity and reservation wages in the periods before benefit exhaustion: both search intensity and reservation wages remain almost constant in the first months of the unemployment spell and then start to move upwards and downwards respectively. After benefit exhaustion, both remain constant. In Figure 1, we also observe that the adjustment becomes steeper as the date of benefit exhaustion gets closer. Indeed, the impact of a drop in benefits far in the future on job seekers' strategy should be small in the model both because of the discounting of future utility flows and because of the chance to leave unemployed before benefits exhaustion. This is consistent with empirical evidence that extensions of unemployment benefits from a long duration at baseline have a limited impact on search behavior at the start of the unemployment spell (Barbanchon et al., 2017).

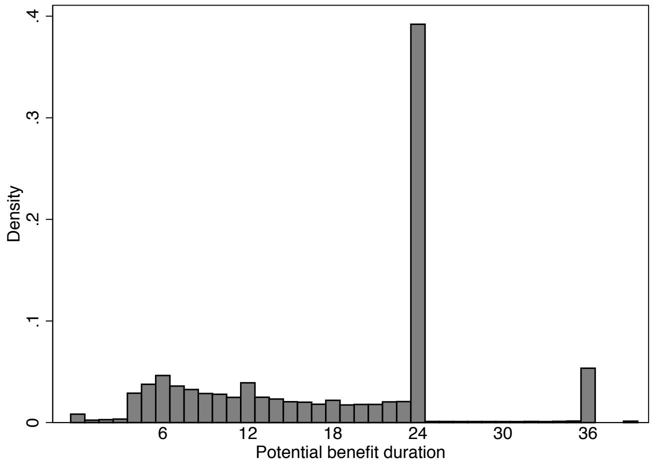
Overall, the model's key predictions are that search intensity increases up to benefit exhaustion and stays constant thereafter, and that the target wage decreases until benefit exhaustion and stays constant thereafter.

3 Institutional setting and data

We track job search behavior using job applications sent on an online search platform (Kuhn and Mansour, 2014; Faberman and Kudlyak, 2016; Belot et al., 2017). A key advantage of our data is that job search behavior can be linked with individual administrative data, and in particular data on UI eligibility.

3.1 Institutional setting

Figure 2: Density of potential benefit duration (PBD) among job seekers eligible to unemployment benefits



Notes: This figure displays the density of potential benefit duration (PBD) in our main sample.

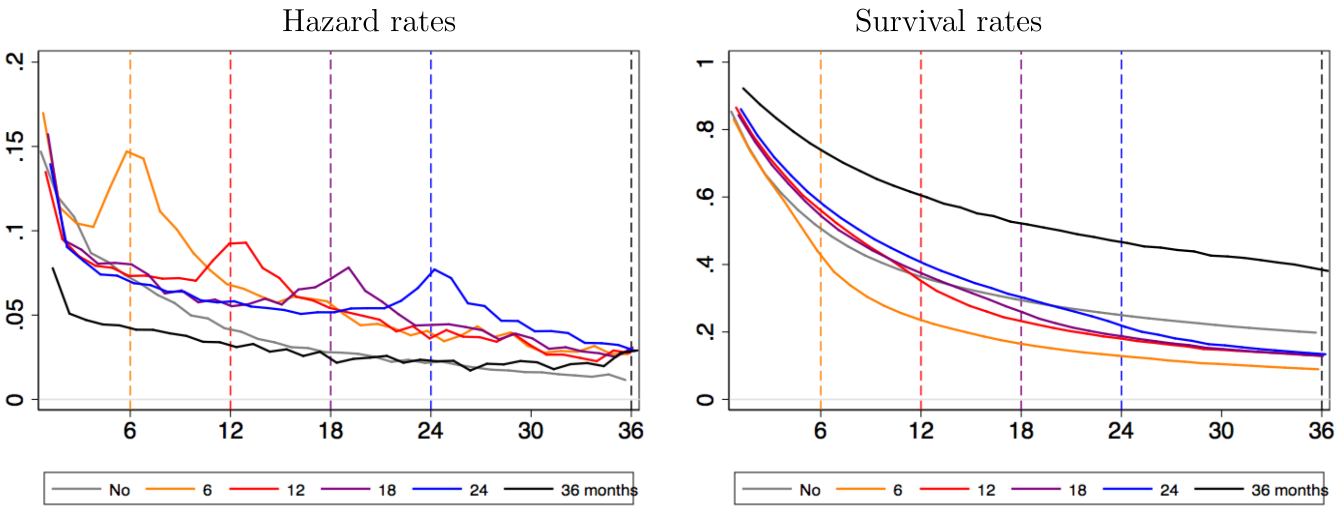
Unemployment insurance in France: In France, workers who lose their job can claim unemployment benefits after registering at the employment agency. When the claim has been processed, workers are informed about the date of the start of their benefits, as well as the amount and potential duration. During the period of analysis, workers are eligible to UI if they have worked more than 4 months during the 28 months preceding job loss (preceding 36 months for workers who become unemployed when they are 50 or older). The potential benefits duration (PBD) depends on the number of days worked during this reference period. The PBD cannot exceed 2 years for workers who become unemployed when they are less than 50 years old and 3 years for workers who become unemployed when they are 50 or older. The amount of benefits depends on the wages received during the last 12 months, and the replacement rate is 57% in most cases (with a minimal and maximal amount). The replacement rate is lower than in most European countries but the PBD is longer. As illustrated in Figure 2, the most frequent PBD are 2 and 3 years, corresponding to the upper bounds below and above 50 years old. Besides, PBD are dispersed between 4 and 24 months, with some over-representation of PBD at 6, 12 and 18 months.[6] After benefit exhaustion, jobseekers can claim a welfare benefit (mainly "allocation de solidarité spécifique" or "Revenu de Solidarité active", which are around 500 euros per month for a single individual). These welfare benefits are also conditional on job seekers being registered as unemployed and actively searching for a job.

All workers registered as unemployed receive counseling, independent of their eligibility to unemployment benefits. Since 2013, they are assigned to one of three types of counselling of various intensity, depending on the risk of long-term unemployment evaluated by a caseworker when they register. All types of counselling include in principle a meeting a

[6]Round periods correspond to common contract durations for fixed-term contracts in France.

the start of the spell, one at 4 months and one at 9 months. The timing of meetings with caseworkers is not synchronized with unemployment benefits duration. Besides, monitoring of search effort is very low and sanctions against job seekers extremely rare. Importantly, caseworkers do not use information on online applications to monitor search effort.

Figure 3: Job finding for different unemployment benefit durations (PBD)



Notes: In the left panel, this Figure presents job finding rates (empirical hazard) over time i.e. the number of exits to employment each quarter divided by the number of workers still unemployed. We present separately the pattern for job seekers eligible to 6, 12, 18, 24 and 36 months of unemployment insurance (UI) and for job seekers not receiving UI. In the right panel, the corresponding the empirical survival rates are graphed.

Unemployment insurance and re-employment: Like in previous literature[7], we document the time path of re-employment rates over the unemployment spell. In panel (1) of Figure 3, we present graphically the evolution of job finding rates for workers without unemployment benefits, and for workers receiving benefits with different potential benefit durations (PBD). We clearly see that job finding rates increase as benefit exhaustion approaches and spike at benefit exhaustion for all UI recipients. In contrast, there is no spike in job finding for workers who do not receive unemployment benefits. Similar spikes in job finding around benefits exhaustion have been found in the literature. Additionally, we note that job finding rates exhibit a general downward trend for all groups. In panel (2) of Figure 3, we present the corresponding survival rates. When comparing each group of UI recipients with non UI recipients, we see that a larger fraction of each group of UI recipients remains without a job until benefits exhaustion, and then it flips (except for workers eligible to 36 months). We also see from this figure that workers finding a job after benefits exhaustion represent a small minority. For instance, more than 70% of workers

[7] Katz (1986), Katz and Meyer (1990a), Katz and Meyer (1990b), Fallick (1991), McCall (1997), Bratberg and Vaage. (2000), Carling and Jansson. (1996), van Ours and Vodopivec (2006), Card et al. (2007b), DellaVigna et al. (2017).

eligible to 2 years of UI find a job before their benefits exhaustion. This helps to put in perspective the importance of the spike in job finding rate.

Overall, these two figures suggest that UI affects individual behavior. But there is no direct mapping between job finding and search behavior because of dynamic selection and potential manipulation of re-employment timing. In order to properly estimate changes in search behavior around benefits exhaustion, it is necessary to complement job finding data with longitudinal data on search behavior.

3.2 Data:

Our data provides an opportunity to follow search intensity and target wages for individuals over time. The data is linked with administrative records on UI and job finding.

Data sources: The unemployment agency administers a popular search platform. In 2013, in an effort to support recruiting, employers were offered the possibility to include in their job ad a link to a standardized application procedure: in that case, job seekers can only apply to the job by filing a detailed form online. The online applications have been tracked on the information system and can be merged with other sources of administrative data collected by the unemployment agency.[8] We exploit online applications sent during the period January 2013 to December 2017. We match information on online applications with three other administrative data sets on unemployment spells, unemployment benefits and re-employment. The unemployment register allows us to identify start and end dates of unemployment spells and collect rich information on individual characteristics at the moment of registration: gender, family status, education, skill level, work experience. We also have some information about job search including a measure of reservation wage, collected during a short survey at the moment of registration (this information was exploited before in Barbanchon et al. (2017) for instance). The unemployment benefits data contain information on insurance eligibility such as the maximum duration of benefits, the replacement rate, previous wage as well as data on actual periods when workers receive their benefits. Finally, we can identify when unemployed workers start a new job using employers' mandatory declarations of new hires.

Online applications: In comparison with measures of search in survey data (such as time use surveys), our data on online applications only covers one search channel. At the same time, our sample size is much larger and contains measures of search behavior over time that are not self-reported. In this section, we describe online applications data and explain why online applications are a good proxy for job search overall.

[8]A new tool was progressively introduced to replace online applications at the end of 2017. As a consequence, the aggregate number of applications diminished and tracking this search channel is more and more difficult.

What do online applications measure? The online job applications channel represents a small fraction of overall search effort: about 4% of the jobs started by workers in our sample are the result of an online application, so this channel approximately captures 4% of overall search. We present characteristics of the activities on the online search platform for individuals in our sample in Table A.13. On average workers send 0.5 applications per month. This mean is low, as expected given that this channel represents only a small share of workers' search effort. The magnitude suggests that the all-channels search effort is equivalent to sending 13.5 online applications per month. Moreover, we document that online applications are positively correlated with future re-employment rates. We estimate that the probability for one job seeker in our sample to start working at the firm where she applies in the year following her application is around 3% (this might under-estimate the rate of application success as it does not include firms that sub-contract workers to other firms). Returns to applying online hence appear low, probably because vacancies on the online search platform receive many applications. This shows that a great deal of search effort is required to find a job, consistent with the assumptions of search models. More generally, we document a clear positive relation between job applications and the probability to start working at any firm. In a Cox proportional hazard model, we estimate that each additional application is associated with a relative increase in the probability to start working by about 3% (Table A.14). Although this estimate does not give the causal impact of job search as sending more applications might be associated with characteristics relevant on the labor market beyond the ones we control for (Faberman and Kudlyak (2016)), this provides evidence that online applications strongly predict re-employment. Looking more closely at the timing of applications around re-employment is also enlightening (Figure A.6): we observe a large increase in the probability of sending an application in the month of a new job and in the preceding months (the highest level is reached one month before). After the start of a new job, we observe a large drop in online applications. Overall, this evidence supports our assumption that online applications are a good proxy for job search overall.

Outcome variables: We focus the analysis on two dimensions of search behavior: intensity and selectivity. First, we measure search intensity using the number of applications sent each month of the unemployment spell. Second, we measure job seekers' selectivity using target wages. The online application data set contains a wide range of information on the job postings: job category, type of contract, weekly hours of work, establishment identifier, employer's requirement in terms of experience, qualification and diploma, and posted hourly wage. However, employers choose to post a wage in only 40% of the vacancies in the sample, and this variable therefore contains many missing values. In order to make use of all the information contained in the job ad, and to assess the quality of the job even when no wage is posted, we use a linear prediction of the hourly wage based on all the observable characteristics of the job (Table A.3). Observable characteristics predict 50% of the variance in the posted wage (the R^2 is 0.49). In particular, the hourly wage is positively correlated with the length of the contract, the size of the establishment, as well as the stated requirements: professional experience, education and qualification level. The predicted wage and the actual wage in our individual panel sample have a very similar distribution (Figure A.1). The predicted wage is more dispersed than the hourly wage, as the latter has a lower bound at the minimum wage. In our empirical analysis, we measure the target wage as the average predicted hourly or monthly wage associated with job postings to which job seekers apply. The hourly wage is widely used to summarize job quality. At the same time, workers who approach benefit exhaustion may compromise on dimensions other than the wage, and we find that hours is another very important adjustment margin. This is the reason why we also include monthly wages as a measure of target wages. Additionally, we build alternative measures of job seekers' selectivity for robustness checks such as the average of wages applied to when vacancies include a posted wage and the minimum wage applied to at each period.

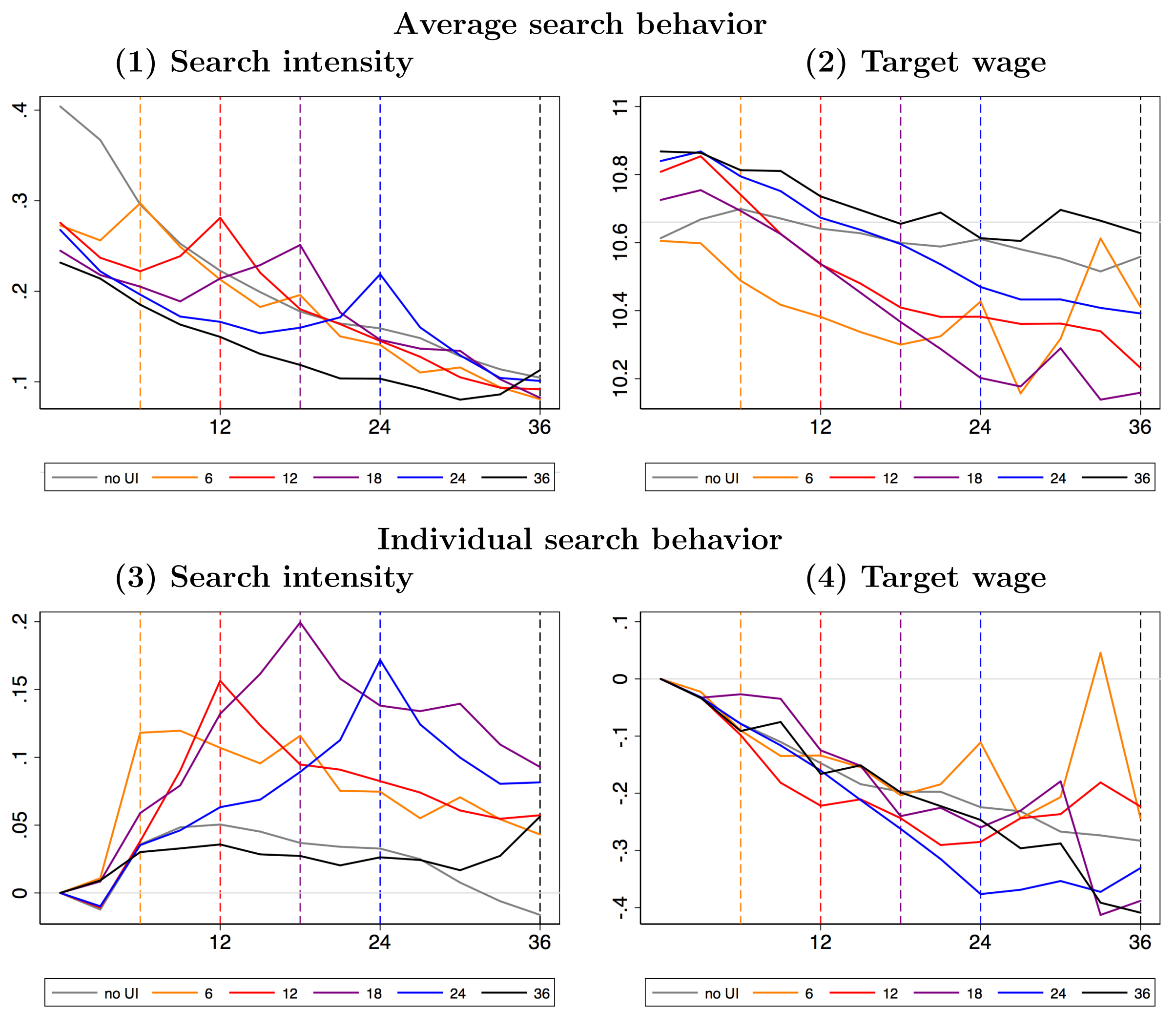
Panel data: For individuals who register as unemployed in 2013-2017, we track online search activities and new jobs until December 2017, following their registration date and for up to three years. We consider that unemployment spells are completed when workers either leave the unemployment register or find a job. We exclude unemployment spells for which we observe no online application. Note that the level of observation is the unemployment spell and not the individual, but very few individuals enter several times our sample (see descriptive statistics in Table A.2). We organize the data as a panel at the unemployment spell and quarter of the unemployment spell level. For each spell, the number of periods of observation can vary between 1 and 12 quarters. Quarters of the unemployment spell in our analysis do not exactly correspond to actual time elapsed since registration, as we exclude days of interruption in benefits collection in order to have the date of benefit exhaustion coincide with the date implied by the potential duration of benefits.[9] We make sure that this does not affect our results by replicating the analysis on the subsample of job seekers who have only very few days of interruption.

3.3 Description of search behavior over the unemployment spell

Figure 4 shows search behavior by quarter of the unemployment spell. In panels (1) and (2), dynamic selection is not accounted for: the composition of the pool of unemployed changes over time as some job seekers exit to jobs or drop out of the labor force. On average as a

[9]While they are eligible to unemployment benefits, job seekers can experience interruption periods during which they do not collect their full unemployment benefits, because they receive training or work for a few hours. We exclude these interruption periods from the unemployment spell and append periods when job seekers actually receive their UI together. That way, for job seekers who exhaust their benefits, the time of the spell in which benefits exhaust in our data coincides with the PBD.

Figure 4: Search behavior and job finding for different unemployment benefit durations (PBD)



Notes: Figure (1)-(2) shows average search intensity (count of applications) and target wages (in euros per hour) among workers who are still unemployed over time of the unemployment spell (in quarters). In Figures (3) and (4) we add spell fixed effects to show within individual variation in search intensity and target wages. In all figures, we present separately the pattern for job seekers eligible to 6, 12, 18, 24 and 36 months of unemployment insurance (UI) and job seekers not receiving UI.

group, unemployed workers first decrease their search intensity and then increase it again as benefit exhaustion approaches (Figure 4, (1)). After benefit exhaustion, search intensity declines. There is a clear spike in search intensity at benefit exhaustion. In contrast, we do not observe any spike in the average search intensity of workers without unemployment benefits (grey line), which is instead continuously decreasing over the unemployment spell.

As for the average target wage (Figure 4, (2)), there is a declining trend over the unemployment spell for all workers, whether they receive unemployment benefits or not. However, the declining trend is more pronounced in the beginning of the spell for workers who have a shorter PBD. After benefit exhaustion, the declining trend seems less steep. Note that the coefficients are less precisely estimated for target wages due to the smaller sample size as we only observe wages in quarters with at least one application sent.

In panels (3) and (4) of Figure 4, we add spell fixed effects in order to depict within individual variation in search intensity and target wage. Unlike *average* search intensity (panel (1)), *individual* search intensity does not decline early on in the unemployment spell, but increases instead. This suggests that the decline in *average* search intensity in the beginning of the spell is driven by the exit of the workers who search the hardest. Individual search intensity increases continuously until benefit exhaustion, and declines slightly after. For workers without unemployment benefits, search intensity is relatively flat over the unemployment spell, increasing slightly over the first year, and decreasing slightly thereafter. In panel (4) of Figure 4, we observe that individuals reduce their target wage more slowly after benefit exhaustion. For example, when comparing workers with 6 months PBD to workers with 12 months PBD, we see that the target wage of those with 6 months PBD declines more slowly between months 6 and 12 than the target wage of those with 12 months PBD. For workers who do not receive unemployment benefits, the target wage declines continuously over the unemployment spell, but at a slower pace than the decline observed before benefit exhaustion for workers who receive unemployment benefits.

These statistics of search behavior show that job seekers change their search behavior around benefits exhaustion. However, it is difficult to assess the path of this change because search behavior appears to also change over the unemployment spell. In the next section, we develop an econometric model to isolate the impact of benefits exhaustion on job search behavior.

4 Empirical strategy

We highlighted search model's predictions about the dynamics of search behavior around benefits exhaustion. To test these predictions, we estimate the effect of benefits exhaustion on search behavior in a panel model with spell and time fixed effects. As theory predicts that job seekers should change their search behavior in anticipation of benefits exhaustion, we allow for very flexible dynamic treatment effects.

4.1 Impact of time to benefits exhaustion on job search:

Study sample: We pool the information on all unemployed workers together and create dummy variables indicating quarters to benefits exhaustion (and equal to zero for workers not eligible to UI). We keep non UI recipients in our study sample for the estimation of time of spell fixed effects. In order to observe one year of search behavior before and after benefits exhaustion for UI recipients, we restrict our sample of UI recipients to those with PBD between 12 and 24 months. But this restriction alone does not guaranty that the sample of UI recipients is balanced around benefits exhaustion as workers might exit at any time: to have a balanced sample, we exclude spells that are completed less than one year after benefits exhaustion (for UI recipients) or less than three years overall (for non UI recipients). This latter restriction allows us to isolate changes in search behavior coming from individual behavior from changes coming from the sample composition. We relax it in some specifications in order to emphasize the role of dynamic selection. We end up with a sample of about 465,000 of unemployment spells of any length and 26,000 long unemployment spells (corresponding to the last sample restriction). We present descriptive statistics for these samples in Table A.2.

Estimation model: Our estimations are based on the following model:

$$Y_{i,t} = \sum_{k \neq -4} \beta_k D^k_{T(i),t} + \nu_i + \tau_t + \epsilon_{i,t} \tag{1}$$

$Y_{i,t}$ represents search behavior for spell i during the quarter of the spell t, conditional on the spell not being completed by t. $D^k_{T(i),t} = \mathbb{1}\{t = T(i) + k\}$ is an indicator for the lapsed unemployment spell t being k months to benefits exhaustion. $T(i)$ denotes the potential duration of benefits, ν_i denotes spell fixed effects and τ_t time of the unemployment spell fixed effects. β_k represents the difference in search outcomes with respect to its baseline level in the reference period four quarters before, in $k = -4$. We estimate one coefficient for each period to benefits exhaustion except the reference period, in order to allow for a flexible dynamic effect of benefits exhaustion.[10] Adding spell fixed effects allows us to control out the average level of search outcomes. We include time fixed effects to isolate the impact of benefit exhaustion from the impact of the time spent unemployed. In all our estimations, we cluster standard errors at the spell level (Bertrand et al. (2004)).

Our measure of search effort, the number of monthly applications, is a count variable with a mass point at zero. Therefore we estimate the variation in search intensity around benefit exhaustion in Poisson count models. In this model, the observed number of applications each month is considered as a realization of a Poisson random variable. Poisson regression models do not suffer from the incidental parameter problem, and allow for convenient inclusion of fixed effects. In order to allow for misspecification of the Poisson distribution, we present coefficients estimated using a quasi-maximum likelihood method (Wooldridge, 2010). We report the incidence rate ratio -1, which can be interpreted as semi-elasticities.

Identification: Here we discuss our identifying assumption and how we address potential threats to our identification. Individuals eligible to different PBD have different employ-

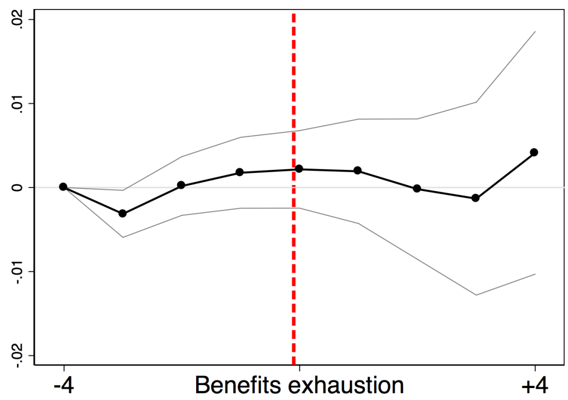
[10]Note that, by construction, all coefficients β_k are estimated on the same sample of spells for k comprised between -3 and $+4$ but not for $k < 4$ or $k > 4$: we do not observe more than 4 quarters of unemployment spells prior to benefits exhaustion for workers eligible to 12 months of UI, and we do not observe more than one year of unemployment spell after benefits exhaustion for workers eligible to 24 months of UI. In result tables, we hence only present the estimates for β_k from $k = -3$ to $k = +4$, but all other time to exhaustion dummies are also included in all regressions.

ment history and are very likely to search differently. Comparing their average level of search behavior can not give the causal impact of UI on search behavior because of this selection. Instead, our strategy relies on the identifying assumption that, with the same PBD, all workers would exhibit the same evolution of search behavior during their unemployment spell. This identifying assumption is similar to the parallel trend assumption in a Differences-in-Differences setting. Is this assumption credible in our setting? It is consistent with the graphical analysis presented in panels (4) and (5) of Figure 3: search intensity and target search of different groups of job seekers exhibit the same trend outside of the 12 months around benefits exhaustion.

A challenge for our estimation is to separately identify the effect of the time to benefits exhaustion from the effect of elapsed unemployment duration. In our context, it is crucial to allow for a very flexible timing of the effect of benefits exhaustion on search behavior as the model predicts that the reaction to benefits exhaustion starts from the start of the spell. We can isolate the effect of the time to benefits exhaustion because we include "never-treated" workers who do not receive UI, in addition to the different onsets of treatment. Without them, we could only identify the dynamic impact of benefit exhaustion *up to a time trend* (Borusyak and Jaravel (2017)). In our main empirical strategy, our identification of the effect of UI comes both from the comparison between unemployed workers not eligible and eligible to UI, *and* from the comparison of workers eligible to different benefits durations. If most of the identification comes from the latter comparison, our estimates might be off due to under-identification (Borusyak and Jaravel (2017)) or if the effect of benefit exhaustion is heterogeneous across PBD groups (de Chaisemartin and D'Haultfoeuille (2019)). Therefore, as a robustness check, we also estimate the dynamic effect of benefits exhaustion using only the comparison with non UI recipients. To do that, we estimate the previous model separately for each PBD group of workers using non UI recipients as controls, and we compute the weighted average of the coefficients.

Any factor that affects online applications with the same timing as benefit exhaustion would represent a confounding factor. In our setting, the main concern is that benefit exhaustion could be systematically associated with substitution between online applications and other search channels. Indeed, we observe only one search channel, and we can infer the impact of benefits exhaustion on search overall from our data only if the allocation of search effort across search channels should not be systematically associated with benefits exhaustion. Note that if job seekers substitute from one search channel to the other over time, this is not a threat to our identification, as it is captured in time of spell fixed effects. There are two scenarios under which the allocation of search effort across search channels might be systematically associated with benefits exhaustion. We discuss each of them and then present tests that our identification is valid. First, if job seekers were using disproportionately online applications as long as they receive UI in order to decreases their risk to get sanctioned for insufficient search effort, our estimates of an increase in search effort at benefits exhaustion would the be biased downward. However there is very little monitoring of search effort and sanctions are extremely rare in France: job seekers are considered searching actively based on their declared search activities and their attendance to their meetings with caseworkers. Importantly, caseworkers do not use information on online applications to monitor search effort. Additionally, we note that in most cases, job seekers are eligible to a welfare benefit after unemployment benefit exhaustion that is also conditional on search effort. Second, our estimates would be biased if job seekers were changing their search channel when they change how selective they are (rather than changing the type of job they apply to within each search channel). In that case, as job seekers are getting less selective around benefits exhaustion, they would use more (resp. less) the search platform relative to other channels if it contains relatively good (resp. bad) jobs.

Figure 5: Proportion of new jobs found via the online search platform



Notes: The graph presents variation in the proportion of jobs found via the online platform. The x-axis indicates the quarter when the job starts relative to benefit exhaustion. The y-axis represents variation in the proportion of jobs started in quarter t that were found via the online search platform (in ppt). The reference level is the proportion of jobs found via the online platform among jobs starting 4 quarters before benefit exhaustion, which corresponds to 3.5%. The model includes time of the spell and potential benefit duration (PBD) group fixed effects. The grey lines denote 95% confidence intervals based on robust standard errors.

To address the concern that there is search channel substitution around benefits exhaustion, we build an empirical test: we compute the proportion of jobs found via the online job search platform among jobs started by workers in our sample at different times of the unemployment spell, and estimate how this proportion evolves around benefits exhaustion. A significant shift in this proportion around benefits exhaustion would indicate that search channel substitution is a confounding factor: an increase would suggest that workers use this platform more relative to other platforms after benefits exhaustion while a decrease would suggest the opposite. We report the result in Figure 5. We find that the ratio of jobs found via the search platform remains constant around benefits exhaustion. This test hence supports our assumption that job seekers do not change their search channel mix around benefits exhaustion.

Beyond search channel substitution, any factors that affect job search behavior with the same timing as benefit exhaustion represent a threat to identification. In particular, one might be worried that meetings with caseworkers would be systematically correlated with benefit exhaustion. However, benefit exhaustion does not coincide with a meeting with caseworkers. Instead, job seekers receive a mail about two months prior to their benefit exhaustion informing them about the timing of their benefit exhaustion and their potential eligibility to welfare benefits (the payment of "allocation de solidarité spécifique" is automatic for eligible workers). We conclude that there is no other plausible event at benefit exhaustion that could influence job search and therefore create a bias in our estimation of the impact of benefit exhaustion.

4.2 Trend in target wages:

Additionally, we are interested in the evolution of target wages within individual over time of the spell both in order to test the predictions of search models and to explain the impact of unemployment insurance duration on re-employment outcomes. We hence estimate the trend in target wages in the following model:

$$w_{i,t} = \gamma \cdot t + \sum_{k \neq -4} \beta_k D^k_{T(i),t} + \nu_i + \epsilon_{i,t} \tag{2}$$

where all notations are similar to the estimation model (1) and γ gives us the linear impact of lapsed time of the unemployment spell on target wages within individuals. The model is practically identical to model (1), except that we impose a linear effect of the lapsed time of the unemployment spell on target wages, instead of allowing for flexible changes at each quarter in order to summarize the information in one economically meaningful parameter. γ will therefore help us test whether there is duration dependence in job search, even in the absence of unemployment insurance. A significant estimate of γ will suggest that job opportunities are not stationary for job seekers as assumed by the standard model, but change with the time spent unemployed.

Note that we only estimate the time trend for target wages and not for search intensity. This is because under the relatively weak assumption that job seekers have the same target wage on different search channels, trend in target wages estimates measure the evolution of selectivity in job search over time.[11] In contrast, we could only interpret a trend in the count of online applications as a trend in search effort under the assumption that job seekers do not progressively substitute from one search channel to the other over time, which appears uncertain.

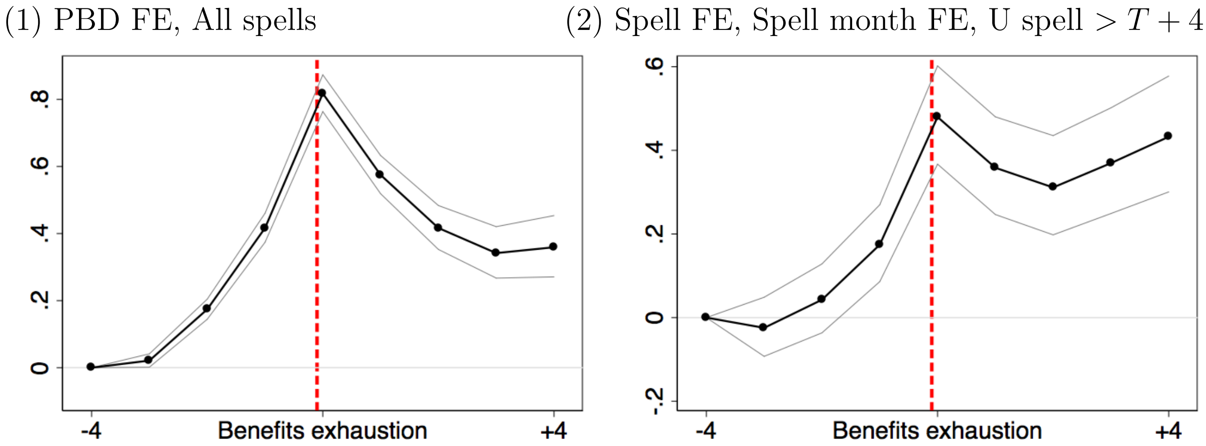
[11] We actually even need a less restrictive assumption as it is enough to assume that, if job seekers have different target wages on different search channels, their ratio remains constant over time.

5 The impact of unemployment insurance on job search

The standard search model predicts an increase in search intensity as benefit exhaustion approaches, and a constant search intensity after exhaustion (see Figure 1). The model also predicts a decrease in target wages, and then constant target wages after exhaustion. In this section, we estimate how search intensity and target wages change around benefit exhaustion and provide a direct test of these predictions. After accounting for dynamic selection, our findings broadly support the search model's predictions.

5.1 The impact of UI on the dynamics of search intensity

Figure 6: Search intensity around benefit exhaustion



Notes: The graphs present results from Poisson regressions of search intensity on time to benefit exhaustion. The x-axis denotes quarter relative to benefit exhaustion while the y-axis denotes relative differences in the number of applications between t and the reference period, i.e. 4 quarters before benefit exhaustion (coefficients displayed are IRR-1). Note that the scales of the y-axis in (1) and (2) are different. We include potential benefit duration (PBD) group fixed effect in specification (1) and in specification (2), we include spell FE and restrict the sample to job seekers who stay unemployed ≥ 4 quarters after benefit exhaustion. The grey lines denote 95% confidence intervals based on standard errors clustered at the spell level. The corresponding coefficients are reported in Appendix in Table A.4.

Figure 6 shows the evolution of search intensity around benefit exhaustion. The comparison between Panels (1) and (2) illustrates the role of dynamic selection: Panel (1) presents the evolution of *aggregate* search intensity while Panel (2) presents the evolution of *individual* search intensity, after accounting for dynamic selection. In Panel (1), we observe a steep increase in search intensity, starting 2 quarters before benefit exhaustion. After benefit exhaustion, we observe a decrease in search intensity, and 3 to 4 quarters after exhaustion, search intensity is about about half as intense as in the quarter of exhaustion. The decline in search intensity after exhaustion is at first blush inconsistent with the model's predictions of a constant level after exhaustion. However, some of the decline in search may be due to dynamic selection.

Panel (2) also clearly exhibits a large increase in applications before benefits exhaustion, which starts a long time before benefit exhaustion, but slowly at first, and becomes steeper in the quarter before exhaustion. After benefit exhaustion, there is a slight transitory decline in search intensity, but by 4 quarters after exhaustion search intensity is roughly at the same level as during the quarter of exhaustion. This shows that the systematic decline in search effort after exhaustion seen in panel (1) is mainly due to dynamic selection: within individual spells, search intensity stays roughly constant after benefit exhaustion, consistent with the predictions of the model. In terms of magnitudes, individual search intensity is 50% greater in the quarter of benefits exhaustion than in the reference period (the coefficients are reported in Appendix in Table A.4).

The discrepancy in the evolution of aggregate and individual search intensity after benefits exhaustion hence highlights that there is substantial heterogeneity in search behavior around benefits exhaustion. Another way to represent graphically this heterogeneity in search behavior around benefits exhaustion is to plot within individual search dynamic separately for job seekers who exit the sample at different times. In Figure A.2, we see that while the dynamic of search is relatively similar for these different groups up to four months before benefits exhaustion, they differ considerably around benefits exhaustion. The increase in search intensity appears considerably larger for job seekers who exit at benefits exhaustion: their number of applications more than doubles relative to the reference period. The graph hence illustrates that some job seekers react more strongly to the exhaustion of their benefits and exit faster, causing dynamic selection in the periods after benefits exhaustion.

Stock-flow and labor demand: The level of search effort that we observe could be determined by labor demand rather than labor supply. Indeed, job seekers might not be able to send their optimal number of applications if there is too few job ads that they can apply to. Standard search models offer a partial equilibrium view that abstracts from such labor demand constraints. Conversely, the stock-flow model (Coles and Smith, 1998; Gregg and Petrongolo, 2005; Coles and Petrongolo, 2008) emphasizes the role of this constraint: in this model, when workers start to search for a job, they can apply to a large number of vacancies because all vacancies are new to them, including those which have been posted for a long time ("the stock"). But after they have applied to all suitable vacancies, they only apply to new ones and their effort is therefore bounded by the rate of arrival of new suitable vacancies ("the flow"). Do labor demand constraints play a role in shaping the application behavior around benefits exhaustion? The labor demand constraint is binding once job seekers have exhausted all vacancies from the stock and rely on vacancies from the flow. Therefore we should observe a drop in the number of applications sent to vacancies from the stock if the constraint becomes binding around benefits exhaustion.

We leverage information on the date when each vacancy is posted and define vacancies from the stock as vacancies posted more than 7, 5 and 1 days before the date of application. In Figure A.3, we presents the evolution of the number of applications from the stock (the corresponding coefficients are reported in Table A.5). For all definitions of the stock, the evolution of applications around benefit exhaustion is essentially the same as the evolution of applications overall (columns (2)-(4)). Therefore, we conclude that labor demand does not represent a binding constraint for job applicants around benefit exhaustion.

Overall, the the dynamics of search intensity is consistent with the predictions of the standard model: search intensity increases as benefits exhaustion approaches, and remain constant afterward.

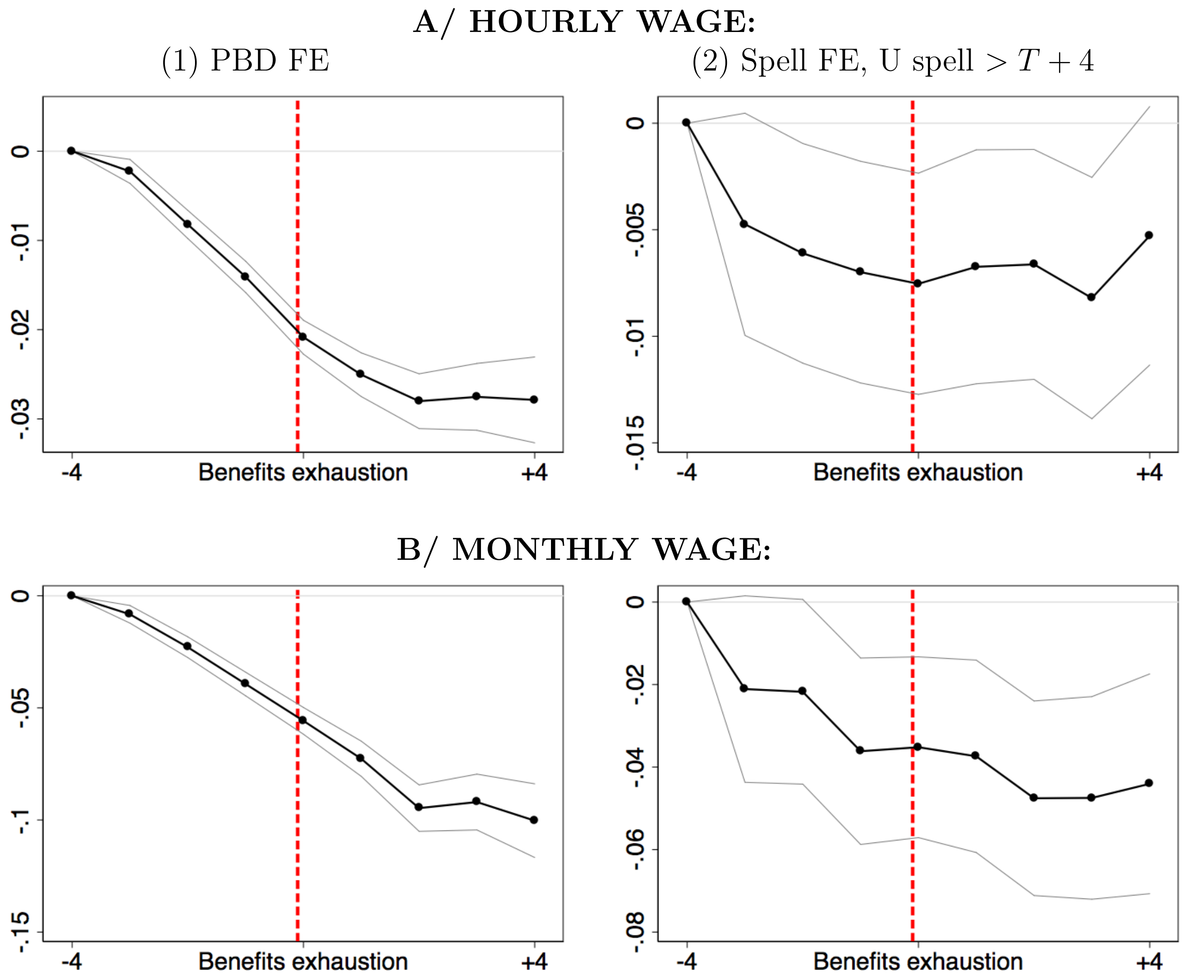
5.2 The impact of UI on the dynamics of search targets:

The search model also predicts that job seekers become less selective in their search as benefit exhaustion approaches and keep a constant target after exhaustion (Figure 1). We document the evolution of target wages around benefits exhaustion and show that it is consistent with the model's prediction. Additionally, we show that job seekers decrease the quality of jobs they target around benefits exhaustion in other dimensions than wages.

Target wages: Figure 7 presents the pattern of two measures of target wages around benefit exhaustion: hourly wages in the upper part and monthly wages in the lower part. As for search intensity, we compare two specifications that allow us to shed light on the role of dynamic selection: Panels (1) show the aggregate evolution of the target wage and panels (2) present the individual evolution of target wages. We first consider the evolution of targeted hourly wages. In panel (1), we observe a decrease in the target wage before benefit exhaustion, which means that job seekers tend to apply to jobs with a lower posted wage as they have fewer quarters of unemployment benefits left. In panel (2), the decrease in target wages before benefit exhaustion within individuals is less steep. The trend in target wage after benefits exhaustion is close to zero. After benefit exhaustion, target wages remain roughly constant. Overall, the dynamics of the target wage are qualitatively consistent with the prediction from the standard search model (Figure 1): a decrease in the target wage until exhaustion, and a constant target wage after exhaustion when job seekers face a stationary environment. The magnitude of the decrease before benefits exhaustion might appear small: individuals decrease their target wage by about 0.8% in anticipation of benefits exhaustion (Table A.6, column (2)).

When considering the context of the labor market, it is however not surprising to observe a small decrease in the targeted hourly wages: workers in our sample tend to target wages around minimum wage from the start. Although it is standard to measure the quality of the jobs using hourly wages, it might not be the relevant margin of adjustment empirically. To highlight the importance of hours, we also present the dynamics of *monthly* wages around benefit exhaustion. Qualitatively, the dynamic pattern is the same as for hourly wages.

Figure 7: Target wages (log) around benefit exhaustion



Notes: The graphs present results from regressions of log target wage on time to benefit exhaustion. The x-axis denotes quarters relative to benefit exhaustion while the y-axis denotes relative differences in the target wage between t and the reference period, i.e. 4 quarters before benefit exhaustion. Note that the scales of the y-axis in (1) and (2) are different. We include potential benefit duration (PBD) group fixed effect in specification (1) and in specification (2), we include spell fixed effects (FE) and restrict the sample to job seekers who stay unemployed ≥ 4 quarters after benefit exhaustion. The grey lines denote 95% confidence intervals based on standard errors clustered at the spell level. Coefficient estimates are reported in Table A.6

But quantitatively, the pattern is different: while hourly wages are less than 1% lower at exhaustion compared to a year before, monthly wages are about 4% lower. The decline in monthly wages is thus four times greater than the decline in hourly wages when benefit exhaustion approaches.

Other dimensions of job quality: We explore other dimensions of job quality in Table 1. While most workers declare searching for a full-time job and a stable contract, applications sent to these jobs decline: workers decrease the proportion of their applications to open-ended contracts by 6 ppt. This decline in job stability is consistent with Jarosch (2015), who shows that the long-lasting impact of mass lay-offs on earnings is not solely ex-

Table 1: Within individual variation in target job quality around benefits exhaustion

	Hourly wage (log)	Monthly wage (log)	Weekly hours (log)	Open-ended contract (ratio)	Experience required (log)	High educ required (ratio)	Wage within occupation (log)	Mean wage in occupation (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T-3$	-0.006**	-0.021*	-0.015	-0.020	-0.004	-0.008	0.001	-0.006***
	(0.003)	(0.012)	(0.011)	(0.016)	(0.004)	(0.012)	(0.002)	(0.002)
$T-2$	-0.007**	-0.022*	-0.014	-0.034**	-0.005	-0.009	-0.002	-0.005*
	(0.003)	(0.011)	(0.011)	(0.016)	(0.004)	(0.012)	(0.002)	(0.002)
$T-1$	-0.006**	-0.036***	-0.029***	-0.030*	-0.006	-0.012	-0.000	-0.005**
	(0.003)	(0.012)	(0.011)	(0.017)	(0.004)	(0.012)	(0.002)	(0.002)
T	-0.008***	-0.035***	-0.027**	-0.062***	-0.009***	-0.023**	-0.002	-0.005**
	(0.003)	(0.011)	(0.011)	(0.016)	(0.003)	(0.012)	(0.002)	(0.003)
$T+1$	-0.008***	-0.037***	-0.029**	-0.045***	-0.009**	-0.006	0.001	-0.008***
	(0.003)	(0.012)	(0.011)	(0.017)	(0.004)	(0.012)	(0.002)	(0.003)
$T+2$	-0.008**	-0.048***	-0.039***	-0.052***	-0.007*	-0.019	-0.000	-0.007***
	(0.003)	(0.012)	(0.012)	(0.018)	(0.004)	(0.013)	(0.002)	(0.003)
$T+3$	-0.008**	-0.047***	-0.039***	-0.051***	-0.011***	-0.015	-0.001	-0.007***
	(0.003)	(0.013)	(0.012)	(0.018)	(0.004)	(0.013)	(0.002)	(0.003)
$T+4$	-0.005	-0.044***	-0.038***	-0.067***	-0.007*	-0.031**	0.000	-0.005
	(0.003)	(0.014)	(0.013)	(0.020)	(0.004)	(0.014)	(0.002)	(0.003)
Spell time fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spell fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	38,893	38,893	39,294	39,348	39,294	39,348	38,893	39,293
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Spell time	-0.002***	-0.003***	-0.000	-0.005***	-0.002***	-0.004***	-0.000***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Time to T fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spell fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	375,210	375,210	378,989	379,534	378,989	379,534	375,210	378,972

Notes: The upper part of the table presents the evolution of job characteristics targeted around benefits exhaustion. Estimates are obtained from the subsample of spells balanced around benefits exhaustion. The lower part of the table presents the impact of the elapsed unemployment spell on the targeted job quality. Estimates are obtained from the full study sample (the same estimates obtained from the subsample of spells balanced around benefits exhaustion are presented in Table A.9). All SE are clustered at the spell level.

plained by the impact on hourly wages at re-employment but also by a persistent negative impact on contracts stability. Job seekers target lower skilled jobs over time: the professional experience required decreases by 1% (col. 5) and the proportion of applications sent to jobs requiring a higher education diploma drops by 2 ppt (col. 6). Additionally, we quantify the decrease in target wages that comes from applying to lower wages within the same occupation (col. 7) and the decrease that comes from applying to lower paying occupations (col. 8): most of the decrease in target wage comes from applying to occupations associated with lower wages on average. These various measures bring systematic evidence that, around benefits exhaustion, workers are willing to take lower quality jobs.

Overall, the impact of PBD on the dynamics of the target wage is consistent with the predictions of the standard model: the target wage decreases as benefits exhaustion approaches, and remains constant afterward. The decrease in target wages is accompanied by decreases in job quality in other respects like hours and contract stability.

5.3 The impact of unemployment duration on search targets:

Our identification strategy allows to separately identify the impact of lapsed unemployment duration on search targets. In Table A.6, we report the estimates for the time trend in search targets: in addition to the drop in target monthly wage before benefits exhaustion, individuals decrease by about 1.2% per year (0.3% per quarter) their target wage as long as they remain unemployed. Additionally, each year of unemployment causes a drop in other dimensions of targeted job quality: the proportion of open-ended contracts drops by 2 ppt (column (12)), the average experience required drops by 0.8% (column (13)), the proportion of job requiring a diploma from higher education drops by 1.6 ppt (column (14)). The decrease in target wages over the unemployment spell seem to reflect a productivity decrease as a worker applies to jobs with characteristics that predict lower and lower wages (columns (15) and (16)). It could be because job seekers experience a depreciation in their skills over time, because they negatively update their beliefs about job finding prospects, or because they anticipate a stigma associated with long unemployment spells (Kroft et al., 2013).

Overall, we find a negative trend in various dimensions of the targeted job quality. This result sheds light on the impact of unemployment insurance on re-employment wages: because of this negative trend, when job seekers delay their applications because of a long PBD, they delay their job finding to a time when the quality of jobs they target is lower. This effect can in some contexts counteract the positive effect of unemployment insurance on targeted job quality at each given point in time (Schmieder et al. (2016), Nekoei and Weber (2017)).

5.4 Robustness checks:

In this section, we discuss potential concerns regarding our strategy of identification and present various tests showing that our results are robust to alternative methods.

A first potential concern in that our main empirical strategy exploits both the comparison between UI recipients and non UI recipients and the comparison within UI recipients between job seekers eligible to different PBD and hence "treated" by benefit exhaustion at different moments of their unemployment spell. The effect of benefits exhaustion might be heterogeneous across PBD groups, and hence job seekers eligible to different PBD might not represent an appropriate control group (de Chaisemartin and D'Haultfoeuille (2019)). As a robustness check, we implement an alternative strategy only relying on the comparison with non UI recipients: we separately estimate the regression model on the sample of non UI recipients and UI recipients with each PBD separately. We then calculate the average of coefficients obtained for different PBD, weighted by the size of each PBD group. The weighted average of coefficients is presented in Table A.7. We see that the coefficients associated with all time to benefits exhaustion are virtually identical to the ones obtained using the main strategy. This shows that our results are not affected by potential problems associated with the comparison between PBD groups.

Another concern is that we might underweight small variations in search effort, because applications in our data are only a small fraction of total effort especially for individuals who do not use the platform frequently: one additional monthly application represents a very large relative increase in search effort and we do not observe variation in effort at relatively low effort levels. In order to test whether our results are sensitive to the importance of the use of this platform, we investigate the evolution of applications for the subsample of individuals who send many applications over their unemployment spell in Figure A.4 and Table A.8 (Panel A). The general pattern of applications around benefit exhaustion is very similar as we restrict to individuals who sent more and more applications on the website. Therefore, our finding that job search effort increases until benefit exhaustion holds in the same way for job seekers who use the platform a lot and those who use it more rarely. Another concern is that our measure of target wage is missing when an individual sends no application. We analyze the evolution of target wages around benefits exhaustion for the same subsamples to test whether this data limitation affects our results. We observe that the pattern of target wages around benefit exhaustion is similar for users who send many applications and for all users (Figure A.4 and Table A.8, Panels B and C). Overall, this demonstrates the robustness of our main finding that target wages decrease until benefit exhaustion and stay constant thereafter.

Additionally, we make sure that our results are not affected by the interruptions periods during unemployment benefits collection: UI recipients can experience interruptions in their UI collection, if they have another source of income due to a training for instance. During these periods, they do not receive unemployment benefits or receive benefits at a lower rate, and are generally not required to search for a job. For simplicity, we have treated these periods as exogenous until now and just excluded them from the analysis. We now test whether this simplification is justified by reproducing the results when excluding all workers who have more than one month or more than two weeks of UI interruption in total (when we sum up all days when they do not receive their full UI). In Table A.11, we show that our estimates for the evolution of search behavior around benefits exhaustion are similar when we exclude individuals with long interruptions in their UI.

Last, we consider various alternative measures of target monthly and hourly wages. In Table A.10, we measure target wages using the actual posted wages instead of the wages predicted based on the characteristics included in job ads (columns (1)-(2) and (5)-(6)). We lose precision due to the decrease in sample size as posted wages are missing for about half of the sample. But the magnitude of the point estimates remains very close to the coefficients from our main specification: we estimate a persistent drop at benefits exhaustion by about 3.5-4% for targeted monthly wages and a smaller persistent drop by about 0.2-0.8% for hourly wages. Second, we study the evolution in the minimum wage that job seekers apply to each quarter instead of the average, in order to have a measure closer to the concept of reservation wage. The pattern looks similar: we observe a persistent drop in minimum monthly wages at benefits exhaustion by about 2-5%, both when using predicted and posted wages (columns (3)-(4)). The drop in minimum hourly wages at benefits exhaustion is smaller and our estimates are not significant when using posted wages (columns (7)-(8)).

Overall, we have shown in this analysis the robustness of our finding of an increase in search intensity and a decrease in target wages around benefit exhaustion, in a pattern that appears mainly consistent with the predictions of the standard search model.

5.5 Heterogeneous reaction to benefits exhaustion

We explore the sources of the heterogeneous reaction to benefits exhaustion that we have documented in Figure A.2. A large reaction to benefits exhaustion indicates a large moral hazard effect of UI on search behavior from the start of the unemployment spell. The standard search model predicts a larger moral hazard and hence a larger reaction to benefits exhaustion for unemployed workers receiving higher UI benefits (if welfare transfers are fixed). Our results support this prediction.

Our rich data on individual characteristics allow us to study many heterogeneity dimensions. Because there are clear theory predictions for this dimension, we focus on the role of unemployment benefits levels. In France, the transition from unemployment benefits to welfare transfers represents a larger income drop for individuals who received higher benefits. This is because the amount of unemployment benefits is based on prior wages while the amount of welfare transfers is fixed for each category of households. We observe individual benefits amount and hence can approximate the magnitude of income loss at benefits exhaustion.[12] Table A.12 presents the correlation between individual characteristics and the magnitude of the change in search behavior between $T-4$ and T. The increase in search intensity is larger for individuals receiving higher levels of unemployment benefits (column (1), Table A.12): 1% higher unemployment benefits are associated with a 0.34% larger increase in search intensity. This is consistent with Katz and Meyer (1990a) who found a positive but insignificant effect of benefit levels on job finding around benefits exhaustion. When we include other heterogeneity dimensions in column (2), the magnitude of the effect of unemployment benefits is even larger (elasticity of 0.48). We also observe that younger individuals tend to react more to benefits exhaustion, potentially because they do not have assets to smooth their consumption. In column (3), we additionally include interactions

[12] This is only an approximation however as we can not calculate welfare benefits, which depend on characteristics we do not observe such the age of children and the housing situation.

with the level of previous wages and observe that this does not affect the magnitude of the other heterogeneity dimensions. Note that the level of the unemployment benefit depends on the prior wage, but the benefit is capped; this is why we can identify the effect separately from the effect of the prior wage. In columns (4) to (6) we do the same analysis for the reaction in target wages. We observe that individuals eligible to higher benefits levels drop their target wage more at benefits exhaustion, but coefficients are imprecisely estimated.

Overall, our heterogeneity analysis shows that higher income drops at benefits exhaustion due to higher benefits levels cause stronger reactions, in particular in search intensity. First, this result confirms a prediction from the standard search model. Second, this result documents the type of dynamic selection that might happen around benefits exhaustion: around benefits exhaustion, individuals experiencing the largest drop in income increase their search intensity more and are more likely to leave unemployment. This type of dynamic selection could hence contribute to explain the decrease in job finding after benefits exhaustion that has been documented in other contexts, as many institutional contexts beyond France generate heterogeneity in the income drop experienced by workers at benefits exhaustion. DellaVigna et al. (2017) observe that the search model that features heterogeneity in the reaction to benefits exhaustion provides the best fit to the pattern of job finding in Hungary. But the authors generate this heterogeneity in the reaction to benefits exhaustion by including several search cost convexity parameters and then decide against this model because it requires more structural parameters than the second best model they consider. Our findings suggest that it is possible to generate such a heterogeneous reaction to benefits exhaustion in the absence of heterogeneity in structural parameters, only by accounting for the diversity of income drops experienced at benefits exhaustion due to the institutional context.

Our empirical findings confirm the general framework of search models: substantial search frictions exist and search behavior is a relevant margin of adjustment to UI for unemployed workers. Moreover, the way unemployment workers adjust their search behavior in response to unemployment insurance appear qualitatively consistent with the predictions of a standard search model. In the next section, we assess quantitatively how well the standard search model fits our results, and test whether adding non standard features gets us a closer fit to the data.

6 Which search model?

Modelling search behavior accurately is important for the welfare analysis of unemployment insurance. Our empirical analysis shows that search models correctly predict that job seekers dynamically adjust their search effort and target wages in response to unemployment insurance. But which search model best predicts the path of this adjustment? Our finding of a decline in search effort after benefit exhaustion is at odds with the predictions of the standard search model, although this decline is small and temporary once we account for dynamic selection. The reference-dependence search model developed in DellaVigna et al. (2017) precisely departs from the standard model in predicting a decline in search effort after benefits exhaustion. Qualitatively, it is hence difficult to rule out that the reference-dependence model offers better predictions than the standard model. Therefore, we turn to structural estimation in order to test quantitatively the standard model against the reference dependence model of DellaVigna et al. (2017). In contrast with DellaVigna et al. (2017), we directly target empirical moments corresponding to *individual* search behavior and therefore do not need to make assumptions about unobserved heterogeneity. We conclude that the standard search model best describes the empirical dynamics of job search behavior.

6.1 Set-up and estimation

Generalized search model: We start from the model we presented in section 2. Our finding of a small and temporary decrease in search intensity after benefits exhaustion in Figure 6 does not exactly match the stationary pattern predicted by the standard model. DellaVigna et al. (2017) suggest incorporating reference dependence in job seekers' utility function to rationalize a decrease in search effort after benefits exhaustion: they assume that individuals do not only derive utility from their current income but also from the gap between their current income level and their reference income level. Hence, job seekers suffer a decrease in utility from their loss of income at benefits exhaustion, but their utility then goes up again as they get used to their new lower level of income. There could be alternative explanations for the decrease in individual search effort after benefits exhaustion such as learning or consumption commitment, but the two-steps unemployment insurance system in Hungary allowed DellaVigna et al. (2017) to rule out these alternative explanations. Therefore, we use the reference-dependent model as the point of comparison for the standard model. To incorporate reference-dependent preferences, we allow for a flexible utility function in our model:

$$u(c_t|r_t) = v(c_t) + \eta[v(c_t) - v(r_t)]$$

$$r_t = \frac{1}{N} \sum_{k=t-N}^{t-1} c_k$$

Where r_t is the reference consumption level in period t while c_t is the current consumption level in period t. N is the time horizon for the reference dependence. We assume a log utility function $v(c) = log(c)$. This generalized model nests the standard model and models with reference dependence: if $\eta = 0$ or $N = 0$ (no reference dependent preferences), and we are back to a standard model predicting constant search behavior after benefits exhaustion due to a stationary environment.

Estimation: We estimate the value of key parameters using the minimum distance method: the estimator chooses the parameters that minimize the weighted distance between the empirical moments and their corresponding predictions in the model. The weights correspond to the inverse of the variance of each empirical moment. We target the quarterly evolution of search intensity and target job quality in the quarters around benefits exhaustion, estimated in models with individual and spell time fixed effects (Figure 6, Panel (2) and Figure 7, B/ Panel (2)); these moments are thus purged of dynamic selection or duration dependence. We have 16 empirical moments: 8 moments for search intensity and 8 moments for target wages. In order to compute the corresponding theoretical moments, we solve the model, derive the optimal search effort and target wage every month of the unemployment spell, and then calculate the evolution of these variables in the quarters around benefits exhaustion. We estimate the reference-dependence parameter η and the time horizon for the reference N to test the standard model against the reference dependence model. We also estimate some incidental parameters: return to search effort α_2, average search costs β_1 and the curvature of the search function β_2. As in section 2, we calibrate the rest of the parameters with information on the context (see Table A.1).

In contrast with DellaVigna et al. (2017), our targeted empirical moments are estimated for the same individuals over time. Therefore, we do not need to make any assumption on the type of unobserved heterogeneity. This crucially improves our ability to test different search models: it is only after making some assumption on unobserved heterogeneity that DellaVigna et al. (2017) can target empirical moments corresponding to job finding rates and estimate the reference-dependence model against standard models. The authors find that the standard search model with heterogeneity in search cost convexity actually fits their data better than the reference-dependent search model but conclude in favor of the reference-dependent search model because it requires fewer structural parameters. As the two models have similar predictions for the evolution of job finding rates but not for the evolution of individual search behavior, our data on individual search behavior brings new elements to the comparison. It appears all the more crucial that we found substantial heterogeneity in job seekers' reaction to benefits exhaustion in our reduced-form analysis.

Identification: The identification of the reference-dependence parameter comes from the pattern of search behavior after benefits exhaustion. η and N are the only parameters causing a shift in individual behavior after benefits exhaustion: η determines the magnitude of this shift while N determines its duration. β_1 mainly affects the extent to which individuals react in their search effort or in their target wage and β_2 determines the magnitude of the reaction of search behavior to benefits exhaustion. We caution against interpreting the magnitude of the estimates we obtain for these β_1 and β_2 parameters because they depend heavily on our calibration of the other parameters, in particular the parameters of the job finding function. We only estimate β_1 and β_2 in order to leave some flexibility in how the model fits the data.

6.2 Results

Table 2: Estimates of the Standard and Reference-Dependent Model

Model:	**Standard**	**Reference-dependence**	
Parameters η, N:	Calibrated	Calibrated	Estimated
	(1)	(2)	(3)
Reference-dependence η	0	4.91	0.01
Time horizon N	-	6.18	6.31
Search cost β_1	8.48	8.19	8.34
Search cost β_2	1.00	0.90	0.98
Goodness of fit	18.30	40.47	18.20
Nb estimated parameters	2	2	4
Nb empirical moments	16	16	16

Notes: The table shows parameter estimates for the standard and the reference-dependent search models. Estimation is based on minimum distance estimation, using empirical moments of search behavior around benefits exhaustion. In column (2), the parameters η and N are calibrated after DellaVigna et al. (2017).

We present the results from the structural estimation in Table 2. In column (1), we estimate the value of the two search cost parameters β_1 and β_2 under the assumption that the utility function is standard. This amounts to calibrating the reference-dependence parameter to $\eta = 0$. Note that in that case, the value of the time horizon parameter N is irrelevant. Graphically (Figure A.5, Panel (1)), the model's predictions appear to match the targeted moments fairly well. This is reflected in the relatively good goodness of fit, 18.30. In column (2), we estimate the value of β_1 and β_2 when we calibrate the two reference-dependence parameters after DellaVigna et al. (2017): the authors estimate a discount parameter $\hat{\eta}$ of 4.91 and a time horizon of the reference income $\hat{N}$ of 6.18 months. We estimate the same number of parameters as in column (1) and can therefore compare the goodness of fit that we obtain under these two alternative calibrations. The goodness of fit that we obtain under the reference-dependence calibration is much worse at 40.47. This shows that the empirical dynamics of job search is better fitted in a standard search model than in a reference dependence model calibrated after DellaVigna et al. (2017). Is it because another calibration would be necessary in our context or because the reference-dependence model is rejected by our data?

To answer this question, we estimate two additional parameters commanding the degree of reference-dependence, η and N. In column (3) of Table 2, we present our estimates, which amount to 0.01 for the reference-dependence discount parameter $\hat{\eta}$ and 6.31 months for the time horizon parameter $\hat{N}$. $\hat{\eta}$ is hence substantially lower than the estimate obtained in

DellaVigna et al. (2017) and very close to 0. Our estimation hence highlights that the best fit is obtained in the standard search model given that the generalized model is equivalent to the standard model if any of the parameters η and N is close to 0. Consistently, we note that all estimates in column (3) are close to the value of parameters in the standard model (col. 1), and that the predictions from both models are virtually identical (Panels (1) and (3) in Figure A.5). Estimating the two additional reference-dependence parameters hence does not substantially improve the goodness of fit. Overall, our structural estimation rejects the reference-dependence model.

We have so far abstracted from discussing models' predictions concerning the evolution search behavior over the unemployment spell. In our reduced-form analysis, we found evidence for substantial negative duration dependence, which is typically not accounted for in search models. One way to incorporate negative duration dependence in our generalized search model is to assume some decrease over time in the job finding parameter α_1. The conclusions from our structural estimation should not be affected by this addition given that we target empirical moments corresponding to search behavior around benefits exhaustion *once we control away average differences across individuals and over time.* We calibrate the model so that it predicts a decrease in target wage by 0.3% each quarter, similar to our reduced-form estimate (Table 1) and we re-estimate the same parameters as in Table 2. We discuss in more details how we adjust the model and our results in Appendix A.3. The results (Table A.16) are very similar to those in Table 2 and we reach the same conclusion that the standard model best predicts search behavior around benefits exhaustion.

Overall, our structural estimation allows us to quantitatively assess how well the standard search model can fit our empirical results compared to the behavioral reference-dependence model. We consistently find that the standard search model predicts better the dynamics of search behavior around benefits exhaustion. While insights from behavioral economics might be very useful to explain some aspects of job search, we conclude that a standard search model is the best tool to analyze the impact of unemployment insurance on job search behavior.

7 Conclusion

The standard search model has been the workhorse of recent literature on unemployment insurance. In this paper, we use unique longitudinal data on job search and unemployment insurance eligibility to test the predictions of the model. After observing in our descriptive statistics that returns to search are positive but low, implying a significant role for search frictions, we focus on the impact of unemployment insurance on search behavior. We exploit variation in the potential benefits duration of French unemployed workers in panel models with spell and time fixed effects to estimate the impact of benefits exhaustion on search behavior. First, we find that job seekers increase their search effort in the year prior to benefits exhaustion, and keep it high and roughly constant after. Second, we show that job seekers decrease their target wage by applying to lower and lower paying occupations in the year prior to benefits exhaustion and keep it at a constant level after. Additionally, we find evidence for negative duration dependence in target wages: time spent unemployed has a negative effect on target wages, independent on unemployment benefits duration.

These findings together help to reconcile findings in prior literature that questioned the validity of the standard search model. In particular, we show that the decline in job search intensity and job finding after benefit exhaustion is due to dynamic selection rather than reference-dependent preferences. Furthermore, the negative duration dependence in target wages helps explain why many prior studies did not find a positive effect of unemployment benefit duration on re-employment wages. We show that, at any given time of the unemployment spell, target wages tend to be higher with longer benefit duration, as predicted by the standard search model. However, longer benefit duration decreases search intensity, which delays job finding to a time when target wages are lower: the overall effect of longer benefit duration on re-employment wages is therefore ambiguous.

Overall, our findings support the predictions of the standard search model and are a odd with predictions of search-free models or a behavioral search model with reference-dependent preferences. Our results hence confirm that unemployment insurance subsidizes search rather than just leisure and validate the standard search model as a critical tool to understand the impact of unemployment insurance on re-employment outcomes and to think about optimal unemployment insurance policies.

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Appendix

A.1 Additional tables and figures

Table A.1: Model calibration

Parameter	Value
Monthly discount factor β	0.996
Previous hourly wage (€)	10.8
Unemployment benefits (€, hourly) b	6.3
Welfare transfers (€, hourly) m	3
Mean of log hourly wages (€) in job offer distribution F	2.15
Standard deviation of log hourly wages in job offer distribution F	0.36
Job destruction rate δ	0.02
Job finding parameter α_1	0.2
Search cost parameter β_1	8.48
Search cost parameter β_2	1.00

Notes: In this Table, we present the value of parameters we use to calibrate our model. To have consistency in units, we convert monthly incomes in hourly income by assuming that they correspond to the payments of 151,67 hours, corresponding to the number of hours of work per month for standard full-time jobs in France.

Table A.2: Sample description

	All spells			Long spells		
	Mean	Median	SD	Mean	Median	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Woman	0.59	1.00	0.49	0.56	1.00	0.50
Age	31.46	29.00	9.86	38.11	38.00	10.74
Single	0.62	1.00	0.48	0.60	1.00	0.49
Full time	0.93	1.00	0.26	0.86	1.00	0.34
Blue collar, unskilled	0.05	0.00	0.22	0.06	0.00	0.24
Blue collar	0.08	0.00	0.27	0.08	0.00	0.28
White collar, unskilled	0.18	0.00	0.38	0.18	0.00	0.39
White collar	0.55	1.00	0.50	0.51	1.00	0.50
Management	0.14	0.00	0.35	0.16	0.00	0.36
Unemployment spell	496.85	405.00	370.41	1291.86	1261.00	262.68
Is eligible to UI	0.57	1.00	0.50	0.53	1.00	0.50
Previous hourly wage (€)	11.78	10.84	4.01	11.51	10.17	4.05
Amount of monthly UI benefits (€)	950.55	962.50	363.02	900.21	875.74	416.98
No. of spells		493,727			21,832	
No. of individuals		466,313			21,563	

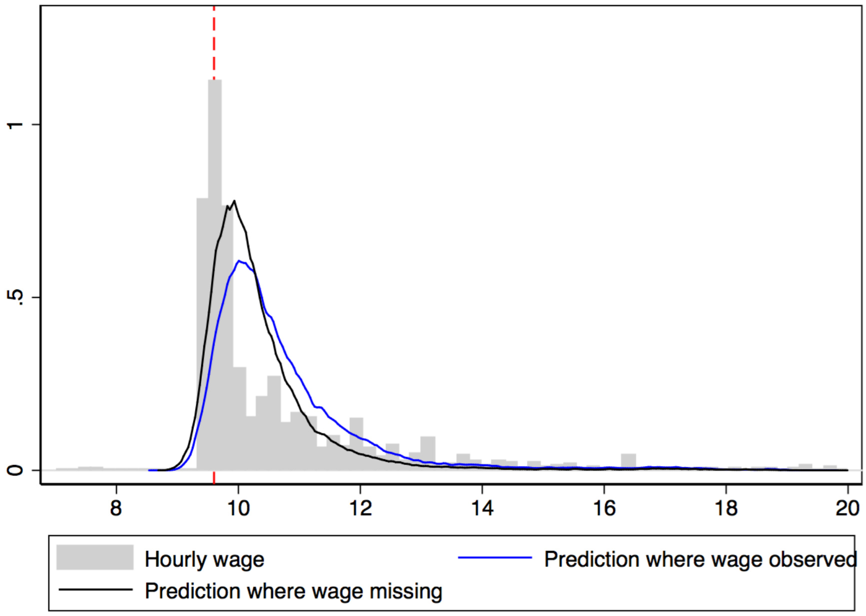
Notes: This Table presents characteristics of the unemployment spells in our study sample: spells of non UI recipients and UI recipients with PBD ranging between 12 and 24 months. From columns (1) to (3), we present statistics for all unemployment spells while from columns (4) to (6), we present characteristics for the sample of long unemployment spells, i.e. lasting more than one year after the end of UI benefits for UI recipients and more than 3 years for non UI recipients, as explained in section 4.1.

Table A.3: Linear model for the prediction of posted hourly wage

Outcome	**Hourly wage**
Full time job	0.116***
	(0.009)
Number of weekly hours	-0.026***
	(0.001)
Contract tern (ref: < 6 months long)	
Permanent contract	0.452***
	(0.005)
Long-term contract	0.111***
	(0.005)
Establishment size (ref: < 5)	
5 to 20 employees	0.048***
	(0.004)
20 to 50 employees	0.098***
	(0.004)
50 employees	0.218***
	(0.004)
Required experience (ref: No experience)	
Some work experience	0.362***
	(0.003)
Required qualification (ref: blue collar, low skill)	
blue collar, high skill	0.222***
	(0.009)
white collar, low skill	0.032***
	(0.008)
white collar, high skill	0.200***
	(0.008)
intermediary position	0.968***
	(0.009)
management position	4.221***
	(0.013)
Required education (ref: no diploma mentioned)	
vocational high school diploma	-0.083***
	(0.005)
general high school diploma	-0.034***
	(0.005)
Higher education diploma	0.450***
	(0.005)
Job category FE	YES
County FE	YES
N	1,200,061
F	14,007.577
R^2	0.485

Notes: In this Table, we present the regression of the posted hourly wage on all characteristics contained in the job ads. The sample is made of all job ads from our sample for which the posted wage is not missing (41% of job ads in our sample).

Figure A.1: Predicted hourly wage



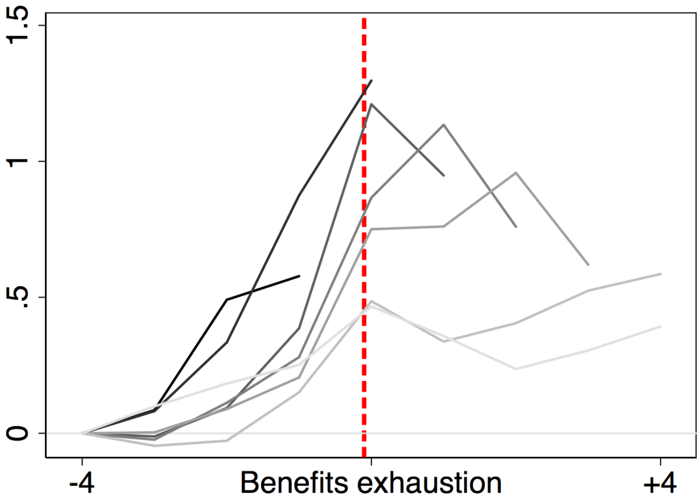
Notes: In this Figure, we present the distribution of hourly wages posted in the job ads in our sample and the predicted hourly wage based on a linear prediction using all characteristics contained in the job ads (Table A.3). The posted wage is missing for 59% of job ads in our sample. We present separately the distribution of predicted hourly wage when the posted wage is observed and when it is missing.

Table A.4: Effect of benefits exhaustion on search intensity

Outcome variable	**Number of applications**	
	Poisson count model	
	(1)	(2)
$T-3$	0.021**	-0.012
	(0.010)	(0.037)
$T-2$	0.174***	0.050
	(0.015)	(0.044)
$T-1$	0.416***	0.210***
	(0.022)	(0.051)
T	0.818***	0.513***
	(0.028)	(0.065)
$T+1$	0.575***	0.370***
	(0.029)	(0.064)
$T+2$	0.417***	0.336***
	(0.033)	(0.067)
$T+3$	0.342***	0.417***
	(0.039)	(0.072)
$T+4$	0.359***	0.468***
	(0.047)	(0.078)
Average of coefficients T to $T+4$	0.492***	0.419***
	(0.021)	(0.061)
Time of spell fixed effects	Yes	Yes
PBD group fixed effects	Yes	No
Spell fixed effects	No	Yes
No. of Obs	2,846,370	274,204

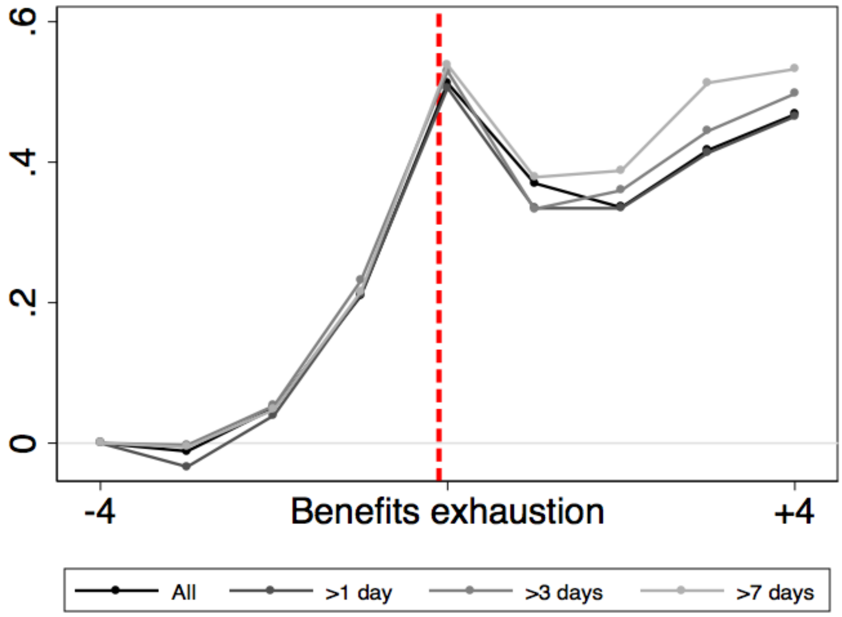
Notes: The table documents the evolution of applications sent in the quarters around benefits exhaustion. In specification (1) we include spell time and PBD group fixed effects, in specification (2) we include spell time and spell fixed effects and restrict our sample to workers unemployed during the time window of analysis. Coefficients displayed are IRR-1 and represent relative variations in the hazard of sending an application, with respect to the reference period $T-4$. Robust SE are clustered at the spell level.

Figure A.2: Heterogeneity in reaction to UI exhaustion



Notes: The figure documents the evolution of applications sent in the quarters around benefits exhaustion for different subsamples of spells: spells that terminate in $T-1$, T, $T+1$, $T+2$, $T+3$, $T+4$ and after $T+4$. Coefficients displayed are IRR-1 and represent relative variations in the hazard of sending an application, with respect to the reference period $T-4$. We include spell time and spell fixed effects. SE are clustered at the PBD spell level.

Figure A.3: Applications to vacancies from the stock around benefits exhaustion



*Notes:*The figure documents the evolution of different types of applications sent in the quarters around benefits exhaustion. We distinguish applications made to vacancies of different durations (in days) on the online platform. Coefficients displayed are IRR-1 and represent relative variations in the hazard of sending an application, with respect to the reference period $T-4$. We include spell time and spell fixed effects and restrict our sample to workers unemployed during the time window of analysis. Corresponding coefficients are reported in table A.5.

Table A.5: Applications to vacancies from the stock around benefits exhaustion

Outcome variable	All	Count of applications to vacancies posted:		
		> 1 day before (61 %)	> 3 days before (49 %)	> 7 days before (34 %)
	(1)	(2)	(3)	(4)
$T-3$	-0.012	-0.034	-0.003	-0.006
	(0.037)	(0.042)	(0.047)	(0.054)
$T-2$	0.050	0.040	0.053	0.048
	(0.044)	(0.049)	(0.053)	(0.060)
$T-1$	0.210***	0.212***	0.231***	0.215***
	(0.051)	(0.057)	(0.062)	(0.068)
T	0.513***	0.506***	0.529***	0.538***
	(0.065)	(0.072)	(0.078)	(0.088)
$T+1$	0.370***	0.334***	0.333***	0.379***
	(0.064)	(0.069)	(0.074)	(0.086)
$T+2$	0.336***	0.334***	0.360***	0.388***
	(0.067)	(0.072)	(0.079)	(0.090)
$T+3$	0.417***	0.413***	0.444***	0.513***
	(0.072)	(0.078)	(0.085)	(0.099)
$T+4$	0.468***	0.465***	0.497***	0.532***
	(0.078)	(0.084)	(0.092)	(0.105)
Average of coefficients T to $T+4$	0.419***	0.409***	0.431***	0.468***
	(0.061)	(0.065)	(0.071)	(0.081)
Time of spell fixed effects	Yes	Yes	Yes	Yes
Spell fixed effects	Yes	Yes	Yes	Yes
No. of Obs	274,204	233,871	210,263	174,416

Notes: The table documents the evolution of different types of applications sent in the quarters around benefits exhaustion. We distinguish applications made to vacancies of different durations (in days) on the online platform. Coefficients displayed are IRR-1 and represent relative variations in the hazard of sending an application, with respect to the reference period $T-4$. We include spell time and spell fixed effects and restrict our sample to workers unemployed during the time window of analysis. Robust SE are clustered at the spell level.

Table A.6: Effect of benefits exhaustion on target wages

Outcome variable	**Target wage (log)**	
	(1)	(2)
$T-3$	-0.002***	-0.006**
	(0.001)	(0.003)
$T-2$	-0.008***	-0.007**
	(0.001)	(0.003)
$T-1$	-0.014***	-0.006**
	(0.001)	(0.003)
T	-0.021***	-0.008***
	(0.001)	(0.003)
$T+1$	-0.025***	-0.008***
	(0.001)	(0.003)
$T+2$	-0.028***	-0.008**
	(0.002)	(0.003)
$T+3$	-0.028***	-0.008**
	(0.002)	(0.003)
$T+4$	-0.028***	-0.005
	(0.002)	(0.003)
Time of spell fixed effects	Yes	Yes
PBD group fixed effects	Yes	No
Spell fixed effects	No	Yes
No. of Obs	710,024	38,893

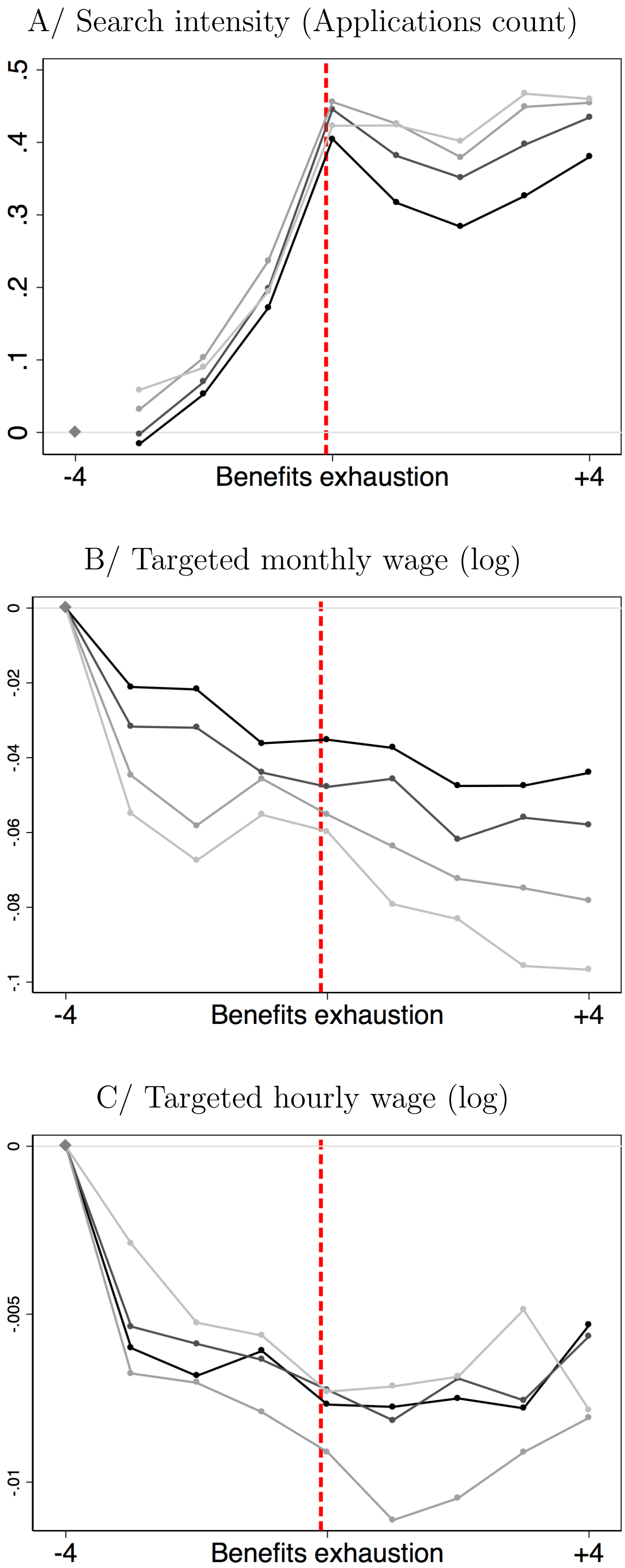
Notes: The table documents the evolution of target wages in the quarters around benefits exhaustion. In specification (1) we include spell time and PBD group fixed effects, in specification (2) we include spell time and spell fixed effects and restrict our sample to workers unemployed during the time window of analysis. SE are clustered at the spell level.

Table A.7: Robustness: Search behavior around UI exhaustion estimated in separate DiD for each PBD group

Outcome	Search intensity	Targeted monthly wage	Targeted hourly wage
	(1)	(2)	(3)
$T-3$	-0.016	-0.025**	-0.008**
	(0.038)	(0.012)	(0.003)
$T-2$	0.011	-0.025**	-0.008***
	(0.043)	(0.012)	(0.003)
$T-1$	0.197***	-0.040***	-0.008***
	(0.051)	(0.012)	(0.003)
T	0.489***	-0.040***	-0.009***
	(0.064)	(0.011)	(0.003)
$T+1$	0.331***	-0.042***	-0.010***
	(0.058)	(0.012)	(0.003)
$T+2$	0.316***	-0.051***	-0.009***
	(0.060)	(0.012)	(0.003)
$T+3$	0.403***	-0.050***	-0.010***
	(0.066)	(0.012)	(0.003)
$T+4$	0.481***	-0.047***	-0.007**
	(0.073)	(0.013)	(0.003)
Time of spell fixed effects	Yes	Yes	Yes
Spell fixed effects	Yes	Yes	Yes
No. of Obs	1,861,504	269,461	269,461

Notes: The table presents the evolution of search behavior in the quarters around benefits exhaustion. In contrast with the main estimation model where all PBD groups are pooled together, we estimate coefficients separately for each PBD group from the comparison with non UI recipients. The table presents the mean of these coefficients weighted by the number of observations in each PBD group. As in previous tables, we estimate variation in search intensity in a Poisson count model and coefficients displayed are IRR-1 (col (1)); while we estimate variation in target wages in a log-linear model (col (2)-(3)). Robust SE are clustered at the spell level.

Figure A.4: Robustness: Search behavior around UI exhaustion for subsamples of spells corresponding to different intensity of platform use



Notes: The figures document the evolution of search behavior in the quarters around benefits exhaustion for different subsamples of job seekers with different intensity of platform use: the black line is for all users, then the lighter and lighter gray lines correspond to sending more than 4 applications (75th percentile), more than 9 applications (90th percentile) and more than 14 applications (95th percentile). We include spell time and spell fixed effects and restrict our sample to workers unemployed during the time window of analysis. In panel A/, coefficients displayed are IRR−1 and represent relative variations in the hazard of sending an application. In panels B/ and C/, coefficients represent relative variations in wages. Corresponding coefficients are reported in Table A.8.

Table A.8: Robustness: Search behavior around UI exhaustion for subsamples of platform users

Sample: Total nb of applications (sample share)	**Any (100%)**	≥ 4 **(25%)**	≥ 9 **(10%)**	≥ 14 **(5%)**
A/ Search intensity (applications count)				
$T-3$	-0.012	0.000	0.025	0.037
	(0.037)	(0.047)	(0.063)	(0.076)
$T-2$	0.050	0.060	0.082	0.061
	(0.044)	(0.057)	(0.077)	(0.092)
$T-1$	0.210***	0.227***	0.249***	0.191**
	(0.051)	(0.065)	(0.089)	(0.102)
T	0.513***	0.537***	0.501***	0.422***
	(0.065)	(0.084)	(0.111)	(0.128)
$T+1$	0.370***	0.414***	0.401***	0.356***
	(0.064)	(0.083)	(0.111)	(0.130)
$T+2$	0.336***	0.384***	0.359***	0.362***
	(0.067)	(0.087)	(0.116)	(0.143)
$T+3$	0.417***	0.464***	0.453***	0.439***
	(0.072)	(0.094)	(0.126)	(0.152)
$T+4$	0.468***	0.482***	0.422***	0.375***
	(0.078)	(0.100)	(0.129)	(0.152)
No. of Obs	274,204	92,839	36,010	19,559
B/ Targeted monthly wages (log)				
$T-3$	-0.018	-0.030***	-0.042***	-0.051***
	(0.011)	(0.012)	(0.014)	(0.017)
$T-2$	-0.019*	-0.030***	-0.056***	-0.065***
	(0.011)	(0.012)	(0.014)	(0.017)
$T-1$	-0.033***	-0.042***	-0.046***	-0.056***
	(0.011)	(0.011)	(0.014)	(0.016)
T	-0.029***	-0.043***	-0.052***	-0.057***
	(0.011)	(0.011)	(0.013)	(0.016)
$T+1$	-0.029**	-0.040***	-0.056***	-0.072***
	(0.011)	(0.012)	(0.015)	(0.018)
$T+2$	-0.039***	-0.056***	-0.066***	-0.077***
	(0.011)	(0.012)	(0.014)	(0.017)
$T+3$	-0.040***	-0.051***	-0.070***	-0.092***
	(0.012)	(0.013)	(0.015)	(0.018)
$T+4$	-0.035***	-0.051***	-0.071***	-0.089***
	(0.013)	(0.013)	(0.016)	(0.020)
No. of Obs	38,893	30,133	16,447	10,425
C/ Targeted hourly wages (log)				
$T-3$	-0.006**	-0.005*	-0.007*	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)
$T-2$	-0.007**	-0.006**	-0.007**	-0.005
	(0.003)	(0.003)	(0.004)	(0.004)
$T-1$	-0.006**	-0.006**	-0.008**	-0.006
	(0.003)	(0.003)	(0.004)	(0.005)
T	-0.008***	-0.007**	-0.009**	-0.007*
	(0.003)	(0.003)	(0.004)	(0.004)
$T+1$	-0.008***	-0.008**	-0.011***	-0.007
	(0.003)	(0.003)	(0.004)	(0.005)
$T+2$	-0.008**	-0.007**	-0.010***	-0.007
	(0.003)	(0.003)	(0.004)	(0.005)
$T+3$	-0.008**	-0.008**	-0.009**	-0.005
	(0.003)	(0.003)	(0.004)	(0.005)
$T+4$	-0.005	-0.006	-0.008*	-0.008
	(0.003)	(0.004)	(0.004)	(0.005)
No. of Obs	38,893	30,133	16,447	10,425

Notes: The table documents the evolution of search behavior in the quarters around benefits exhaustion for job seekers with different intensity of platform use, measured by the total number of applications during their spell. We include spell time and spell fe and restrict our sample to workers unemployed during the time window of analysis. In panel A/, we estimate variation in search intensity in a Poisson count model and coefficients displayed are IRR−1. In panels B/ and C/, we estimate variation in target wages in a log-linear model. Robust SE are clustered at the spell level.

Table A.9: Robustness: The effect on elapsed unemployment spell on target job quality estimated on the subsample of long spells

	Hourly Wage (log)	Monthly Wage (log)	Weekly Hours (proportion)	Open-ended contract (log)	Experience Required (log)	High educ Required (proportion)	Wage within Occupation (log)	Mean Wage in Occupation (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Spell time	-0.002***	-0.001	0.001	-0.003***	-0.001***	-0.003***	-0.001***	-0.001***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Time to exhaustion FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spell FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table presents the impact of the elapsed unemployment spell on targeted job quality, estimated in panel models including spell and time-to-benefits-exhaustion fixed effects. We define long spells as spells lasting more than one year after the end of UI benefits for UI recipients and more than 3 years for non UI recipients. We use this spells subsample in our main analysis in order to estimate the dynamic effect of benefits exhaustion in the two years around benefits exhaustion on a balanced sample, as explained in section 4.1. SE are clustered at the spell level.

Table A.10: Robustness: Evolution of targeted wage, using different measures of targeted wage

Outcome	**Targeted monthly wage**				**Targeted hourly wage**			
	Average Predicted	Average Posted	Minimum Predicted	Minimum Posted	Average Predicted	Average Posted	Minimum Predicted	Minimum Posted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T-3$	-0.021*	-0.016	-0.025*	-0.012	-0.006**	0.009	-0.007**	0.007
	(0.012)	(0.016)	(0.013)	(0.017)	(0.003)	(0.007)	(0.003)	(0.007)
$T-2$	-0.022*	-0.013	-0.023*	-0.007	-0.007**	0.000	-0.007**	-0.000
	(0.011)	(0.016)	(0.013)	(0.017)	(0.003)	(0.007)	(0.003)	(0.007)
$T-1$	-0.036***	-0.038**	-0.047***	-0.024	-0.006**	0.003	-0.007**	0.005
	(0.012)	(0.017)	(0.013)	(0.018)	(0.003)	(0.008)	(0.003)	(0.008)
T	-0.035***	-0.034**	-0.046***	-0.029	-0.008***	-0.002	-0.010***	-0.000
	(0.011)	(0.017)	(0.013)	(0.018)	(0.003)	(0.007)	(0.003)	(0.008)
$T+1$	-0.037***	-0.023	-0.053***	-0.019	-0.008***	-0.003	-0.010***	-0.003
	(0.012)	(0.017)	(0.014)	(0.019)	(0.003)	(0.008)	(0.003)	(0.008)
$T+2$	-0.048***	-0.041**	-0.055***	-0.042**	-0.008**	-0.003	-0.010***	-0.005
	(0.012)	(0.019)	(0.014)	(0.020)	(0.003)	(0.009)	(0.003)	(0.009)
$T+3$	-0.047***	-0.045**	-0.061***	-0.043*	-0.008**	0.001	-0.011***	-0.001
	(0.013)	(0.021)	(0.015)	(0.022)	(0.003)	(0.009)	(0.003)	(0.009)
$T+4$	-0.044***	-0.036	-0.071***	-0.040*	-0.005	-0.004	-0.008**	-0.005
	(0.014)	(0.022)	(0.016)	(0.023)	(0.003)	(0.010)	(0.003)	(0.010)
Time of spell fixed effects	Yes	Yes	Yes	Yes				
Spell fixed effects	Yes	Yes	Yes	Yes				
No. of Obs	38,893	18,089	38,893	18,089	38,893	18,089	38,893	18,089
Spell time	-0.003***	-0.007***	-0.001**	-0.005***	-0.002***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Time to UI exhaustion FE	Yes	Yes	Yes	Yes				
Spell FE	Yes	Yes	Yes	Yes				
No. of Obs	375,210	171,243	375,210	171,243	375,210	171,243	375,210	171,243

Notes: The upper part of the table documents the evolution of target wages in the quarters around benefits exhaustion. We include spell time and spell fixed effects and restrict our sample to workers unemployed during the time window of analysis. The lower part of the table estimates the effect of time spent unemployed, controlling for time to benefits exhaustion and spell fixed effects. SE are clustered at the spell level.

Table A.11: Robustness: Evolution of search behavior estimated on the subsample of job seekers with very short UI interruptions

Outcome	**Targeted monthly wage**		**Targeted monthly wage**		**Targeted hourly wage**	
Subsample: Total days of UI interruptions	< 30 days	< 15 days	< 30 days	< 15 days	< 30 days	< 15 days
	(1)	(2)	(3)	(4)	(5)	(6)
$T-3$	0.001	-0.012	-0.006**	-0.009***	-0.023**	-0.028**
	(0.039)	(0.042)	(0.003)	(0.003)	(0.012)	(0.013)
$T-2$	0.049	0.034	-0.006**	-0.006**	-0.024**	-0.037***
	(0.046)	(0.049)	(0.003)	(0.003)	(0.012)	(0.013)
$T-1$	0.225***	0.219***	-0.005*	-0.008**	-0.040***	-0.044***
	(0.053)	(0.058)	(0.003)	(0.003)	(0.012)	(0.013)
T	0.546***	0.540***	-0.007***	-0.009***	-0.037***	-0.043***
	(0.068)	(0.074)	(0.003)	(0.003)	(0.011)	(0.013)
$T+1$	0.414***	0.403***	-0.008***	-0.010***	-0.040***	-0.045***
	(0.068)	(0.073)	(0.003)	(0.003)	(0.012)	(0.013)
$T+2$	0.381***	0.394***	-0.007**	-0.010***	-0.050***	-0.057***
	(0.071)	(0.078)	(0.003)	(0.003)	(0.012)	(0.013)
$T+3$	0.464***	0.447***	-0.008**	-0.010***	-0.048***	-0.052***
	(0.076)	(0.081)	(0.003)	(0.003)	(0.013)	(0.014)
$T+4$	0.520***	0.481***	-0.005	-0.007*	-0.044***	-0.052***
	(0.082)	(0.087)	(0.003)	(0.004)	(0.014)	(0.015)
No. of Obs	265,041	240,939	37,725	34,462	37,725	34,462

Notes: The table presents the evolution of search intensity and target wages in the quarters around benefits exhaustion. We include spell time and spell fixed effects and restrict our sample to workers unemployed during the time window of analysis. SE are clustered at the spell level.

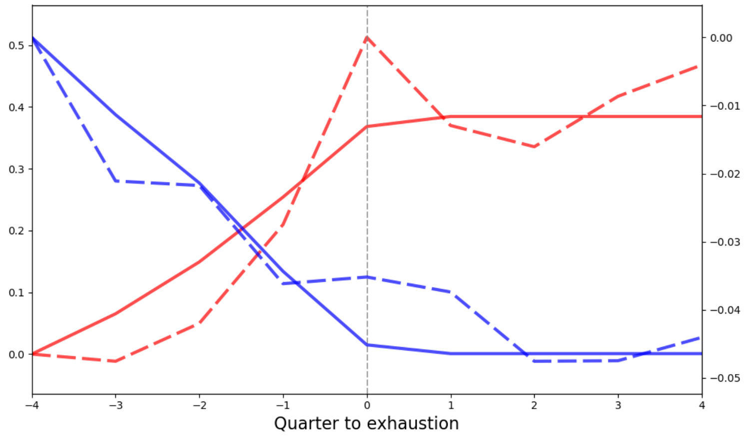
Table A.12: Heterogeneity of shift in search behavior at benefits exhaustion

	Search intensity (count)			Target wage (log)		
	(1)	(2)	(3)	(4)	(5)	(6)
UI level (log) $*T$	0.345***	0.482***	0.511***	-0.027	-0.026	-0.035
	(0.053)	(0.061)	(0.077)	(0.019)	(0.023)	(0.033)
Man, no kid $*T$		-0.157**	-0.134*		0.014	0.009
		(0.068)	(0.069)		(0.023)	(0.024)
Woman, no kid $*T$		0.041	0.055		0.019	0.013
		(0.063)	(0.063)		(0.023)	(0.024)
Man, kid $*T$		0.053	0.080		0.025	0.023
		(0.078)	(0.079)		(0.027)	(0.028)
Age: 25-35 $*T$		-0.109	-0.068		-0.036	-0.046
		(0.095)	(0.099)		(0.039)	(0.046)
Age: 35-45 $*T$		-0.130	-0.085		-0.030	-0.036
		(0.097)	(0.101)		(0.040)	(0.046)
Age: 45-55 $*T$		-0.342***	-0.302***		-0.012	-0.015
		(0.101)	(0.104)		(0.040)	(0.047)
Age: $> 55 * T$		-0.610***	-0.562***		-0.018	-0.031
		(0.112)	(0.116)		(0.044)	(0.050)
Education level: intermediate $*T$		-0.021	-0.020		-0.024	-0.031
		(0.055)	(0.056)		(0.019)	(0.020)
Education level: high $*T$		-0.066	-0.054		-0.058***	-0.065***
		(0.058)	(0.059)		(0.020)	(0.021)
Qualification level: intermediate $*T$		-0.040	-0.035		-0.022	-0.013
		(0.056)	(0.056)		(0.022)	(0.023)
Qualification level: high $*T$		-0.205**	-0.186**		0.026	0.041
		(0.085)	(0.087)		(0.033)	(0.036)
Full time $*T$		-0.282***	-0.302***		-0.007	-0.008
		(0.065)	(0.067)		(0.025)	(0.026)
Experience: 1 year $*T$		0.008	0.003		0.017	0.021
		(0.106)	(0.110)		(0.047)	(0.050)
Experience: 2 year $*T$		0.037	0.026		-0.009	-0.011
		(0.100)	(0.105)		(0.044)	(0.047)
Experience: 3-5 year $*T$		0.058	0.044		-0.032	-0.031
		(0.097)	(0.097)		(0.044)	(0.046)
Experience: $>$ 5 year $*T$		0.014	0.020		-0.022	-0.025
		(0.089)	(0.091)		(0.043)	(0.044)
Past U: 1 year $*T$		-0.084	-0.052		0.039	0.035
		(0.073)	(0.073)		(0.026)	(0.030)
Past U: 2 year $*T$		0.005	0.012		-0.008	-0.016
		(0.072)	(0.073)		(0.025)	(0.028)
Past U: $>$ 2 year $*T$		-0.066	-0.063		-0.003	-0.010
		(0.061)	(0.063)		(0.021)	(0.023)
Previous wage $*T$			-0.090			-0.017
			(0.117)			(0.054)
X_i*Time of spell FE	Yes	Yes	Yes	Yes	Yes	Yes
Spell FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	978,466	978,466	977,142	164,700	164,700	164,554

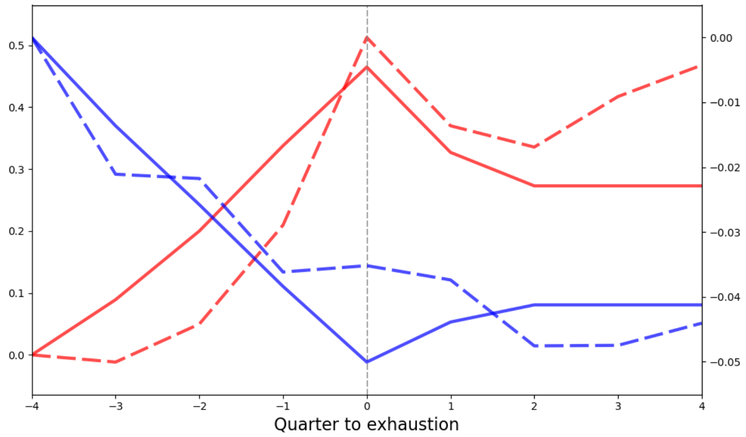
Notes: The table documents the evolution of search behavior between $T-4$ and T. We include spell fixed effects and time of the spell fixed effects interacted with individual covariates (corresponding to heterogeneity dimensions presented in the table). We restrict our sample to spells that terminate after T. In columns (1)-(3), we estimate the evolution of search intensity in a Poisson count model. Coefficients displayed are IRR-1 and represent relative variations in the hazard of sending an application. In columns (4)-(6), we estimate a log-linear model and coefficients represent variations in target wages. Robust SE are clustered at the spell level.

Figure A.5: Empirical moments and predictions from different models without negative duration dependence

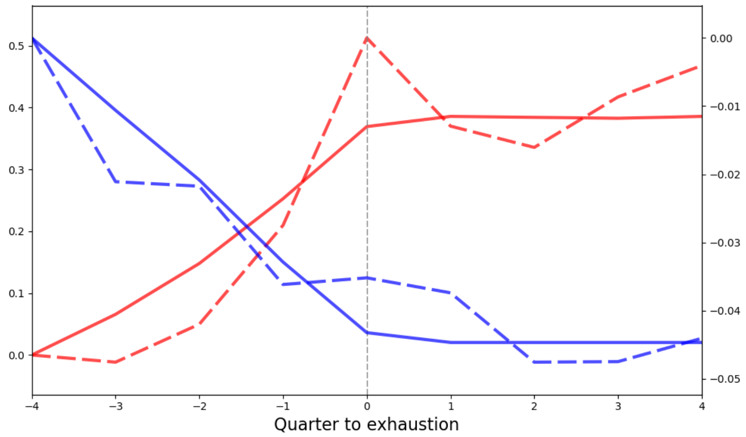
(1) Standard model



(2) Reference-dependence model, η, and N calibrated after DellaVigna et al. (2017)



(3) Reference-dependence, η, and N calibrated with our estimates



Notes: These figures compare the empirical moments that we are targeting in the structural estimation and the model predictions. The empirical moments are presented in dashed lines: the evolution of search intensity (in red) and target wages (in blue) in the quarters around benefits exhaustion when we control for spell and time of the spell fixed. The corresponding predictions from different models are presented in continuous lines in panels (1) to (3): the standard model (1), the reference-dependent model where the reference-dependence parameters η, and N are calibrated after DellaVigna et al. (2017) (2), and the reference-dependent model with our estimates (3). The models are calibrated using estimates obtained using minimum-distance and presented in 2.

A.2 Search activity on the public platform

A.2.1 Descriptive statistics on online applications

Where do job seekers apply? Job seekers tend to apply to jobs with a predicted wage very slightly inferior to the wage at their prior job. This is consistent with previous evidence that reservation wages are slightly below past wages (Barbanchon et al., 2017).

Table A.13: Characteristics of online applications

Sample:	**All**			**UI recipients**			**Not UI recipients**		
	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Monthly count:									
All applications	0.55	0.27	0.89	0.54	0.25	0.84	0.58	0.29	0.98
App to long-term contract	0.34	0.14	0.62	0.33	0.14	0.59	0.35	0.15	0.67
App to open-ended contract	0.23	0.07	0.49	0.24	0.08	0.48	0.23	0.06	0.52
App to higher education job	0.11	0.00	0.34	0.12	0.00	0.34	0.10	0.00	0.32
App to management job	0.06	0.00	0.23	0.06	0.00	0.23	0.06	0.00	0.22
App to job in same skill level	0.25	0.07	0.54	0.25	0.07	0.52	0.25	0.06	0.56
App to job in same occupation	0.17	0.00	0.44	0.17	0.00	0.43	0.17	0.00	0.45
Characteristics:									
Posted hourly wage (€)	10.85	10.07	1.94	10.89	10.12	1.96	10.76	10.00	1.88
Posted monthly wage (€)	1528.71	1501.00	412.06	1537.26	1513.00	416.76	1512.32	1500.00	402.40
Posted weekly hours	31.78	35.00	6.18	31.78	35.00	6.19	31.78	35.00	6.14
Posted wage/previous wage	0.98	0.96	0.26	0.98	0.96	0.26	.	.	.
Posted wage/reservation wage	1.01	1.01	0.19	1.00	1.00	0.19	1.02	1.01	0.19
Predicted hourly wage (€)	10.69	10.32	1.30	10.71	10.35	1.30	10.65	10.27	1.30
Predicted monthly wage (€)	1363.62	1405.37	332.45	1367.02	1409.61	335.80	1356.76	1397.26	325.48
Ad with posted wage	0.55	0.60	0.42	0.56	0.60	0.42	0.54	0.50	0.42
Time ad was posted (days)	14.69	7.00	22.49	14.33	7.00	22.35	15.40	7.83	22.77
Number of obs.		643,102			429,897			213,205	

Notes: This table presents the characteristics of online applications sent during their unemployment spell for individuals with an unemployment episode starting between 2013 and 2017 and with at least one application during their unemployment spell. We only observe previous wages for UI recipients.

A.2.2 Online applications and job finding

Are online applications data offering a valid measure of job search activity? We conduct a series of sanity checks to make sure that activities on the online search platform provide a good proxy for search intensity overall. We cannot estimate the causal impact of online applications on job finding due to selection, but we estimate the relation between online application and re-employment in a Cox proportional hazard model when we control for a large range of individual characteristics in Table Table A.14. Note that the outcome is the exit to any job in the same month, not necessarily the job that corresponds to the application. We estimate that one online application is associated with a 3% increase in the probability to start a job in the same month. Additionally we study the timing of online applications around the start of a new job in Figure A.6. For this exercise, in contrast with the rest of the article, we keep tracking online applications after we observe a new contract. Note that individuals can keep on applying anytime, even if they are not registered as unemployed. Hence this analysis offers a meaningful test of the ability to measure job search with online applications. We observe a large spike in job applications in the month preceding the start of a new job, and a clear drop afterwards. This is consistent with what the timing of job search overall should be and therefore provides an additional validation of the quality of our measure of search effort.

Table A.14: Online applications and hazard of starting of job

Outcome	Duration to the next job			
	(1)	(2)	(3)	(4)
Online applications	1.031***	1.031***	1.032***	1.031***
	(0.003)	(0.003)	(0.003)	(0.003)
Individual covariates	No	Yes	Yes	Yes
PBD group fixed effects	No	No	Yes	Yes
UI benefits levels, conditional on UI	No	Yes	Yes	Yes
No. of Obs.	1,1034,794	1,1034,794	1,1034,794	1,1034,794

Notes: This table presents the relationship between online applications and the hazard of starting a job the same month, estimated in a Cox proportional hazard model. Robust SE are clustered at the PBD group level.

A.2.3 Characteristics of platform users

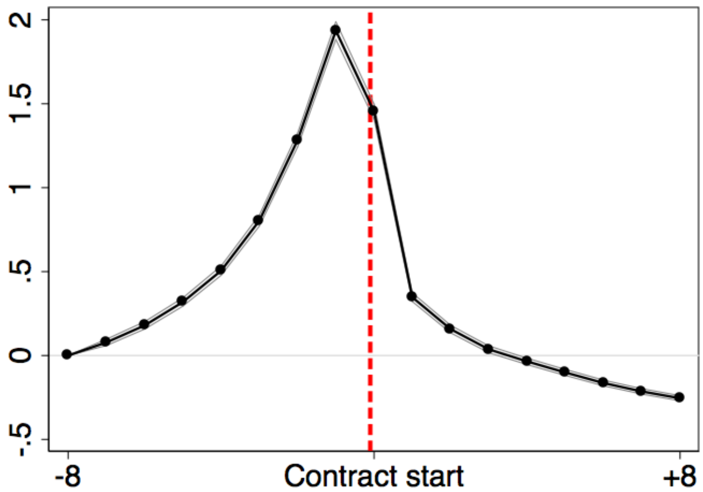
Although a relatively large share of registered unemployed have sent at least one application on the search platform, the platform users are not perefectly representative of the population. In Table A.15, we document the selection of unemployed workers who are using the online search platform, using data on all unemployment spells starting in 2014 (including both insured and uninsured unemployment spells). We can detect an online application for about one fifth of these spells, which suggests that this tool is widely used. Unemployment spells with an online application differ from all spells in the following ways: they correspond to job seekers who are more likely to be women (55% versus 49% in total), tend to be younger (on average 31 years old versus 34), more educated (27 % of them have a higher education degree versus 25%), tend to be white collars (72% versus 66%), tend to stay unemployed longer and have unemployment spells more frequently. Overall, the unemployed who use the site are comparable to the overall population of the unemployed.

Table A.15: Selection of the unemployed workers applying on the online search platform

	Mean All population	Mean > 0 online application	Difference (2)-(1)	T stat (1)=(2)
	(1)	(2)	(3)	(4)
Female	0.49	0.55	0.07	123.82
Age	34.12	31.23	-3.63	-295.29
Single	0.62	0.65	0.04	76.32
Look for full time job	0.90	0.92	0.03	97.26
Education				
No diploma	0.04	0.02	-0.03	-143.65
Middle school	0.13	0.10	-0.04	-116.47
Vocational high school	0.34	0.34	0.01	17.80
General high school	0.24	0.27	0.04	96.78
Higher education	0.25	0.27	0.02	45.94
Qualification				
Blue collar, low skill	0.09	0.07	-0.03	-87.18
Blue collar, high skill	0.12	0.10	-0.02	-67.82
White collar, low skill	0.22	0.22	-0.00	-1.28
White collar, high skill	0.44	0.50	0.07	136.86
Intermediary	0.07	0.08	0.01	28.92
Management	0.06	0.04	-0.03	-112.84
Duration of unemployment spell	389.58	486.91	122.06	300.66
Number of previous registrations	0.49	2.05	1.96	1909.08
Number of spells	5,392,835	1,092,584		

Notes: Among all unemployment spells started in 2014, we compare those for which we observe at least one application on the online search platform with the population.

Figure A.6: Applications sent around a contract start



Notes: The figure documents the evolution of search behavior in the months around the start of a contract estimated in a Poisson count model. Coefficients displayed are IRR−1 and represent relative variations in the hazard of sending an application. Robust SE are clustered at the spell level and the corresponding CI are presented in grey.

A.3 Structural estimation of search models with negative duration dependence

In order to account for our finding of a negative trend in targeted job quality over the unemployment spell, we incorporate a form of negative duration dependence in our generalized search model.

Set-up: We modify the job finding function to allow for a decrease in job opportunities over time (as assumed by Nekoei and Weber (2017)):

$$\lambda(s,w) = (\alpha_1 \cdot (1-\gamma))s^{\alpha_2} \cdot (1 - F(\phi^{-1}(w))$$

with γ representing the negative effect of time on job finding. We calibrate the job opportunities depreciation parameter $\gamma = 0.01$ in order to generate a decrease in target wage during the first year of the unemployment spell by 0.3% each quarter, corresponding to our reduced form estimate (Table A.6, column (10)).

Consequently, we need to change how we compute the predicted moments corresponding to our targeted empirical moments. We target the estimates for the evolution of search behavior around benefits exhaustion obtained when *controlling for the effect of time of unemployment*. We cannot directly derive the predicted moments from the optimal search intensity and target wage at each period of the unemployment spell of workers eligible to 24 months UI, as we did before. Indeed, the evolution of the optimal search behavior is both determined by unemployment insurance and past unemployment duration. In order to isolate the evolution of the optimal search behavior associated with unemployment insurance, we solve the model both for individuals eligible to 24 months of UI and for individuals ineligible to UI. We then compute the evolution in *the difference between the behavior of these two types* around benefits exhaustion (relative to the level of search behavior 4 quarters before benefits exhaustion for UI recipients). As in our empirical strategy, the comparison with non UI recipient hence allow us isolate the evolution of search behavior determined by UI.

Results: In Table A.16 we present estimates obtained in models with duration dependence (i.e. $\gamma = 0.01$) while we presented estimates obtained in the model without duration dependence (i.e. $\gamma = 0$) in Table 2. In column (1), we estimate the two search cost parameters β_1 and β_2 in a standard search model with negative duration dependence. In comparison with Table 2, we see that the estimates of the search cost parameters take different values but the model fit does not significantly change. If anything, adding negative duration dependence appears to improve the fit even if we did not take into account the targeted moments when choosing the value of γ, only the trend in target wages. Graphically, we see that the standard model with or without duration dependence generates

Table A.16: Estimates of the Standard and Reference-Dependent Model

Model:	**Standard**	**Reference-dependence**	
Parameters η, N:	Calibrated	Calibrated	Estimated
	(1)	(2)	(3)
Ref.-dependence η	0	4.91	0.02
Time horizon N	-	6.18	3.72
Search cost β_1	4.86	6.10	5.02
Search cost β_2	1.12	0.97	1.10
Goodness of fit	18.25	38.24	18.21
Nb estimated parameters	2	2	4
Nb empirical moments	16	16	16

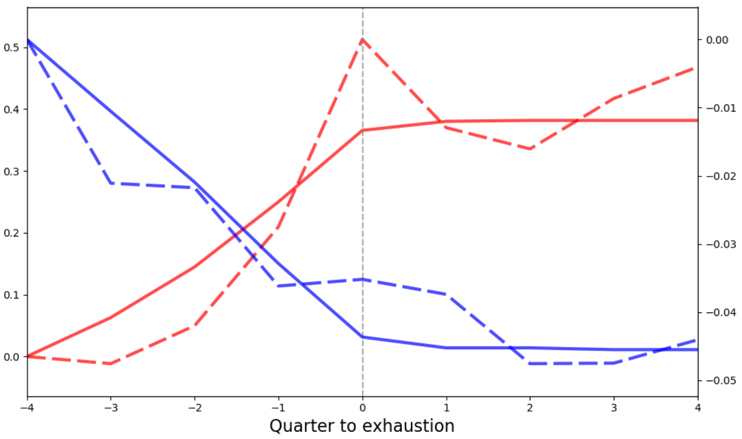
Notes: The table shows parameter estimates for the standard and the reference-dependent search models. Estimation is based on minimum distance estimation, using empirical moments of search behavior around benefits exhaustion. In column (2), the parameters η and N are calibrated after DellaVigna et al. (2017).

almost identical theoretical moments for the dynamics of search behavior around benefits exhaustion *once we control for past unemployment duration* (Panel (1) (Figure A.5) and Panel (4) (Figure A.7)). This suggests that we can study in isolation the impact of unemployment insurance and the impact of the lapsed time of unemployment on job search in this setting. Hence, adding negative duration dependence to the model should not change the comparison between the standard and the reference-dependence model.

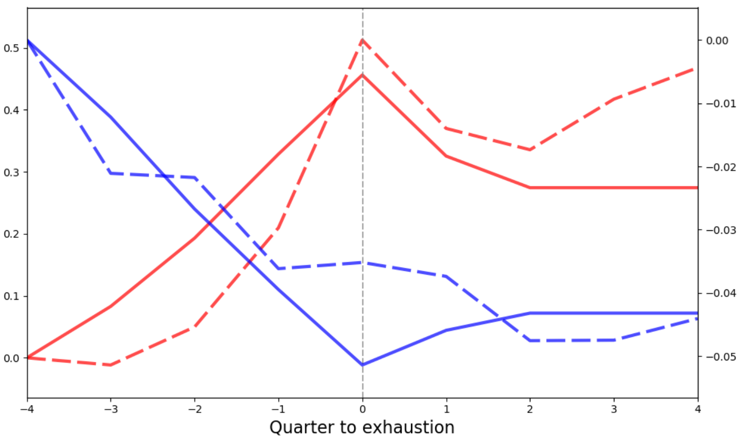
In columns (2) and (3), we add reference-dependence to the negative duration dependence model. As in the case of the model without duration dependence, the comparison between the standard model calibration and the reference-dependence model calibration after DellaVigna et al. (2017) highlights that the standard model fits our data better: the goodness of fit worsens from 18.25 (col. (1)) to 38.24 (col. (2)) when moving from the standard to the reference-dependent model. Moreover, when we directly estimate the two reference-dependence parameters (col. (3)), our estimate for the reference-dependence discount parameter $\hat{\eta}$ is very close to 0, exactly like in the model without duration dependence. The goodness of fit (18.25), and the pattern of the model prediction (Panels (1) and (3) in Figure A.7) are hence virtually unchanged (to the second decimal) when we estimate these two additional parameters. Therefore, we conclude that the standard model offers the best predictions of the dynamic of search behavior around benefits exhaustion.

Figure A.7: Empirical moments and predictions from different models with negative duration dependence

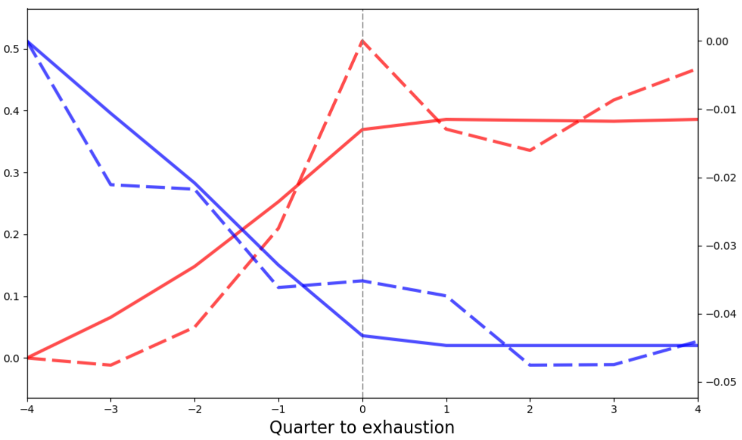
(1) Standard model



(2) Reference-dependence model, η, and N calibrated after DellaVigna et al. (2017)



(3) Reference-dependence, η, and N calibrated with our estimates



Notes: These figures compare the empirical moments that we are targeting in the structural estimation and the model predictions with negative duration dependence. The empirical moments are presented in dashed lines: the evolution of search intensity (in red) and target wages (in blue) in the quarters around benefits exhaustion when we control for spell and time of the spell fixed. The corresponding predictions from different models are presented in continuous lines in panels (1) to (3): the standard model (1), the reference-dependent model where the reference-dependence parameters η, and N are calibrated after DellaVigna et al. (2017) (2), and the reference-dependent model with our estimates (3). The models are calibrated using estimates obtained using minimum-distance and presented in Table A.16.