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The Lock-in Effects of Part-time Unemployment Benefits

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Abstract

We ran a large randomized controlled experiment among about 150,000 recipients of unemployment benefits insurance in France in order to evaluate the impact of part-time unemployment benefits. We took advantage of the lack of knowledge of job seekers regarding this program and sent emails presenting the program. The information provision had a significant positive impact on the propensity to work while on claim, but reduced the unemployment exit rate, showing important lock-in effects into unemployment associated with part-time unemployment benefits. The importance of these lock-in effects implies that increasing the marginal tax rate on earnings from work while on claim in the neighborhood of its current level would not decrease labor supply and would decrease the expenditure net of taxes of the unemployment insurance agency.

Key words: Unemployment insurance; Part-time unemployment benefits; Lock-in effects; Unemployment duration.

JEL classification: H5, J64, J65

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1 Introduction

Part-time unemployment benefits provided to persons working on non-regular jobs who are seeking a regular job play an increasingly important role in unemployment insurance systems.[1] The rise in the incidence of such alternative work arrangements as temporary work, part-time work, self-employment, and the new kinds of work relationship emerging in the "online gig economy" has increased the part-time unemployment take-up in several countries. In France, almost one over two unemployment benefit recipients works while on claim during his unemployment spell. Part-time unemployment benefits are also widespread in Belgium, Finland, Austria and Germany.[2]

In principle, part-time unemployment benefits aim at supplying incentives to job seekers who are looking for regular jobs to accept non-regular jobs in the mean time. This may increase overall employment and shorten unemployment spells if non-regular jobs act as stepping stones towards regular jobs. However, such benefits may also induce lock-in effects by discouraging unemployed workers from searching for regular jobs. Knowing the relative importance of stepping stone and lock-in effects which condition the access to regular employment is essential to evaluate the impact of part-time unemployment benefits on labor supply and on unemployment insurance expenditure. Unfortunately, little is known on these issues because the potential selection into part-time unemployment of individuals with non-observable characteristics correlated with their exit rate from unemployment makes the evaluation of part-time unemployment insurance very difficult.

To evaluate the impact of part-time unemployment insurance, we ran a large randomized controlled experiment among about 150,000 recipients of unemployment insurance benefits in France in which we provide them with information about the existence of part-time unemployment benefits. Then, we deduce the impact of part-time unemployment insurance on the behavior of unemployed workers from the change in their behavior induced by the provision of information. The choice of this strategy is justified by the lack of knowledge about part-time unemployment insurance among job seekers. A survey conducted by the employment agency (Unédic (2012)) has shown that 41,2% of job seekers do not know of the existence of the program and that 33,6% are aware of its existence, but do not know the rules. In our experiment, individuals who had recently entered unemployment were randomly allocated either to a treated group or to a control group. Individuals assigned to the treated

[1] Regular jobs usually include permanent full-time jobs or full-time temporary jobs of long duration.
[2] See Ek Spector (2015) and Cahuc (2018).

group were sent emails that contained a description of the part-time unemployment insurance scheme. Individuals in the control group did not receive any message, while otherwise facing identical conditions in terms of employment services. To investigate how the treatment affects the behavior of unemployed workers, we combine administrative data from public employment services and from hiring intentions registers, which allow us to know whether individuals who exit unemployment do find jobs. Comparing the outcomes between treated and untreated individuals provides a clean identification of the average causal effects of providing information about part-time unemployment benefits.

To interpret the consequences of information provision, we provide a simple job search model which shows that the propensity to work while on claim decreases with the marginal tax rate on earnings from work while on claim. We show that an information provision which raises the propensity to work while on claim is equivalent to a revision of beliefs according to which the marginal tax rate drops. Moreover, we are able to show that apart from providing incentives to work on non-regular jobs while on claim, a drop in the marginal tax rate exerts effects on the search for regular jobs through two channels. The first is an *anticipation* channel reflecting the impact of part-time unemployment insurance schemes on the expected gains of unemployed workers. This channel necessarily reduces the exit rate from unemployment towards regular jobs when the marginal tax drops because improving the expected gains from work while on claim raises the expected gains of unemployed workers, which increases their reservation wage and reduces their job search effort. The other channel arises from the *direct effect of work while on claim* on the exit rate from unemployment toward regular jobs. Working while on claim may generate more job opportunities than remaining on the dole. But working while on claim may also leave less time to look for regular jobs. Therefore, this second channel can either increase or decrease the exit rate from unemployment towards regular jobs.

We find that the information provision has a significant positive impact on the propensity to work on while on claim: The probability that treated individuals will take work while on claim increases by about 6% three months after receiving the information compared with non treated individuals. The positive effect of the information provision on part-time unemployment benefits take-up means that the treatment has improved the gains expected from work while on claim for the treated group taken as a whole. We explore the potential heterogeneity of the effects of the treatment to see whether the information provision has effects of different signs on the propensity to take work on non-regular jobs for different groups generated with the machine learning approach developed by Chernozhukov et al.

(2018). We find no evidence that the information provision has negative effects on the propensity to work while on claim. For all groups, the effects are either non-significant or positive, suggesting that individuals usually underestimate the gains associated with working while on claim. Moreover, the observable characteristics of individuals of the treated group working while on claim are not statistically different from those of the control group working while on claim, suggesting that our field experiment can be relevant for analyzing the impact of a drop of the marginal tax rate to its actual level on the behavior of the whole population of newly registered unemployed persons.

The hike in the propensity to work while on claim is associated with a drop in the exit rate from unemployment. The information provision raises the probability that individuals remain unemployed until the initial exhaustion date of their unemployment benefits.[3] The effect is significant: a 6% increase in the probability that job seekers will take work while on claim 3 months after the start of the treatment is associated with 1.5% hike in the probability that they will remain unemployed the last month before the initial benefits exhaustion date. Therefore, it is clear that increasing part-time unemployment benefits exerts lock-in effects. We find that these lock-in effects raise the unemployment insurance expenditure net of taxes.

Our paper makes contributions to two strands of the literature.

The first is the empirical literature on part-time unemployment insurance, which has used different approaches to identify the effects of part-time unemployment benefits. The seminal contribution of McCall (1996) exploits variations in the design of part-time unemployment benefits across U.S. states from 1986 to 1992. An increase in the disregard is estimated to raise the probability of part-time re-employment and to reduce expected joblessness.[4] Using kinks in the U.S. benefit-withdrawal schedule, Le Barbanchon (2020) provides evidence that workers take into account the value of future benefit entitlement when they make their labor supply decision. Ait Bihi Ouali et al. (2020) rely on a regression discontinuity design to show that an increase in the tax on earnings from work while on claim which occurred in France in 2006 reduced the propensity to work while on claim. Several studies, focused on European countries, rely on the timing-of-events approach (Abbring and Van Den Berg (2003)) or matching methods. They look at the effects of working on non-regular

[3]As explained below, working while on claim moves the exhaustion date of the unemployment benefits scheduled at the date of entry into unemployment. Throughout this paper, by initial exhaustion date we mean the exhaustion date which is scheduled at the start of the unemployment spell.

[4]Recipients accepting part-time jobs can earn up to a specific amount, called the "disregard", with no reduction in benefits during the reference period, which can be the week or the month. Above the disregard, the current benefits are reduced in proportion to the labor earnings. There is a disregard in several U.S. states, in Australia, Austria, Belgium, Canada, Czech Republic, Germany, Luxembourg, Poland.

jobs on the access to regular employment in Austria (Böheim and Weber (2011), Eppel and Mahringer (2019), Belgium (Cockx et al. (2013)), Denmark (Kyyrä et al. (2013)), Finland (Kyyrä (2010)), France (Fremigacci and Terracol (2013), Auray and Lepage-Saucier (2021)), Germany (Caliendo et al. (2012)), Norway (Godøy and Røed (2016)), Slovakia (Van Ours (2004)), Switzerland (Gerfin et al. (2005)). They find mixed results, showing generally significant lock-in effects while individuals work on non-regular jobs and more positive effects on the access to regular jobs after non-regular jobs end. It is clear that these approaches can potentially identify the effects of working non-regular jobs on the exit rate from unemployment, but cannot identify the effects of any part-time unemployment benefits scheme per se, insofar as they do not account for the *anticipation* channel described above. The papers of O'Leary (1997) and Lee et al. (2019) are the most closely related to ours. They analyze the consequences of the Washington State Unemployment Insurance Earnings Deduction Experiment in which for one year, starting in October 1994, Washington conducted a large randomized experiment to investigate the effects of reducing the amount of benefits deducted from claimants who worked while on claim. They find that the tax reduction had no positive effects on labor supply and increased the unemployment insurance expenditure because it raised the propensity to claim benefits. We complement their contribution in several respects. First, our study covers a more recent period than theirs, which dates from the mid-1990s; this is important since the internet has changed the way the labor market works (Bhuller et al. (2019), Martellini and Menzio (2020). Second, like Lee et al. (2019), we find that the tax drop has no impact on overall labor supply and increases unemployment insurance expenditure. But by relying on rich administrative data and following individuals for 3 years after the treatment, we can analyze the dynamic impact of part-time unemployment benefits and show that the tax drop has two countervailing effects on labor supply: an increase in the propensity to work while on claim and a drop in the rate of exit from unemployment toward stable jobs. Moreover, in our context, the unemployment insurance expenditure increase arises from mechanical effects –i.e. effects of tax change when behaviors remain unchanged – and is not amplified by behavioral effects.

Our contribution also adds to the literature devoted to the analysis of the consequences of information provision in a variety of economic applications, including job search (Altmann et al. (2018), Belot et al. (2018), Crépon et al. (2018), Darling et al. (2016)), labor supply (Chetty and Saez (2013)), the take-up of social benefits (Currie (2006)), unemployment benefits (Blank and Card (1991), Fontaine and Ketteman (2019)) and training programs (Crépon et al. (2018). From this perspective, our paper is the first to provide information about part-time unemployment benefits. This allows us to show how information provision can influence the beliefs held by individuals about part-time unemployment insurance rules from its impact on the behavior of unemployed workers. We find that the take-up of individuals who benefited from the information increased. This confirms the results of the literature which finds that the take-up of most social benefits programs is reduced by the lack of information. We find that the lack of information persists over a long horizon (at least 36 months) after the start of our experiment, suggesting that the spread of information about the program among uninformed unemployed workers is very slow. To analyze potential spillover effects, we compare the behavior of non-treated individuals registered with employment agencies where half of individuals have been treated with the behavior of individuals registered with employment agencies where nobody has been treated. These two types of non-treated individuals behave similarly, meaning that information provision had no spillover effects among unemployed workers. This suggests that the information about part-time unemployment benefits did not spread from treated to non-treated individuals registered with the same unemployment agency and that the hike in non-regular employment of treated individuals did not crowd out that of individuals of the control group. This result can be compared to that of Crépon et al. (2013) and Gautier et al. (2018) who do find important spillover effects from job placement assistance programs.

The paper is organized as follows. Section 2 presents the part-time unemployment benefits program and the knowledge of unemployment workers about the program. Section 3 presents the theoretical framework which allows us to interpret the potential consequences of providing information about the program. The experimental design and the data are presented in Section 4. The impact of the informational treatment on part-time unemployment, on the unemployment exit rate and on the unemployment insurance payout are discussed in Section 5. Section 6 provides concluding comments.

2 Institutional Background

2.1 Program structure

At the start of their unemployment spell, eligible unemployed workers get an initial unemployment insurance capital B_0 which allows them to get unemployment benefits, denoted by b. Both the initial capital and the unemployment benefits depend on the individual's past employment history.[5] The benefits paid each month are deducted from the capital B_t. This capital yields, in each month of unemployment t, unemployment benefits equal to

$$b(B_t) = \begin{cases} b > 0 & \text{if } B_t \geq b \\ \max(B_t, 0) & \text{otherwise} \end{cases} \tag{1}$$

The part-time unemployment insurance scheme allows unemployed workers to take work while on claim. There is no specific eligibility condition for part-time unemployment insurance. Claimants must only meet the usual eligibility requirements for unemployment insurance. They are allowed to work for any employer, including their past employers. For each euro earned from work, current benefits are reduced by the marginal benefit reduction rate τ=87%.[6] To put it differently, the part-time unemployment scheme allows individuals to combine their unemployment benefits and the share $1-\tau$ of their labor earnings z_t in the periods where they work while on claim. More precisely, the monthly income of a worker whose labor earnings amount to z_t in month t is equal to

$$\max[b(B_t) + (1-\tau)z_t, z_t] \tag{2}$$

τ and b are set to ensure that by working while on claim job seekers cannot get a monthly income higher than the past monthly income used to compute their unemployment benefits. Hence, individuals whose labor earnings in the current month are larger than the monthly income used to compute their unemployment benefits, do not get unemployment benefits at the end of the month.

Figure 1 illustrates the part-time unemployment insurance schedule. From a static point of view, there are low incentives to work while on claim: the blue line, which displays the relation between the monthly labor earnings of people working while on claim and their income, is almost flat. Yet the reduction in benefits is not lost, it can be paid in a later month. The corresponding benefit reduction delays the exhaustion date. Figure 2 illustrates the dynamic aspects of the part-time unemployment insurance schedule which are critical for understanding its incentivation effects. If job seekers are totally unemployed throughout their claim and receive their benefits each month, their benefits will lapse after their exhaustion date. When job seekers are only paid part of their benefits in a given month $b(B_t) - \tau z_t \geq 0$,

[5] See Appendix A.1 for more details

[6] For the sake of simplicity, we describe the rules in *net* terms for a job seeker who earned the minimum wage before unemployment. Appendix A.1 provides details on this point.

the unpaid amount $\min[\tau z_t, b(B_t)]$ is not deducted from their insurance capital B_t. This implies that the earnings from the days worked while on claim make it possible to extend the duration of the claim. The exhaustion date can be delayed without any limitation. Hence, the unemployment insurance capital evolves according to the law of motion[7]

$$B_{t+1} = \max\left(B_t - b(B_t) + \min[\tau z_t, b(B_t)], 0\right) \tag{3}$$

2.2 Knowledge of unemployed workers about the program

A survey conducted by the employment agency (Unédic (2012)) as well as interviews from the field (Issehnane et al. (2016)) show that the knowledge of unemployed workers about part-time unemployment benefits is very limited. The survey conducted in 2012 shows that 41,2% of job seekers do not know of the existence of the program and 33,6% know of its existence without being able to explain the rules framing the part-time unemployment benefits program. This lack of knowledge about the program is striking.

Le Barbanchon and Gonthier (2016) also conclude that a large proportion of job seekers do not know the rules. The authors study the rules prevailing before 2006. At this time, specific criteria had to be met to be eligible for part-time benefits. First, the number of hours worked could not exceed 136 hours per month, which amounts to 86% of a full-time job. Second, the corresponding gross wage could not go beyond 70% of the wage earned before the unemployment spell. This implies that earnings drop at those thresholds (136 hours per month or 70% of the last wage). These notches should create incentives to move from a point just above the notch, in particular in the dominated area, to a point just below the notch. However, the authors do not observe bunching at those cutoffs. The lack of knowledge regarding the rules may explain why a large proportion of job seekers do not bunch at cutoffs.

[7] When the insurance capital is exhausted, individuals can be eligible for a new entitlement period. To do so, they must have worked at least 150 hours while on claim over the last 28 months. The new initial capital is computed on the basis of the daily wage of periods of work while on claim and according to the rule "one day of work yields one day of compensation". We neglect the opening of a new entitlement period to lighten the presentation, but it is taken into account when we come to compute the dynamic marginal tax rate in Section 5.4.

3 Theoretical framework

This section starts by presenting a simple job search model which explains the consequences of part-time unemployment benefits on the behavior of unemployed workers before analyzing the impact of the transmission and reception of information about the existence of this scheme.

3.1 The model

We analyze the behavior of unemployed workers who look for regular jobs that yield a present value higher than the present value of unemployment. The value of these jobs is denoted by W and the effort devoted to job search is denoted by e. The per period utility derived from consumption $c \geq 0$ and search effort $e \geq 0$ is equal to

$$v(c) - e$$

where v is an increasing and concave function. Engaging in search effort e yields regular job arrival probability equal to $\lambda(e)$, where $\lambda(e) \in (0, 1)$ is an increasing and concave function of the search effort. Time is discrete and the discount factor is denoted by $\beta \in (0, 1)$.

To account for the possibility of working on non-regular jobs, it is assumed that, in each period, unemployed workers can get an offer to work on a one-period job. In each period t, the earnings z_t associated with these jobs are drawn in a stationary distribution.[8] There is a fixed cost of working denoted by $\kappa > 0$. Moreover, we start by assuming that $\lambda(e)$, the exit rate from unemployment toward regular jobs, does not directly depend on the choice to work on non-regular jobs while on claim. This assumption, which will be modified later on, allows us to clearly exhibit an important source of lock-in effects.

As explained above, the part-time unemployment scheme allows individuals to combine their unemployment benefits and the share $1 - \tau$ of their labor earnings, implying that their monthly income in period t is equal to $\max[b(B_t) + (1 - \tau)z_t, z_t]$ where $b(B_t)$ is defined by equation (1) and B_t by the law of motion (3).

In every period, unemployed workers choose their search effort and whether to take work

[8] Note that this distribution may have a support including zero earnings which could be interpreted as a situation without job offer.

while on claim or not. The value function of unemployed workers is

$$U(B_t) = \mathbb{E}_t \left\{ \max_{(e_t, \Omega_t)} v(c_t) - e_t + \beta \left[\lambda(e_t) W + (1 - \lambda(e_t)) U(B_{t+1}) \right] \right\} \tag{4}$$

where

$$c_t = \Omega_t \left(\max[b(B_t) + (1-\tau) z_t, z_t] - \kappa \right) + (1 - \Omega_t) b(B_t)$$

subject to the law of motion (3). $\mathbb{E}_t$ is the expectation operator conditional on the information available in period t; and $\Omega_t \in \{0, 1\}$ is an indicator variable equal to 1 if the unemployed worker decides to work while on claim and to zero otherwise.

The optimal decision to work while on claim relies on the comparison of the gains, equal to the earnings z_t, with the costs equal to the sum of the taxed earnings and the fixed cost κ. The tax on earnings from work while on claim depends on the instantaneous tax τ and on the probability that the taxed earnings will be retrieved after the benefits exhaustion date. More precisely, the dynamic marginal tax rate is[9]

$$m_t = \tau \left[1 - \beta^{T-t} \mathbb{E}_t \left(\prod_{j=t}^{T-1} [1 - \lambda(e_j)] \right) \right] \tag{5}$$

where $T > t$ denotes the benefits exhaustion date.

The model implies that it is worth working while on claim if the net gains, equal to $(1 - m_t) z_t$, are larger than the costs κ, or

$$(1 - m_t) z_t > \kappa \tag{6}$$

The decision to work while on claim crucially depends on the dynamic marginal tax rate m_t, which has two components: the proportional tax rate τ on current earnings and the expected returns induced by current earnings reported at the end of the entitlement period, that will be obtained only if the person is still unemployed in this period. The dynamic marginal tax rate is higher for people who exit unemployment faster, because the probability that they will reach the exhaustion date while unemployed is smaller. The dynamic marginal tax rate decreases over time because the probability that they will reach the exhaustion date while unemployed increases over time. This means that the incentives to work while on claim increase along the unemployment spell, implying that some individuals may decide to work while on claim only after a certain unemployment spell.

[9] See Appendix A.2 which presents the solution of the model.

The forward-looking nature of the optimization problem of unemployed workers implies that the value function $U(B_t)$ of an individual who does not work while on claim in period t can depend on the future values of the dynamic marginal tax rate, if the individual anticipates that it could be worth working while on claim in the future. This means that part-time unemployment benefits can influence job search effort from the beginning of the unemployment spell, even for individuals who do not work while on claim, because the possibility of working while on claim in the future influences current job search behavior.

The properties of the model are illustrated on Figure 3 which displays the exit rate from unemployment and the dynamic marginal tax rate in two cases: 1/ when the dynamic marginal tax rate m_t is smaller than one ($\tau = 0.9$) meaning that it can be worth working while on claim; 2/ when $m_t \geq 1$, meaning that there are no incentives to work while on claim. In the first case, the dynamic marginal tax rate, displayed in the right panel of Figure 3, decreases during the unemployment spell. The exit rate is lower from the beginning of the unemployment spell when there are incentives to work while on claim, even though working while on claim does not start from the beginning of the unemployment spell. In this example, the unemployed worker starts working while on claim from the sixth month. Thereafter, he continues working while on claim until the benefits exhaustion date, because it is assumed that he gets offers of non-regular jobs (each lasting one period only) with identical earnings z in each period. The exhaustion date of benefits is postponed by one month when the unemployed individual works while on claim, because this slows down the drop in his unemployment insurance capital.

To this point, the model implies that the possibility of working while on claim has lock-in effects which arise only from the increase in the value of unemployment induced by the possibility of working while on claim. The stepping stone effect, which has so far been left out of consideration, can arise from the relation between work on non-regular jobs and the arrival rate of regular job offers. This relation can be incorporated into the model by assuming that the arrival rate of regular job offers λ is a function of the job search effort *and* of the decision to work while on claim: $\lambda(e_t, \Omega_t)$. The stepping stone effect arises if the arrival rate of regular job offers increases when individuals work on non-regular jobs while on claim; this might happen because working on non-regular jobs improves work experience, sends good signals to employers, or facilitates the access to information about regular job offers through networks. The stepping stone effect induces individuals to work while on claim more frequently and sooner in the unemployment spell.[10]

However, the relation between the arrival rate of regular job offers and work on non-regular jobs while on claim can also amplify the lock-in effect if working on non-regular jobs reduces the time available to hunt for regular jobs or sends a negative signal about the quality of workers to employers (Farber et al. (2015)). In this case, individuals have less incentive to work on non-regular jobs while on claim.

All in all, the model shows that there is a monotone mapping between the dynamic marginal tax rate on earnings from work while on claim and the propensity to work while on claim; and that part-time unemployment benefits programs influence the unemployment exit rate through two effects: the *anticipation effect*, which reflects the impact of the possibility of working while on claim on the search effort, and the *direct effect of working while on claim*, $d\lambda(e_t, \Omega_t)/d\Omega_t$.[11]

3.2 The consequences of information provision

The provision of information to the treatment group is justified by the assumption that individuals are not fully informed about the part-time unemployment insurance scheme. The impact of this type of treatment can be interpreted from our theoretical model, which shows that there is a monotone mapping between the dynamic marginal tax rate on earnings from work while on claim (defined equation (5)) and the propensity to work while on claim. From this perspective, the impact of the treatment on the behavior of the treated can be interpreted as the consequence of informing them that the actual dynamic marginal tax rate on earnings from work while on claim is different to what they believed before the treatment.

Individuals can underestimate the gains from working while on claim, for instance because they think that they would lose all their labor earnings or their unemployment benefits if they were working while on claim. For these individuals, our model shows that the provision of information is equivalent to the announcement of a drop in the dynamic marginal tax rate, which should boost part-time unemployment.

[10]The gain from working while on claim, equal to

$$\Delta \simeq [z_t(1-\tau) - \kappa]\, v'(b) + \alpha z U'(B_t) + \beta\, [\lambda(e_t, 1) - \lambda(e_t, 0)]\, [W - U(B_{t+1})]$$

is higher in the presence of stepping stones effects, *i.e.* $\lambda(e_t, 1) - \lambda(e_t, 0) > 0$.

[11]Hence, as stressed by Kyyrä (2010), the timing-of-events approach, which estimates the direct effect of working while on claim can be relevant to an estimate of the effect of working on non-regular jobs under the existing unemployment insurance scheme, but cannot estimate the full impact of part-time unemployment insurance schemes.

For individuals who overestimate the gains, the information provision is equivalent to the announcement of an increase in the dynamic marginal tax rate which should induce less work on non-regular jobs while on claim.

Hence, the fact that we find a positive average impact of our treatment on the part-time unemployment benefits take-up, as will be shown below, means that treated individuals overestimated, on average, the dynamic marginal tax rate on earnings from work while on claim before the treatment.[12] The model shows that this decrease in the dynamic marginal tax rate has an impact of ambiguous sign on labor supply and on unemployment duration. Our empirical analysis aims at exploring this impact.

4 Experimental Design and Data

4.1 Treatment

Our experiment consists in sending information about the part-time unemployment benefits scheme to unemployed workers eligible for unemployment benefits and recently registered at the unemployment agency. Individuals of the treated group received 3 successive emails on 31 January, 28 February, and 31 March 2017. The emails were sent from the employment agency's mailing platform. The main text of the emails is as follows:

We inform you that you can work without losing your unemployment benefits. This opportunity to combine your wage and benefits allows you to:

- *Have earnings higher than your benefits, though without exceeding the amount of your former gross wage. Pôle Emploi only reduces your benefits by 70 cents per gross euro earned.*

- *Be entitled to benefits for a longer period. The number of days of benefits not received due to the accumulation of your earnings while on benefits are credited to your account.*

At the exhaustion of your benefits, you will be able to get new entitlement to unemployment benefits if you have done at least 150 hours of salaried activity.

This main text is accompanied by an example which introduces a hypothetical worker and

[12]It is very unlikely that our information provision could have been interpreted as a threat likely to modify job search behavior in the French context where there is almost no control of job search activity. In line with our interpretation, Crépon et al. (2018) do not find any threat effect of notifications of training proposals in France.

displays what happens to his benefits if he works while on claim. An attached file provides further information about the example. The message also comprises a link to a web page of the public employment agency where it is possible to simulate the disposal income as a function of labor earnings.[13]

4.2 Implementation

The experimental design relies on three experimental groups : treated workers (the "treated group"), untreated workers in treated areas (the "control group"), untreated workers in non-treated areas (the "super control" group).

The steps taken to implement the experiment were very similar to those described in Crépon et al. (2013). Randomization was implemented at both the labor market and individual levels. There are 856 public unemployment agencies, scattered across France. Each agency represents a small labor market, within which we may observe treatment externalities which may arise from information spillovers or displacement effects. On the other hand, the agencies cover areas that are sufficiently large, and workers in France are sufficiently immobile, that we can assume that no spillovers take place across areas covered by different agencies. To identify spillovers, we used a "super control" group as in Crépon et al. (2013). First we stratified our sample at the agency level.[14] Within each stratum we randomly divided the 856 agencies into three groups that covered areas similar in size and with comparable local populations. One of the three groups consists of the non-treated areas, i.e. the "super control" group. The two other groups consist of the treated areas. Half of job seekers in the treated areas have been effectively treated (i.e. received emails). For each treated area, we stratified the job seekers. Within each stratum we randomly assigned treatment with a probability of one-half.

4.3 Data

We use three sources of data. First, an administrative database on job seekers provided by the employment agency (*Fichier National des Allocataires*). These records provide the individual

[13]The exact contents of the emails is presented in appendix A.6. We sent two different types of email. One type presents the gains from labor earnings in net terms (i.e. after payment of the employee's social contributions. Income taxes, which depend on the situation of each person, cannot be computed at this stage) and the other type in gross terms. Insofar as we do not detect any statistically significant difference between the effects induced by these two types of message, we do not consider this heterogeneity of treatment in what follows.

[14]We present summary statistics for the variables that were used for stratification in Table 2.

socio-demographic characteristics (age, gender, education level, family situation,living area) and detailed information about all previous registrations (date of registrations, reason for registration, start and end dates of unemployment spells, the level of unemployment benefits, earnings and hours of work while on claim...).

A second data set comes from the hiring intentions of firms (*Déclarations Préalables A l'Embauche).* Prior to hiring each employee, any employer from the private and semi-private sector has to fill out a form indicating the starting day, the type (permanent contract or fixed-term contract) and the expected duration of the contract. This allows us to acquire information about the employment status of all randomized individuals. As this form only reports the intention to hire, we do not know whether the individual has actually been hired[15] and whether the individual stays in the firm for the entire expected contract duration.

Our third source of data is email tracking statistics. The information treatment was sent by email from the employment agency's mailing tool (*Gestion des Messages Entrants*). For all treated individuals, it lists basic email activity: whether they have opened the email and/or clicked within the email.

4.4 Sample and summary statistics

The randomization was implemented in December 2016. The effects of the experiment critically depend on the knowledge of job seekers about part-time unemployment insurance. Job seekers with multiple spells have a better knowledge of the unemployment system, and are thus less likely to react to our information intervention. We identified job seekers who registered for the very first time for unemployment benefits between 1 July 2016 and 30 November 2016. We excluded job seekers subject to very specific rules, such as recurrent temporary workers (in temp agencies), childminders, entrepreneurs, artists, and technicians working in the culture sector, as well as job seekers who had already worked while on claim between their entry into unemployment and November 2016.

This procedure resulted in an experimental sample of 147,878 job seekers who have been randomized into treated (T), control (C) and super control groups (SC). Table 1 summarizes the experimental lay-out. In the treatment effect analysis, we apply an additional filter to the experimental sample, retaining only individuals who were still on claim and did not experience part-time unemployment between the randomization date and the first sending. Our final sample is then composed of 115,547 individuals.

[15] 90% of hiring intentions do become effective hires.

Table 2 presents summary statistics regarding the final sample for the treated group, the control group and the super control group before program assignment, as well as balancing tests.[16] A large share of individuals (38%) is under 25 years old in our sample while they are 14% in the whole population of job seekers. This is not surprising given that we only select job seekers who have never been eligible for unemployment benefits. Nearly half of job seekers are women and 33% of the sample has a university degree. At the date of the first email (January 31, 2017), individuals have on average been unemployed for 108 days, which is consistent with the selection of job seekers who registered between 1 July 2016 and 30 November 2016. Finally, mean potential benefits duration is equal to 621 days and this potential duration is longer than 2 years (2 years being the maximum benefits duration for individuals under 53) for 56% of job seekers. Figure 4 displays the distribution of potential benefits duration from the date of entry into unemployment and the distribution of the *initial* dates of benefits exhaustion. 43% of individuals are entitled to 730 days of benefits against 30% in the whole population of job seekers. This also reflects the fact that we select individuals who have never been unemployed. In this case, they are more likely to have experienced a long period of employment.

The last five rows of Table 2 present summary statistics about the employment agencies. The average number of job seekers by employment agency is 4,362 among which 224 are in our sample. The unemployment rate is around 13.7%. Both the share of part-time unemployed workers and the share of recurrent job seekers is about 43%.

The last three columns of Table 2 report the p-values for the difference between those assigned to treatment (T) and those assigned to control (C) (column 5), the difference between those assigned to treatment (T) and the non assigned (C + SC), and for the joint significance of assignment status (T, C and SC). We do not observe any significant differences between our groups.

5 Results

This section provides information about the intensity of the informational treatment before looking at its impact on work while on claim, on unemployment and on unemployment

[16] Table B1 in Appendix B reports summary statistics for the whole sample, before dropping the observations for individuals who were not on claim or who had already experienced part-time unemployment at the date of the first sending. It shows that the share of individuals who were still on claim and the share of those who had never experienced part-time unemployment at the date of the first sending are not statistically different in the treated group, the control group and the super control group before program assignment. Figures C4 and C5 in Appendix C provide additional descriptive statistics on work while on claim by group.

insurance expenditure.

5.1 Treatment intensity

Results concerning treatment intensity are reported in Table 3. The share of treated individuals who opened at least one email after the three mailings is about 85%. This figure is relatively high and can be related to the fact that we targeted first time claimants. Furthermore, among these 85%, the vast majority opened the first email. The proportion of claimants who used the simulator is much lower: about 7.5% used it at least once.

Regarding the heterogeneity of the opening rate, we observe that the share of job seekers who opened at least one email is high, above 70%, among all groups reported in Table 3. The most substantial differences in opening rates are associated with education: + 18,1 percentage points for individuals with higher education levels compared to people with lower education levels; age: + 7,6 percentage points for prime age people compared to seniors; gender: + 4,1 percentage points for women; and the daily reference wage: + 3,7 percentage points for people with a daily reference wage above the mean.

5.2 Work while on claim

This section is devoted to the effects of the treatment on work while on claim. Work while on claim includes all those who work while continuing to receive unemployment benefits during the current month.[17] Hence, for our purposes hours of work while on claim are defined as the hours of work of individuals who do continue to receive unemployment benefits during the current month. We start by presenting our statistical model before looking at the effects of the treatment by comparing the treated, the control, and the super control groups. We also explore the potential heterogeneous effects of the treatment within the treated group. We then go on to compare the characteristics of individuals who work while on claim in the treated and control groups, in order to gauge the external validity of our results.

[17] According to the regulations, individuals whose monthly earnings exceed the earnings used to compute their unemployment benefits do not get any unemployment benefits in the current month but are still on claim if they continue to register with the unemployment agency at the end of the month. By definition, an individual continues to be registered in the current month only if he registers during that month. Individuals who do not register during the current month lose the benefits associated with registration. Registration at the unemployment agency can be beneficial for reasons other than receiving unemployment benefits, e.g. getting counselling to find a better job, avoiding the time-consuming process of launching a fresh entitlement period from scratch, getting free access to several public services... We take the view that such individuals — registered at the unemployment agency and eligible for unemployment benefits but not actually receiving them because their earnings are too high — are not unemployed, and therefore not part-time unemployed.

5.2.1 Statistical model

The intention to treat (ITT) estimates are obtained from the following model :

$$y_i = \alpha + \beta Z_i + \delta C_i + \gamma X_i + \epsilon_i \tag{7}$$

where Z_i is a dummy for being treated and C_i is a dummy for being in a treated area (i.e. being either in the treated group or in the control group but not in the super control group). Then, β is the difference between the treated group and the control group. δ is the difference between the control group and the super control group i.e. the effect of being untreated in a treated zone. X_i is a vector of control variables that includes the variables reported in the summary statistics (Table 2) as well as entry months and regional fixed effects.

5.2.2 Treated group versus control group

Regarding the difference between the treated group and the control group (β), we first consider the impact of the treatment on work while on claim at the extensive margin (i.e. the choice between working or not working while on claim), which is measured by the indicator variable equal to one from the first month in which the individual starts working while on claim. Figure 5 shows that the treatment has a quick positive impact on the extensive margin, which becomes significant three months after the first email, where work while on claim increases by 0.4 percentage points, which corresponds to an increase of 6% compared to non-treated individuals – see Table B2, Column 1. Work while on claim increases until six months after the first email by 0.5 percentage points. After six months, the impact of the treatment stops increasing and remains positive. The fluctuations in the effect of the treatment, which is stronger in spring and summer, is associated with the seasonality of work while on claim illustrated on Figure C3.

Figure 6 shows that the treatment has a significant effect on the number of hours of work while on claim. The impact amounts to about 7 supplementary hours after 36 months for people assigned to treatment. It is striking that the impact of the treatment does not dampen over a quite long period of time, up to three years. This suggests that whatever information members of the control group were able to acquire about part-time unemployment benefits over the period after the treatment did not sufficiently improve to catch up to the level of supplementary information provided by our emails.

Table 4 reports the results for the estimation of equation (7) for different outcomes and time horizons. From Panel A, we can see that the assignment to treatment increases the frequency of months in which individuals work while on claim by about 4.5% from 3 months to 36 months after the treatment. Panels B and C show that the treatment has about the same impact, in percentage terms, on the cumulative number of hours of work and on cumulative earnings from work while on claim, 3, 12 and 36 months after the treatment.

Table 5 reports the results for the effects of the treatment at the intensive margin, i.e. on the number of hours of work while on claim and on the earnings from work while on claim for the subset of job seekers who work at least one day while on claim. Table 5 shows that the impact of the treatment on the number of hours of work while on claim and on the earnings while on claim *conditional* on working while on claim is barely significant and very small. This means that the treatment has a negligible impact on work while on claim at the intensive margin.

The robustness of these results to randomization based inference is presented in Appendix A.3 and in Table B3. Overall, the p-values obtained with randomization inference tests are very close to the cluster-robust model based p-values, which is not surprising, considering the sample size in our experiment. Both conventional and randomized based inference thus support the conclusion that the treatment did have a statistically significant effect on the propensity to work while on claim.

5.2.3 Control group versus super control group

The propensity to work while on claim of the control group can be impacted by the informational treatment through two effects: *i*) The transmission of information from treated individuals, which can increase take-up in the control group, as well as in the treated group. *ii*) Displacement effects arising from the increase in the take-up of treated individuals. These displacement effects can decrease the take-up in the control group, as suggested by Crépon et al. (2013), who show that unemployed workers more intensively supported by public employment services crowd out other job seekers in a context similar to ours.

Figure 7 shows that the number of hours worked while on claim is not statistically different in the control and the super control group at all available time horizons. This result is confirmed by Tables 4 and 5 which show that there is no statistically significant difference between any outcome of the control group and of the super control group.

It is possible that the lack of spillover documented in Tables 4 and 5 arises from the absence of any effects of the treatment on the control group. But it is also possible that the two effects cancel each other out. Crépon et al. (2013) identify displacement effects from variations in the share of treated individuals in each unemployment agency. This does not help us to identify the relative impact of the two effects since the strength of both effects is expected to increase with the share of treated individuals: when more individuals are treated, both information transmission and displacement effects may increase.

However, Crépon et al. (2013) find displacement effects only in weak labor markets where the unemployment rate is high. Thus, in labor markets with a low unemployment rate, only the transmission of information is likely to have a significant impact on the control group if there are informational spillovers. This means that one should observe a positive impact of the treatment on the part-time unemployment take-up of the control group in labor markets where the unemployment rate is low if the provision of information spreads to the control group. To test this assumption, we estimate the following model for individuals in the control and the super control groups:

$$y_i = \alpha_0 + \alpha_1 C_i + \alpha_2 U_i + \alpha_3 (C_i \times U_i) + \alpha_4 X_i + \epsilon_i \tag{8}$$

where y_i is a measure of part-time unemployment take-up of individual i, U_i is an indicator function equal to one if individual i is located in a commuting zone in the bottom tercile of local unemployment rates ; C_i is a dummy for being in the control group – i.e. in a treated area but not in the treated group since it is excluded from the sample here. $(C_i \times U_i)$ denotes the interaction between C_i and U_i. As previously, X_i is a vector of control variables that includes the variables reported in the summary statistics (Table 2) as well as unemployment entry months and regional fixed effects. Coefficient α_3 is positive if the provision of information spreads to the control group.

Table 6 shows that there is no evidence that the part-time unemployment take-up of the control group increases, compared with the super control group, when the local unemployment rate is low. This suggests that there are no significant information spillovers to the control group arising from the treatment. Accordingly, the absence of spillover – from both displacement effects and information transmission – reported in Tables 4 and 5 is likely the consequence of the absence of any significant impact of the informational treatment on the control group. Hence, we can be confident that the comparison of the outcomes of the treated group and the control group yields the net effect of the treatment on those who were assigned to it.

5.2.4 Heterogeneous effects of the treatment

To investigate the heterogeneity of the treatment effect in a disciplined fashion, we apply the machine-learning approach developed by Chernozhukov et al. (2018). This allows us to analyze potential heterogeneous effects while being agnostic about the source of heterogeneity, which can arise from any combination of our covariates. More specifically, we test for the presence of heterogeneity and estimate average treatment effects sorted by groups as well as average characteristics of the most and least affected units. To analyze treatment effect heterogeneity, we restricted our analysis to observations from the treated group and the control group. Details for the estimation procedure are presented in Appendix A.4.

Table B4 shows that the absence of heterogeneity can be rejected (at 10% significance level) for one outcome, namely the probability to work while on claim at least once one year after the treatment. Apart from this, we do not detect any significant heterogeneity for the other outcomes of interest (cumulative part-time unemployment activity and exit from unemployment). Overall, these results provide only limited evidence of heterogeneity in the treatment effect. This may be due to the absence of such heterogeneity or to the inability of our machine-learning proxies to detect it.

Focusing on the heterogeneity in the treatment effect on the probability to work while on claim at least once one year after the treatment, Figure 8 reports the estimated conditional average treatment effect (CATE) for five heterogeneous groups induced by our machine-learning proxy. Although point estimates show some evidence of heterogeneous effects, differences across groups are not statistically different from the whole average effect. Looking at each group separately, confidence intervals indicate that the treatment had no significant effect on part-time unemployment benefits take-up among the four least affected groups, but a significantly positive effect among the most impacted group, which corresponds to the top 5% (p-value = 0.038 with Linear Regression proxy). If we focus on the most affected group vs. the least affected group (bottom 50%), we are able to reject the null hypothesis that the two coefficients are equal at 5% significance level (p-value = 0.047) (see Table B5). Finally, we can observe that all point estimates are positive (or very mildly negative), indicating that our informational treatment did not induce any group to work less while on claim.

Table 7 provides further evidence by comparing the characteristics of individuals in the most affected vs. less affected groups. Looking at demographic characteristics, the most affected are more likely to be young and to have an intermediate educational level. Regarding unemployment spell related variables, individuals in the most affected group are found to have a higher daily reference wage, entering unemployment after shorter duration contracts and having a lower potential benefit duration. Looking at local environment characteristics, people are more impacted by the treatment when unemployment is lower and part-time unemployment more frequent.

The heterogeneity of the impact of the informational treatment on the probability to work while on claim may arise from differences in dealing with information received by email, and from differences in the propensity to work while on claim. The next section examines this issue.

5.2.5 Characteristics of individuals working while on claim in the treated group

It is possible that the informational treatment impacted individuals particularly sensitive to information received by email, implying that those induced to work while on claim by the treatment are very different from those who work while on claim in the absence of our treatment. Knowing whether individuals induced to work while on claim because they received our information about part-time unemployment benefits resemble other individuals working while on claim is important when it comes to gauging the external validity of our analysis; or, to put it differently, when it comes to gauging whether the effect of the treatment can be compared to the effect of changes in the marginal tax on earnings from work while on claim. We examine this issue in two different ways. First, we compare the characteristics of individuals working while on claim in the treatment and in the control groups. Second, we use the super control group to predict the individual characteristics associated with the propensity to work while on claim and we analyze how treated individuals react to the treatment depending on these characteristics.

Comparison of individuals working while on claim in the treated group and control group Table 8 reports the means of the characteristics of individuals who worked while on claim at least once six months after the treatment, which corresponds to the period in which the treatment has the largest impact on the number of job seekers working while on claim. It is clear that the characteristics of treated individuals working while on claim do not differ from those of other individuals also working while on claim, except for the duration of the last contract before the entry into unemployment. Individuals of the treated group in part-time unemployment had contracts whose duration was more frequently below 3 months before starting their unemployment spell compared with other individuals in part-time unemployment. This means that the informational treatment has larger effects on the propensity to work on non-regular jobs for individuals who worked on such jobs in the past. This is likely because those individuals are more inclined or have more opportunities to work on non-regular jobs. Apart from this difference, the characteristics of individuals of the treated group in part-time unemployment are not statistically different from those of other individuals who work while on claim.

Treatment impact conditional on predicted characteristics associated with work while on claim Now, let us analyze whether the informational treatment has a stronger impact on the probability to work while on claim for individuals more likely to work while on claim in the absence of the treatment. We start by regressing the probability to work while on claim on the covariates displayed in the summary statistics (Table 2) as well as month of entry into unemployment and regional fixed effects for individuals belonging to the super control group.[18] This allows us to rely on out-of-sample untreated units to predict the probability to work while on claim conditional on these covariates.[19] Overall, Table 9 shows that the impact of the treatment on all measures of the intensity of the propensity to work while on claim is more important for individuals whose observable characteristics are associated with a probability above the median to work while on claim. This indicates that the treatment induces individuals to work while on claim whose observable characteristics are similar to those who have a high propensity to work while on claim, which is a situation that should arise if the marginal tax on work while on claim drops.

5.3 Unemployment

To analyze the impact of the treatment on unemployment, we start by looking at the effect on the number of days of compensated unemployment and the number of months (with at least one day) of compensated unemployment. Table 10, panels A and B, show that the number of days and the number of months of compensated unemployment are not statistically different

[18]Tables B6, B7, B8 report the results of this first stage for our outcomes of interest measured one 3, 12 and 36 months after the start of the treatment respectively. We can perceive that most of the characteristics associated with a higher probability to work while on claim at least once are also the characteristics that are prevalent in the most affected group from the CLAN analysis in Table 7. The only exception is the potential benefit duration, which is positively associated with part-time unemployment whereas it is on average lower in the most affected group.

[19]Abadie et al. (2018) stress the importance of using out-of-sample untreated units to proceed to this type of analysis.

in the treated and the control groups in the first, second and third year after the treatment, and in the whole period after the treatment. Hence, the number of days of compensated unemployment of the treated group did not significantly drop compared to the control group, although individuals of the treated group worked more while on claim than those of the control group, as shown by Table 4. The absence of a significant drop in the number of days of unemployment in the treated group indicates that the increase in the number of days of work while on claim induced by the treatment is compensated by a drop in the exit from unemployment. To put it differently, the negative effects of the supplementary days of work while on claim on the number of days of unemployment are cancelled by the drop in the exit rate from unemployment.

Table 10, panel C, shows that the lower exit from unemployment of the treated group corresponds to lower exit toward stable jobs, whose duration is at least three months. The probability of exiting unemployment toward stable jobs is lower at 5% confidence level during the second year after the treatment, meaning that job seekers postpone their exit toward stable jobs when they work while on claim.

The impact of the treatment on unemployment duration is further documented by Table 11 which shows that the treatment has a negative impact on the probability to have exited from unemployment in the last quarter and in the last month before the benefits exhaustion date.[20] Hence, the treatment has significant and sizeable lock-in effects: it increases by 6% the share of job seekers working while on claim 3 months after the start of the treatment and raises by 1.5% (Table 11, Panel B col. 1) the probability to remain unemployed the last month before the exhaustion date. The lock-in effects are larger for individuals whose potential benefits duration is longer: the treatment increases the probability to be unemployed the last month before the exhaustion date by 2.8% when the potential benefits duration is between 2 and 3 years whereas the effect on the propensity to work while on claim is only slightly higher than for the overall sample (+5.7%).

The robustness of these results to randomization based inference is presented in Appendix A.3 and in Table B10. As previously, for the effects of the treatment on the propensity to work while on claim, the p-values obtained with randomization inference tests are very close to the cluster-robust model based p-values. Therefore, both conventional and randomized based inference indicate that the treatment had a statistically significant effect on unem-

[20] Let us remind the reader that by exhaustion date we mean the date scheduled at the start of the entitlement period which corresponds to the exhaustion date of individuals who do not work while on claim. As explained above, working while on claim delays the exhaustion date.

ployment duration.

5.4 Unemployment insurance expenditure

In order to evaluate the impact of the informational treatment on unemployment insurance expenditure, we compute the difference in cumulative unemployment benefits net of taxes between the treated and control groups. Since we have limited information on tax receipts, we also provide information about the effect of the treatment on cumulative unemployment benefits gross of taxes.[21]

Despite the significant impact of the treatment on part-time unemployment and on the unemployment exit rate exhibited above, Table 12 shows that the treatment has no statistically significant effects on unemployment insurance payments, either gross or net, at any time horizon. Three years after the start of the treatment, the cumulative benefits-net-of-taxes difference between the treated and the control group is very small and not significant: it is equal to the tiny amount of 66 euros (p-value $= 0.46$ for the null hypothesis of difference equal to zero) compared to the average cumulative amount equal to 14,131 euros. Table 12, Panel B, also shows that there is a non-significant negative drop in cumulative benefits in the treated group in the first year after the treatment. The negative sign reflects the positive impact of the treatment on part-time unemployment, but it is counteracted by the lock-in effects, implying that the drop in cumulative benefits is not statistically significant. Then, as time elapses, cumulative benefits tend to be larger in the treated group, although the difference is not statistically significant. All in all, these results confirm the importance of lock-in effects associated with part-time unemployment benefits insofar as the positive effects of a drop in the dynamic marginal tax rate on labor supply, through its positive impact on the propensity to work while on claim, is cancelled by its negative impact on the exit rate from unemployment toward stable jobs.

Our analysis shows that the behavioral response to a drop in the dynamic marginal tax

[21] Tax receipts from unemployment insurance are computed by applying the unemployment insurance payroll tax rate to labor earnings, equal to 6.5%, for all hourly wages below about 25 euros, and to zero above this threshold. We have no information on earnings of individuals who definitively exit unemployment in our period. The monthly earnings are estimated by assuming that they are equal to the past daily wage used to compute the unemployment benefits times 30, which corresponds to the monthly earnings of a person working full time for the corresponding daily wage. It is likely that this overestimates the amount of tax receipts since all job seekers do not work full-time when they exit unemployment, meaning that we get a lower bound of the effect of the treatment on unemployment insurance expenditure net of taxes. For this reason, we provide results for the impact of the treatment on gross unemployment insurance payments (i.e. neglecting tax receipts), which yields an upper bound for the effect of the treatment on unemployment insurance expenditure net of taxes.

rate has no effects on the unemployment insurance expenditure net of taxes. Since the impact of tax changes on expenditure is equal to the sum of the mechanical effects (i.e. the impact of tax changes keeping behavior unchanged) and of the behavioral effects, a drop in taxes necessarily increases the expenditure net of taxes when behavioral effects are equal to zero.[22]

Therefore, it is clear that reducing the dynamic marginal tax rate on earnings from work while on claim in the neighborhood of its current level would raise the unemployment insurance expenditure net of taxes.[23] Nevertheless, the welfare effects of changes in the dynamic marginal tax rate and their comparison with those induced by the adjustment of other parameters of the unemployment insurance system remain open questions insofar as it is not possible to compare the welfare impact of a change in expenditure induced by changes in various parameters without acquiring information or making assumptions about the willingness to pay for each parameter change.[24]

6 Conclusion

Our paper shows that the transmission of information about part-time unemployment benefits can be used to evaluate the impact of the marginal tax rate on earnings from work while on claim. Our main finding is that drops in the marginal tax rate in the neighborhood of its current level induce significant lock-in effects into compensated unemployment. It is striking that these lock-in effects exist despite the positive impact of working while on claim on the exit from compensated unemployment, documented by the previous literature in France (Fremigacci and Terracol (2013) and Auray and Lepage-Saucier (2021) and in other countries.[25] This result, which is in line with those of Lee et al. (2019) and Le Barbanchon (2020), points to the empirical importance of the *anticipation* channel exhibited in the job search model: the possibility of combining earnings from work while on claim with unemployment benefits reduces the incentives to exit from compensated unemployment. We find that these lock-in effects imply that reducing the marginal tax rate in the neighborhood of its current level would reduce the exit rate from unemployment toward stable jobs and raise the unemployment insurance expenditure net of taxes.

[22]see Appendix A.5.

[23]Figures C6 and C7 display the distribution of the estimates of the dynamic marginal tax rate for each individual $\times$ month observation and the evolution of the average dynamic marginal tax rate over the employment spell.

[24]see Appendix A.5.

[25]See the references provided above in the introduction.

Our contribution, focused on labor supply and unemployment insurance expenditure, does not analyze the impact of part-time unemployment insurance on welfare. Such an analysis, which is beyond the scope of this paper, is an important area for future research insofar as part-time unemployment insurance, which is already an important component of unemployment insurance in many countries, is expected to play a growing role in the face of the development of unstable jobs.

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7 Tables

Table 1: Experimental lay-out

1^{st} level of randomization : Local agencies assignment				
	Treated areas		Untreated areas	All
Assignment prob.	4/5		1/5	
Number of agencies	687		171	858
Number of job seekers	118 229		29 649	147 878
2^{nd} level of randomization : Job seekers assignment				
	Treated (T)	Control (C)	Super-control (SC)	All
Assignment prob.	1/2	1/2		
Number of job seekers	59 112	59 117	29 649	147 878

Note: The upper part of this table reports the assignment to treatment probability of local agencies, the number of agencies and the number of job seekers assigned to treatment. The bottom part displays the assignment to treatment probability of job seekers in agencies assigned to treatment and the number of workers belonging to the treatment group (i.e. who received the emails), to the control group (i.e. who did not receive the emails but who were located in agencies in which other job seekers received emails) and to the super-control group (i.e. who were located in agencies in which nobody received the emails).

Table 2: Summary statistics on the final sample

	Means				p-value of the difference		
	All	T	C	SC	T - C	T - (C + SC)	T = C = SC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job seekers characteristics							
Female	.472	.473	.473	.467	.967	.496	.335
Age	32.645	32.639	32.632	32.683	.935	.831	.972
Young	.378	.375	.377	.386	.398	.82	.406
Prime age	.461	.464	.462	.449	.545	.475	.318
Senior	.161	.161	.16	.165	.77	.46	.7
Lower education level	.239	.239	.236	.242	.256	.21	.406
Intermediate education level	.432	.427	.432	.444	.101	.926	.081
Higher education level	.329	.334	.332	.313	.485	.362	.301
Last contract duration $\leq$ 12 months	.338	.335	.336	.344	.743	.656	.675
Last contract duration $\leq$ 3 months	.089	.088	.09	.091	.249	.559	.465
Potential benefit duration	621.096	621.506	621.507	619.456	.999	.793	.948
... < 730 days	.44	.44	.441	.441	.652	.793	.9
... $\geq$ 730 days	.56	.56	.559	.559	.652	.793	.9
Daily Reference Wage	62.948	63.137	63.166	62.138	.93	.652	.901
... $\leq$ the mean	.678	.678	.677	.678	.961	.973	.999
... > the mean	.322	.322	.323	.322	.961	.973	.999
Unemployment entry month							
July 2016	.157	.158	.156	.159	.234	.196	.42
August 2016	.163	.164	.165	.158	.622	.181	.137
September 2016	.279	.279	.279	.281	.823	.699	.909
October 2016	.229	.228	.231	.229	.273	.296	.51
November 2016	.171	.17	.17	.174	.769	.462	.623
Local agencies characteristics							
Unemployment rate	13.761	13.771	13.757	13.749	.676	.955	.912
Share of part time unemployment	.434	.433	.432	.438	.309	.35	.425
Share of long-term unemp	.429	.429	.429	.429	.398	.979	.668
Exit rate from unemp	.064	.064	.064	.064	.193	.431	.337
Number of claimants	4361.794	4366.773	4377.762	4320.004	.305	.624	.477
Number of participants	224.45	226.913	227.873	212.704	.213	.108	.127
N	115547	46191	46200	23156			

Note: This table reports descriptive statistics for the sample of individuals in January 2017, after dropping observations for individuals who were not on claim or who had already worked while on claim on 31 January 2017. Columns (1), (2), (3) and (4) report the means of individual characteristics for the treatment, the control and the super control sub-samples, respectively. Columns (5)–(7) report the p-values for the difference between assigned to treatment (T) and assigned to control (C) (column 5), the difference between assigned to treatment (T) and non assigned (C + SC), and for the joint significance of assignment status (T, C and SC). *Female* equals 1 if the participant is female. *Age* is the age of the participant when the first email was sent. *Young* equals 1 if the participant is younger than 25 years old. *Prime age* equals 1 if the participant is between 25 and 50 years old. *Senior* equals 1 if the participant is above 50 years old. *Lower education level* equals 1 if the participant did not pass the Baccalauréat. *Intermediate education level* equals 1 if the participant passed the Baccalauréat. *Higher education level* equals 1 if the participant has a university degree. *Potential benefit duration* represents the maximum duration of unemployment when the participant does not work while on claim. *Daily reference wage* represents the daily wage earned prior unemployment. *Days since entry* represents the number of days since entry into unemployment when the first email was sent. *Unemployment entry month* represents the starting month of the participant's unemployment spell. Variables mentioning < *mean* (> *mean*) equal 1 for participants whose value of the variable in question is respectively below or above the mean. *Last contract duration* $\leq$ *n months* equals 1 for participants who entered into unemployment after a contract shorter than n months. *Unemployment rate*: unemployment rate in the area of the employment agency in December 2016. *Share of part-time unemp*: agency share of job seekers working while on claim in December 2016. *Share of long-term unemp*: agency share of job seekers whose unemployment duration is longer than one month in the area of the employment agency in December 2016. *Exit rate from unemp*: agency average unemployment exit rate in December 2016. *Number of claimants*: number of job seekers by agency in December 2016. *Number of participants*: number of individuals included in our sample by agency.

Table 3: Treatment intensity in the final sample

	% of treated ind. who opened the email				% of treated ind. who used the simulator			
	At 1^{st} sending (1)	At 2^{nd} sending (2)	At 3^{rd} sending (3)	At least once (4)	At 1^{st} sending (5)	At 2^{nd} sending (6)	At 3^{rd} sending (7)	At least once (8)
All	75.4	69.3	67.8	84.8	3.4	2.6	2.3	7.5
Female	78.1	72.1	70.6	87	3.5	2.9	2.5	8
Male	72.9	66.7	65.2	82.9	3.3	2.4	2.1	7
Young	74.3	67.8	66.2	85.6	3.3	2.4	2.4	7.4
Prime age	77.6	71	69.6	86.3	3.3	2.4	2	7.1
Senior	71.6	67.6	66.2	78.7	3.9	3.6	3	9
Lower education level	63.1	58.5	57.5	73.7	3.5	2.5	2.5	7.6
Intermediate education level	75.4	68.9	67.5	85.5	3.4	2.7	2.3	7.6
Higher education level	84	77.4	75.5	91.8	3.2	2.6	2.2	7.4
Last contract $\leq$ 12 months	73.6	67.6	66.3	84.2	3.5	2.4	2.4	7.7
Last contract $\leq$ 3 months	72.3	66.8	65.7	83	3.7	2.4	2.3	7.9
Potential Benefit Duration $<$ 730 days	73.5	67.3	65.9	84.1	3.5	2.4	2.3	7.5
Potential Benefit Duration $\geq$ 730 days	76.9	70.8	69.3	85.3	3.3	2.8	2.3	7.5
Daily Reference Wage below the mean	73.3	67.1	65.7	83.6	3.3	2.5	2.3	7.3
Daily Reference Wage above the mean	79.8	73.8	72.2	87.3	3.6	2.7	2.3	7.9
Days since entry in unemp. $\leq$ 3 months	76.1	70	68	84.8	3.3	2.6	2.4	7.6
Days since entry in unemp. between 4 and 6 months	74.9	68.8	67.7	84.8	3.4	2.6	2.3	7.5
Nb. of individuals: 115,547								

Note: Columns (1), (2), (3), and (4) report the share of treated participants who opened the first email (1), the second email (2), the third email (3) or at least one email (4). Columns (5), (6), (7), and (8) report the share of treated participants who used the simulator in the first email (5), in the second email (6), in the third email (7) or at least in one email (8). See Table 2 for a description of the variables.

Table 4: Treatment effect on part-time unemployment: extensive margin

	3 months		12 months		36 months	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A : Cumulative number of months with work while on claim						
Treated (β)	0.0052*	0.0052*	0.0254**	0.0260**	0.0782***	0.0812***
	(0.0027)	(0.0027)	(0.0109)	(0.0108)	(0.0293)	(0.0290)
	[0.053]	[0.051]	[0.020]	[0.016]	[0.008]	[0.005]
In a treated area (δ)	-0.0017	0.0004	0.0035	0.0163	-0.0303	0.0082
	(0.0037)	(0.0033)	(0.0166)	(0.0130)	(0.0502)	(0.0366)
	[0.642]	[0.912]	[0.834]	[0.209]	[0.546]	[0.823]
Mean super control	0.10		0.57		1.70	
Panel B : Cumulative number of hours worked while on claim						
Treated (β)	0.3230	0.3259	2.1532**	2.2149**	6.4473**	6.7340**
	(0.2016)	(0.2001)	(0.9633)	(0.9485)	(2.8676)	(2.8181)
	[0.109]	[0.104]	[0.026]	[0.020]	[0.025]	[0.017]
In a treated area (δ)	-0.2362	-0.0676	-0.8573	0.0625	-4.6537	-1.6120
	(0.2607)	(0.2422)	(1.4521)	(1.1837)	(5.0166)	(3.6733)
	[0.365]	[0.780]	[0.555]	[0.958]	[0.354]	[0.661]
Mean super control	5.75		40.70		135.62	
Panel C : Cumulative earnings (in euro) from work while on claim						
Treated (β)	5.6210**	5.6575**	33.0513**	33.7244***	104.3254***	107.4585***
	(2.5364)	(2.5167)	(12.8756)	(12.6225)	(39.8029)	(38.4577)
	[0.027]	[0.025]	[0.010]	[0.008]	[0.009]	[0.005]
In a treated area (δ)	-4.7117	-2.9677	-17.3072	-8.7657	-70.3628	-44.2654
	(3.5402)	(3.2363)	(20.2628)	(15.6455)	(71.5434)	(49.5247)
	[0.184]	[0.359]	[0.393]	[0.575]	[0.326]	[0.372]
Mean super control	69.46		501.78		1709.82	
N	115547	115547	115547	115547	115547	115547
Covariates	No	Yes	No	Yes	No	Yes

Note: Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. p-values are reported in brackets. Each duration (i.e. 3, 12, and 36 months) indicates the elapsed time since treatment. Covariates include all stratum variables reported in Table 2 as well as entry months and regional fixed effects. "Treated" designates individuals who were assigned to treatment (ITT estimate), "In treated area" refers to those registered at employment agencies where half of individuals have been treated and "super control" designates individuals registered at employment agencies where nobody has been treated. The number of observations N corresponds to the number of individuals.

Table 5: Treatment effect on part-time unemployment: intensive margin

	3 months		12 months		36 months	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A : Cumulative number of hours worked while on claim at the intensive margin						
Treated (β)	-0.0200	-1.4426	7.1282*	5.5718	16.7444**	11.3161
	(2.3061)	(2.2151)	(3.9264)	(3.4865)	(8.3361)	(7.5458)
	[0.993]	[0.515]	[0.070]	[0.110]	[0.045]	[0.13 4]
In a treated area (δ)	-0.8517	0.7068	-2.6126	-2.5034	0.4418	-0.9476
	(3.0287)	(2.6508)	(6.1278)	(4.6174)	(14.1505)	(9.3651)
	[0.779]	[0.790]	[0.670]	[0.588]	[0.975]	[0.919]
Mean super control	89.20		215.80		446.51	
Panel B : Cumulative earnings (in euro) from work while on claim at the intensive margin						
Treated (β)	27.4618	-1.6892	122.7403**	88.6023**	289.2814**	191.0127*
	(29.5058)	(26.7263)	(54.6951)	(44.5939)	(117.8574)	(100.0897)
	[0.352]	[0.950]	[0.025]	[0.047]	[0.014]	[0.057]
In a treated area (δ)	-40.0733	-18.0860	-68.2410	-74.0666	-34.6073	-73.2656
	(46.4326)	(33.8810)	(96.6964)	(57.1514)	(223.4429)	(121.3045)
	[0.388]	[0.594]	[0.481]	[0.195]	[0.877]	[0.546]
Mean super control	1076.53		2656.41		5619.95	
N	7435	7435	21840	21840	34317	34317
Covariates	No	Yes	No	Yes	No	Yes

Note: This table reports the estimates of the impact of the treatment on the cumulative number of hours of work while on claim and on the cumulative earnings from work while on claim for the subset of job seekers who worked while on claim at least one day. Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. *p*-values are reported in brackets. Each duration (i.e. 3, 12, and 36 months) indicates the elapsed time since treatment. Covariates include all stratum variables reported in Table 2as well as entry months and regional fixed effects. "Treated" designates individuals who were assigned to treatment (ITT estimate), "In treated area" refers to those registered at employment agencies where half of individuals have been treated and "super control" designates individuals registered at employment agencies where nobody has been treated. The number of observations N corresponds to the number of individuals.

Table 6: Spillover effects on part-time unemployment

	3 months		12 months		36 months	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A : Cumulative number of months with work while on claim						
Control	-0.0015	0.0006	0.0047	0.0142	-0.0367	-0.0114
	(0.0043)	(0.0041)	(0.0187)	(0.0162)	(0.0545)	(0.0430)
	[0.725]	[0.891]	[0.799]	[0.379]	[0.501]	[0.790]
Low	0.0025	-0.0035	0.0545**	-0.0219	0.2887***	-0.0278
	(0.0066)	(0.0075)	(0.0236)	(0.0276)	(0.0691)	(0.0754)
	[0.707]	[0.638]	[0.021]	[0.429]	[0.000]	[0.713]
Low X Control	-0.0005	-0.0003	-0.0018	0.0012	0.0316	0.0309
	(0.0079)	(0.0073)	(0.0301)	(0.0267)	(0.0879)	(0.0723)
	[0.946]	[0.970]	[0.953]	[0.965]	[0.719]	[0.669]
Mean super control	0.10		0.57		1.70	
Panel B : Cumulative number of hours worked while on claim						
Control	-0.2188	-0.0466	-0.4772	0.2655	-3.7746	-1.3492
	(0.3031)	(0.2926)	(1.5610)	(1.3726)	(5.2196)	(4.1148)
	[0.471]	[0.873]	[0.760]	[0.847]	[0.470]	[0.743]
Low	0.7206	-0.0510	8.7680***	0.2101	39.7589***	3.5531
	(0.5002)	(0.5525)	(2.1647)	(2.3707)	(7.4701)	(7.7616)
	[0.150]	[0.926]	[0.000]	[0.929]	[0.000]	[0.647]
Low X Control	-0.0246	-0.0472	-0.8199	-1.0094	-1.1072	-3.0131
	(0.5859)	(0.5532)	(2.7197)	(2.4288)	(9.3550)	(7.6591)
	[0.966]	[0.932]	[0.763]	[0.678]	[0.906]	[0.694]
Mean super control	5.75		40.76		135.85	
Panel C : Cumulative earnings (in euro) from work while on claim						
Control	-2.9422	-0.9830	-7.4255	0.2810	-38.7499	-12.8498
	(3.9135)	(3.6114)	(22.1168)	(17.4544)	(73.9316)	(53.5499)
	[0.452]	[0.786]	[0.737]	[0.987]	[0.600]	[0.810]
Low	13.4765*	2.6427	142.4420***	15.2339	641.1864***	106.4218
	(7.1747)	(7.7183)	(31.2417)	(31.7882)	(112.2593)	(104.2902)
	[0.061]	[0.732]	[0.000]	[0.632]	[0.000]	[0.308]
Low X Control	-4.9249	-5.9131	-24.7816	-33.4379	-71.7663	-122.5675
	(8.0957)	(7.6851)	(38.4159)	(33.3205)	(137.1450)	(107.4938)
	[0.543]	[0.442]	[0.519]	[0.316]	[0.601]	[0.255]
Covariates	No	Yes	No	Yes	No	Yes
Mean super control	69.46		501.78		1709.82	
N	69356	69356	69356	69356	69356	69356

Note: This table reports the estimates of coefficients α_1, α_2 and α_3 of equation (8). Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. p-values are reported in brackets. Dependent variables are the same as in Table 4. Each duration (i.e. 3, 12, and 36 months) indicates the elapsed time since treatment. Covariates include all stratum variables reported in Table 2 as well as entry months and regions fixed effects. The sample comprises the control group and the super control group only. "Control" (coefficient α_1) is a dummy for individuals in treated area but not treated. "Low" (coefficient α_2) is a dummy for areas in the bottom tercile of the unemployment rate. "Low $\times$ Control" (coefficient α_3) is the interaction term. The number of observations N corresponds to the number of individuals.

Table 7: Summary statistics for those most and least affected by the treatment
Outcome: Prob. to work while on claim at least once

	Linear Regression			Elastic Net		
	Most Affected	Least Affected	Difference	Most Affected	Least Affected	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Job seekers characteristics						
Female	0.480	0.462	0.020	0.491	0.452	0.035
	-	-	[0.127]	-	-	[0.003]
Elderly	0.123	0.187	-0.064	0.101	0.203	-0.099
	-	-	[0.000]	-	-	[0.000]
Young	0.485	0.330	0.151	0.471	0.326	0.147
	-	-	[0.000]	-	-	[0.000]
Intermediary aged	0.380	0.489	-0.102	0.412	0.474	-0.066
	-	-	[0.000]	-	-	[0.000]
Lower education	0.196	0.281	-0.086	0.163	0.286	-0.119
	-	-	[0.000]	-	-	[0.000]
Upper education	0.527	0.392	0.143	0.520	0.379	0.147
	-	-	[0.000]	-	-	[0.000]
Higher education	0.269	0.324	-0.045	0.291	0.336	-0.038
	-	-	[0.000]	-	-	[0.001]
Last contract inf to 3 m	0.274	0.024	0.256	0.315	0.023	0.285
	-	-	[0.000]	-	-	[0.000]
Last contract inf to 12 m	0.494	0.269	0.235	0.540	0.273	0.271
	-	-	[0.000]	-	-	[0.000]
Daily reference wage	69.34	57.85	11.730	83.62	56.84	26.350
	-	-	[0.000]	-	-	[0.000]
PBD	567.1	640.0	-73.81	557.5	649.8	-95.27
	-	-	[0.000]	-	-	[0.000]
Local agencies characteristics						
Number of participants	179.4	226.9	-46.65	198.4	231.8	-33.43
	-	-	[0.000]	-	-	[0.000]
Number of claimants	3901	4319	-430.6	3998	4400	-430.4
	-	-	[0.000]	-	-	[0.000]
Share of part-time unemployed	0.444	0.429	0.011	0.427	0.429	-0.002
	-	-	[0.000]	-	-	[0.416]
Share of recurrent job seekers	0.426	0.427	-0.001	0.420	0.429	-0.008
	-	-	[0.554]	-	-	[0.000]
Unemployment rate	13.37	14.05	-0.668	13.04	14.02	-0.961
	-	-	[0.000]	-	-	[0.000]

Note: The outcome is measured 12 months after the treatment date. The results are presented for the two best ML methods regarding this outcome : Linear Regression and Elastic Net. The most affected group refers to the top 5% of the distribution of $\hat{S}(X_i)$ whereas the least affected group refers to the bottom 50%. The parameter estimates and p-values - displayed in brackets - are computed as medians over 100 splits, with nominal levels adjusted to account for the splitting uncertainty.

Table 8: Summary statistics on individuals working while on claim at least once 6 months after the start of the treatment

	Means				p-value of the difference		
	All	T	C	SC	T - C	T - (C + SC)	T = C = SC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job seekers characteristics							
Female	.504	.508	.501	.5	.503	.431	.728
Age	31.169	31.08	31.213	31.266	.547	.451	.751
Young	.418	.422	.413	.42	.345	.447	.636
Prime age	.462	.461	.466	.456	.639	.895	.774
Senior	.12	.117	.121	.125	.474	.308	.563
Lower secondary education	.236	.234	.239	.235	.53	.625	.805
Upper secondary education	.488	.488	.489	.486	.92	1	.978
Higher education	.276	.278	.272	.279	.477	.661	.732
Last contract inf to 12 m	.353	.357	.347	.354	.272	.365	.535
Last contract inf to 3 m	.103	.108	.098	.104	.077	.137	.18
Potential benefit duration	611.635	611.155	612.156	611.589	.833	.852	.975
PBD inf to 730 days	.448	.451	.448	.445	.759	.664	.905
PBD sup or eq to 730 days	.552	.549	.552	.555	.759	.664	.905
Daily Reference Wage	60.125	60.546	59.673	60.155	.281	.422	.547
DRW below the mean	.66	.663	.663	.648	.994	.554	.581
DRW above the mean	.34	.337	.337	.352	.994	.554	.581
Days since entry in unemp	105.976	106.241	105.793	105.789	.569	.548	.835
Tenure inf to 3 months	.423	.426	.423	.416	.772	.586	.754
Tenure between 4 and 6 months	.577	.574	.577	.584	.772	.586	.754
Local agencies characteristics							
Number of participants	214.148	217.323	214.428	206.974	.177	.18	.33
Number of claimants	4356.972	4371.09	4340.28	4361.041	.322	.706	.637
Share of part time unemp	.444	.443	.443	.449	.797	.46	.571
Share of long-term unemp	.431	.431	.431	.431	.866	.962	.988
Exit rate from unemp	.064	.064	.064	.064	.535	.547	.781
Unemployment rate	13.817	13.761	13.917	13.733	.102	.48	.296
N	13240	5419	5218	2603			

Columns (1), (2), (3) and (4) report the means of characteristics of individuals working while on claim at least once after the start of the treatment in our final sample, for the treatment, the control and the super control group, respectively. Columns (5)–(8) report the *p*-values for the difference between assigned to treatment (T) and assigned to control (C) (column 5), the difference between assigned to treatment (T) and non assigned (C + SC), and for the joint significance of assignment status (T, C and SC). See Table 2 for a description of the variables.

Table 9: Treatment heterogeneity conditional on predicted part-time unemployment activity

	After 3 months	After 12 months	After 36 months
	(1)	(2)	(3)
Panel A : Prob. to work while on claim at least once			
Treated	0.001	-0.000	0.001
	(0.0018)	(0.0032)	(0.0037)
	[0.611]	[0.892]	[0.873]
Treated × Above median	0.010**	0.010*	0.007
	(0.0040)	(0.0055)	(0.0060)
	[0.011]	[0.069]	[0.218]
Mean super control	0.06	0.19	0.30
Panel B : Cumulative number of months with work while on claim			
Treated	0.001	0.006	0.038
	(0.0032)	(0.0114)	(0.0250)
	[0.833]	[0.574]	[0.133]
Treated × Above median	0.013**	0.048**	0.100
	(0.0063)	(0.0234)	(0.0649)
	[0.037]	[0.039]	[0.123]
Mean super control	0.10	0.57	1.70
Panel C : Cumulative number of hours worked while on claim			
Treated	-0.102	-0.565	1.696
	(0.1952)	(0.8271)	(1.8660)
	[0.601]	[0.494]	[0.364]
Treated × Above median	1.591***	7.105***	12.116*
	(0.5294)	(2.1583)	(6.3581)
	[0.003]	[0.001]	[0.057]
Mean super control	5.75	40.76	135.85
Panel D : Cumulative earnings (in euro) from work while on claim			
Treated	-0.445	-7.187	14.584
	(2.1089)	(8.4265)	(18.8816)
	[0.833]	[0.394]	[0.440]
Treated × Above median	21.132***	102.325***	210.609**
	(7.0557)	(28.4939)	(84.0406)
	[0.003]	[0.000]	[0.012]
Mean super control	69.46	501.78	1709.82
Covariates	Yes	Yes	Yes
N	92391	92391	92391

Note: Levels of significance: * $<$ 0.10, ** $<$ 0.05, *** $<$ 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. p-values are reported in brackets. Each panel (outcome) $*$ column (duration) displays the results from a different regression. Each regression include the list of covariates reported in the summary statistics (see Table 2) as well as entry months and regions fixed effects. "Treated" designates individuals who were assigned to treatment (ITT estimate). "Above median" designates individuals for whom the predicted outcome is above the median. For each outcome $*$ duration, the predicted outcome is estimated by an OLS regression using individuals from the super control group only. Individuals from the super control group are not included in the regressions presented in this table to avoid potential bias arising from endogenous stratification as described in Abadie et al. (2018). The number of observations N corresponds to the number of individuals.

Table 10: Treatment effect on unemployment

	1st year		2nd year		3rd year		All years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A : Number of days of unemployment								
Treated (β)	-0.2729	-0.0612	-0.0439	-0.0532	0.6404	0.6301	0.3236	0.5158
	(0.8795)	(0.7682)	(0.8216)	(0.6924)	(0.6386)	(0.5874)	(1.7315)	(1.4446)
	[0.756]	[0.937]	[0.957]	[0.939]	[0.316]	[0.284]	[0.852]	[0.721]
In a treated area (δ)	2.0622	-0.0325	-0.5512	-0.5738	-1.5087	-0.5686	0.0022	-1.1749
	(1.9739)	(1.2097)	(1.4923)	(0.9803)	(1.0131)	(0.8028)	(3.1347)	(2.2030)
	[0.296]	[0.979]	[0.712]	[0.558]	[0.137]	[0.479]	[0.999]	[0.594]
Mean super control	320.89		112.32		54.87		488.07	
Panel B : Number of months with at least one day of unemployment								
Treated (β)	0.0225	0.0244	0.0149	0.0153	0.0307	0.0309	0.0680	0.0706
	(0.0276)	(0.0239)	(0.0292)	(0.0250)	(0.0241)	(0.0223)	(0.0628)	(0.0528)
	[0.416]	[0.308]	[0.609]	[0.540]	[0.203]	[0.167]	[0.279]	[0.182]
In a treated area (δ)	0.0304	-0.0162	-0.0393	-0.0257	-0.0698*	-0.0268	-0.0787	-0.0687
	(0.0538)	(0.0324)	(0.0522)	(0.0361)	(0.0406)	(0.0313)	(0.1107)	(0.0751)
	[0.572]	[0.617]	[0.452]	[0.477]	[0.086]	[0.392]	[0.478]	[0.360]
Mean super control	7.59		4.32		2.27		14.17	
Panel C : Exit from unemployment toward employment for at least 3 months								
Treated (β)	-0.0038	-0.0044	-0.0068**	-0.0075**	-0.0037	-0.0041	-0.0035	-0.0041
	(0.0034)	(0.0032)	(0.0031)	(0.0030)	(0.0031)	(0.0030)	(0.0028)	(0.0027)
	[0.261]	[0.169]	[0.029]	[0.014]	[0.241]	[0.176]	[0.211]	[0.137]
In a treated area (δ)	-0.0068	-0.0019	-0.0012	-0.0000	0.0021	0.0040	-0.0037	-0.0006
	(0.0068)	(0.0046)	(0.0051)	(0.0040)	(0.0047)	(0.0038)	(0.0048)	(0.0037)
	[0.323]	[0.682]	[0.819]	[1.000]	[0.650]	[0.302]	[0.441]	[0.873]
Mean super control	0.50		0.66		0.67		0.77	
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
N	115547	115547	115547	115547	115547	115547	115547	115547

Note: Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. p-values are reported in brackets. Each duration (i.e. 3, 12, and 36 months) indicates the elapsed time since treatment. Covariates include all stratum variables reported in Table 2as well as entry months and regions fixed effects. "Treated" designates individuals who were assigned to treatment (ITT estimate), "In treated area" refers to those registered at employment agencies where half of individuals have been treated and "super control" designates individuals registered at employment agencies where nobody has been treated. The number of observations N corresponds to the number of individuals. The outcome in panel C is a dummy equal to one if we observe a period of employment of at least 3 consecutive months.

Table 11: Treatment effect on unemployment in the last quarter before benefit exhaustion

			Potential Benefit Duration			
	All sample		< 730 days		≥ 730 days	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A : Prob. to be out of unemployment in the last quarter						
Treated (β)	-0.0048	-0.0052*	0.0012	0.0000	-0.0093**	-0.0096**
	(0.0032)	(0.0031)	(0.0047)	(0.0044)	(0.0044)	(0.0043)
	[0.129]	[0.094]	[0.792]	[0.995]	[0.035]	[0.028]
In a treated area (δ)	-0.0025	-0.0019	-0.0052	-0.0070	-0.0006	0.0028
	(0.0055)	(0.0044)	(0.0075)	(0.0062)	(0.0063)	(0.0055)
	[0.648]	[0.660]	[0.487]	[0.263]	[0.927]	[0.609]
Mean super control	0.47		0.41		0.51	
Panel B : Prob. to be out of unemployment in the last month						
Treated (β)	-0.0056*	-0.0059**	0.0033	0.0020	-0.0122***	-0.0125***
	(0.0031)	(0.0030)	(0.0047)	(0.0045)	(0.0043)	(0.0042)
	[0.068]	[0.046]	[0.493]	[0.648]	[0.004]	[0.003]
In a treated area (δ)	0.0024	0.0015	-0.0019	-0.0052	0.0055	0.0072
	(0.0053)	(0.0042)	(0.0074)	(0.0060)	(0.0062)	(0.0055)
	[0.655]	[0.725]	[0.798]	[0.385]	[0.371]	[0.193]
Mean super control	0.40		0.34		0.44	
Covariates	No	Yes	No	Yes	No	Yes
N	115547	115547	50887	50887	64660	64660

Note : Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors are reported in parenthesis, they are robust to heteroskedasticity and clustered at the local agency level. p-values are reported below standard errors in brackets. Each duration (i.e. 3, 12, and 36 months) indicates the elapsed time since treatment. Covariates include all stratum variables reported in table 2 as well as entry months and regions fixed effects. N indicates the number of observations which is equal to the number of individuals. Outcome in panel A is a dummy equal to one if the individual is out of unemployment during all 3 months before the benefit exhaustion date. The outcome in panel B is a dummy equal to one if the individual is out of unemployment in the last month before the benefit exhaustion date.

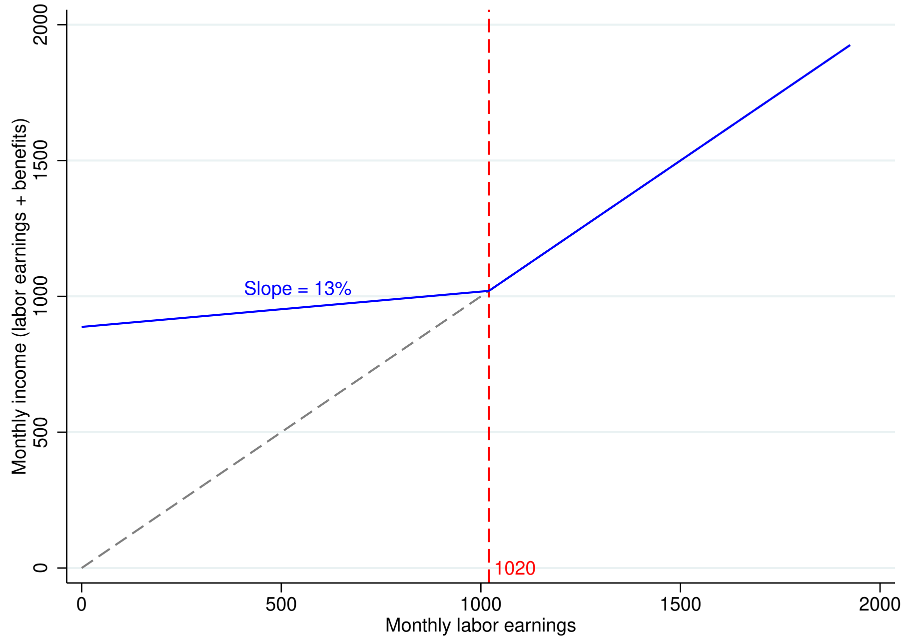
Table 12: Treatment effect on unemployment insurance payments

	1st year		2nd year		3rd year		All years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A : Unemployment insurance payments (in euro) net of taxes								
Treated (β)	17.8523	14.3936	17.5196	11.8149	44.1053	39.9145	79.4772	66.1230
	(60.8117)	(37.3070)	(57.7522)	(43.5648)	(44.1595)	(38.9552)	(136.3212)	(88.9861)
	[0.769]	[0.700]	[0.762]	[0.786]	[0.318]	[0.306]	[0.560]	[0.458]
In a treated area (δ)	209.4736	7.7940	55.5871	-34.8871	-38.6731	-27.2595	226.3877	-54.3526
	(331.1745)	(59.8563)	(250.3965)	(55.2242)	(101.4381)	(52.9725)	(664.6942)	(133.9399)
	[0.527]	[0.896]	[0.824]	[0.528]	[0.703]	[0.607]	[0.733]	[0.685]
Mean super control	8037.85		4359.63		1733.18		14130.67	
Panel B : Unemployment insurance payments (in euro)								
Treated (β)	-21.8523	-19.6775	15.7559	9.6450	43.6383	39.0961	77.9293	63.5818
	(70.4514)	(40.6618)	(56.4778)	(40.5892)	(42.8495)	(36.4314)	(136.1165)	(83.6473)
	[0.757]	[0.629]	[0.780]	[0.812]	[0.309]	[0.284]	[0.567]	[0.447]
In a treated area (δ)	277.5063	32.5086	61.9056	-33.9465	-23.3730	-22.2426	243.1289	-51.6785
	(406.8660)	(85.8022)	(263.1796)	(51.9653)	(116.3471)	(50.8493)	(701.5659)	(128.4427)
	[0.495]	[0.705]	[0.814]	[0.514]	[0.841]	[0.662]	[0.729]	[0.688]
Mean super control	12098.31		4981.52		2447.24		15811.83	
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
N	115547	115547	115547	115547	115547	115547	115547	115547

Note : This table reports the effect of the treatment on unemployment insurance payments in the first, second, third year after the start of the treatment and during all 3 years after the start of the treatment. Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. p-values are reported in brackets. Covariates include all stratum variables reported in Table 2as well as entry months and regions fixed effects. "Treated" designates individuals who were assigned to treatment (ITT estimate), "In treated area" refers to those registered at employment agencies where half of individuals have been treated and "super control" designates individuals registered at employment agencies where nobody has been treated. The number of observations N corresponds to the number of individuals.

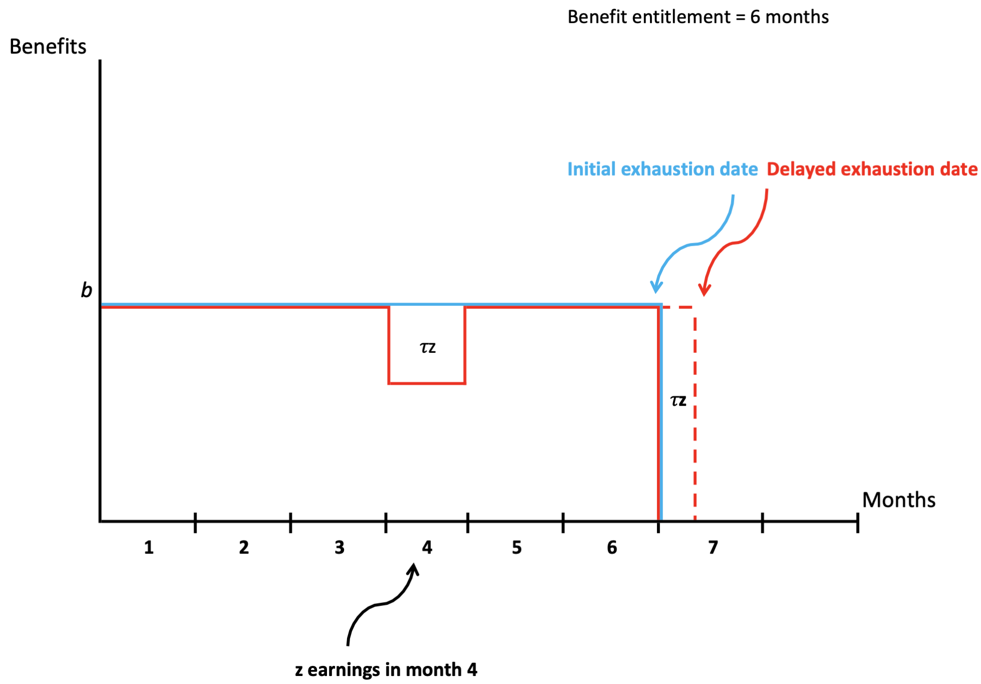
8 Figures

Figure 1: The relation between earnings when working while on claim and income



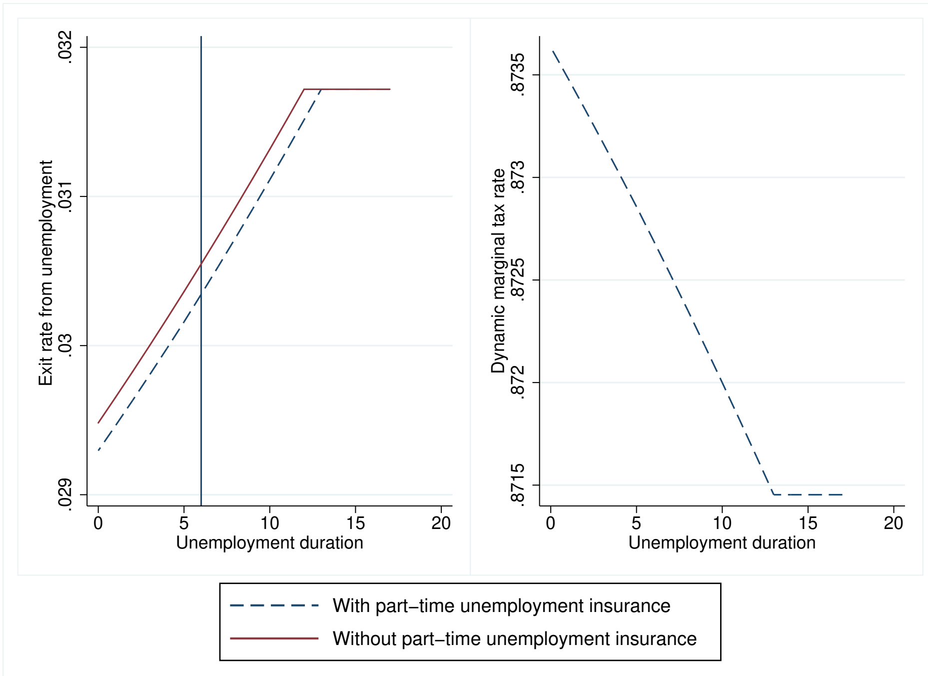
Note: This figure shows the relation between labor earnings (horizontal axis) and income (vertical axis) of individuals eligible for unemployment benefits whose monthly wage was equal to €1020 before their unemployment spell. Labor earnings and income are net of social contributions.

Figure 2: The dynamic aspects of the schedule



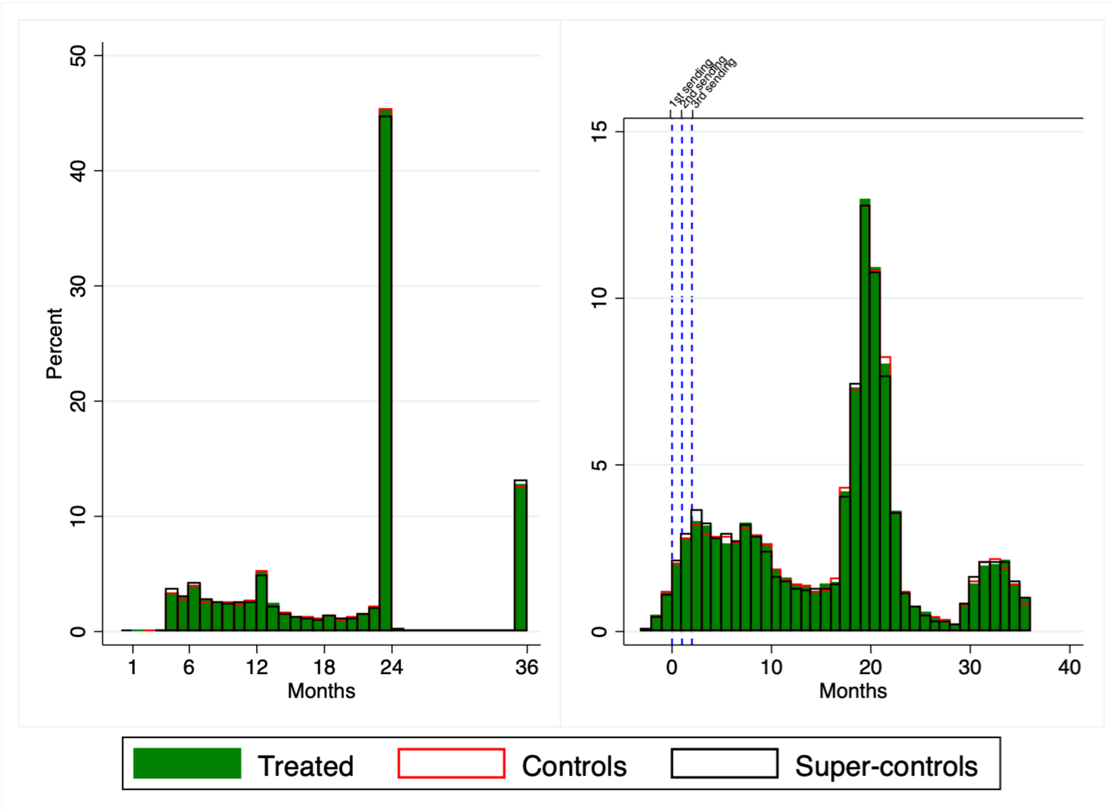
Note: This figure displays the monthly benefits b of an individual eligible for 6 months of benefits at the start of her unemployment spell. She earns z for work while on claim in the fourth month. These earnings are taxed at rate τ, implying that benefits are reduced by the amount τz in month four. These saved benefits are carried over to the end of the initial entitlement period.

Figure 3: The exit rate from unemployment (left panel) and the dynamic marginal tax rate (right panel)



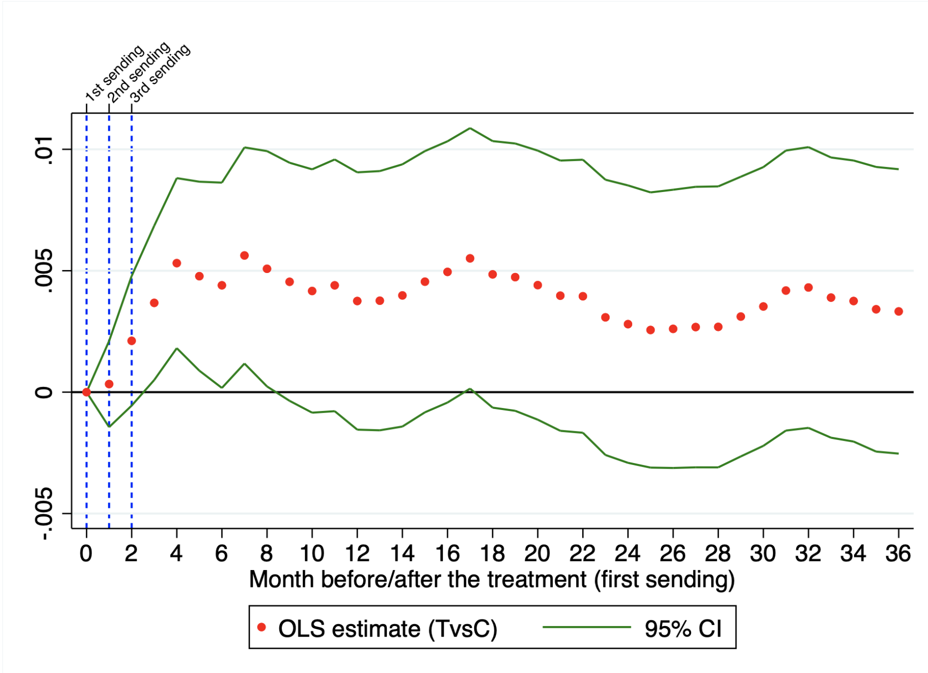
Note: The vertical bar on the left panel reports the unemployment spell at which the unemployed worker starts working while on claim. The job search model is simulated assuming that the monthly discount factor $\beta = 0.996$, which corresponds to an annual discount rate equal to 5%; $v(c) = \log(c)$; $\lambda(e) = \lambda_0 \left(1 - \exp^{-\gamma e}\right)$; $\gamma = 0.5$; $\lambda_0 = 0.05$; the value of benefits is normalized to one: $b = 1$; the replacement ratio is equal to 0.5 implying that the wage of regular jobs, the duration of which is infinite and which yield the value W is equal to 2; the initial potential benefits duration equals 12 months; individuals still unemployed after the benefits exhaustion date get benefits equal to 0.3; the tax rate on earnings from work while on claim $\tau = 0.9$; the share α of current earnings reported at the end of the entitlement period, that will be obtained only if the person is still unemployed in this period, is equal to τ; the distribution of earnings from work while on claim z_t is a mass point equal to 0.15, which implies that the unemployed worker can get labor earnings equal to 0.15 in each period of unemployment; the fixed cost of work while on claim $\kappa = 0.12$.

Figure 4: Potential benefits duration at registration date (left panel) and treatment date (right panel)



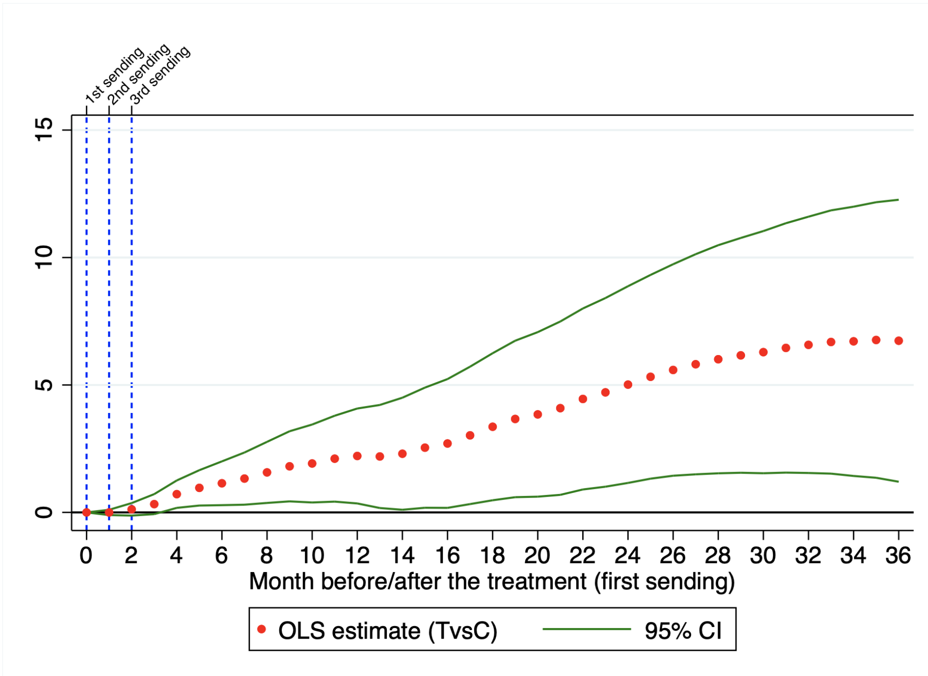
Note: This figure displays the histogram of potential benefits duration at registration date (left panel) and treatment date (right panel) for the treated group, the control group and the super control group.

Figure 5: Intention to treat effects on work while on claim at the extensive margin



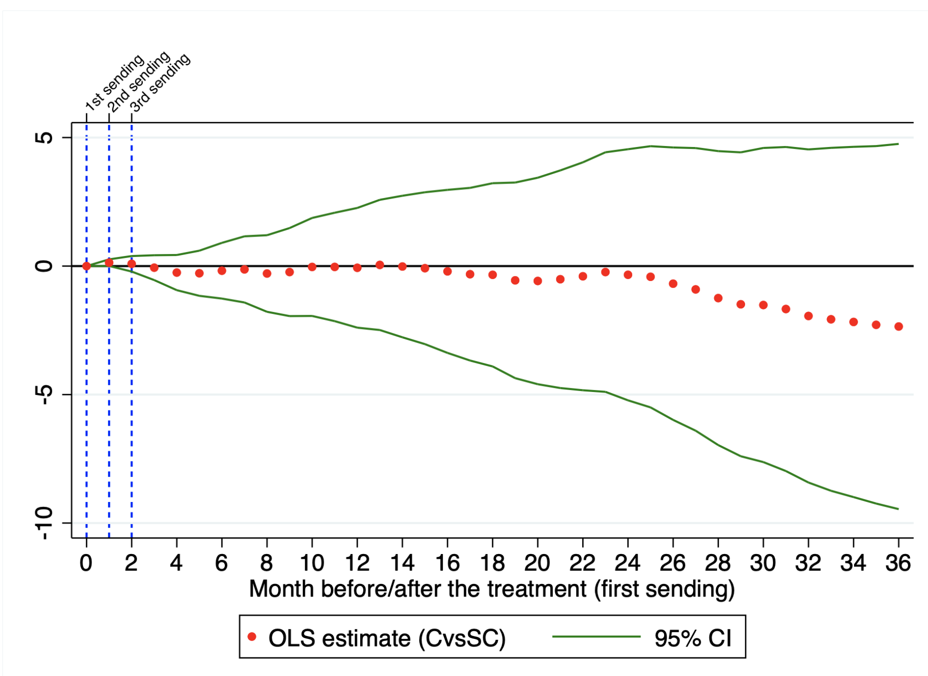
Note: Each red dot denotes the point estimate for intention to treat effect at a given time horizon based on OLS regressions (i.e. coefficient β in equation (7)) on the indicator variable equal to one from the first month in which the individuals starts working while on claim (the variable remains equal to one in months in which the individual does not work while on claim but has worked while on claim previously). The green lines denote 95% confidence interval for the corresponding point estimate where standard errors are clustered at the agency level. All estimations include covariates that correspond to stratum variables reported in Table 2 as well as entry months and regional fixed effects. The results for 3, 6, 12 and 36 months durations are presented in Table B2 in Appendix B.

Figure 6: Intention to treat effects on the cumulative number of hours worked while on claim



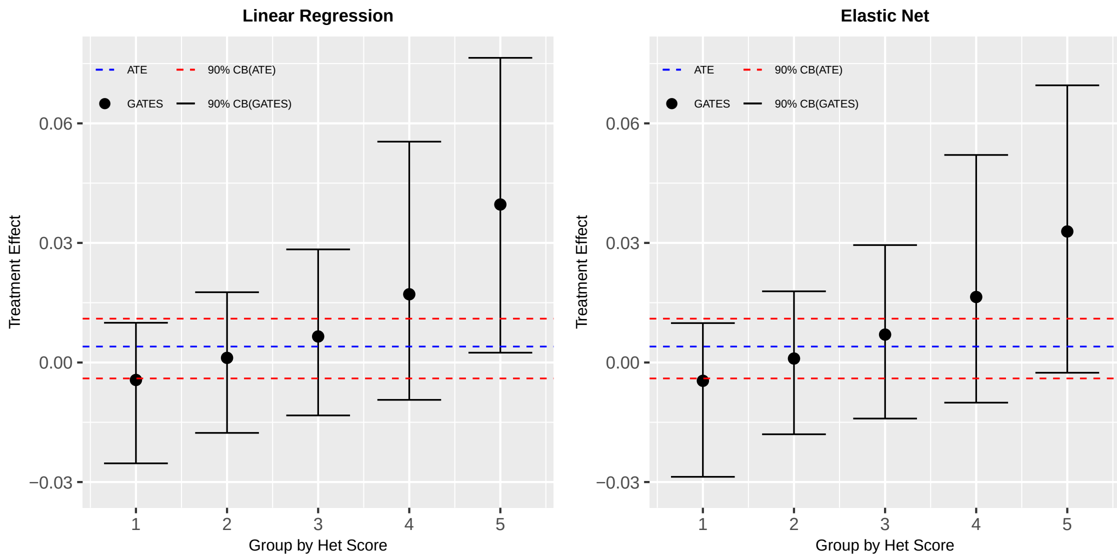
Note: Each red dot denotes the point estimate for intention to treat effect at a given time horizon based on OLS regressions (i.e. coefficient β in equation (7)). The green lines denote 95% confidence interval for the corresponding point estimate where standard errors are clustered at the agency level. All estimations include covariates.

Figure 7: Comparison of the cumulative number of hours worked while on claim between control and super control group



Note: Each red dot denotes the point estimate for being assigned to the control group compared to super control group at a given time horizon based on OLS regressions (i.e. coefficient δ in equation (7)). The green lines denote 95% confidence interval for the corresponding point estimate where standard errors are clustered at the agency level. All estimations include covariates.

Figure 8: GATES of prob. to work while on claim at least once



Note: The outcome - probability to work while on claim at least once - is measured 12 months after the treatment date. The results are presented for the two best ML methods regarding this outcome : Linear Regression and Elastic Net. Heterogeneity groups are formed using the ML proxy distribution $\hat{S}(X_i)$ which we cut at 50^{th}, 75^{th}, 90^{th}, 95^{th} percentiles. For example, Group 1 corresponds to the bottom 50% of $\hat{S}(X_i)$ and Group 5 to the top 5%. The parameter estimates and confidence intervals are computed as medians over 100 splits, with nominal levels adjusted to account for the splitting uncertainty.

A Appendix

A.1 Unemployment Insurance in France

Eligibility conditions

To qualify for unemployment benefits, the claimant must satisfy the following conditions:

- reside in France,
- have worked at least 122 days or 610 hours (4 months) in the last 28 months (or in the last 36 months for job seekers aged 50 and over) before becoming unemployed,
- have involuntarily lost his/her job (termination by the employer, the end of a fixed-term employment contract or an assignment contract, termination by mutual agreement or resignation for a valid reason),
- be registered as a job seeker with "Pôle emploi",
- be actively seeking employment.

Potential benefit duration

The potential benefit duration is computed based on the principle of "a day of work equals a day of compensation". Claimants must have worked at least 4 months before becoming unemployed. Benefits are then paid for a minimum period of 4 months and a maximum period of 24 months for job seekers aged under 50, and 36 months for job seekers aged over 50.

Benefits

Benefits are calculated on the basis of a daily reference wage. The reference wage is based on earnings subject to contributions during the 12 calendar months prior to the last day of paid work[26]. It is calculated as follows:

$$\text{Daily reference wage } = \frac{\text{Earnings during the past 12 months}}{\text{Number of working days during the past 12 months (up to 365 days)}}$$

The daily benefit is equal to the highest of the following amounts:

- 40.4% of the daily reference wage + a set amount (11.84 euros in 2017)
- 57% of the daily reference wage

This amount cannot be below 28.86 euros or exceed 75% of the daily reference wage.

Monthly benefits, denoted b in the text, are then computed as the number of days in a month times daily benefit.

[26] Up to a limit of 4 times the social security ceiling (13,076 euros per month).

Part-time benefits

The part-time unemployment insurance scheme allows unemployed workers to work on non-regular jobs while on claim. They are allowed to work for any employer, including their past employers. For the sake of simplicity, the text only describes the rules in *net* terms for a job seeker who earned the minimum wage before unemployment. Nevertheless, the rules have been designed in *gross* terms. The marginal benefit reduction rate in gross terms is 70%, meaning that for each euro earned from work, 0.70 cents are deducted from the benefits.

When both the social contributions paid on the wage and on the benefits are deducted, the net financial gain of working is much lower as explained in the text. The contributions on wage amount to around 23% of the gross wage. Moreover, the social contributions on benefits for a job seeker who earned the minimum wage before unemployment represent 4.5%. For job seekers who earned more than the minimum wage before unemployment, the social contributions on benefits represent 9.6%. The net marginal benefit reduction rate is then comprised between 82% ($= \frac{70\%}{1-23\%}(1-9.6\%)$) and 87%($= \frac{70\%}{1-23\%}(1-4.5\%)$).

Evolution of the unemployment insurance capital

At the beginning of her claim, the job seeker is informed about her monthly benefits b and about her potential benefit duration. The initial unemployment insurance capital B_0 is equal to the potential benefit duration times the level of benefits. If job seekers are totally unemployed all along their claim and receive their benefits each month, their benefits will lapse after their potential benefit duration. When job seekers are only paid part of their benefits in a given month, the unpaid amount is rolled over to a later month in the claim, so the capital depreciates at a slower pace. Working while on claim is thus a way to delay the initial exhaustion date. The exhaustion date can be delayed without any limitation. Besides, after the initial benefit entitlement has expired, individuals can be eligible for a new entitlement period at the exhaustion of the unemployment benefits related to their current entitlement period. To do so, job seekers must meet less restrictive eligibility requirements. They must have worked at least 1 month while on claim (instead of 4 months for a first claim). The new potential benefit duration is still calculated on the principle of "a day of work while on claim equals a day of compensation".

A.2 Job search model solution

Maximization of program (4) with respect to the search effort e_t yields the first order condition:

$$1 = \lambda'(e_t)\beta \left[W - U(B_{t+1})\right] \tag{A1}$$

This equation defines the optimal search effort e_t in each period. In order to analyze how e_t evolves over time one needs to know how $U(B_{t+1})$ evolves. We know that B_t decreases over time. Therefore, it suffices to know the sign of the derivative of U to know how e_t evolves. One can show that $U'(B) > 0$. The envelope theorem implies that

$$U'(B_t) = \begin{cases} \beta\left[1 - \lambda(e_t)\right]U'(B_{t+1}) & \text{if } B_t \geq b \\ v'(c_t) & \text{otherwise} \end{cases} \tag{A2}$$

In equation (A2), the case where $U'(B_t) = v'(c_t)$ arises the period just before the total exhaustion of the unemployment insurance capital B_t. It shows that $U'(B_t) = v'(c_t) > 0$ in this period. Then, solving backward, condition $U'(B_t) = \beta\left[1 - \lambda(e_t)\right]U'(B_{t+1})$ in the top of the right hand side of equation (A2) shows that $U'(B_t) > 0$ in all periods, implying that $U(B_t)$ decreases over time since B_t decreases over time. Since $\lambda''(e_t) < 0$, differentiation of equation (A1) implies that

$$\frac{\mathrm{d}e_t}{\mathrm{d}U(B_{t+1})} = \frac{\lambda'(e_t)}{\lambda''(e_t)\left[W - U(B_{t+1})\right]} < 0 \tag{A3}$$

and then that the search effort e_t increases over time since $U(B_t)$ decreases over time.

Now, let us look at the choice of working while on claim. Since we look for the reservation level of earnings from work while on claim in situations where individuals accumulate unemployment benefits b and earnings from work while on claim z_t, which arise when $z_t < b+(1-\tau)z_t$, we can focus on the case $z_t < b/\tau$ without loss of generality to determine this reservation level. Maximization of program (4) with respect to Ω_t implies that individuals prefer to work while on claim (i.e. choose $\Omega_t = 1$) if and only if this yields utility gains $\Delta > 0$. The first order approximation of the utility gains from work while on claim can be computed using equation (4):

$$\Delta \simeq \left[z_t(1-\tau) - \kappa\right]v'(b) + \beta\left[1 - \lambda(e_t)\right]U'(B_{t+1})\frac{\mathrm{d}B_{t+1}}{\mathrm{d}z_t}$$

Since equation (3) implies that $\mathrm{d}B_{t+1}/\mathrm{d}z_t = \tau$, using equation (A2) we get:

$$\Delta \simeq \left[z_t(1-\tau) - \kappa\right]v'(b) + \tau z_t U'(B_t) \tag{A4}$$

The first term of the right hand side, $\left[z_t(1-\tau) - \kappa\right]v'(b)$, corresponds to the increase in the marginal utility of the current period induced by the increase in current consumption and the second term, $\tau z_t U'(B_t)$, corresponds to the increase in the future expected consumption. From equation (A2) we know that $U'(B_t)$ increases along the unemployment spell, because $\beta(1 - e_t\lambda) < 1$ implies that $U'(B_t) < U'(B_{t+1})$. This property, together with equation (A4), implies that the incentives to work while on claim increase over time.

Now, let us show that equation (A4) implies that the effects of the part-time unemployment insurance scheme on the propensity to work while on claim depend on a single parameter, the dynamic marginal taxation rate, which encapsulates all the parameters of the part-time unemployment insurance scheme.

The expected discounted income from work while on claim in period t for an individual who gets benefits until the exhaustion date T – i.e. period T where $B_T = 0$ and $B_{T-1} > 0$ according to the law of motion (3)– is equal to the instantaneous income, $z_t(1-\tau)$, plus the future income that the individual can expect T if she is still unemployed in that period $T-1$. Note that, for the sake of simplicity in this discrete time framework, we assume that the taxed earnings from work while on claim increase the income in the last period before the exhaustion date, and neglect the situation where these taxed earnings move the exhaustion date, without loss of generality. Thus, the expected discounted income from working while on claim in period t in the neighborhood of $c_T = b$ is equal to

$$y_t = z_t(1-\tau) + \tau z_t \beta^{T-t} \mathbb{E}_t \left(\prod_{j=t}^{T-1} [1 - \lambda(e_j)] \right)$$

By definition, the dynamic marginal taxation rate in period t, denoted by m_t, is equal to $1 - (\mathrm{d}y_t/\mathrm{d}z_t)$, which yields, from the previous equation

$$m_t = \tau \left[1 - \beta^{T-t} \mathbb{E}_t \left(\prod_{j=t}^{T-1} [1 - \lambda(e_j)] \right) \right] \tag{A5}$$

Using equation (A2) to compute $U'(B_t)$ recursively from the last period T in which unemployed benefits are collected, we get, in the neighborhood of $c_T = b$:

$$U'(B_t) = \beta^{T-t} \mathbb{E}_t \left(\prod_{j=t}^{T-1} [1 - \lambda(e_j)] \right) v'(b) \tag{A6}$$

From equations (A5) and (A6), we get

$$\tau U'(B_t) = v'(b) \left(\tau - m_t \right) \tag{A7}$$

Substituting this expression of $\tau U'(B_t)$ in equation (A4) yields

$$\Delta \simeq z_t v'(b) \left(1 - m_t - \frac{\kappa}{z_t} \right) \tag{A8}$$

where m_t is defined by equation (A5). Equation (A8) implies that it is worth working while on claim in period t if and only if

$$z_t(1 - m_t) > \kappa$$

A.3 Randomization Inference

This appendix evaluates the robustness of our results to randomization based inference.

Contrary to conventional inference (cluster-robust p-value based on large sample approximations) which aims to account for sampling uncertainty, randomization based inference accounts for the uncertainty created by the treatment assignment itself. This method, first proposed by Fisher (1936), is increasingly used in experimental papers as an alternative method to perform statistical inference (Bloom et al. (2006), Ichino and Schündeln (2012), Fujiwara and Wantchekon (2013)). Moreover, Young (2019) recently demonstrated that a substantial part of seemingly significant results, obtained with conventional methods, appear to be insignificant when statistical tests are conducted with randomization based methods.

The idea behind randomization inference is intuitive. It makes use of the knowledge that the researcher has on the randomization process to generate placebo estimates of the treatment effect. Thus, the observed ITT estimate, coming from the actual treatment assignment, can be compared to the distribution of these placebo estimates to test for its statistical significance.

A.3.1 Implementation

First, we randomly re-assigned "treatment" in the same way as was done in the experimental setting, that is, a 2 levels stratified sampling as described in section 4.2. Then, we re-estimate the two placebo treatment effect parameters: β_r (Treated vs Control) and δ_r (Control vs Super-control) based on the same estimating equation as equation (7):[27]

$$y_i = \alpha_r + \beta_r Z_{r,i} + \delta_r C_{r,i} + \gamma_r X_i + \eta_{r,i}$$

where $Z_{r,i}$ is a dummy for being assigned to the treated group and $C_{r,i}$ is a dummy for being assigned to a treated area (i.e. being either in the treated group or in the control group but not in the super control group) in random re-assignment r.

We repeat this procedure 5000 times.[28] Finally, for a given outcome, randomization based p-value are obtained by computing the share of randomized based placebo estimates that are superior or equal (in absolute value) to the corresponding experimental estimate. For instance, we have for $\hat{\beta}$:

$$p - \text{value}^{\text{RI}}(\hat{\beta}) = \frac{\sum_{r=1}^{R} \mathbb{1}(\hat{\beta}_r \geq \hat{\beta})}{R}$$

where R is the total number of random draws (i.e. R = 5000 in our setting).

A.3.2 Results

Tables B3 and B10 present the results of randomization inference tests. In particular, Table B3 presents the results for part-time unemployment and Table B10 presents the results for unemployment. We only present the results for outcomes on which we measured a statistically significant treatment effect with cluster-robust p-value.

[27] All the results reported below are based on the specification including covariates.

[28] As a comparison Young (2019), used 10 000 repetitions but did not detect any appreciable difference above 2000 draws.

Overall, the p-values obtained with randomization inference tests are very close to the cluster-robust model based p-values. To some extent this was expected, considering the relatively large sample size in our experiment. In particular, almost all (i.e. 7 out of 8) estimates that are statistically significant at 5% with model based inference are still significant at 5% with randomization based inference. Both conventional and randomized based inference thus support the view that the treatment had a statistically significant effect on both the propensity to work while on claim and the probability to exit from unemployment (i.e. lock-in effect).

A.4 Heterogeneous treatment effects

This appendix describes the estimation of heterogeneous treatment effects following the approach of Chernozhukov et al. (2018).

The Conditional Average Treatment Effect (CATE) function is:

$$s_0(X) = E[Y(1)|X] - E[Y(0)|X]$$

where X denotes a vector of covariates and Y is the outcome of interest.

We start by splitting evenly the whole sample into a *main* subsample, used to predict $s_0(X)$, and an *auxiliary* subsample, used to estimate the key features of $s_0(X)$. The auxiliary sample is used to predict $s_0(X)$ with machine learning (e.g. Elastic Net, Random Forest). We estimate the model separately for observations in the treatment and control groups, resulting in two prediction models. We then compute the estimated outcome for each observation in the main sample under both treatment statuses, i.e. $\hat{Y}^T(X_i)$ and $\hat{Y}^C(X_i)$ and the estimated propensity score $\hat{p}(X_i)$. Finally we compute $\hat{S}(X_i) = \hat{Y}^T(X_i) - \hat{Y}^C(X_i)$ our proxy for the true CATE, $s_0(X_i)$. However, except under strong assumptions about the ML estimator, this proxy predictor is likely to be an inconsistent estimate of $s_0(X_i)$. This motivates the second step of the procedure where the ML proxy is *post-processed* into the estimates of the key features of $s_0(X_i)$.

To estimate the best linear predictor of the conditional average treatment effect function we run the following weighted regression

$$y_i = \alpha + \beta_1(Z_i - \hat{p}(X_i)) + \beta_2(Z_i - \hat{p}(X_i))(\hat{S}(X_i) - \mathbb{E}\hat{S}(X_i)) + \theta\hat{Y}^C(X_i) + \epsilon_i \tag{A9}$$

where Z_i is an indicator variable equal to 1 for treated individuals, $\mathbb{E}$ denotes the empirical expectation with respect to the main sample and the weights are equal to

$$w(X_i) = \frac{1}{\hat{p}(X_i)(1 - \hat{p}(X_i)))}$$

Chernozhukov et al. (2018) show that $\beta_1 + \beta_2(\hat{S}(X_i) - \mathbb{E}\hat{S}(X_i))$ identifies the best linear predictor of the conditional average treatment effect $s_0(X_i)$. Besides, β_1 identifies the average treatment effect (ATE) and rejecting the null hypothesis that $\beta_2 = 0$ therefore means that there is both heterogeneity and $\hat{S}(X_i)$ captures a relevant part of this heterogeneity. Table B4 presents our estimates of the best linear predictor of the conditional average treatment effect.

Next we estimate the sorted group average treatment effects. Here the parameters of interest are $\mathbb{E}[s_0(X_i)|G]$, where G is an indicator of group membership based on our proxy predictor $\hat{S}(X_i)$. As shown by Chernozhukov et al. (2018), we can recover these parameters by estimating the following weighted regression:

$$y_i = \alpha + \sum_{k=1}^{5} \gamma_k(Z_i - \hat{p}(X_i)) * \mathbb{1}(G_k) + \theta\hat{Y}^C(X_i) + \epsilon_i \tag{A10}$$

where the weights are the same as in equation (A9) and $\mathbb{1}(G_k)$ is equal to 1 if $\hat{S}(X_i)$ lies in the k^{th} interval and 0 otherwise. We cut $\hat{S}(X_i)$ at 50^{th}, 75^{th}, 90^{th}, 95^{th} percentiles. In particular, Group 1 corresponds to the observations that lie in the bottom 50% of $\hat{S}(X_i)$ and Group 5 corresponds to the observations that lie in the top 5% $\hat{S}(X_i)$. Table B5 displays the results we obtained by estimating equation (A10).

A.5 Welfare effects

This appendix provides an analysis of the welfare impact of part-time unemployment benefits in the standard static framework of Baily (1978) and Chetty (2006). We start by presenting the standard decomposition between the mechanical and the behavioral effects on unemployment insurance expenditure induced by changes in the unemployment insurance parameters. Then, we analyze the welfare impact of a change in expenditure induced by changes in various parameters.

A.5.1 Mechanical and behavioral effects

The welfare function of a representative unemployed worker

$$W(b, u)$$

depends on the vector $b = (b_1, ..., b_n)$ of n unemployment insurance parameters, that can include the unemployment benefit level, the tax rate, the potential benefit duration, rules about part-time unemployment benefits, eligibility rules and any other relevant parameter. The welfare function also depends on u, the unemployment rate, i.e. the share of the period spent unemployed. The unemployment rate chosen by the unemployed worker, which depends on b, is denoted by $u(b) = \arg\max_u W(b, u)$.

The expenditure net of tax of the unemployment insurance agency

$$E(b, u(b))$$

depends on the vector b and on the unemployment rate.

The unemployment insurance agency maximizes the welfare of the unemployed worker subject to the budget constraint:

$$\max_b W(b, u(b)) \text{ subject to } E(b, u(b)) \leq B$$

where B is an exogenous endowment.

The Lagrangian of this maximization problem is

$$\mathcal{L} = W(b, u(b)) + \lambda \left[B - E(b, u(b))\right]$$

where $\lambda \geq 0$ stands for the Lagrange multiplier.

Assuming that the maximization problem is well-behaved, the optimal vector of unemployment insurance parameters satisfies the budget constraint

$$E(b, u(b)) = B$$

and the first order conditions

$$\frac{\partial W(b, u(b))}{\partial b_i} = \lambda \left[\frac{\partial E(b, u(b))}{\partial b_i} + \frac{\partial E(b, u(b))}{\partial u}\frac{\partial u(b)}{\partial b_i}\right], i = 1, .., n \tag{A11}$$

The right-hand side of this equation shows that the effect of a change in parameter b_i on the unemployment insurance expenditure can be decomposed into a mechanical effect, equal to $\frac{E(b,u(b))}{\partial b_i}$, and a behavioral effect, equal to $\frac{E(b,u(b))}{\partial u}\frac{\partial u(b)}{\partial b_i}$, accounting for the reaction of the unemployed worker. Since our experiment shows that the behavioral effect is equal to zero when the dynamic marginal tax rate on earnings from work while on claim drops, decreasing this marginal tax rate necessarily increases the expenditure as a consequence of the mechanical effect.

A.5.2 Welfare effects of a change in expenditure induced by changes in various parameters

From the optimality conditions, it can be shown that changing the net expenditure by the amount $\mathrm{d}B$ with different parameters b_i has the same (first-order) welfare effect in the neighborhood of the optimal vector b but has different welfare effects that cannot be compared outside the optimum without further assumptions on the welfare function.

To show this, let us assume that the unemployment insurance agency changes parameter b_i only when B changes by the amount $\mathrm{d}B$. This implies that

$$\left[\frac{\partial E(b,u(b))}{\partial b_i}+\frac{\partial E(b,u(b))}{\partial u}\frac{\partial u(b)}{\partial b_i}\right]\mathrm{d}b_i=\mathrm{d}B$$

Thus, the welfare effect of the change $\mathrm{d}B$ is equal to

$$\mathrm{d}W=\frac{\partial W(b,u(b))}{\partial b_i}\mathrm{d}b_i=\frac{\partial W(b,u(b))}{\partial b_i}\frac{1}{\frac{\partial E(b,u(b))}{\partial b_i}+\frac{\partial E(b,u(b))}{\partial u}\frac{\partial u(b)}{\partial b_i}}\mathrm{d}B \tag{A12}$$

Equations (A11) and (A12) show that

$$\frac{\mathrm{d}W}{\mathrm{d}B}=\lambda \text{ for all } b_i$$

at the optimum only, meaning that outside the optimum the welfare impact of an increase in the unemployment insurance expenditure depends on the parameter that is adjusted. To see what occurs outside the optimum, it is useful to rewrite equation (A12) as follows

$$\mathrm{d}W=\frac{\eta_i}{1+\gamma_i}\mathrm{d}B \tag{A13}$$

where $\eta_i=\frac{\partial W(b,u(b))}{\partial b_i}/\frac{\partial E(b,u(b))}{\partial b_i}$ is the welfare gain associated with an increase of one euro in expenditure induced by change in b_i and $\gamma_i=\left(\frac{\partial E(b,u(b))}{\partial u}\frac{\partial u(b)}{\partial b_i}\right)/\frac{\partial E(b,u(b))}{\partial b_i}$ is the ratio of the behavioral over the mechanical effects, also called the fiscal externality. This equation clearly shows that the fiscal externality reduces the welfare gains associated with change in parameter b_i that raises expenditure. However, the change in welfare also depends on η_i

In general $\eta_i\neq\eta_j$ when $i\neq j$, as illustrated for example by Schmieder and von Wachter (2016) when comparing the welfare effects of changes in unemployment benefits level and unemployment benefits potential duration. Therefore, equation (A13) implies that differences in behavioral effects associated with parameters b_i or b_j do not yield insights about the relative welfare impact of changes in b_i versus b_j outside the optimum without information about η_i and η_j.

To go farther, it is possible to make assumptions like Lee et al. (2019) who assume that $\eta_i\approx\eta_j$

when comparing changes in taxation of earnings from work while on claim and changes in benefit level, or Schmieder and von Wachter (2016) who make functional form assumptions when comparing the welfare effects of changes in unemployment benefits level and unemployment benefits potential duration. Another way lies in acquiring information about the willingness to pay for each parameter change in the spirit of Hendren and Sprung-Keyser (2020). Given the complexity of the part-time unemployment benefit schemes, we leave these issues for future research.

A.6 Emails contents

Figure A1: Screenshot of the message received by job seekers (example with gains in gross terms)

pole-emploi.fr

Vos services en ligne

- Accéder à votre espace personnel
- Votre recherche d'emploi
- Vos droits et démarches
- Les conseils de Pôle emploi
- Emploi en régions
- Foire aux questions

Accueil pole-emploi.fr

Bonjour,

Vous êtes aujourd'hui demandeur d'emploi indemnisable au titre de l'Allocation de Retour à l'Emploi (ARE). **Nous vous informons que vous pouvez travailler sans perdre votre allocation chômage.** Cette possibilité de cumuler votre salaire et votre allocation vous permet:
- **De disposer d'un revenu plus élevé** que votre seule allocation mais sans dépasser le montant de votre ancien salaire brut. Pôle emploi ne retire que 70 centimes d'allocation par euro brut gagné.
- **D'être indemnisé plus longtemps**. Le nombre de jours d'allocations non perçues en raison de votre cumul reste acquis.

A la fin de vos allocations, vous pouvez bénéficier de nouveaux droits grâce à cette activité dès que vous avez exercé 150 heures d'activité réduite.

Illustration:
Mme Dubois augmente son revenu mensuel de 180 euros brut si elle travaille 9 jours dans le mois au SMIC.

Mme Dubois bénéficie d'une allocation de 930 euros pour un mois de 31 jours sans activité. Elle travaille 9 jours sur un mois donné pour un salaire brut de 600 euros. Pôle emploi retire 70 centimes par euro brut gagné. Pôle emploi retire donc 420 euros brut (=0,7 x 600 euros) et continue à verser 510 euros d'allocation. Mme Dubois obtient un revenu mensuel brut de 1110 euros (600 euros de salaire brut + 510 euros d'allocation brute restante), **supérieur de 180 euros** aux allocations perçues pour un mois de chômage complet (930 euros).

Simuler le montant de votre allocation en cas de reprise d'activité

En pratique:
Chaque mois, l'activité professionnelle doit être déclarée au moment de votre actualisation mensuelle. Une copie du bulletin de salaire doit être envoyée aux services de Pôle emploi.

Pour plus d'information:
Les règles de cumul de votre allocation avec un salaire sont détaillées en pièce jointe.

Cordialement,
L'équipe Pôle emploi

Attention :
Ce courriel vous est envoyé automatiquement, merci de ne pas utiliser la fonction "répondre à l'expéditeur".

Vous disposez d'un droit d'accès et de rectification aux informations qui vous concernent auprès de Pôle emploi conformément à la loi du 6 janvier 1978, modifiée, relative à l'informatique,aux fichiers et aux libertés.

Figure A2: Screenshot of the message received by job seekers (example with gains in net terms)

pole-emploi.fr

Vos services en ligne

- Accéder à votre espace personnel
- Votre recherche d'emploi
- Vos droits et démarches
- Les conseils de Pôle emploi
- Emploi en régions
- Foire aux questions

Accueil pole-emploi.fr

Bonjour,

•••

Mme Dubois augmente son revenu mensuel de 60 euros net si elle travaille 9 jours dans le mois au SMIC.

Mme Dubois bénéficie d'une allocation de 930 euros brut pour un mois de 31 jours sans activité, soit 889 euros net. Elle travaille 9 jours sur un mois donné pour un salaire brut de 600 euros, soit 462 euros net. Pôle emploi retire 70 centimes par euro brut gagné. Pôle emploi retire donc 420 euros brut (=0,7 x 600 euros) et continue à verser 510 euros brut d'allocation, soit 487 euros net. Mme Dubois obtient un revenu mensuel net de 949 euros (462 euros de salaire net + 487 euros d'allocation nette restante), **supérieur de 60 euros** aux allocations perçues pour un mois de chômage complet (889 euros).

Simuler le montant de votre allocation en cas de reprise d'activité

En pratique:
Chaque mois, l'activité professionnelle doit être déclarée au moment de votre actualisation mensuelle. Une copie du bulletin de salaire doit être envoyée aux services de Pôle emploi.

Pour plus d'information:
Les règles de cumul de votre allocation avec un salaire sont détaillées en pièce jointe.

Cordialement,
L'équipe Pôle emploi

Attention :
Ce courriel vous est envoyé automatiquement, merci de ne pas utiliser la fonction "répondre à l'expéditeur".

Vous disposez d'un droit d'accès et de rectification aux informations qui vous concernent auprès de Pôle emploi conformément à la loi du 6 janvier 1978, modifiée, relative à l'informatique,aux fichiers et aux libertés.

B Supplementary Tables

Table B1: Summary statistics on the overall sample

	Means				p-value of the difference		
	All	T	C	SC	T - C	T - (C + SC)	T = C = SC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Job seekers characteristics							
Worked while on claim before treatment	.127	.126	.126	.13	.868	.371	.414
Still on claim at treatment date	.901	.901	.9	.905	.858	.354	.404
Female	.477	.479	.479	.472	.946	.403	.138
Age	31.5	31.511	31.498	31.484	.863	.97	.977
Young	.419	.416	.418	.43	.436	.514	.265
Prime age	.442	.446	.445	.429	.735	.24	.237
Senior	.139	.139	.137	.141	.531	.342	.632
Lower education level	.224	.224	.222	.228	.321	.237	.462
Intermediate education level	.435	.431	.433	.446	.332	.531	.195
Higher education level	.341	.345	.345	.326	.887	.219	.365
Last contract duration $\leq$ to 12 months	.367	.365	.365	.375	.941	.374	.567
Last contract duration $\leq$ to 3 months	.106	.105	.106	.109	.898	.669	.754
Potential benefit duration	601.958	602.089	602.836	599.949	.632	.522	.807
... < 730 days	.469	.47	.468	.471	.659	.677	.891
... ≥ 730 days	.531	.53	.532	.529	.659	.677	.891
Daily Reference Wage	60.245	60.457	60.472	59.371	.957	.603	.866
... ≤ the mean	.669	.667	.669	.673	.492	.964	.698
... > the mean	.331	.333	.331	.327	.492	.964	.698
Unemployment entry month							
July 2016	.156	.157	.154	.156	.146	.17	.315
August 2016	.161	.161	.163	.157	.352	.091	.126
September 2016	.288	.288	.288	.289	.89	.774	.938
October 2016	.232	.231	.233	.231	.389	.398	.648
November 2016	.163	.163	.162	.167	.781	.401	.522
Local Agencies characteristics							
Unemployment rate	13.705	13.712	13.712	13.678	.983	.922	.994
Share of part time unemp	.435	.434	.434	.44	.245	.329	.318
Share of recurrent job seekers	.429	.429	.429	.428	.37	.958	.612
Exit rate from unemp	.064	.064	.064	.064	.215	.526	.416
Number of claimants	4365.983	4367.24	4378.652	4338.219	.227	.701	.398
Number of participants	223.505	225.884	226.813	212.166	.172	.119	.129
N	147878	59112	59117	29649			

Note: This table reports descriptive statistics for the sample of individuals on January 2017 before dropping observations for individuals who were not on claim or who had already worked while on claim on 31 January 2017. Columns (1), (2), (3) and (4) report the means of individual characteristics for the treatment, the control and the super control sub-samples, respectively. Columns (5)–(7) report the p-values for the difference between assigned to treatment (T) and assigned to control (C) (column 5), the difference between assigned to treatment (T) and non assigned (C + SC), and for the joint significance of assignment status (T, C and SC). See Table 2 for the definition of each covariate.

Table B2: Treatment effect on the probability to work while on claim

	3 months		6 months		12 months		36 months	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A : Prob. to work while on claim at least once								
Treated (β)	0.0037**	0.0037**	0.0044**	0.0044**	0.0037	0.0038	0.0033	0.0033
	(0.0016)	(0.0016)	(0.0022)	(0.0022)	(0.0027)	(0.0027)	(0.0030)	(0.0030)
	[0.025]	[0.023]	[0.046]	[0.041]	[0.177]	[0.164]	[0.277]	[0.264]
In a treated area (δ)	-0.0021	-0.0006	0.0005	0.0037	-0.0017	0.0026	-0.0107*	-0.0038
	(0.0024)	(0.0020)	(0.0034)	(0.0026)	(0.0045)	(0.0032)	(0.0063)	(0.0040)
	[0.384]	[0.765]	[0.874]	[0.147]	[0.708]	[0.417]	[0.090]	[0.345]
Mean super control	0.06		0.11		0.19		0.30	
Panel B : Prob. to work while on claim at least two months								
Treated (β)	0.0013	0.0013	0.0033**	0.0033**	0.0045**	0.0046**	0.0037	0.0038
	(0.0010)	(0.0010)	(0.0017)	(0.0016)	(0.0022)	(0.0022)	(0.0027)	(0.0027)
	[0.221]	[0.219]	[0.044]	[0.041]	[0.043]	[0.037]	[0.184]	[0.163]
In a treated area (δ)	-0.0002	0.0005	0.0003	0.0023	0.0011	0.0045*	-0.0057	0.0002
	(0.0013)	(0.0013)	(0.0023)	(0.0019)	(0.0034)	(0.0026)	(0.0052)	(0.0036)
	[0.887]	[0.719]	[0.910]	[0.233]	[0.734]	[0.083]	[0.275]	[0.965]
Mean super control	0.03		0.06		0.12		0.23	
Panel C : Prob. to work while on claim at least three months								
Treated (β)	0.0003	0.0003	0.0030**	0.0030***	0.0038**	0.0039**	0.0047**	0.0049**
	(0.0005)	(0.0005)	(0.0012)	(0.0012)	(0.0018)	(0.0018)	(0.0024)	(0.0024)
	[0.624]	[0.616]	[0.011]	[0.009]	[0.035]	[0.029]	[0.050]	[0.037]
In a treated area (δ)	0.0005	0.0005	-0.0006	-0.0001	0.0008	0.0029	-0.0041	0.0001
	(0.0007)	(0.0006)	(0.0016)	(0.0015)	(0.0027)	(0.0023)	(0.0044)	(0.0032)
	[0.434]	[0.430]	[0.694]	[0.955]	[0.771]	[0.203]	[0.345]	[0.969]
Mean super control	0.01		0.03		0.08		0.17	
Covariates	No	Yes	No	Yes	No	Yes	No	Yes
N	115547	115547	115547	115547	115547	115547	115547	115547

Note: Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. p-values are reported in brackets. Each duration (i.e. 3, 6, 12 and 36 months) indicates the elapsed time since treatment. Covariates include all stratum variables reported in Table 2 as well as entry months and regional fixed effects. "Treated" designates individuals who were assigned to treatment (ITT estimate), "In treated area" refers to those registered at employment agencies where half of individuals have been treated and "super control" designates individuals registered at employment agencies where nobody has been treated. The number of observations N corresponds to the number of individuals.

Table B3: Treatment effect on part-time unemployment : model vs randomization based inference

	3 months			12 months			36 months		
	Coeff.	p-value		Coeff.	p-value		Coeff.	p-value	
	estimate	model based	rand. inference	estimate	model based	rand. inference	estimate	model based	rand. inference
Panel A : Extensive margin									
Panel A.1 : Cumulative number of months with work while on claim									
Treated (β)	0.0052	0.0505	0.061	0.0260	0.0156	0.015	0.0812	0.0052	0.005
In a treated area (δ)	0.0004	0.9116	0.903	0.0163	0.2090	0.210	0.0082	0.8230	0.816
Panel A.2 : Cumulative number of hours worked while on claim									
Treated (β)	0.3246	0.1043	0.115	2.2044	0.0196	0.022	6.7753	0.0156	0.021
In a treated area (δ)	-0.0628	0.7950	0.807	0.0595	0.9598	0.962	-1.5359	0.6735	0.672
Panel A.3 : Cumulative earnings (in euro) from work while on claim									
Treated (β)	5.6575	0.0246	0.027	33.7244	0.0075	0.007	107.4585	0.0052	0.007
In a treated area (δ)	-2.9677	0.3591	0.337	-8.7657	0.5753	0.572	-44.2654	0.3714	0.366
Covariates		Yes			Yes			Yes	
N		115547			115547			115547	
Panel B : Intensive margin									
Panel B.1 : Cumulative number of hours worked while on claim									
Treated (β)	-1.4552	0.5109	0.499	5.5382	0.1105	0.136	11.5298	0.1239	0.139
In a treated area (δ)	0.7782	0.7681	0.765	-2.5141	0.5842	0.577	-0.7025	0.9397	0.939
Panel B.2 : Cumulative earnings (in euro) from work while on claim									
Treated (β)	-1.6892	0.9496	0.953	88.6023	0.0469	0.061	191.0127	0.0563	0.070
In a treated area (δ)	-18.0860	0.5935	0.581	-74.0666	0.1950	0.207	-73.2656	0.5459	0.574
Covariates		Yes			Yes			Yes	
N		7435			21840			34317	

Note: This table presents the results obtained for the outcomes related to part time unemployment for both extensive margin (*Panel A*) and intensive margin (*Panel B*), that is, only for people who worked at least one hour while on claim in the period. Each duration (i.e. 3, 12, and 36 months) indicates the elapsed time since treatment. For each duration, the first two columns display the coefficient estimate and the model based p-value that are presented in section 5.2.2 and the third column corresponds to the p-value based on a two-sided randomization inference test statistic.

Table B4: Best Linear Predictor of the conditional average treatment effect

ATE (β_1)		HET (β_2)		Best ML method
Coeff.	p-value	Coeff.	p-value	
(1)	(2)	(3)	(4)	(5)
Part-time unemployment at least once - 12 months after treatment				
0.004	[0.649]	0.266	[0.080]	Linear Regression
Cumulative nb. of months worked in part-time unemployment - 12 months after treatment				
0.025	[0.196]	0.090	[1.000]	Linear Regression
Cumulative earnings from work while on claim - 12 months after treatment				
31.84	[0.144]	0.336	[0.364]	Elastic Net
Out of unemployment in last month before benefit exhaustion				
0.005	[0.417]	-0.066	[0.737]	Boosting

Note: The parameter estimates and p-values - displayed in brackets - are computed as medians over 100 splits, with nominal levels adjusted to account for the splitting uncertainty.

Table B5: GATES of Most and Least Affected Groups

Heterogeneity group			Best ML method
Top 5% (γ_5)	Bottom 50% (γ_1)	Difference ($\gamma_5 - \gamma_1$)	
(1)	(2)	(3)	(4)
Part-time unemployment at least once - 12 months after treatment			
0.038	-0.001	0.038	Linear Regression
[0.038]	[1.000]	[0.047]	
Cumulative nb. of months worked in part-time unemp. - 12 months after treatment			
0.113	0.027	0.088	Linear Regression
[0.274]	[0.696]	[0.579]	
Cumulative earnings from work while on claim - 12 months after treatment			
194.80	16.16	175.80	Elastic Net
[0.500]	[0.665]	[0.605]	
Out of unemployment in last month before benefit exhaustion			
-0.012	-0.001	-0.011	Boosting
[1.000]	[1.000]	[1.000]	

Note: The parameter estimates and p-values - displayed in brackets - are computed as medians over 100 splits, with nominal levels adjusted to account for the splitting uncertainty.

Table B6: Correlations between individual and local characteristics and the probability of part-time unemployment 3 months after the treatment in the super control group

Outcome measured 3 months after the treatment	Prob. to work while on claim at least once	Cumulated nb. of months worked while on claim	Cumulated nb. of hours worked while on claim	Cumulated earnings from work while on claim
	(1)	(2)	(3)	(4)
Job seekers characteristics				
Female	0.012***	0.023***	1.044**	14.795**
	(0.0033)	(0.0055)	(0.4290)	(6.2267)
Young	0.006	0.002	-0.868*	-5.699
	(0.0040)	(0.0070)	(0.4909)	(6.4642)
Senior	-0.021***	-0.032***	-2.207**	-24.535*
	(0.0058)	(0.0103)	(0.8530)	(12.4490)
Higher education	-0.015***	-0.026***	-0.801	-4.669
	(0.0040)	(0.0068)	(0.4973)	(6.2285)
Lower secondary education	-0.009**	-0.017**	-1.177***	-10.093*
	(0.0042)	(0.0070)	(0.4414)	(5.3815)
Potential benefit duration	0.000	0.000	0.001	0.016
	(0.0000)	(0.0000)	(0.0014)	(0.0193)
Daily Reference Wage	0.000**	0.000***	0.035***	0.698***
	(0.0000)	(0.0001)	(0.0072)	(0.1613)
Last contract inf. to 3 m.	0.009	0.018	1.483*	15.822
	(0.0075)	(0.0116)	(0.8350)	(9.8805)
Last contract inf. to 12 m.	0.013**	0.012	0.941	10.170
	(0.0055)	(0.0094)	(0.6926)	(9.3814)
Local agencies characteristics				
Number of participants	-0.000	-0.000	-0.006	-0.034
	(0.0001)	(0.0001)	(0.0051)	(0.0830)
Number of claimants	0.000*	0.000*	0.000	0.002
	(0.0000)	(0.0000)	(0.0003)	(0.0038)
Share of part-time unemp.	0.049	0.055	1.488	0.951
	(0.0431)	(0.0704)	(5.5228)	(88.3497)
Exit rate from unemp	-0.133	0.022	3.992	-75.241
	(0.3174)	(0.4961)	(37.5766)	(492.3760)
Share of recurrent job seekers	-0.057	-0.067	3.723	68.471
	(0.0684)	(0.1109)	(7.2266)	(103.8840)
Unemployment rate	-0.000	-0.000	-0.052	-0.826
	(0.0004)	(0.0006)	(0.0429)	(0.5294)
Region FE	Yes	Yes	Yes	Yes
Entry month FE	Yes	Yes	Yes	Yes
N	23156	23156	23156	23156
R^2	0.007	0.006	0.006	0.009

Note: Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. Each column displays the results from an OLS regression of the associated outcome on the listed covariates as well as region and cohort (defined by the calendar month of entry into unemployment) fixed effects. The number of observations N corresponds to the number of individuals.

Table B7: Correlations between individual and local characteristics and the probability of part-time unemployment 12 months after the treatment in the super control group

Outcome measured 12 months after the treatment	Prob. to work while on claim at least once	Cumulated nb. of months worked while on claim	Cumulated nb. of hours worked while on claim	Cumulated earnings from work while on claim
	(1)	(2)	(3)	(4)
Job seekers characteristics				
Female	0.035***	0.193***	13.562***	169.492***
	(0.0052)	(0.0231)	(2.1664)	(28.2983)
Young	0.008	-0.103***	-12.496***	-117.510***
	(0.0068)	(0.0250)	(2.3262)	(31.3109)
Senior	-0.109***	-0.300***	-24.269***	-285.148***
	(0.0100)	(0.0446)	(4.1396)	(58.4379)
Higher education	-0.039***	-0.124***	-4.981*	-16.307
	(0.0067)	(0.0274)	(2.5520)	(32.9411)
Lower secondary education	-0.004	-0.048*	-5.076**	-38.191
	(0.0059)	(0.0248)	(2.1947)	(28.0274)
Potential benefit duration	0.000***	0.000***	0.027***	0.307***
	(0.0000)	(0.0001)	(0.0061)	(0.0788)
Daily Reference Wage	0.000**	0.002***	0.355***	6.632***
	(0.0001)	(0.0004)	(0.0510)	(0.9395)
Last contract inf. to 3 m.	0.012	0.039	1.774	14.672
	(0.0111)	(0.0345)	(2.8504)	(33.7341)
Last contract inf. to 12 m.	0.002	-0.040	-2.660	-39.970
	(0.0089)	(0.0348)	(3.0241)	(38.5039)
Local agencies characteristics				
Number of participants	-0.000***	-0.001***	-0.075***	-0.889**
	(0.0001)	(0.0002)	(0.0237)	(0.3426)
Number of claimants	0.000***	0.000***	0.003***	0.043**
	(0.0000)	(0.0000)	(0.0012)	(0.0170)
Share of part-time unemp.	0.165***	0.578***	24.608	210.025
	(0.0605)	(0.2168)	(21.7140)	(324.3254)
Share of recurrent job seekers	0.091	0.426	54.738	638.739
	(0.0978)	(0.3727)	(35.4824)	(476.4667)
Exit rate from unemp.	0.290	0.507	94.238	809.370
	(0.4377)	(1.7558)	(174.9111)	(2261.9591)
Unemployment rate	0.001	-0.002	-0.307	-5.034*
	(0.0005)	(0.0022)	(0.1964)	(2.6034)
Region FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	23156	23156	23156	23156
R^2	0.018	0.019	0.026	0.035

Note: Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. Each column displays the results from an OLS regression of the associated outcome on the listed covariates as well as region and cohort (defined by the calendar month of entry into unemployment) fixed effects. The number of observations N corresponds to the number of individuals.

Table B8: Correlations between individual and local characteristics and the probability of part-time unemployment 36 months after the treatment in the super control group

Outcome measured 36 months after the treatment	Prob. to work while on claim at least once	Cumulated nb. of months worked while on claim	Cumulated nb. of hours worked while on claim	Cumulated earnings from work while on claim
	(1)	(2)	(3)	(4)
Job seekers characteristics				
Female	0.058***	0.754***	58.392***	733.635***
	(0.0062)	(0.0641)	(6.2670)	(80.8263)
Young	0.018**	-0.430***	-43.769***	-354.968***
	(0.0075)	(0.0667)	(6.5472)	(87.0175)
Senior	-0.154***	-0.538***	-50.469***	-581.447***
	(0.0126)	(0.1187)	(12.4086)	(182.4914)
Higher education	-0.076***	-0.366***	-23.598***	-150.368
	(0.0080)	(0.0713)	(7.6686)	(102.1160)
Lower secondary education	0.009	-0.126*	-18.880**	-149.567
	(0.0076)	(0.0743)	(7.4010)	(94.7158)
Potential benefit duration	0.000***	0.002***	0.125***	1.399***
	(0.0000)	(0.0002)	(0.0155)	(0.2088)
Daily Reference Wage	0.000***	0.010***	1.548***	29.057***
	(0.0001)	(0.0012)	(0.1536)	(2.7619)
Last contract inf. to 3 m.	0.027*	0.109	3.562	3.077
	(0.0139)	(0.0809)	(7.1952)	(89.1138)
Last contract inf. to 12 m.	-0.003	-0.166**	-14.454*	-198.793*
	(0.0102)	(0.0793)	(8.2918)	(110.1325)
Local agencies characteristics				
Number of participants	-0.000**	-0.003***	-0.268***	-3.381***
	(0.0001)	(0.0007)	(0.0780)	(1.0473)
Number of claimants	0.000	0.000**	0.009**	0.125**
	(0.0000)	(0.0000)	(0.0042)	(0.0581)
Share of part-time unemp.	0.164*	2.404***	177.679**	2327.809**
	(0.0923)	(0.6474)	(75.8056)	(1098.0432)
Exit rate from unemp	1.199**	1.979	48.165	-3301.319
	(0.5670)	(5.2555)	(547.9057)	(7248.3622)
Share of recurrent job seekers	0.239*	1.044	92.367	528.277
	(0.1225)	(1.0487)	(111.2905)	(1566.6654)
Unemployment rate	0.001	-0.008	-1.070*	-18.106**
	(0.0007)	(0.0060)	(0.5970)	(8.1095)
Region FE	Yes	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes
N	23156	23156	23156	23156
R^2	0.031	0.043	0.051	0.065

Note: Levels of significance: * < 0.10, ** < 0.05, *** < 0.01. Standard errors, reported in parenthesis below the coefficients, are robust and clustered at the local agency level. Each column displays the results from an OLS regression of the associated outcome on the listed covariates as well as region and cohort (defined by the calendar month of entry into unemployment) fixed effects. The number of observations N corresponds to the number of individuals.

Table B9: Treatment effect on part-time unemployment
Depending on the potential benefit duration when entering into unemployment

	$\geq$ 12 months		$\geq$ 24 months	
	(1)	(2)	(3)	(4)
Panel A : Cumulative amount of hours worked while on claim				
Treated	3.4018*	3.5381*	3.5299	3.7951
	(1.9272)	(1.9049)	(2.7031)	(2.6892)
In a treated area	-3.1762	-0.0661	-2.8777	-0.1643
	(3.1084)	(2.3865)	(4.0403)	(3.2688)
Mean super control	77.73		98.43	
N	74815	74815	50527	50527
Panel B : Monthly dummy of working while on claim				
Treated	0.0023**	0.0022**	0.0021	0.0022*
	(0.0011)	(0.0011)	(0.0013)	(0.0013)
In a treated area	-0.0002	0.0011	-0.0000	0.0010
	(0.0013)	(0.0013)	(0.0016)	(0.0016)
Mean super control	0.06		0.06	
N	1789111	1789111	1442918	1442918
Covariates	No	Yes	No	Yes

Note : Levels of significance: * $<$ 0.10, ** $<$ 0.05, *** $<$ 0.01. Standard errors are robust and clustered at the agency level in panel A and at the individual level in panel B to account for repeated observations across individuals, they are reported in parenthesis. Covariates include all the stratum variables reported in Table 2 as well as entry months and regions fixed effects. "Treated" designates individuals who were assigned to treatment (ITT estimate), "In treated areas" refers to those registered at employment agencies where half of individuals have been treated and "super control" designates individuals registered at employment agencies where nobody has been treated. The number of observations N corresponds to the number of individuals in panel A and to the number of individuals times the number of months over the corresponding time horizon in panel B.

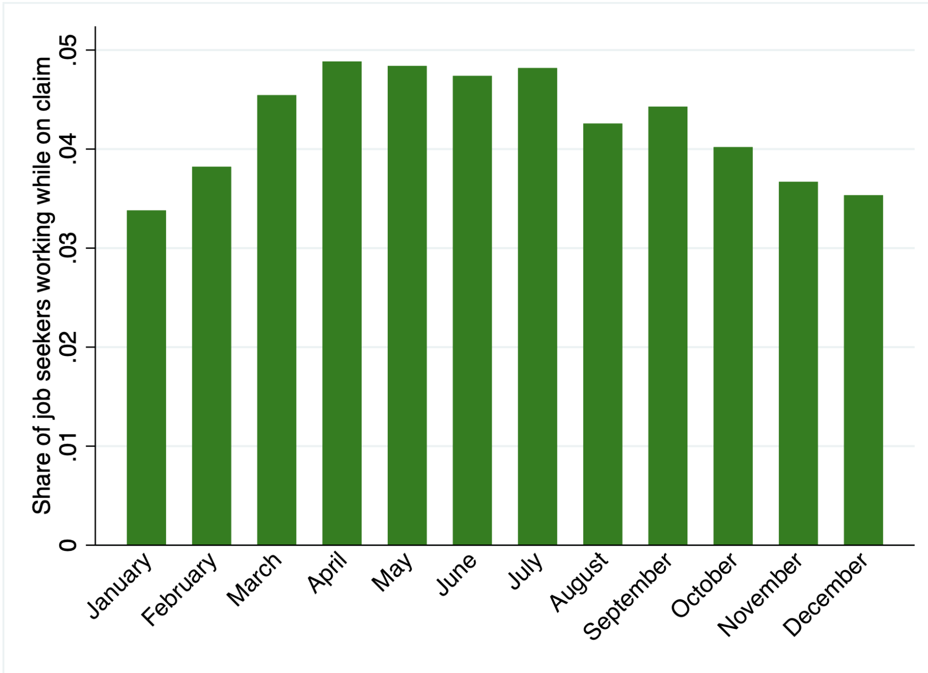
Table B10: Treatment effect on unemployment : model vs randomization based inference

	Potential Benefit Duration								
	All sample			< 730			≥ 730		
	Coeff.	p-value		Coeff.	p-value		Coeff.	p-value	
	estimate	model based	rand. inference	estimate	model based	rand. inference	estimate	model based	rand. inference
Panel A : Prob. to be out of unemployment in the last month									
Treated (β)	-0.0059	0.0452	0.053	0.0020	0.6477	0.635	-0.0125	0.0031	0.002
In a treated area (δ)	0.0015	0.7247	0.693	-0.0052	0.3843	0.346	0.0072	0.1924	0.164
Panel B : Prob. to be out of unemployment in the last quarter									
Treated (β)	-0.0052	0.0935	0.093	0.0000	0.9949	0.995	-0.0096	0.0273	0.020
In a treated area (δ)	-0.0019	0.6598	0.611	-0.0070	0.2625	0.215	0.0028	0.6091	0.589
N		115547			50887			64660	
Covariates		Yes			Yes			Yes	

Note: This table presents the results obtained for the outcomes related to unemployment in the last quarter before benefit exhaustion. For each group (i.e. all sample, PBD < 730 and PBD ≥ 730) the first two columns display the coefficient estimate and the model based p-value that are presented in section 5.3 and the third column corresponds to the p-value based on a two-sided randomization inference test statistic.

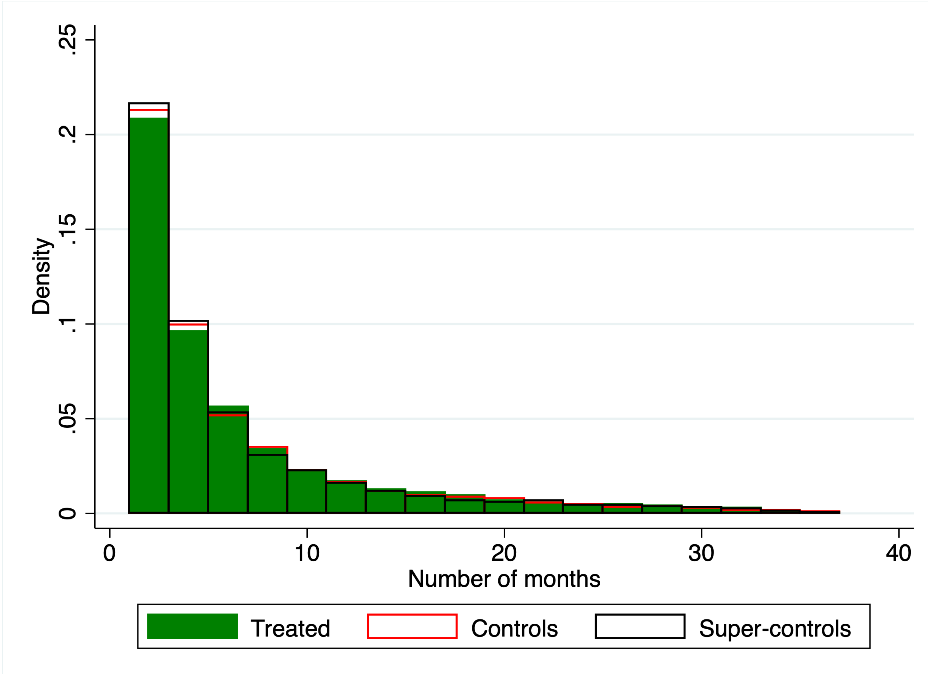
C Supplementary Figures

Figure C3: Frequency of work while claim by calendar month



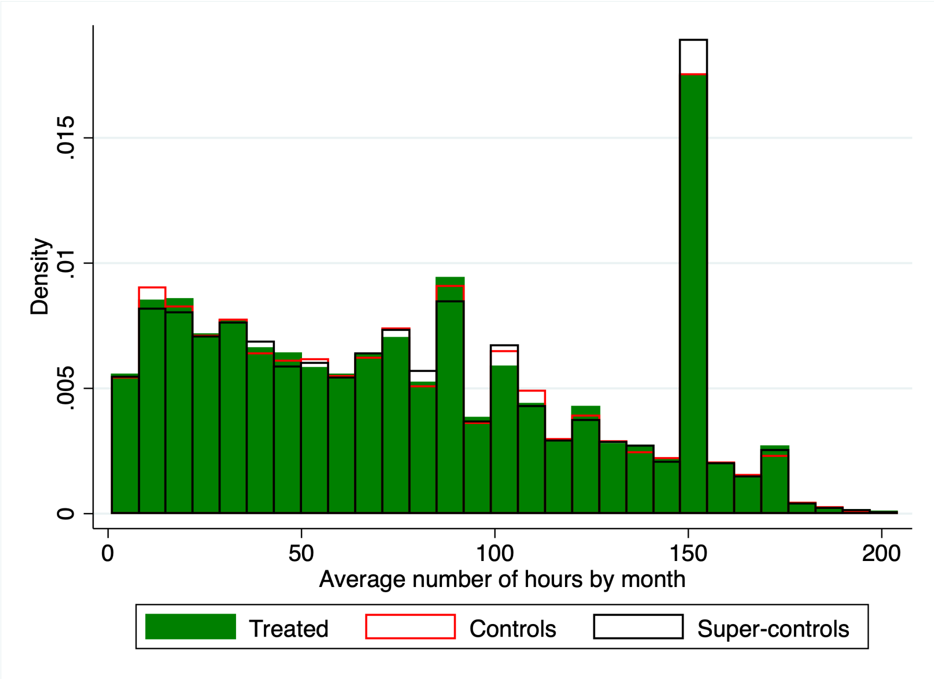
Note: This figure displays the calendar month average value of the indicator variable equal to one when the job seeker works while on claim for individuals belonging to the control group or the super control group.

Figure C4: Distribution of the number of months in part-time unemployment among those who worked while on claim



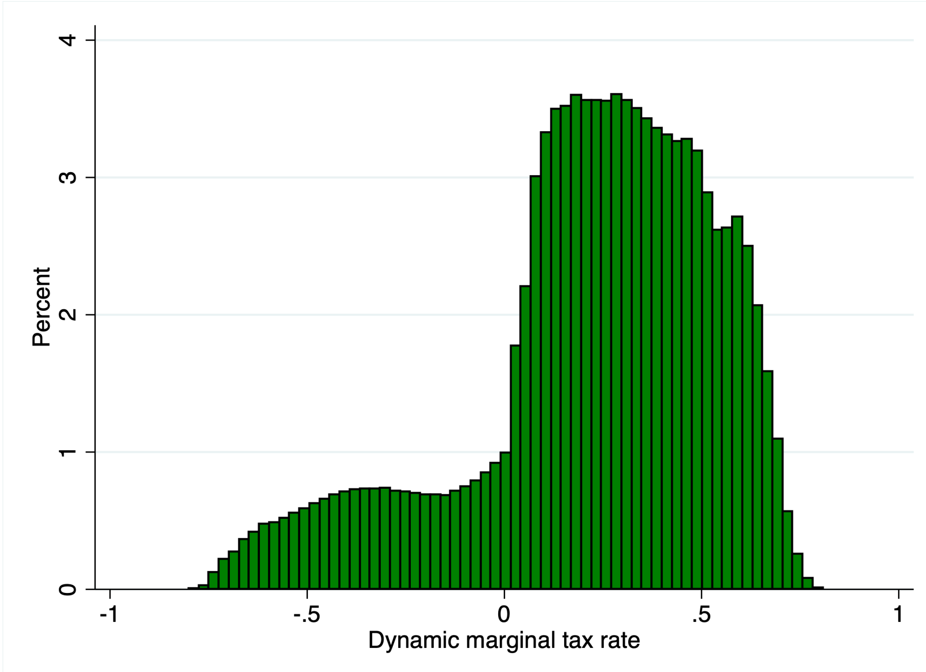
Note: This figure displays the distribution of the number of months with work while on claim by group over the 36 months of the study, conditional on working while on claim. The small number of observations per bin implies that the differences observed between groups are usually not significant. Only 2 bins display a significant difference between the supercontrol and the control groups. As for differences between the treated group and the supercontrol group or the control group, the few significant differences indicate that the treated are less present in the bottom of the distribution.

Figure C5: Distribution of the monthly number of hours worked in part-time unemployment among those who worked while on claim



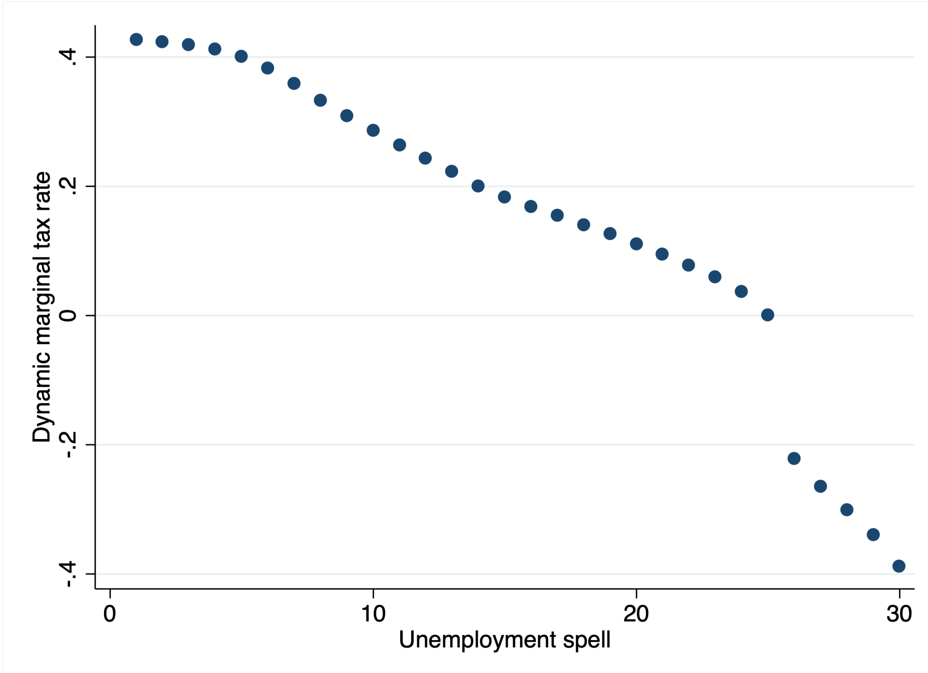
Note: This figure displays the distribution of the average number of hours worked while on claim by group over the 36 months of the study, conditional on working while on claim. The small number of observations per bin implies that the differences observed between groups are usually not significant. Only 2 bins display a significant difference between the supercontrol and the control groups. As for differences between the treated group and the supercontrol group or the control group, the few significant differences indicate that the treated are less present in the bottom of the distribution.

Figure C6: The distribution of dynamic marginal tax rates



Note: This figure displays the distribution of the dynamic marginal tax rate for each individual $\times$ month observation. For each individual and each month, the benefits exhaustion date, which depends on the cumulative number of hours of work while on claim, is computed according to the legal rules. The individual survival probability until the benefits exhaustion date, equal to $\prod_{j=t}^{T-1} [1 - \lambda(e_j)]$ in equation (5), is estimated from a Cox proportional hazards model with covariates including gender, age, education, the reference wage, and the local unemployment rate. The monthly discount factor β is equal to =0.996, which corresponds to an annual discount rate equal to 5%.

Figure C7: Evolution of the average dynamic marginal tax rate over the employment spell



Note: This figure displays the average dynamic marginal tax rate month by month from the start of the unemployment spells. For each individual and each month, the benefits exhaustion date, which depends on the cumulative number of hours of work while on claim, is computed according to the legal rules. The individual survival probability until the benefits exhaustion date, equal to $\prod_{j=t}^{T-1}[1-\lambda(e_j)]$ in equation (5), is estimated from a Cox proportional hazards model with covariates including gender, age, education, the reference wage, and the local unemployment rate. The monthly discount factor β is equal to =0.996, which corresponds to an annual discount rate equal to 5%.