Quasi-experimental Evidence on Take-up and the Value of Unemployment Insurance*

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Abstract

A large fraction of the eligible workers does not claim for unemployment benefits. The existing literature, focusing on the determinants of take-up (TU), has shown that it is sensitive to both the costs and the benefits of claiming. This paper shows that variation in TU behavior can be used to determine the workers' value of unemployment insurance (UI). Using Austrian data and exploiting a quasi-experimental setting, we first estimate how eligibility for severance payments and extended unemployment benefits affect TU. Using a simple model, we show that these estimates can be used to derive bounds on a monetary equivalent of the UI value taking into account take-up costs. Among claimants, we estimate that the value is above 2.5 monthly wages for the median individual. For the non-claimants, our results point towards large costs of collecting benefits. Finally, we show that the UI value rises with experience, age and that it is lower for male workers.

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1 Introduction

Unemployment insurance (hereafter UI) helps individuals to smooth consumption when they are unemployed. From this perspective, unemployment insurance take-up is an intriguing phenomenon. In most of the existing studies, it lies between 25% and 75% (see Table 1), suggesting that claiming costs are high in comparison with the value of unemployment insurance. In this paper, we try to quantify the net value of UI by finding a monetary equivalent of the intertemporal utility of claiming and receiving UI relative to not doing so. For this purpose, we study a large Austrian administrative database where discontinuities in eligibility for severance payments (SP) and extended unemployment benefits (EB) create variation in take-up rates and in the exit rate from unemployment. We first provide a simple search model where workers face a cost of claiming for unemployment benefits and can partially smooth consumption using savings. In the spirit of Card, Chetty, and Weber (2007), we show that reduced-form estimates of the impact of SP and EB on take-up rates and exit rates can be used to compute bounds on a money metric for the net value of UI.

Country	Source	Estimated take-up	Time period
Canada	Storer and van Audenrode (1995)	77%	1981 – 1986
France	Blasco and Fontaine (2012)	27% - 45%	2001 – 2002
United Kingdom	DWP[1] (2012)	49% - 84%	1997 – 2010
United States	Anderson and Meyer (1997)	24% - 50%	1979 – 1982
	Blank and Card (1991)	68% - 75%	1977 – 1987
	McCall (1995)	65%	1982 – 1991

Table 1: Overview of estimated take-up in existing studies

Following seminal work by Moffitt (1983) on welfare benefits, previous studies on UI take-up primarily focused on empirical investigations of its determinants. These are surveyed in Currie (2004) and Hernanz, Malherbet, and Pellizzari (2004). Notable examples are Blank and Card (1991), McCall (1995) and Anderson and Meyer (1997), all finding that generosity of UI is a significant determinant of take-up[2] which is consistent with agents comparing costs and benefits of UI take-up. Claiming costs *per se* have been the focus of a number of studies (e.g. Bhargava and Manoli (2015), Budd and McCall (1997), Ebenstein and Stange (2010), Kopczuk and Pop-Eleches (2007)). While existing evidence is inconclusive as to their exact composition (physical costs, psychological costs or administrative barri-

[1]The British Department for Work and Pensions (DWP) is one of the few government agencies that regularly publish estimates of take-up rates.

[2]Burtless (1983) is probably among the first to document the stylized fact and to explore possible explanations.

ers to filing; see descriptive evidence in Vroman (2009)), they point to a significant role for take-up costs. Finally, low take-up rates could be understood as the result of errors in individuals' assessment of their eligibility. Following this idea, a recent paper (Hertel-Fernandez and Wenger (2013)) describes an experiment where randomly selected unemployed were provided accurate information about UI eligibility requirements. Contrary to expectation, treated individuals actually displayed lower participation. The authors interpret the finding as a consequence of uncertainty about actual take-up costs. In comparison with existing studies, we try to quantify directly the two sides of the take-up choice, namely the claiming costs and the welfare gains from UI.

Only recently have there been attempts to come up with structural models to explain the take-up process in more detail. One of them is Blasco and Fontaine (2012), who incorporate a take-up decision in a detailed partial equilibrium job search model and estimate it on administrative data. They show that the take-up decision, job search behavior and expectations are deeply interrelated and that the elasticity of the exit rate to unemployment benefits depends on the elasticity of the take-up rate. In this paper, we allow the take-up rate to depend on job search efficiency and the search behavior to be affected by claiming, while focusing on the quantification of the value of UI.

Recent studies by Auray, Fuller, and Lkhagvasuren (2013), Auray and Fuller (2016), Chodorow-Reich and Karabarbounis (2014) and Kettemann (2015) incorporate UI take-up in an equilibrium model. The first two are only relevant for a system where firms are experience rated and pay higher payroll taxes if more of their previous employees collected benefits. In this case, since firms prefer workers not taking up UI, these will enjoy higher job arrival rates and workers will select endogenously into registered and non-registered unemployment. Chodorow-Reich and Karabarbounis (2014) introduce a take-up decision into a DSGE model with matching frictions and a representative household in order to calculate the cyclicality of the opportunity cost of employment. Kettemann (2015) introduces a take-up decision in a search and matching model with linear preferences, hence abstracting from savings, and endogenous search effort. He shows that take-up and search effort interact to amplify fluctuations of labor market aggregates along the business cycle. Moreover, he demonstrates that endogenous take-up can have important consequences for the optimal time structure of unemployment benefits, potentially making the schedule upward sloping. In all cases, the strategy and purpose is different from ours. Our main objective is to identify the distribution of the net value of UI using data on take-up behavior and exit rates from unemployment. Moreover, by relying on estimates from a regression discontinuity design, we are, to our knowledge, the first to come up with quasi-experimental evidence on UI take-up.

The data, together with some information on the institutional background, are presented in section 2. We then develop a simple search model with UI take up in section 3, from which we build our empirical strategy in section 4. Section 5 is devoted to the empirical findings, while section 6 concludes.

2 Institutional Background and Data

In this section we briefly describe the institutional background motivating our empirical strategy. We are going to use two discontinuities in the data: the first is related to eligibility for severance payments, the second to eligibility for extended UI benefits.

On the one hand, firms are required to make a lump-sum transfer at the time of the layoff, whose size depends on a step function of the worker's tenure in the firm.[3] In particular, jobs below three years of tenure at the time of the separation are not eligible for mandatory severance pay. After three years, firms have to make a transfer of at least two monthly salaries.

In addition, workers having lost their job can collect benefits if they have acquired a sufficient work history (those who quit face a waiting period of 28 days). Workers who have worked at least twelve months out of the two years preceding job loss are able to claim. The maximum benefit duration, in turn, depends on the months worked in the five years preceding job loss. If a worker was employed for below 36 months, she is eligible for up to twenty weeks of benefits, while those having worked for more than 36 months are eligible for 30 weeks. Benefits replace approximately 55% of previous earnings up to a minimum and a maximum, though the maximum is attained by very few people. Importantly, unemployment insurance has to be claimed personally at the local office of the public employment service Austria (AMS) and there is no waiting period in terms of benefits payments.

As discussed by Card, Chetty, and Weber (2007), this setting implies a "double-disconinuity" problem. For around 50% of all jobs in our baseline sample[4], the threshold of receiving severance pay coincides with the threshold of receiving extended benefits. Card, Chetty, and Weber (2007) show that the effects of eligibility for severance pay and extended benefits can still be separated since labor market experience and job tenure are not perfectly correlated for all individuals.

We use data from the Austrian Social Security Database (ASSD). ASSD covers the universe of Austrian private sector workers (about 80% of the entire workforce), providing longitudinal information from 1972 onwards. The data have been collected in order to verify old-age pension claims and hence covers all information relevant for this aim. In particular, it reports individuals' complete earnings and employment history, as well as other labor market states, such as registered unemployment, sickness or maternal leave.

For our analysis, we focus on terminations from jobs that started between January 1, 1981 and December 31, 2002. For all jobs starting after January 1, 2003, the severance payment scheme was abolished in favor of an occupational pension scheme. In order to limit the interaction with special programs for older workers, we drop workers above 50 years of age at the time of their job loss and/or retir-

[3]For all jobs starting as of January 1, 2003, mandatory severance pay was abolished and succeeded by a system of occupational pensions.

[4]The number is 20% in Card, Chetty, and Weber (2007), as they use a larger bandwidth and also include very young (< 25 years) workers.

ing within the same calendar year. We also exclude workers below 25 (as their jobs are often fixed-term apprenticeships), terminations from jobs in the construction industry (as they are subject to a different severance regulation). Following Card, Chetty, and Weber (2007), we exclude terminations from hospitals, schools, and other public sector service industries, as some of these jobs are fixed-term. Lastly, we exclude workers recalled to their previous employer, as they might not be searching for a job, and those that never return to a job.

Unfortunately, the ASSD does not record non-registered unemployment (non take-up) explicitly and we have to infer this from a gap in the working history. We code such a nonemployment spell as registered if it overlaps with an unemployment insurance spell in the data, while we code it as non-registered if no such spell is observed. While the requirement that the workers in our sample return to the labor market at a later stage ensures some labor force attachment, we are not entirely able to distinguish between non-registered unemployment and non-participation. Due to unobserved non-participation, there is a long tail of extremely long nonemployment durations in the data. To limit their influence on the results, we follow Card, Chetty, and Weber (2007) and censor spells at 2 years.

Moreover, while many spells apart from employment and registered unemployment are observed in the data (such as sickness, retirement, maternal leave, etc.), there are certain labor market states that are not recorded in the data, such as self-employment or a stay abroad. This might lead to some of these states being erroneously coded as non-registered unemployment. As will become apparent later on, however, this limitation will not have a crucial effect on our results if we can assume that all relevant unobserved states trend smoothly around the two discontinuities.

In Table 2, we list some summary statistics for all job terminations and the estimation sample, using a bandwidth of 12 months around the cutoffs for severance pay and extended benefits. The sample selection criteria we have to apply result in some obvious differences between the entire population and the estimation sample. By construction, we focus on workers with relatively high tenure at their previous employer, while on average jobs have a quite low duration. Workers in the sample are also more likely to be female, slightly older, more experienced, and facing a slightly longer unemployment spell. The take-up rate is also considerably higher, which is also due to the fact that many workers in the entire population are not eligible for unemployment insurance. Then again, it is reassuring that the sample at hand does not seem to differ much from the overall population in terms of the pre-displacement wage.

	All Job Terminations	Estimation Sample
Female (%)	48.65	66.18
Age	31.29	34.43
Experience (years)	5.98	6.71
Austrian citizen (%)	83.00	78.19
Tenure at previous job (years)	1.89	2.78
Nonemployment duration	253.54	321.08
Take-up rate (%)	36.80	66.05
Blue-collar worker (%)	58.85	64.79
Monthly wage (year 2000 Euros)	1458.06	1457.68
Observations	7753856	83451

Table 2: Summary statistics for all job losers and the estimation sample

3 Theoretical Framework

We provide a model where workers are, among other things, heterogeneous in terms of wealth when entering unemployment. When becoming unemployed, they face a cost of claiming for unemployment benefits and evaluate the gain from unemployment insurance by taking into account their ability to smooth consumption using savings. For some of them, claiming is too costly and they will thus only rely on their accumulated wealth in doing so, which will, in turn, affect their search behavior. Besides, since eligibility for severance payments is similar to a wealth shock, it will likely affect both search behavior and willingness to claim. The same applies for eligibility for extended benefits which renders unemployment insurance more attractive. In the following model, we will give a formal derivation of (i) how exit rates react to eligibility for extended benefits, and (ii) how the take-up rate responds to eligibility for severance pay and extended benefits.

3.1 The Model

Time is discrete and the first period is 0. When a worker becomes unemployed, she decides whether to claim unemployment benefits, which is costly. The claiming cost is denoted by ϕ and it is assumed to be distributed in the population of unemployed workers according to a distribution with cdf F and pdf f. If unemployment benefits have been claimed when entering unemployment, income during unemployment is b_t^I, if not, it is $b_t^{\bar{I}}$. We also assume that for each state, there might be other costs/benefits, denoted by δ_t^j, $j \in \left\{I, \bar{I}\right\}$, that represent social or administrative constraints, stigma or psychological costs and benefits. This means that, while there is a fixed cost of claiming, individuals may also have to bear costs for every period they collect benefits. In the same way, there can be benefits beyond benefit collection. We introduce these costs and benefits in terms of a monetary equivalent. Adding a second argument to the utility function, in addition to consumption, wouldn't affect our results[5].

[5]The main reason is that we don't have to go beyond deriving the behavioral response to a change in wealth and to longer benefit duration.

For a worker with A_0 asset holdings, $U_0^I(A_0)$ denotes the intertemporal value of the claimants and $U_0^{\bar{I}}(A_0)$ the intertemporal value of non-claimants, both in period 0. The worker collects unemployment benefits if

$$U_0^I(A_0) - U_0^{\bar{I}}(A_0) \geq \phi.$$

Then, in each period, the timing is the following. First, workers make their consumption choices. Workers can save or dissave but, due to borrowing constraints, there is a lower limit on A (this is not explicit below to simplify the presentation[6]). Then they choose their search intensity s_t^j ($j = I$ if collecting benefits, $j = \bar{I}$ if not), equal to the probability of obtaining an offer, at a cost $\psi(s_t^I)$. If they get an offer, they become immediately employed with an intertemporal value $V_{t+1}^j(A_{t+1})$, if not they stay unemployed. The intertemporal values at time t in both states satisfy, with β the discount rate and r the interest rate,

$$\begin{aligned} U_t^j(A_t) = u\Big(A_t - (1+r)^{-1}A_{t+1} + b_t^j - \delta_t^j\Big) - \psi(s_t^j) \\ + \beta\Big(s_t^j V_{t+1}^j(A_{t+1}) + (1-s_t^j)U_{t+1}^j(A_{t+1})\Big), \end{aligned}$$

where $j \in \{0, 1\}$. The value of employment in t is denoted by $V_t^j(A_t)$ and depends on the level of assets and possibly on the state of origin (claimants or non-claimants).

3.2 Job Search and Take-up Choices

In the following, we characterize optimal behavior, focusing on the effects we will use later on, namely the effect of assets and extended benefits on take-up and the effect of extended benefits on the exit rate. The first-order condition for search intensity reads

$$\psi'(s_{jt}) = \beta\left(V_{t+1}^j(A_{t+1}) - U_{t+1}^j(A_{t+1})\right), \tag{1}$$

with $j \in \{I, \bar{I}\}$. The effect of a future benefit increase in period $t+s$ on exits in period t, using (1) and the envelope condition, follows as

$$\frac{ds_{It}}{db_{t+s}^I} = -\frac{1}{\psi''(s_{It})}\beta^s p_{t+s|t+1}u'(c_{It+s}), \tag{2}$$

where $p_{t+s|t+1} \equiv \prod_{i=t+1}^{t+s-1}(1-s_{Ii})$ for $s > 1$, and 1 otherwise, denotes the probability of being unemployed in period $t+s$ if unemployed after $t+1$ periods. Because they raise the value of unemployment, future benefits decrease current search effort. The particular ordering of the effects on the exit rates from s_{I0} to s_{IT-1} depends on the

[6]As such, the derivation reported here assume that the credit constraint is never binding. We show in Appendix F.3 that the computation of the metric would be unaffected if the credit constraint was binding.

changes in $\psi''(s_{It})$ and c_{It+s}[7] and is theoretically ambiguous.

Another way of expressing it, which will be more convenient especially when dealing with extensions of unemployment insurance over many periods, is to express it in terms of the marginal effect on *intertemporal* utility in period T, where T denotes the first period where the extension takes place. Denote by b^e the benefit level during the extension period and E the number of periods of this extension. The total effect on exits in period t is then given by

$$\frac{ds_{It}}{db^e} = -\frac{1}{\psi''(s_{It})}\beta^{T-t}p_{T|t+1}\frac{\partial U_T^I}{\partial b^e}. \tag{3}$$

Considering, as we will later on, the effect of becoming eligible for extended benefits on search effort in the last period prior to the extension, $T-1$, one gets

$$\frac{ds_{IT-1}}{db^e} = \frac{ds_{IT-1}}{db_T^I} + ... + \frac{ds_{IT-1}}{db_{T+E}^I} \tag{4}$$

where $b_T^I = ... = b_{T+E}^I$.

We now look at the incentive to claim for unemployment benefits. Savings help workers to smooth consumption in unemployment and decrease the incentive to exit unemployment quickly. Notice that while the agent knows the claiming cost, we don't observe this cost in the data. From the econometrician's point of view, take-up can thus be considered probabilistic. The worker collects unemployment benefits if

$$U_0^I(A_0) - U_0^{\bar{I}}(A_0) \geq \phi,$$

which happens with probability $F\left(U_0^I(A_0) - U_0^{\bar{I}}(A_0)\right)$. The effects of assets and extended benefits on this take-up probability, denoted by ℓ, are:

$$\frac{d\ell}{dA_0} = f\left(U_0^I - U_0^{\bar{I}}\right)\left(u'(c_{I0}) - u'(c_{\bar{I}0})\right) \tag{5}$$

$$\frac{d\ell}{db^e} = f\left(U_0^I - U_0^{\bar{I}}\right)\beta^{T-1}p_{T|1}\frac{\partial U_T^I}{\partial b^e} \tag{6}$$

Eligibility for extended benefits increases unambiguously the probability of claiming by raising the value of unemployment insurance. In the same way, as long as $c_{I0} > c_{\bar{I}0}$, a one-dollar increase in wealth will affect utility of the non-claimants by more than the utility of the benefit recipient due to decreasing marginal utility of consumption. Thus, the utility difference and the incentive to claim decrease. Both reactions are scaled by the density of marginal workers.

[7] If net benefits, $b_t^I - \delta_t^I$, are decreasing over time, consumption is decreasing as well.

4 Empirical Strategy

Our empirical strategy borrows from Card, Chetty, and Weber (2007) and Chetty (2008). The idea is to identify the value of UI using reduced-form estimates of the impacts of extended benefits (EB) and severance payments (SP) on the exit rates and on the take-up rate. For the sake of presentation, we explain our strategy in reverse order. We start by defining our money metric, assuming that we have estimates for the individual take-up probabilities, the effects of EB and SP, and estimates of the claiming cost distribution and the search cost function. Second, we show how reduced-form estimates can be used to get parameters for the two latter objects. Finally, we present the RDD which captures the behavioral response to EB and SP.

The general idea of our empirical strategy is the following. We don't observe individual claiming costs, ϕ. However, the estimated take-up probabilities are informative about the intertemporal utility difference, $U_0^I - U_0^{\bar{I}}$. The higher the probability, the bigger this difference. Moreover, the fact that workers react differently to eligibility for extended benefits or severance pay is indicative about how a money transfer impacts their welfare. Under parametric assumptions for F and ψ, this enables us to create a money metric for the value of UI.

4.1 The Value of Unemployment Insurance

We are looking for the asset transfer ΔA such that a non-claimant is indifferent between claiming and not claiming:

$$U_0^I(A_0) - \phi = U_0^{\bar{I}}(A_0 + \Delta A)$$

By definition, we have $\Delta A > 0$ for claimants, as they would have to be compensated for not claiming. This transfer compensates for the benefits they forgo but is reduced by the fact that they don't have to face the claiming costs. On the contrary, $\Delta A < 0$ for non-claimants. These individuals face high claiming costs relative to their value of unemployment benefits: They have enough assets or expect a quick exit from unemployment. They are thus willing to give up assets for not claiming.

A first-order Taylor approximation implies

$$\begin{aligned} \Delta A &\approx \left(U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \phi\right)\left(\frac{dU_0^{\bar{I}}(A_0)}{dA_0}\right)^{-1} \\ &= \frac{U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \phi}{u'(c_{\bar{I}0})}, \end{aligned} \tag{7}$$

where the second step follows from the envelope theorem. Effectively, our approximation yields the difference in intertemporal utility, normalized by the utility value of one additional euro of consumption for the non-claimants. Note that, due to the concavity of the value function, a first-order compared to a second-order approximation will likely result in a downward biased ΔA (in absolute terms). If anything our measure underestimates the value of unemployment insurance among the claimants.

In the following, we will connect (7) to objects for which we have estimates: the take-up probability, the effect of assets and extended benefits on take-up, and the effect of extended benefits on the exit rate from unemployment. We need to determine the value of three elements: the intertemporal utility difference $U_{i0}^{I}-U_{i0}^{\bar{I}}$, the take-up cost ϕ and the marginal utility $u'(c_{\bar{I}0})$. Denote by p_i the take-up probability of individual i. First, observe that $U_{i0}^{I}-U_{i0}^{\bar{I}} = F^{-1}(p_i)$. Workers that have a high probability of claiming are those for whom the intertemporal utility difference is largest. Under parametric assumption for F and if we manage to get estimates of F's parameters, we can pin down this utility difference.

The fixed cost, ϕ_i, on the other hand, cannot be identified exactly. However, if we have an estimate of the probability of claiming, and since we observe the take-up decision, we can compute the expected value of ϕ_i among claimants and non-claimants,

$$\bar{\phi}_{i1} = \int_0^{F^{-1}(p_i)} \frac{x}{p_i}\, dF(x), \text{ and} \tag{8}$$

$$\bar{\phi}_{i0} = \int_{F^{-1}(p_i)}^{\phi^{sup}} \frac{x}{1-p_i}\, dF(x), \tag{9}$$

respectively. Note that this directly implies $U_0^{I}(A_0) - U_0^{\bar{I}}(A_0) - \bar{\phi}_0 < 0 \leq U_0^{I}(A_0) - U_0^{\bar{I}}(A_0) - \bar{\phi}_1$. Intuitively, a worker who claims despite having a low predicted take-up propensity is expected to have a low claiming cost (and vice versa).

$u'(c_{\bar{I}0})$, in turn, is impossible to pin down given our estimates. However, we can bound it. One insight we can use here is that a higher marginal value of consumption in the case where the individual does not collect benefits will translate into a stronger reaction of the take-up probability to a wealth shock. Remember that, in the data, eligibility for severance pay is equivalent to a wealth shock when entering unemployment. For a lower bound, observe that

$$u'(c_{\bar{I}0}) > u'(c_{\bar{I}0}) - u'(c_{I0}),$$

which can be connected to the marginal effect of assets on the claiming probability. Indeed, (5) directly implies

$$u'(c_{\bar{I}0}) - u'(c_{I0}) = -\frac{d\ell}{dA_0} \frac{1}{f\left(F^{-1}(p_i)\right)}$$

and thus $u'(c_{\bar{I}0}) - u'(c_{I0})$ is identified by the effect of assets on take-up. If one worker is more reactive than another to a wealth shock, it means that the utility value of one additional euro is higher for her than for the other. For the same intertemporal utility difference $U_0^{I}(A_0) - U_0^{\bar{I}}(A_0) - \phi$ this implies a lower *monetary* equivalent for the more responsive worker because her marginal value of consumption is higher.

For an upper bound, we use that

$$u'(c_{\bar{I}0}) = u'(c_{\bar{I}0}) - u'(c_{I0}) + u'(c_{I0}) \leq u'(c_{\bar{I}0}) - u'(c_{I0}) + u'(c_{IT}),$$

where the second equality holds as long as $c_{IT} \leq c_{I0}$[8] by the concavity of the utility function. We have already shown that $u'(c_{\bar{I}0}) - u'(c_{I0})$ is identified if we know the take-up response to a change in wealth. $u'(c_{IT})$, in turn, can be bounded using the effect of extended benefits on exits the period before the extension takes place, ds_{iIT-1}/db^e. Again, more responsive workers are those for whom one additional euro has a higher value in terms of utility. Assume that the UI extension takes place in period T and lasts until period $T+E$. The total marginal effect of increasing the benefit level in all E periods is given by

$$\frac{ds_{IT-1}}{db^e} = \frac{ds_{IT-1}}{db_T^I} + \ldots + \frac{ds_{IT-1}}{db_{T+E}^I}$$

Using (2), and again using that consumption is non-increasing over time, we find (note that $ds_{IT-1}/db_T < 0$)

$$\begin{aligned} \frac{ds_{IT-1}}{db^e} &= \frac{ds_{IT-1}}{db_T^I}\left[1 + \beta p_{T+1|T}\frac{u'(c_{IT+1})}{u'(c_{IT})} + \ldots + \beta^E p_{T+E|T}\frac{u'(c_{IT+E})}{u'(c_{IT})}\right] \\ &\leq \frac{ds_{IT-1}}{db_T^I}\underbrace{\left[1 + \beta p_{T+1|T} + \ldots + \beta^E p_{T+E|T}\right]}_{\equiv B}. \end{aligned}$$

Substituting for ds_{IT-1}/db_T using (2), we conclude

$$u'(c_{IT}) \leq -\frac{ds_{IT-1}}{db^e}\frac{\psi''(s_{IT-1})}{\beta B},$$

where B corrects for the fact that the extension affects multiple time periods.

Combining all previous steps, we conclude that the equivalent wealth transfer to the claimants satisfies

$$\frac{F^{-1}(p_i) - \bar{\phi}_1}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))} - \frac{ds_{IT-1}}{db^e}\frac{\psi''(s_{IT-1})}{\beta B}} \leq \Delta A \leq \frac{F^{-1}(p_i) - \bar{\phi}_1}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))}}, \tag{10}$$

while for the non-claimants

$$\frac{F^{-1}(p_i) - \bar{\phi}_0}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))}} \leq \Delta A \leq \frac{F^{-1}(p_i) - \bar{\phi}_0}{-\frac{d\ell}{dA_0}\frac{1}{f(F^{-1}(p_i))} - \frac{ds_{IT-1}}{db^e}\frac{\psi''(s_{IT-1})}{\beta B}}. \tag{11}$$

4.2 Estimation of the Structural Parameters

In order to implement (10) and (11), we need estimates for the parameters of the claiming cost distribution and the search cost function. Start with p_i, the estimated probability of a given individual of being observed as receiving unemploy-

[8]This is the case if $b_t^I - \delta_t^I$ is non-increasing over time.

ment benefits. Assume we have such a value for each individual. Under parametric assumptions for $F(\phi)$, we can link this probability to the value of unemployment insurance:

$$U_{i0}^{I} - U_{i0}^{\bar{I}} = F^{-1}(p_i)$$

Together with (3) and (6) this directly implies

$$\begin{aligned} \frac{d\ell_i/db^e}{ds_{iIT-1}/db^e} \equiv M_i &= -f\left(U_{i0}^{I} - U_{i0}^{\bar{I}}\right)\beta^{T-2}p_{T|1}\psi_i''(s_{iIT-1}) \\ &= -f\left(F^{-1}(p_i)\right)\beta^{T-2}p_{T|1}\psi_i''(s_{iIT-1}). \end{aligned} \tag{12}$$

Equation (12) links the estimated probability of claiming and the behavioral response to eligibility for extended benefits to the parameters of the claiming cost distribution and the search cost function. We will specify these functions in subsection 5.2. However, we can already point out that these sets of parameters, denoted by θ and a, can be estimated by least squares, solving

$$\{\theta, a\} = \arg\min \sum_i \left(\ln(-M_i) - \ln\left(f\left(F^{-1}(p_i)\right)\beta^{T-2}p_{T|1}\psi_i''(s_{iIT-1})\right)\right)^2.$$

Intuitively, θ and a are identified by the variation of the relative response in take-up and search to extended benefits. The first depends on the take-up probability (driven by the F distribution, parameterized by θ) and the second hinges on the job-finding rate which is linked to the search cost function (parameterized by a). A high value of $-M_i$, indicating that the reaction of the take-up probability relative to the reaction of the job-finding rate to extended benefits is large, can be for two reasons: (i) A strong reaction in take-up if the density of the claiming cost distribution is high at the point determined by p_i $(f(F^{-1}(p_i)))$. (ii) A small reaction in unemployment exits if the curvature in the marginal costs $\psi_i''(s_{iIT-1})$ is high at s_{iIT-1}. Finally, notice that since the marginal utility of consumption enters in the same way in $d\ell_i/db^e$ as in ds_{iIT-1}/db^e, the moment M_i does not depend on the shape of the utility function, meaning that we can avoid having to make any parametric assumptions here.

4.3 Estimating the Effect of Extended Benefits and Severance Payments

Identification. The identification strategy is similar to Card, Chetty, and Weber (2007). We use the quasi-experiment created by the sharp discontinuity in eligibility for severance pay and extended unemployment benefits in Austria. Eligibility for the former depends on job tenure, while eligibility for extended benefits depends on the number of months worked in the five preceding years. The effects of severance pay and extended benefits can thus be separated as job tenure in months, denoted by JT, and the number of months worked in the past, denoted by MW, are not perfectly correlated. On the one hand, there are workers who have lost a job having job tenure below three years, while having acquired around three years of work experience in the preceding five years. On the other hand, there are also workers who have around three years tenure while having surpassed three years work experience in the preceding five years. As in these cases only one of the two assignment variables jumps, the effects are identified.

Take-up probability. We use a probit model for take-up. We allow for cubic polynomials in the running variables and control for observed characteristics. We denote by S_i the eligibility dummy for severance pay and by E_i the eligibility for extended benefits. X_i is a vector of observable characteristics[9]. MW and JT are centered around the cutoffs, meaning that MW equals zero at 36 months worked and JT at 36 months of job tenure. The probability of collecting benefits, p_i, is assumed to satisfy

$$p_i = \Phi(y_i), \tag{13}$$

where

$$\begin{aligned} y_i = &\beta_S S_i + \beta_E E_i + \beta_1 JT_i + \beta_2 MW_i + \beta_3 JT_i S_i + \beta_4 MW_i E_i \\ &+ \beta_5 JT_i^2 + \beta_6 MW_i^2 + \beta_7 JT_i^2 S_i + \beta_8 MW_i^2 E_i \\ &+ \beta_9 JT_i^3 + \beta_{10} MW_i^3 + \beta_{11} JT_i^3 S_i + \beta_{12} MW_i^3 E_i + \gamma' X_i, \end{aligned}$$

and Φ denotes the c.d.f. of the standard normal distribution. The parameters of interest are in the first line: β_S and β_E, which identify the effects of severance pay and extended benefits.

Exit rates from non-employment. We model exits from unemployment as a discrete duration model where the probability of exiting in a given period is modeled as a probit.[10] Again, we allow for third order polynomials in the running variables. We denote by $h_{ij}(t)$ the hazard of exiting non-employment in period t for the UI recipients ($j = I$) and non-recipients ($j = \bar{I}$). We consider discrete time intervals of variable length. That is, for unemployment durations up to 30 weeks we use intervals of 2 weeks, while above we fix intervals at 10 weeks. As mentioned above, we censor at 2 years. This accounts for two things. On the one hand,

[9] We control for age, age squared, experience, experience squared, gender, Austrian nationality, and four industry categories, log previous wage, and log previous wage squared.

[10] We depart from the convention of modelling period exit rates using an exponential specification: On the one hand, since we allow for time intervals of up to 10 weeks, the exponential specification for the exit probability is prone to exceed 1, which makes it hard for the estimation to converge. On the other hand, opting for a probit specification makes it straightforward to introduce unobserved heterogeneity correlated with the take-up dimension, as explained later on.

we have more observations for shorter durations which allows us to estimate the effects more precisely. On the other hand, it will be more crucial to have precisely estimated effects at shorter horizons for our structural analysis.

Our specification for the hazard of exiting unemployment reads

$$h_{ij}(t) = \Phi(\lambda_{ij}(t)), \tag{14}$$

where

$$\begin{aligned}\lambda_{ij}(t) = &\beta_j^S S_i + \alpha_{jt}^S S_i + \beta_j^E E_i + \alpha_{jt}^E E_i \\ &+ \beta_{j1} JT_i + \beta_{j2} MW_i + \beta_{j3} JT_i \times S_i + \beta_{j4} MW_i \times E_i \\ &+ \beta_{j5} JT_i^2 + \beta_{j6} MW_i^2 + \beta_{j7} JT_i^2 \times S_i + \beta_{j8} MW_i^2 \times E_i \\ &+ \beta_{j9} JT_i^3 + \beta_{j10} MW_i^3 + \beta_{j11} JT_i^3 S_i + \beta_{j12} MW_i^3 E_i \\ &+ \alpha_{jt} + \gamma_j' X_i.\end{aligned}$$

The parameters of interest are again in the first line: β_j^S identifies the effect of severance pay on the exit rate in period 0, while α_{jt}^S denotes the differential effect of severance pay on exit rates in period t (that is, the total effect of S_i on the exit rate in period t is $\beta_j^S + \alpha_{jt}^S$). The same holds for the effect of extended benefits. Thus, the effect of severance pay and extended benefits on exits from unemployment is allowed to change over the non-employment spell, which is consistent with theory. By including α_{jt}, we control for a piecewise constant baseline hazard of arbitrary form and thus account for duration dependence. X_i is a vector of observable characteristics[11]. In Appendix A, we give more details on the estimation procedure.

Selection around the discontinuity. Our main identification assumption is that all observable and unobservable worker characteristics evolve smoothly around the discontinuities defining eligibility for severance pay and extended benefits. While this cannot be tested directly, we can gain intuition on the validity of the assumption by checking whether the number of observations and observed characteristics display any salient features, in particular bunching or jumps, at the threshold. Much of the following has already been demonstrated by Card, Chetty, and Weber (2007) and we will replicate much of their analysis to demonstrate that similar conclusions hold in our sample.

One threat to our identification would be that firms attempt to avoid mandatory severance payments by firing workers just before the three-year threshold. This behavior should show up as an excess mass just before and missing mass just after the eligibility threshold. As we can see from Figure 7(a) in Appendix B, however, we cannot discern any sign of strategic firing in the data. As argued by Card, Chetty, and Weber (2007), this finding is not surprising as any such behavior is

[11] We again control for age, age squared, experience, experience squared, gender, Austrian nationality, and four industry categories, log previous wage, and log previous wage squared.

illegal and leads to bad reputation effects. For completeness, we also demonstrate that similar conclusions hold for the experience criterion as well (Figure 7(b)).

To investigate potential differences of observables around the discontinuity, we plot the average pre-displacement wage observed in our baseline sample by previous job tenure and the months worked in the preceding five years in Figure 8 in Appendix B. We conclude that there is no visible jump in either panel (a) or panel (b), suggesting that there is no differential selection around either discontinuity. This contrasts with the finding by Card, Chetty, and Weber (2007), who find a small discontinuity in previous wages at the tenure threshold, but then argue that this discontinuity is negligible in terms of behavior. Our findings differ because we use a different baseline sample. In particular, we exclude workers below 25, whose jobs are often fixed-term (apprenticeships). In any case, mirroring the conclusion by Card, Chetty, and Weber (2007), we conclude that there is no sign of quantitatively important selection around the discontinuities.

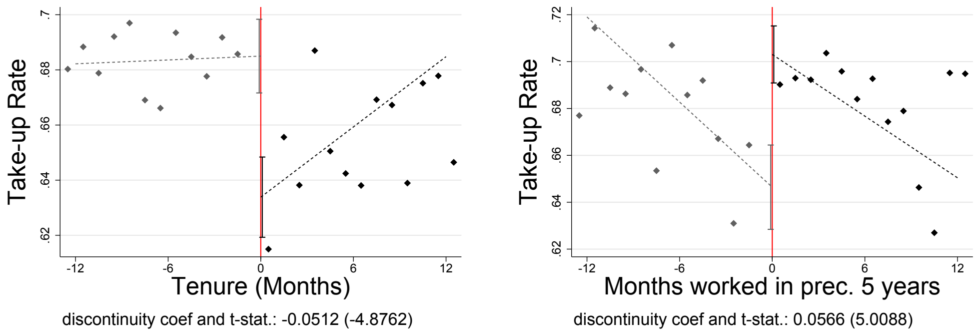
5 Empirical Findings

5.1 Descriptive Results

Take-up probability. To get an impression how the take-up rate and eligibility for severance pay and extended benefits correlate, we show descriptive discontinuity plots, based on local linear regressions of the form

$$p = \pi_0 + \pi_1 S + \pi_2 JT + \pi_3 JT \times S + \varepsilon,$$

for the effect of severance pay and analogously for the effect of extended benefits. For both regressions, we only include workers for whom the discontinuities do not coincide (effectively, this means $MW > JT$). We put more weight on observations close to the cutoff by using a triangular kernel following the suggestions by Porter (2003) and Hahn, Todd, and Van der Klaauw (2001). The reported t-statistics are based on a bootstrap with 1000 replications.



(a) Effect of SP

(b) Effect of EB

Figure 1: Effect on take-up of eligibility for severance pay and for extended benefits

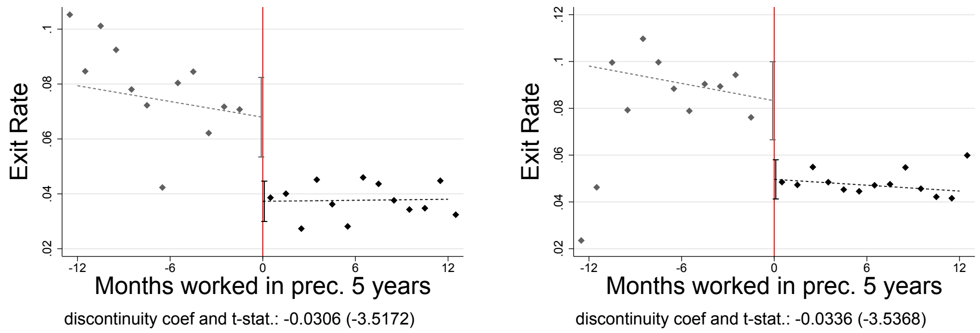
Note: These figures plot average take-up rates per monthly tenure/experience bin. The lines correspond to local linear regressions estimates (individual level) on both sides separately and bootstrapped (1000 replications) confidence intervals, clustered by individual to account for correlation between spells.

As predicted by theory, workers respond to a severance payment by claiming unemployment insurance less often—the take-up rate decreases by around 5.1% (Figure 1). The effect also goes into the right direction where extended benefits are concerned, as take-up increases by 5.7% at the discontinuity. These descriptive figures are only instructive, however, and a joint estimation of both discontinuities is needed, which we will conduct in the next section.

Exit rates from non-employment. One way of getting a graphical intuition for the effects of extended benefits on exits is by estimating regressions of the form

$$d(t) = \xi_0^t + \xi_1^t E + \xi_2^t MW + \xi_3^t MW \times E + \varepsilon,$$

where $d(t)$ is a dummy variable equal to 1 if a worker exits from non-employment in period t and we include all individuals having non-employment duration of at least t periods. Since we could produce a discontinuity plot for every period and running variable, we will concentrate on the most important moment for our identification, the effect of extended benefits on exits just before regular benefits run out, dh_{iIT-1}/dE_i.



(a) Claimants: Exit in weeks 19-20 (b) Claimants: Exit in weeks 21-22

Figure 2: Eligibility for extended benefits and probability of exiting before and after benefit extension

Note: These figures plot the probability of finding a job 19-20 weeks and 21-22 weeks after becoming unemployed, conditional on being unemployed for at least 18 weeks, for the claimants. The lines correspond to local linear regressions estimates (individual level) on both sides separately and bootstrapped (1000 replications) confidence intervals, clustered by individual to account for correlation between spells.

Eligibility for extended benefits is likely to have stronger effects around the moment where regular benefits end. Figure 2 focuses on benefit recipients and looks at the effect of the extension two weeks before and after it takes place. There is a clearly discernible downward jump for the registered unemployed—the exit rate falls by over three percentage points from baseline level of around 7% and 8%.

5.2 Estimates

We estimate the model explained in Section 4.3, jointly considering both discontinuities, by maximum likelihood. We focus on individuals that are at most 12 months away from either cutoff. The standard errors are clustered at the individual level to account for unobserved correlation across various spells.

The point estimates are shown in Table 8 in Appendix C. The marginal effects of becoming eligible for severance pay and extended benefits on the take-up probability are displayed in column 1 of Table 3. While we now control for both running variables simultaneously as well as for nonlinear terms and observed heterogeneity, the main conclusions of the descriptive analysis are unaffected. Eligibility for severance pay reduces the take-up probability by around 7 percent, while the effect of eligibility for extended benefits is positive, increasing the probability of collecting benefits by around 4 percent. We also probe the robustness of our results to the model assumptions in various ways: If we leave out control variables (column 2), the effects stay comparable. A classical RDD uses a linear outcome specification—if we do so by estimating a linear probability model (column 3), the results do not change much, either. One concern might be that workers are fired selectively around the discontinuity. Even though we already concluded in Section 4.3 that there is no sign of selective firing, we can also address this question by focusing on mass layoffs: arguably, layoffs involving multiple workers limit even more the likeliness of selective displacements. If we conduct the same analysis focusing on workers having lost their job along with at least three other workers in the same month, we find even more pronounced effects (column 4).

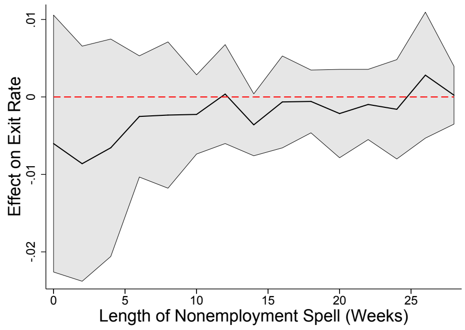
	(1) Baseline	(2) w/o Controls	(3) LPM	(4) $\geq$ 4 Layoffs by Firm
Severance Pay	-0.0747***	-0.0875***	-0.0699***	-0.101***
	(0.0183)	(0.0182)	(0.0166)	(0.0304)
Extended Benefits	0.0429**	0.0368**	0.0408**	0.0766**
	(0.0185)	(0.0183)	(0.0181)	(0.0301)
Observations	83451	83451	83451	30791

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
z-statistics (based on delta-method) in parentheses

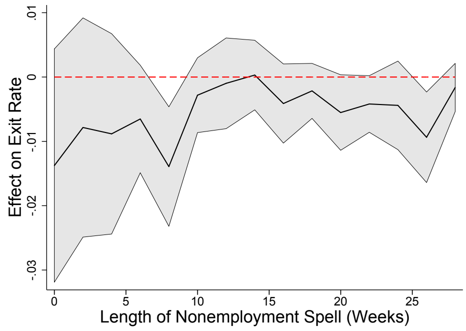
Table 3: Effect of severance pay and extended benefits on take-up

Note: The numbers correspond to the predicted change in the take-up probability if either eligibility for severance pay or extended benefits are switched on. All running variables are set to 0, while covariates are set to their mean values. Standard errors are calculated using the delta method. Column 1 is calculated using the estimates from our baseline model. Column 2 replicates column 1 leaving out control variables X_i. In column 3, we replace the probit by a linear probability model we estimate by OLS. Column 4 restricts our sample to job separations resulting from mass layoffs, which we define as at least four layoffs within one month from the same firm.

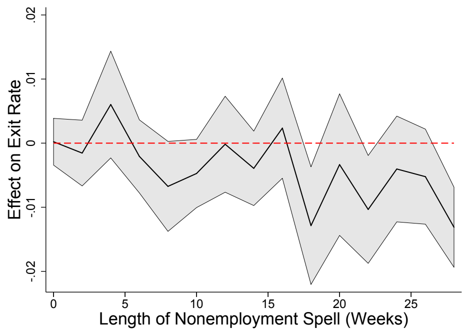
We give a graphical representation of the effect on exit rates over time in Figure 3. Extended benefits affect exits negatively just before and after benefits run out for claimants, while non-claimants are unaffected. This is consistent with our model. The effect is stronger close to the benefit extension because workers account for the probability of exiting unemployment before the extension and because they discount the future. When entering unemployment, the value of the benefit extension is thus very small. It might be more surprising that we appear to find almost no effects of severance pay, while Card, Chetty, and Weber (2007) document negative effects. While we use a different sample, the main reason is that we allow the effect of severance pay to change over the course of the spell, while they estimate the overall effect on the job finding hazard during the first 20 weeks of unemployment. In Appendix D, we demonstrate that we get comparable results if we use Card, Chetty, and Weber (2007)'s strategy and look for an overall effect on exits during the first 20 weeks of unemployment.



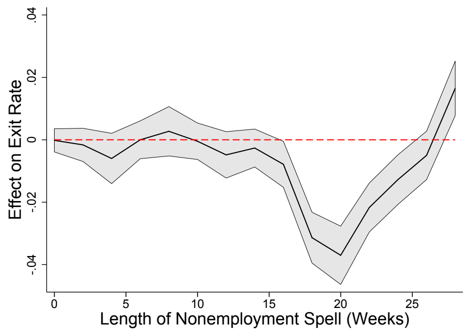
(a) Non-claimants, SP



(b) Non-claimants, EB



(c) Claimants, SP



(d) Claimants, EB

Figure 3: Effect of severance pay and extended benefits on the exits from unemployment

Note: The plots show the effect of becoming eligible for severance pay or extended benefits, respectively, on the probability of exiting unemployment over time. Covariates are fixed at their average value while the respective running variables take the threshold value. The confidence bands are based on standard errors clustered at the individual level.

We explore the robustness of our estimates in a similar way as for take-up by focusing on the effect of extended benefits on exits of claimants one period before the extension takes place, dh_{iIT-1}/dE_i, which is the moment featuring most prominently in our further analysis. Column 1 of Table 4 displays the marginal effect implied by our baseline estimates for period $T-1$ only. The probability of exiting during the last period before a benefit extension is predicted to decrease by around 3.2 percentage points, which, given a baseline probability of around 7% for the non-eligible, corresponds to a large effect. This estimate is not sensitive to either leaving out control variables or estimating a linear specification[12] (columns 2 and 3). If we restrict the sample to mass layoffs, the size of the effect decreases, but remains highly significant.

[12] In Appendix A, we explain in detail how the linear approximation to our baseline model works.

	(1) Baseline	(2) w/o Controls	(3) LPM	(4) $\geq$ 4 Layoffs by Firm
Extended Benefits	-0.0321***	-0.0322***	-0.0325***	-0.0201***
	(0.00415)	(0.00407)	(0.00417)	(0.00615)
Observations	83451	83451	83451	30791

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
z-statistics (based on delta-method) in parentheses

Table 4: Effect of severance pay and extended benefits on exits from unemployment one period before regular benefits run out ($T-1$)

Note: The numbers correspond to the predicted change in the probability of exiting unemployment (claimants) in the period before regular benefits run out if eligibility for extended benefits is switched on. All running variables are set to 0, while covariates are set to their mean values. Standard errors are calculated using the delta method. Column 1 is calculated using the estimates from our baseline model. Column 2 replicates column 1 leaving out control variables X_i. In column 3, we replace the probit by a linear probability model we estimate by OLS. See Appendix A for details. Column 4 restricts our sample to job separations resulting from mass layoffs, which we define as at least four layoffs within one month from the same firm.

One additional concern might be that there is heterogeneity driving both take-up and job search, leading to correlation across the two margins. In Appendix E, we describe an estimator which allows for correlated unobserved heterogeneity between both decisions. As can be seen from Table 10 in Appendix E, we estimate a correlation across both decisions which is not statistically different from zero, and the parameter estimates are thus only marginally affected. Arguably, the observed covariates already do a sufficient job in controlling for correlation. If we estimate the same model without covariates, on the other hand, we estimate a strongly negative correlation between both decisions which is consistent with our model[13].

Estimation of the structural parameters. The econometric model, along with the estimated parameters, gives us predictions for the effect of extended benefits on take-up and on exits from unemployment based on individual characteristics. Call v_E the cash value of extended benefits and denote by E_i whether individual i is eligible for extended benefits. The estimated marginal effects can be connected to the theoretical effects by realizing that

$$\frac{dh_{iIT-1}}{dE_i} \approx \frac{ds_{iIT-1}}{db^e} v_E$$
$$\frac{dp_i}{dE_i} \approx \frac{d\ell_i}{db^e} v_E.$$

where v_E denotes the cash value of extended benefits.

Combining these results, we obtain

$$M_i = \frac{d\ell_i/db^e}{ds_{iIT-1}/db^e} \approx \frac{dp_i/dE_i}{dh_{iIT-1}/dE_i}.$$

[13]The results are available on request.

The ultimate goal is to solve for the parameters in equation (12), by solving

$$\{\theta, a\} = \arg\min \sum_i \left(\ln(-M_i) - \ln \left(f\left(F^{-1}(p_i)\right) \beta^{T-2} \left(\prod_{\tau=1}^{T-1} (1 - s_{I\tau}) \right) \psi_i''(s_{iIT-1}) \right) \right)^2 .$$

To make progress, we assume that take-up costs ϕ are Weibull distributed. Other distributions are possible but the Weibull distribution is flexible and it has delivered the best fit to the empirical moments[14]. Letting $\Delta_i \equiv U_{i0}^I - U_{i0}^{\bar{I}}$, this assumption implies

$$\ell_i = F(\Delta_i) = 1 - \exp\left(-(\Delta_i/\theta_{i0})^{\theta_1}\right),$$

where $\{\theta_0, \theta_1\}$ are the parameters of the cost distribution to be estimated. We also assume that the search cost function is isoelastic, satisfying $\psi(s) = a_{0i}s^{a_1}$. We account for observed heterogeneity by assuming $a_{0i} = a_0 \exp(X_i'\xi)$ and $\theta_{0i} = \theta_0 \exp(X_i'\pi)$, where X_i is a vector of covariates.

In Appendix F.1, we show that, given our assumptions, we obtain the following estimable equation

$$y_i = K + \frac{\theta_1 - 1}{\theta_1} \ln(-\ln(1 - p_i)) + (a_1 - 2) \ln h_{iIT-1} + X_i'\gamma, \tag{15}$$

where $\gamma \equiv \xi - \pi$, $y_i \equiv \ln \frac{dp_i}{dE_i} - \ln\left(-\frac{dh_{iIT-1}}{dE_i}\right) - \ln(1 - p_i) - \ln\left(\prod_{\tau=1}^{T-1}(1 - h_{iI\tau})\right)$ and $K \equiv \ln\frac{\theta_1}{\theta_0} + \ln \beta^{T-2} + \ln(a_0 a_1(a_1 - 1))$.

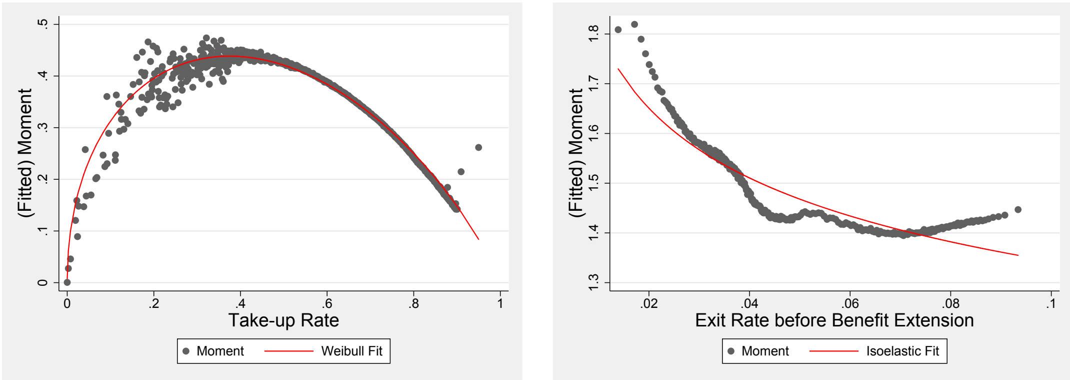
By estimating (15) by OLS, we get estimates of the shape parameter of the take-up cost distribution, θ_1, as well as of the curvature of the search cost function, a_1. By controlling for X_i, we effectively control for how observables drive the relative importance of the take-up and the search margin. ξ and π are not separately identified but separate identification is not necessary to compute our metric. β is not identified separately, either, and we will have to calibrate it later on.

	Estimate	95% CI (Delta Method)
θ_1	1.886	[1.411,2.360]
a_1	1.872	[1.862,1.882]

Table 5: Implied structural parameters

The regression results are shown in Table 9 in Appendix C, while Table 5 lists the implied structural parameters. Search costs are almost quadratic, which is consistent with previous work (see, e.g., Yashiv 2000 on Israeli data and Christensen, Lentz, Mortensen, Neumann, and Werwatz 2005 on Danish data). The Weibull distribution reduces to the exponential distribution for $\theta_1 = 1$, which can be re-

[14]We have also come up with a strategy which does not rely on any distributional assumption. The results are almost unaffected, which is due to the fact that the Weibull already fits the empirical moments very well. We thus decided to stick with the more parsimonious parametric approach.



(a) Weibull fit (b) Isoelastic fit

Figure 4: Fit of the Weibull and isoelastic specification to the empirical moments

Note: In the left figure we asses the fit of of he Weibull distribution to the empirical moments by plotting $\exp(y_i + \ln(1-p_i) - \hat{K} - (\hat{a}_1 - 2)\ln h_{iIT-1} - X_i'\hat{\gamma})$ (gray dots) against $\exp(((\hat{\theta}_1 - 1)/\hat{\theta}_1)\ln(-\ln(1-p_i)) + \ln(1-p_i))$ (red line), where hats denote estimated coefficients, based on equation (15). In the right figure we asses the fit of the isoelastic search cost by plotting $\exp(y_i - \hat{K} - ((\hat{\theta}_1 - 1)/\hat{\theta}_1)\ln(-\ln(1-p_i) - X_i'\hat{\gamma})$ (gray dots) against $\exp((\hat{a}_1 - 2)\ln h_{iIT-1})$ (red line), where hats denote estimated coefficients, based on equation (15). In the left figure, the dots correspond to averages within take-up rate bins of width 0.001. The dots in the right figure correspond to means within 300 quantiles of the exit rate (to take care of outliers).

jected. The R^2 is above 95%, which suggests that the parametric assumptions do a good job in describing the data. Figure 4 gives an additional sense of how well our specification fits the data: We rewrite (15) so as to isolate either p_i or h_{iIT-1} on the right-hand side and then plot the right-hand side against the left-hand side.

In Figure 4(a), we can see that the Weibull distribution succeeds in describing the hump-shaped relationship between the take-up rate and the empirical moment. It makes sense that the reaction of take-up is strongest for a take-up probability around 50%, while most observations are in the downward sloping part. The downward sloping line in Figure 4(b) is due to an estimated elasticity of search costs of less than two (quadratic search costs would imply a flat relationship). This implies a slightly stronger reaction of search effort if the exit rate is already high.

5.3 The value of unemployment insurance.

The distribution of UI value. We are now able to calculate bounds on the value of unemployment insurance, using our estimates for the marginal effects, the estimates of the structural parameters and equations (10) and (11) for the bounds. In order to connect empirical estimates to theoretical marginal effects, we use the approximation

$$\frac{dp_i}{dS_i} \approx \frac{d\ell_i}{dA_0} v_S$$
$$\frac{dh_{iIT-1}}{dE_i} \approx \frac{ds_{iIT-1}}{db^e} v_E,$$

where S_i and E_i indicate eligibility for severance pay and extended benefits, respectively, and v_S and v_E denote the cash value of severance pay and extended benefits.

In Appendix F.2, we show the exact expressions for the bounds we implement.

Following Card, Chetty, and Weber (2007), we assume that $v_E \approx 0.85w$ and $v_S \approx 2.69w$, where w is the after-tax individual monthly wage[15]. In order to implement our formula, we need to translate v_E to one period in our empirical model. Since the extension affects five two-weekly periods, we use $v_E = (0.85/5)w = 0.17w$. For the baseline results, we assume an annual discount rate of 5%. While this has no effect by construction on the upper bound for claimants and the lower bound for non-claimants, we show in Table 6 in Appendix B that alternative assumptions have a negligible effect on the other bounds.

(a) Lower bound (b) Upper bound

Figure 5: Bounds on wealth transfer to claimants

Note: The plots show c.d.f.'s of the lower and upper bound on ΔA based on equations (10) and (11), for claimants of UI. ΔA is the asset transfer to a non-claimant required to make her indifferent between claiming and not claiming. It is a monetary equivalent to the difference in intertemporal utilities between claimants and non-claimants net of claiming costs and thus is, by construction, positive for claimants and negative for non-claimants. We only display observations between the 1st and the 99th percentile.

In Figure 5, we plot the distribution of the resulting lower and upper bounds for claimants, who have a positive ΔA. We find that for the median individual the relative value of collecting benefits net of claiming costs is equivalent to at least 2.5 monthly wages. This is the minimum amount, implied by her behavioral responses to severance pay and extended benefits, which one needs to transfer when she enters unemployment so as to make her indifferent between collecting benefits or not. The lower bound appears reasonable given a quick back-of-the-envelope calculation. The median number of weeks unemployed among the claimants in our baseline sample is 23. With a replacement rate of 0.55, the expected total sum of UI payments (ignoring discounting) is $(23/52) \cdot 12 \cdot 0.55 = 2.92$ monthly wages for those eligible for extended benefits and $(20/52) \cdot 12 \cdot 0.55 = 2.54$ for the non-eligible. Our metric also accounts for take-up costs, discounting and non-monetary benefits of collecting benefits but this shows that our lower bound is a credible estimate of the value of the insurance and its distribution. The upper bound, around 11 monthly wages for the median, appears on the contrary less informative.

[15]The value of extended benefits is an approximation because one needs to account for unemployment assistance, whose generosity depends on household earnings that we do not observe. As in Card, Chetty, and Weber (2007), we assume that the individual has a partner with a net wage of 1200 euros per month and two children.

(a) Lower bound (b) Upper bound

Figure 6: Bounds on wealth transfer to non-claimants

Note: The plots show c.d.f.'s of the lower and upper bound on ΔA based on equations (10) and (11), for non-claimants of UI. See notes of Figure 5 for further details. We only display observations between the 1st and the 99th percentile.

The results for non-claimants are shown in Figure 6. Their relative value of UI net of claiming costs is negative, meaning they would be willing to give up part of their wealth to avoid having to claim for UI. We find that the median individual would have to lose the equivalent of *at least* 2 monthly wages to become claimant. Again the other bound, above nine months for the median, appears less informative. In any case, even just focusing on the first bound, these numbers suggest that the perceived take-up costs are sizable for many workers who don't collect, caused by, for instance, a combination of intrinsic aversion to the welfare state (induced by stigma for example), administrative costs of filing a claim and the set of constraints imposed on those who collect benefits.

How UI value is related to individual characteristics. One of the advantages of our method is that we don't have to make parametric assumptions about the shape of the utility function, the distribution of δ_t^j, the costs/benefits to be paid during unemployment, or the worker income $b_t^{\bar{I}}$ if she is not receiving benefits. The values we derived for each individual still reflect these elements, as they affect the responses to severance pay and/or extended benefits as well as non-employment duration. The drawback is that we can't fully identify the mechanisms that explain how the value changes with individual characteristics. Nonetheless, looking at how the values are distributed is informative about who benefits most from unemployment insurance and gives indirect clues about the possible mechanisms at play.

In the following, we consider how values change with individual characteristics by focusing on the bounds that are most informative: the lowest bound for the claimants and the highest bound for the non-claimants. Remember that these two bounds have the same formula

$$\frac{U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \phi}{u'(c_{\bar{I}0}) - u'(c_{I0}) + u'(c_{IT})}. \tag{16}$$

The only difference comes from the fact that if an individual is observed as claiming, this implies that the numerator (the net difference in inter-temporal utility) is positive. It would be negative for an individual who does not collect.

Our metric relies on two conceptually different elements. The first is the difference in inter-temporal utility net of claiming costs. Its estimated value is tightly linked with the probability of claiming. The second is the value of one additional euro in consumption in terms of marginal utility (for those who do not collect benefits). One important source of identification here comes from the estimated behavioral responses to the discontinuities. Workers that react strongly are those who have a high value of consumption (see (10) and (11)). The two elements may be correlated and are indeed positively correlated in the data: workers with the highest difference in utility are also those with the highest valuation of consumption. This is consistent with the idea that workers who expect the highest utility gain from the insurance are those whose consumption levels without insurance are lowest.

There is a substantial dispersion in insurance value. In our framework, this reflects differences in individual characteristics that affect the take-up probability and the behavioral responses to severance payments and benefit extensions. If two individuals are similar in the data (same characteristics) we would infer the same bound for the marginal value of consumption (the denominator). In the same way, because we predict the same take-up probability, we would infer the same inter-temporal difference, $U_0^I(A_0) - U_0^{\bar{I}}(A_0)$. This is not necessarily true for the take-up cost which depends on the observed take-up behavior on top of the individual characteristics. If a worker has a high take-up probability but does not collect benefits in the data, we infer a high take-up cost, ϕ.

To investigate the role of individual characteristics, we regress our metric (equation (16)) on the set of characteristics used for our estimations (Table 7 in Appendix). First, the value is lower for men both because they have lower marginal utility of consumption and lower inter-temporal gains. Second, taking experience and past wage as given, the value of the insurance is increasing with age. Older individuals are estimated to experience larger gains (or smaller losses) in inter-temporal utility since their take-up probability increases with age. However, our proxy for their marginal value of consumption is increasing only for the first half of the sample (the younger) with but then decreases. At the end, the overall effect of age is positive which means that even in the case where they value more consumption, other possible factors, like a drop in the take-up costs with age or a decrease in their reemployment prospects (that we do find in the data), increases the UI monetary value sufficiently to compensate.

Third, because they are predicted to have a higher claiming probability, more experienced workers also have larger estimated absolute gains (or smaller losses). In the same time, they value consumption less as experience rises, except for the highest quartile of the experience distribution. Both elements together cause the monetary value to increase with experience. It is interesting to see that it goes against the idea that more experienced workers, because they could accumulate higher savings, display a lower value of unemployment insurance. In the same way, as for how values change according to past wages, the results prevent any simple interpretation. Given the estimates, we see an inverse u-shaped relationship between past wage and UI values (first rising and then decreasing). The same relationship is observed for all the elements of our metric. Again, past wages are likely to capture an important part of the heterogeneity not already captured by the other variables. It is likely to be related to wealth but also to workers' skills and ability to claim.

6 Conclusion

Using variation in take-up and job search behavior, this paper infers bounds on the value of unemployment insurance while taking into account the existence of take-up costs. Using Austrian administrative data and a double discontinuity, one in the eligibility for severance pay, one in the eligibility for extended unemployment benefits, we first document that the probability of claiming is lower if workers are eligible for severance pay, which is equivalent to a wealth shock when entering unemployment. On the contrary, eligibility for extended benefits increases the take-up probability and lowers the exits from unemployment around the time where the extension occurs. Then, using a simple job search model where workers face a cost of claiming for unemployment benefits, we show that these estimates can be used to derive bounds on the insurance value. For the workers who collect benefits, we find that the median value of the insurance is at least equal to a transfer of 2.5 monthly wages at the beginning of the unemployment spell. For the workers who don't claim, the value is by definition negative with an upper bound of around two monthly wages for the median individual. This suggests that, for a significant share of the individuals, take-up costs, stigma and/or constraints imposed on those who collect are sizable. Finally, we show that the UI value rises with experience, age and that it is lower for male workers.

References

Allison, P. D. (1982): "Discrete-Time Methods for the Analysis of Event Histories," *Sociological Methodology*, (13), 61–98.

Anderson, P. M., and B. D. Meyer (1997): "Unemployment Insurance Takeup Rates and the After-Tax Value of Benefits," *Quarterly Journal of Economics*, 112(3), 913–37.

Auray, S., and D. Fuller (2016): "Eligibility, Experience Rating and Unemployment Insurance Take-up.," *Mimeo*.

Auray, S., D. Fuller, and D. Lkhagvasuren (2013): "Unemployment Insurance Take-up Rates in an Equilibrium Search Model," *Mimeo*.

Bhargava, S., and D. Manoli (2015): "Why are Benefits Left on the Table? Assessing the Role of Information, Complexity, and Stigma on Take-up with an IRS Field Experiment," *Mimeo*.

Blank, R. M., and D. E. Card (1991): "Recent Trends in Insured and Uninsured Unemployment: Is There an Explanation?," *Quarterly Journal of Economics*, 106(4), 1157–89.

Blasco, S., and F. Fontaine (2012): "Unemployment Duration and the Takeup of the Unemployment Insurance," *Mimeo*.

Budd, J. W., and B. McCall (1997): "The Effect of Unions on the Receipt of Unemployment Insurance Benefits," *Industrial and Labor Relations Review*, 50(3), 478–492.

Burtless, G. (1983): "Why Is Insured Unemployment So Low?," *Brookings Papers on Economic Activity*, 14(1), 225–254.

Card, D., R. Chetty, and A. Weber (2007): "Cash-On-Hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market," *Quarterly Journal of Economics*, 122(4), 1511–1560.

Chetty, R. (2008): "Moral Hazard versus Liquidity and Optimal Unemployment Insurance," *Journal of Political Economy*, 116(2), 173–234.

Chodorow-Reich, G., and L. Karabarbounis (2014): "The Cyclicality of the Opportunity Cost of Employment," Harvard University Working Paper 126541.

Christensen, B. J., R. Lentz, D. T. Mortensen, G. R. Neumann, and A. Werwatz (2005): "On-the-Job Search and the Wage Distribution," *Journal of Labor Economics*, 23(1), 31–58.

Currie, J. (2004): "The Take Up of Social Benefits," NBER Working Paper 10488.

Ebenstein, A., and K. Stange (2010): "Does Inconvenience Explain Low Take-up? Evidence from Unemployment Insurance," *Journal of Policy Analysis and Management*, 29(1), 111–136.

Hahn, J., P. Todd, and W. Van der Klaauw (2001): "Identification and Estimation of Treatment Effects with a Regression-Discontinuity Design," *Econometrica*, 69(1), 201–09.

Hernanz, V., F. Malherbet, and M. Pellizzari (2004): "Take-Up of Welfare Benefits in OECD Countries: A Review of the Evidence," OECD Social, Employment and Migration Working Papers 17.

Hertel-Fernandez, A., and J. B. Wenger (2013): "Taking Up Social Benefits: A Cautionary Tale from an Unemployment Insurance Survey Experiment," *Mimeo.*

Jenkins, S. P. (1995): "Easy Estimation Methods for Discrete-Time Duration Models," *Oxford Bulletin of Economics and Statistics*, 57(1), 129–38.

Kettemann, A. (2015): "The Macroeconomics of Incomplete Unemployment Insurance Take-up," *Mimeo.*

Kopczuk, W., and C. Pop-Eleches (2007): "Electronic Filing, Tax Preparers and Participation in the Earned Income Tax Credit," *Journal of Public Economics*, 91(7-8), 1351–1367.

McCall, B. P. (1995): "The Impact of Unemployment Insurance Benefit Levels on Recipiency," *Journal of Business & Economic Statistics*, 13(2), 189–98.

McEwen, R., and B. Parresol (1991): "Moment Expressions and Summary Statistics for the Complete and Truncated Weibull Distribution," *Communications in Statistics – Theory and Methods*, 4(20), 1361–1372.

Moffitt, R. (1983): "An Economic Model of Welfare Stigma," *American Economic Review*, 73(5), 1023–35.

Porter, J. (2003): "Estimation in the Regression Discontinuity Model," *Mimeo.*

Storer, P., and M. A. van Audenrode (1995): "Unemployment Insurance Take-Up Rates in Canada: Facts, Determinants, and Implications," *Canadian Journal of Economics*, 28(4a), 822–835.

Vroman, W. (2009): "Unemployment Insurance Recipients and Nonrecipients in the CPS.," *Monthly Labor Review*, October, 44–53.

Yashiv, E. (2000): "The Determinants of Equilibrium Unemployment," *American Economic Review*, 90(5), 1297–1322.

A Details on the Discrete Duration Model

As noticed early, discrete time duration model can conveniently be estimated as binary models (see Allison (1982) or Jenkins (1995)). Let t denote unemployment duration. Individual i's likelihood contribution is then given by

$$\ell_i = \left[\Pr\left(T_i = t_i\right)\right]^{d_i} \left[\Pr\left(T_i > t_i\right)\right]^{1-d_i},$$

where d_i takes the value 1 if i's observation is non-censored. As described in the main text, we denote by $h_{ij}(t)$ the hazard of individual i with take-up status $j \in \left\{I, \bar{I}\right\}$ of exiting unemployment in period t. We obtain

$$\begin{aligned}
\ell_i &= \left[h_{ij}(t) \prod_{s=1}^{t_i-1} (1 - h_{ij}(s))\right]^{d_i} \left[\prod_{s=1}^{t_i} (1 - h_{ij}(s))\right]^{1-d_i} \\
&= \left[\frac{h_{ij}(t_i)}{1 - h_{ij}(t_i)}\right]^{d_i} \prod_{s=1}^{t_i} (1 - h_{ij}(s))
\end{aligned}$$

and hence

$$\begin{aligned}
\log \ell_i &= d_i \log\left(\frac{h_{ij}(t)}{1 - h_{ij}(t)}\right) + \sum_{s=1}^{t_i} \log(1 - h_{ij}(s)) \\
&= \sum_{s=1}^{t_i} y_{it} \log\left(\frac{h_{ij}(s)}{1 - h_{ij}(s)}\right) + \sum_{s=1}^{t_i} \log(1 - h_{ij}(s)),
\end{aligned}$$

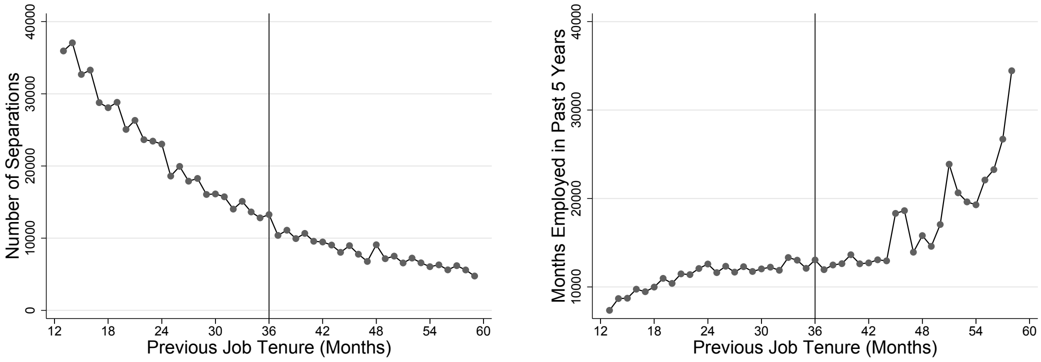
where y_{it} is a dummy which takes the value 1 if individual i exits in period t. The log-likelihood is then

$$\mathcal{L} = \sum_{i=1}^{N} \sum_{s=1}^{t_i} y_{it} \log(h_{ij}(s)) + \sum_{i=1}^{N} \sum_{s=1}^{t_i} (1 - y_{it}) \log(1 - h_{ij}(s)).$$

Looking closely at the resulting expression, we realize that it is equivalent to a set of binary regressions for $1, \ldots, t_i$. Estimation of the duration model amounts to treating periods $1, \ldots, t_i$ for each individual as separate observations and setting the dependent variable y_{it} equal to 1 if individual i exits in t and 0 otherwise. Choosing a functional form for $h_{ij}(t)$, we estimate the resulting model by maximum likelihood.

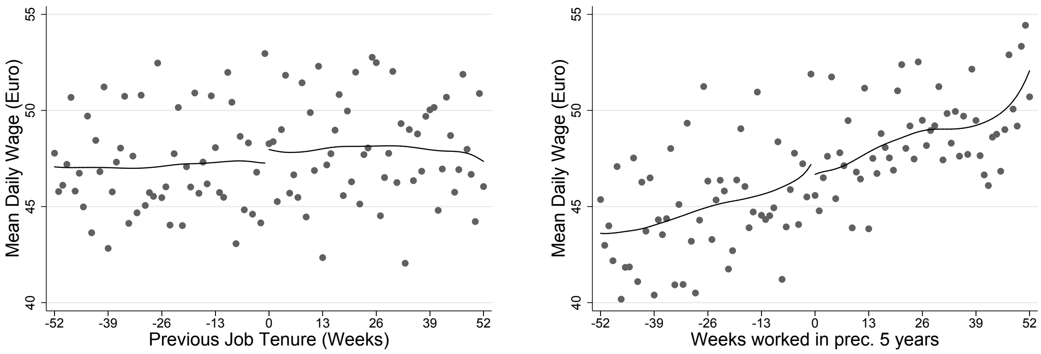
In our baseline specification, we assume $h_{ij}(t)$ to be of probit form. This naturally restricts the probability to be between zero and one and it enables to introduce correlated unobserved heterogeneity as robustness exercise. In our result tables, we also present the results in the case where we assume $h_{ij}(t)$ to be linear, estimating the resulting specification by OLS. This is what we call "LPM" in Table 4.

B Additional Figures and Tables



(a) By Job Tenure (b) By Months Worked

Figure 7: Frequency of Separations by Job Tenure



(a) By Job Tenure (b) By Months Worked

Figure 8: Previous Wage according to Previous Job Tenure and Months Worked in Preceding 5 Years

Annual Discount Rate	1 %	5 %	10 %	20 %
Upper Bound (Non-Claimants)	-2.321	-2.293	-2.259	-2.198
Lower Bound (Claimants)	2.580	2.549	2.512	2.445

Table 6: Different assumptions on the annual discount rate and implied median values for the bounds

	(1) Value of Insurance	(2) Absolute Gain	(3) Marg. Value of Cons.
Age	0.263***	0.0532***	0.00689***
	(0.0144)	(0.00234)	(0.0000640)
Age sq./100	-0.265***	-0.0576***	-0.0103***
	(0.0196)	(0.00321)	(0.0000880)
Experience	-0.00333	-0.00429***	-0.00340***
	(0.00601)	(0.00114)	(0.0000550)
Experience sq./100	0.100***	0.0426***	0.0192***
	(0.0284)	(0.00565)	(0.000300)
Log Daily Previous Wage	8.171***	1.253***	0.164***
	(0.461)	(0.0347)	(0.00191)
Log Daily Previous Wage sq.	-1.101***	-0.168***	-0.0213***
	(0.0636)	(0.00480)	(0.000265)
Female	0.625***	0.114***	0.00276***
	(0.0225)	(0.00337)	(0.000101)
Austrian	0.194***	0.0331***	-0.000270***
	(0.0199)	(0.00337)	(0.0000901)
Industry Class 2	0.465***	0.0925***	0.0161***
	(0.0390)	(0.00616)	(0.000151)
Industry Class 3	0.335***	0.0780***	0.0239***
	(0.0373)	(0.00586)	(0.000142)
Industry Class 4	0.0611	0.0180***	0.0147***
	(0.0379)	(0.00591)	(0.000142)
Constant	-20.50***	-3.384***	-0.247***
	(0.922)	(0.0774)	(0.00377)
Observations	83451	83451	83451
Adjusted R^2	0.117	0.110	0.673

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

Table 7: Value of unemployment insurance and personal characteristics

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors robust to heteroskedasticity in parentheses. Industry class 2 corresponds to manufacturing, electricity, gas, steam and air conditioning supply, water supply, sewerage, waste management and remediation activities and construction; industry class 3 corresponds to wholesale and retail trade; repair of motor vehicles and motorcycles, accommodation and food service activities and transportation and storage, while industry class 3 covers all remaining services. The omitted category is agriculture, forestry and fishing as well as mining and quarrying.

C Estimation Results

	(1) Exit uninsured	(2) Exit insured	(3) Take-up
Severance Pay	-0.0319	0.00467	-0.194***
	(0.0446)	(0.0394)	(0.0473)
Severance Pay × Period 1	-0.0197	-0.0258	
	(0.0368)	(0.0413)	
Severance Pay × Period 2	-0.0122	0.0418	
	(0.0393)	(0.0384)	
Severance Pay × Period 3	-0.00394	-0.0299	
	(0.0503)	(0.0412)	
Severance Pay × Period 4	0.00420	-0.0676*	
	(0.0504)	(0.0396)	
Severance Pay × Period 5	-0.0243	-0.0690	
	(0.0600)	(0.0430)	
Severance Pay × Period 6	0.0389	-0.00625	
	(0.0545)	(0.0410)	
Severance Pay × Period 7	-0.0859	-0.0553	
	(0.0653)	(0.0439)	
Severance Pay × Period 8	0.0176	0.0172	
	(0.0614)	(0.0423)	
Severance Pay × Period 9	0.00977	-0.110**	
	(0.0746)	(0.0448)	
Severance Pay × Period 10	-0.0195	-0.0269	
	(0.0666)	(0.0430)	
Severance Pay × Period 11	-0.00186	-0.0997**	
	(0.0772)	(0.0456)	
Severance Pay × Period 12	-0.0000625	-0.0420	
	(0.0610)	(0.0445)	
Severance Pay × Period 13	0.0793	-0.0590	
	(0.0617)	(0.0450)	
Extended Benefits	-0.0707	-0.00377	0.118**
	(0.0471)	(0.0400)	(0.0509)
Extended Benefits × Period 1	0.0266	-0.0182	
	(0.0361)	(0.0395)	
Extended Benefits × Period 2	0.0144	-0.0454	
	(0.0385)	(0.0370)	
Extended Benefits × Period 3	-0.0190	0.00376	
	(0.0489)	(0.0395)	
Extended Benefits × Period 4	-0.102**	0.0272	
	(0.0483)	(0.0379)	
Extended Benefits × Period 5	0.00626	-0.00221	
	(0.0592)	(0.0410)	
Extended Benefits × Period 6	0.0534	-0.0426	
	(0.0543)	(0.0393)	
Extended Benefits × Period 7	0.0786	-0.0293	
	(0.0641)	(0.0417)	
Extended Benefits × Period 8	-0.0193	-0.0750*	
	(0.0604)	(0.0405)	
Extended Benefits × Period 9	-0.00838	-0.290***	
	(0.0731)	(0.0409)	
Extended Benefits × Period 10	-0.0598	-0.292***	
	(0.0632)	(0.0402)	
Extended Benefits × Period 11	-0.0790	-0.214***	
	(0.0745)	(0.0423)	
Extended Benefits × Period 12	-0.0143	-0.122***	
	(0.0596)	(0.0425)	
Extended Benefits × Period 13	-0.109*	-0.0474	
	(0.0606)	(0.0434)	
Log-Likelihood	-66356.567	-159209.240	-51777.868
Observations	83451	83451	83451

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

Table 8: Effect of severance pay and extended benefits on exits from unemployment and take-up

	Estimate	95% CI
$\ln(-\ln(1-p_i))$	0.470	[0.336,0.603]
$\ln h_{iIT-1}$	-0.128	[-0.138,-0.118]
Observations	83451	
R^2	0.953	

95% confidence intervals (robust to heteroskedasticity) in brackets.

Table 9: Regression results (equation (15))

D The Effect of Severance Pay and Extended Benefits on Exits during the First 20 Weeks

In this section, we show that we obtain similar conclusions if we apply Card, Chetty, and Weber (2007)'s strategy to our dataset. In particular, in order to estimate the effect of eligibility for SP on overall exits from unemployment during the first 20 weeks, we censor all observations with unemployment duration above 20 weeks. We then estimate

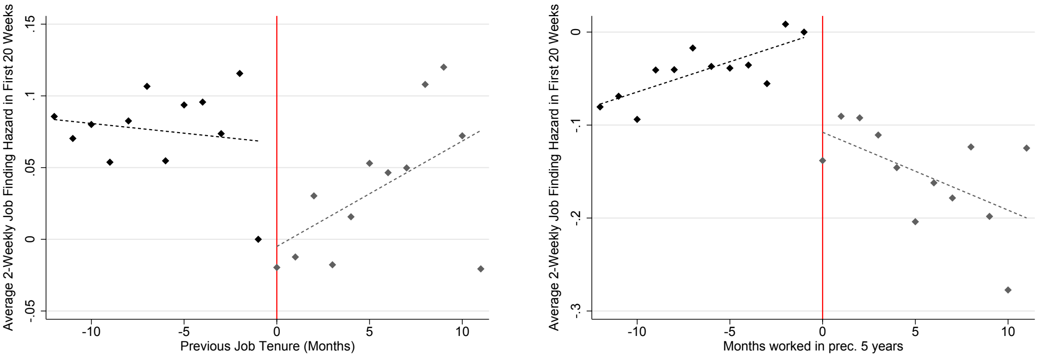
$$h(t) = \exp(\lambda_t),$$

where

$$\begin{aligned}\lambda_t = \alpha_t + \theta_1 \mathbb{1}\left[JT = -12\right] + \ldots + \theta_{11} \mathbb{1}\left[JT = -2\right] \\ + \theta_{13} \mathbb{1}\left[JT = 0\right] + \ldots + \theta_{24} \mathbb{1}\left[JT = 12\right] \\ + \beta_1 E + \beta_2 MW + \beta_3 MW \times E + \beta_4 MW^2 + \beta_5 MW^2 \times E \\ + \beta_6 MW^3 + \beta_7 MW^3 \times E,\end{aligned}$$

and t is in discrete time with two-weekly intervals and α_t controls for the baseline hazard. Note that $JT = -1$ is the omitted category. The θs hence give us the difference in the two-weekly job-finding probability relative to an individual just below the eligibility threshold for SP. We can do the analogous analysis for the effect of EB.

We plot the estimated θs in Figure 9. The discontinuities are roughly comparable in size to Card, Chetty, and Weber (2007), who report an effect between -0.094 and -0.125 for SP and -0.064 and -0.093 for EB.



(a) Effect of SP

(b) Effect of EB

Figure 9: Effect of severance pay and benefit extension on exits from unemployment during the first two weeks among claimants

E Allowing for Correlated Unobserved Heterogeneity in Take-up and Search Effort Choices

Assume the probability of claiming UI can be represented by the following equation

$$\ell_i = \text{Prob}\left\{\theta_i^\ell + \varepsilon_i^\ell > 0\right\}$$

where

$$\begin{aligned}\theta_i^\ell = &\beta_S S_i + \beta_E E_i + \beta_1 JT_i + \beta_2 MW_i + \beta_3 JT_i S_i + \beta_4 MW_i E_i \\ &+ \beta_5 JT_i^2 + \beta_6 MW_i^2 + \beta_7 JT_i^2 S_i + \beta_8 MW_i^2 E_i + \gamma' X_i.\end{aligned}$$

Moreover, the probability that a job is found in period t, given that i is unemployed up to period t, for take-up status $j \in \{0, 1\}$, is given by

$$\lambda_{ij}(t) = \text{Prob}\left\{\theta_{ij}^\lambda(t) + \varepsilon_i^\lambda > 0\right\}, \tag{17}$$

where

$$\begin{aligned}\theta_{ij}^\lambda(t) = &\beta_S S_i + \sum_{\tau=1}^{T} \alpha_\tau^S \mathbb{1}[t = \tau] \times S_i + \beta_E E_i + \sum_{\tau=1}^{T} \alpha_\tau^E \mathbb{1}[t = \tau] \times E_i \\ &+ \beta_1 JT_i + \beta_2 MW_i + \beta_3 JT_i \times S_i + \beta_4 MW_i \times E_i \\ &+ \beta_5 JT_i^2 + \beta_6 MW_i^2 + \beta_7 JT_i^2 \times S_i + \beta_8 MW_i^2 \times E_i + \\ &+ \beta_9 JT_i^3 + \beta_{10} MW_i^3 + \beta_{11} JT_i^3 \times S_i + \beta_{12} MW_i^3 \times E_i + \gamma' X_i,\end{aligned}$$

where we suppressed the dependence of all parameters on j to simplify notation.

To capture unobserved heterogeneity correlated across decisions, we assume that

$$\begin{bmatrix} \varepsilon_i^\ell \\ \varepsilon_i^\lambda \end{bmatrix} |(\theta_i^\ell, \theta_{ij}^\lambda) \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right).$$

For identifiability, we need to assume that ε_i^λ's conditional distribution does not depend on the takeup-status.

Consider worker i and assume i claims UI and exits after t_i periods. His contribution to the log-likelihood is given by

$$\begin{aligned} &\ln \mathrm{Prob}\left\{ \theta_i^\ell + \varepsilon_i^\ell > 0 \right\} \\ &\qquad + \sum_{\tau=1}^{t_i-1} \ln \left(1 - \mathrm{Prob}\left\{ \theta_{ij}^\lambda(\tau) + \varepsilon_i^\lambda > 0 | \theta_i^\ell + \varepsilon_i^\ell > 0 \right\} \right) \\ &\qquad\qquad + \ln \mathrm{Prob}\left\{ \theta_{ij}^\lambda(t) + \varepsilon_i^\lambda > 0 | \theta_i^\ell + \varepsilon_i^\ell > 0 \right\}. \end{aligned}$$

Using the properties of the bivariate normal distribution, this is equivalent to

$$\ln \Phi(\theta_i^\ell) + \sum_{\tau=1}^{t_i-1} \ln \left(\frac{\Phi_2(-\theta_{ij}^\lambda(\tau), \theta_i^\ell, -\rho)}{\Phi(\theta_i^\ell)} \right) + \ln \left(\frac{\Phi_2(\theta_{ij}^\lambda(t), \theta_i^\ell, \rho)}{\Phi(\theta_i^\ell)} \right),$$

where Φ_2 denotes the c.d.f. of the bivariate normal distribution.

Define f_{it} which takes the value 1 if i exits in period t and 0 otherwise. Then, the likelihood contribution can be written as $\sum_1^{t_i} l_{i\tau}$, where

$$l_{i\tau} = \mathbb{1}\{\tau = 1\} \cdot \ln \Phi(\theta_i^\ell) + (1 - f_{it}) \ln \left(\frac{\Phi_2(-\theta_{ij}^\lambda(\tau), \theta_i^\ell, -\rho)}{\Phi(\theta_i^\ell)} \right) + f_{it} \ln \left(\frac{\Phi_2(\theta_{ij}^\lambda(\tau), \theta_i^\ell, \rho)}{\Phi(\theta_i^\ell)} \right).$$

More generally, let $q_i^\ell = 2 \cdot \ell_i - 1$ and $q_i^{fj} = 2 \cdot f_{it}^j - 1$ for $j \in \{0, 1\}$. Then the likelihood contribution of period τ of worker i is given by

$$l_{i\tau} = \mathbb{1}\{\tau = 1\} \cdot \ln \Phi(q_i^\ell \theta_i^\ell) + \ln \left(\frac{\Phi_2(q_i^{fj} \theta_{ij}^\lambda(\tau), q_i^\ell \theta_i^\ell, q_i^\ell q_i^{fj} \rho)}{\Phi(q_i^\ell \theta_i^\ell)} \right).$$

If we impose $\rho = 0$, we obtain our baseline model as a special case.

	Exit uninsured	Exit insured	Take-up
Severance Pay	-0.0511	-0.00908	-0.196***
	(0.0785)	(0.0575)	(0.0478)
Severance Pay × Period 1	-0.0196	-0.0258	
	(0.0365)	(0.0411)	
Severance Pay × Period 2	-0.0122	0.0414	
	(0.0390)	(0.0383)	
Severance Pay × Period 3	-0.00406	-0.0298	
	(0.0499)	(0.0410)	
Severance Pay × Period 4	0.00395	-0.0674*	
	(0.0500)	(0.0394)	
Severance Pay × Period 5	-0.0243	-0.0688	
	(0.0596)	(0.0429)	
Severance Pay × Period 6	0.0384	-0.00629	
	(0.0542)	(0.0409)	
Severance Pay × Period 7	-0.0855	-0.0551	
	(0.0649)	(0.0437)	
Severance Pay × Period 8	0.0173	0.0170	
	(0.0609)	(0.0422)	
Severance Pay × Period 9	0.00953	-0.110**	
	(0.0741)	(0.0446)	
Severance Pay × Period 10	-0.0196	-0.0269	
	(0.0661)	(0.0428)	
Severance Pay × Period 11	-0.00159	-0.0994**	
	(0.0766)	(0.0454)	
Severance Pay × Period 12	-0.000233	-0.0418	
	(0.0605)	(0.0443)	
Severance Pay × Period 13	0.0785	-0.0587	
	(0.0614)	(0.0448)	
Extended Benefits	-0.0585	0.00431	0.117**
	(0.0635)	(0.0468)	(0.0510)
Extended Benefits × Period 1	0.0264	-0.0181	
	(0.0359)	(0.0393)	
Extended Benefits × Period 2	0.0144	-0.0451	
	(0.0382)	(0.0369)	
Extended Benefits × Period 3	-0.0188	0.00377	
	(0.0486)	(0.0393)	
Extended Benefits × Period 4	-0.101**	0.0272	
	(0.0483)	(0.0378)	
Extended Benefits × Period 5	0.00634	-0.00211	
	(0.0588)	(0.0408)	
Extended Benefits × Period 6	0.0532	-0.0423	
	(0.0540)	(0.0391)	
Extended Benefits × Period 7	0.0782	-0.0291	
	(0.0637)	(0.0416)	
Extended Benefits × Period 8	-0.0191	-0.0746*	
	(0.0600)	(0.0404)	
Extended Benefits × Period 9	-0.00825	-0.288***	
	(0.0726)	(0.0417)	
Extended Benefits × Period 10	-0.0592	-0.291***	
	(0.0629)	(0.0410)	
Extended Benefits × Period 11	-0.0783	-0.213***	
	(0.0741)	(0.0427)	
Extended Benefits × Period 12	-0.0141	-0.121***	
	(0.0592)	(0.0425)	
Extended Benefits × Period 13	-0.108*	-0.0471	
	(0.0605)	(0.0433)	
Estimated Correlation	.1401(.466)		
Log-Likelihood	-277343.452		
Observations	83451		

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

Table 10: Effect of severance pay and extended benefits on exits from unemployment and take-up, allowing for unobserved heterogeneity

F Omitted Results [FOR ONLINE PUBLICATION]

F.1 Derivation of the Estimable Equation

Letting $\Delta_i \equiv U_{i0}^{I} - U_{i0}^{\bar{I}}$ and assuming ϕ is Weibull distributed, the take-up probability satisfies

$$\ell_i = F(\Delta_i) = 1 - \exp\left(-(\Delta_i/\theta_{0i})^{\theta_1}\right),$$

where $\{\theta_{0i}, \theta_1\}$ are the parameters of the cost distribution to be estimated. Inverting this relationship, we find

$$\Delta_i = F^{-1}(\ell_i) = \theta_{0i}\left[-\ln(1-\ell_i)\right]^{1/\theta_1}.$$

Since the p.d.f. satisfies

$$f(\Delta_i) = \frac{\theta_1}{\theta_{0i}}\left(\frac{\Delta_i}{\theta_{0i}}\right)^{\theta_1 - 1}\exp\left(-(\Delta_i/\theta_{0i})^{\theta_1}\right),$$

we conclude

$$f\left(F^{-1}(\ell_i)\right) = \frac{\theta_1}{\theta_{0i}}\left[-\ln(1-\ell_i)\right]^{\frac{\theta_1-1}{\theta_1}}(1-\ell_i).$$

Moreover, assuming that the search cost function is isoelastic, satisfying $\psi(s) = a_{0i}s^{a_1}$, we obtain

$$\psi''(s) = a_{0i}a_1(a_1-1)s^{a_1-2}.$$

Plugging into the regression equation and replacing theoretical by estimated values, we find

$$\begin{aligned}
&\ln\frac{dp_i}{dE_i} - \ln\left(-\frac{dh_{iIT-1}}{dE_i}\right) = \\
&\quad \ln\frac{\theta_1}{\theta_{0i}} + \frac{\theta_1 - 1}{\theta_1}\ln(-\ln(1-p_i)) + \ln(1-p_i) + \ln\beta^{T-2} + \ln\left(\prod_{\tau=1}^{T-1}(1-h_{iI\tau})\right) \\
&\qquad\qquad + \ln(a_{0i}a_1(a_1-1)) + (a_1-2)\ln h_{iIT-1}.
\end{aligned}$$

We account for observed heterogeneity by assuming $a_{0i} = a_0\exp(X_i'\xi)$ and $\theta_{0i} = \theta_0\exp(X_i'\pi)$, where X_i is a vector of covariates. Define $\gamma \equiv \xi - \psi$. Simplifying and collecting terms, we get the estimable equation

$$y_i = K + \frac{\theta_1 - 1}{\theta_1}\ln(-\ln(1-p_i)) + (a_1-2)\ln h_{iIT-1} + X_i'\gamma, \tag{18}$$

where $y_i \equiv \ln\frac{dp_i}{dE_i} - \ln\left(-\frac{dh_{iIT-1}}{dE_i}\right) - \ln(1-p_i) - \ln\left(\prod_{\tau=1}^{T-1}(1-h_{iI\tau})\right)$ and $K \equiv \ln\frac{\theta_1}{\theta_0} + \ln\beta^{T-2} + \ln(a_0a_1(a_1-1))$.

F.2 Implementation of Bounds on Money Metric

Following the results derived by McEwen and Parresol (1991) for the truncated Weibull distribution, the expected take-up cost can be written as

$$\bar{\phi} = \begin{cases} \theta_0 \frac{\gamma(1/\theta_1+1, -\ln(1-p_i))}{p_i} & \text{if registered,} \\ \theta_0 \frac{\Gamma(1/\theta_1+1)-\gamma(1/\theta_1+1,-\ln(1-p_i))}{1-p_i} & \text{if not registered,} \end{cases}$$

where $\Gamma(z) \equiv \int_0^\infty x^{z-1} \exp(-x)\, dx$ denotes the Gamma function and $\gamma(z,u) \equiv \int_0^u x^{z-1} \exp(-x)\, dx$ denotes the incomplete Gamma function.

For claimants, it follows by plugging into (10) and replacing theoretical by estimated values that

$$\frac{[-\ln(1-p_i)]^{1/\theta_1} - \gamma(1/\theta_1+1, -\ln(1-\ell_i))/p_i}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}\left[-\ln(1-p_i)\right]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i} + \left[-\frac{dh_{IT-1}}{dE_i}\frac{1}{Bv_E}\right]\beta^{-1}\frac{a_{0i}}{\theta_{0i}}a_1(a_1-1)h_{IT-1}^{a_1-2}}$$
$$\leq \Delta A \leq \frac{[-\ln(1-p_i)]^{1/\theta_1} - \gamma(1/\theta_1+1, -\ln(1-\ell_i))/p_i}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}\left[-\ln(1-p_i)\right]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i}},$$

while for the non-claimants, using 11), it follows that

$$\frac{[-\ln(1-p_i)]^{1/\theta_1} - \left[\Gamma(1/\theta_1+1) - \gamma(1/\theta_1+1, -\ln(1-\ell_i))\right]/(1-p_i)}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}\left[-\ln(1-p_i)\right]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i}} \leq \Delta A \leq$$
$$\frac{[-\ln(1-p_i)]^{1/\theta_1} - \left[\Gamma(1/\theta_1+1) - \gamma(1/\theta_1+1, -\ln(1-\ell_i))\right]/(1-p_i)}{\left[-\frac{dp_i}{dS_i}\frac{1}{v_S}\right]\frac{1}{\theta_1}\left[-\ln(1-p_i)\right]^{(1-\theta_1)/\theta_1}\frac{1}{1-p_i} + \left[-\frac{dh_{IT-1}}{dE_i}\frac{1}{Bv_E}\right]\beta^{-1}\frac{a_{0i}}{\theta_{0i}}a_1(a_1-1)h_{IT-1}^{a_1-2}}.$$

F.3 Metric derivation in the general case

In the main text, we derive everything under the implicit assumption that the credit constraint is never binding. In the following, we show that our argument still goes through if this is not the case. Remember that in deriving our metric, we departed from

$$\Delta A \approx \left(U_0^I(A_0) - U_0^{\bar{I}}(A_0) - \phi\right)\left(\frac{\partial U_0^{\bar{I}}(A_0)}{\partial A_0}\right)^{-1}.$$

Consider first the denominator. Our strategy is to compute bounds on $\partial U_0^{\bar{I}}(A_0)/\partial A_0$. First, following the same line of argument as in the unconstrained case, we have

$$\frac{\partial U_0^{\bar{I}}(A_0)}{\partial A_0} - \frac{\partial U_0^I(A_0)}{\partial A_0} \leq \frac{\partial U_0^{\bar{I}}(A_0)}{\partial A_0} \leq \frac{\partial U_0^{\bar{I}}(A_0)}{\partial A_0} - \frac{\partial U_0^I(A_0)}{\partial A_0} + \frac{\partial U_T^I(A_T)}{\partial b_T}. \tag{19}$$

The first inequality is always true if $\partial U_0^I(A_0)/\partial A_0 \geq 0$ and $\left(\partial U_0^{\bar{I}}(A_0)/\partial A_0 - \partial U_0^I(A_0)/\partial A_0\right)$ is obtained using

$$\frac{d\ell}{dA_0} = f\left(F^{-1}(p)\right)\left(\frac{\partial U_0^I(A_0)}{\partial A_0} - \frac{\partial U_0^{\bar{I}}(A_0)}{\partial A_0}\right)$$

with p the estimated take-up probability for a given individual. We will show at the end of this appendix that the moments we fit to estimate the parameters of F are not affected by the credit constraint. Assume for the moment that we have such estimates.

Let's now consider the right-hand side of (19). As before, the second inequality holds as long as consumption is non-increasing over the unemployment spell since $\partial U_T^I(A_T)/\partial b_T^I = \partial U_T^I(A_T)/\partial A_T \geq \partial U_0^I(A_0)/\partial A_0$. We can bound $\partial U_T^I(A_T)/\partial b_T^I$. For that, we proceed as before, using

$$\frac{ds_{IT-1}}{db^e} = \frac{ds_{IT-1}}{db_T^I} + \ldots + \frac{ds_{IT-1}}{db_{T+E}^I} = \frac{ds_{IT-1}}{db_T^I}\left(1 + \frac{\partial U_T}{\partial b_{T+1}^I}\left(\frac{\partial U_T}{\partial b_T^I}\right)^{-1} + \ldots + \frac{\partial U_T}{\partial b_{T+E}^I}\left(\frac{\partial U_T}{\partial b_T^I}\right)^{-1}\right).$$

As an example, consider the effect of an increase in benefits tomorrow on your intertemporal utility today. One gets, using the envelope theorem,

$$\frac{\partial U_T}{\partial b_{T+1}^I} = -\lambda_T dA_{T+1}/db_{T+1}^I + \beta(1 - s_T)\frac{\partial U_{T+1}}{\partial b_{T+1}^I},$$

with λ_T the Langrange multiplier associated with the asset constraint. If the agent is constrained in period T, $\lambda_T > 0$ but $dA_{T+1}/db_{T+1}^I = 0$ because the agent is unable to reduce savings to adjust to the *future* income shock as she would if unconstrained: $A_{T+1} = \underline{A}$. More generally, the effect of future benefits on current inter-temporal utility is simply

$$\frac{\partial U_T}{\partial b_{T+j}^I} = \beta^j(1 - s_T)\ldots(1 - s_{T+j-1})\frac{\partial U_{T+j}}{\partial b_{T+j}^I},$$

which is true even if the worker is constrained. Again, when constrained, the worker cannot adjust her savings to *future* income shocks and savings will stay at their lower bound. Formally, if constrained in period $T + s$, with $s < j$, $\lambda_{T+s} > 0$ but $dA_{T+s}/db_{T+j}^I = 0$ such that $\lambda_{T+s} dA_{T+s}/db_{T+j}^I = 0$. With respect to our derivations, this means that the formula for the response of search intensities to *future* benefit changes is left unchanged.

We thus get

$$
\begin{aligned}
\frac{ds_{IT-1}}{db^e} &= \frac{ds_{IT-1}}{db^I_T}\left[1+\beta p_{T+1|T}\frac{\partial U_{T+1}}{\partial b^I_{T+1}}\left(\frac{\partial U_T}{\partial b^I_T}\right)^{-1}+\ldots+\beta^E p_{T+E|T}\frac{\partial U_{T+E}}{\partial b^I_{T+E}}\left(\frac{\partial U_T}{\partial b^I_T}\right)^{-1}\right] \\
&\leq \frac{ds_{IT-1}}{db^I_T}\underbrace{\left[1+\beta p_{T+1|T}+\ldots+\beta^E p_{T+E|T}\right]}_{\equiv B}.
\end{aligned}
$$

since $\partial U_T/\partial b^I_T \leq \partial U_{T+1}/\partial b^I_{T+1}$ as long as consumption is non-increasing over time. In the end, we get the same inequality derived under the hypothesis that the worker never hits the constraint.

To compute our metric, we finally need $U^I_0(A_0) - U^{\bar{I}}_0(A_0) - \phi$. As explained in the main text, this is achieved by inverting $F(.)$ and computing the expected take-up costs given observed behavior: the formulas used hold irrespective of the credit constraint. However, we need to consider how the estimation of the structural parameters itself could be affected. For that, we need to look at the theoretical counterpart to the moments used for the structural estimation. Again, because the formula for the response of search intensities to *future* benefit changes is left unchanged, we have

$$
\frac{d\ell/db^e}{ds_{IT-1}/db^e} = -f\left(U^I_0 - U^{\bar{I}}_0\right)\beta^{T-2}p_{T|1}\psi''_i(s_{IT-1})
$$

which corresponds to what we use for our estimation.