Online Appendix

A Mathematical appendix

A.1 Proof of Theorem 1

A.1.1 Proof of Lemma 2 (ii)

Akin to Equation (3.2), for any triple $(w, w', \tilde{w}) \in \Omega_w^3$:

$$\begin{pmatrix} \ln\left(\frac{h_{ww}^{ss'}}{\lambda^{ss'} f_w^{s'} - h_{ww}^{ss'}}\right) + \ln\left(\frac{h_{ww}^{s's}}{\lambda^{s's} f_w^{s} - h_{ww}^{s's}}\right) \\ \ln\left(\frac{h_{ww}^{ss'}}{\lambda^{ss'} f_w^{s'} - h_{ww}^{ss'}}\right) + \ln\left(\frac{h_{ww}^{s's}}{\lambda^{s's} f_w^{s} - h_{ww}^{s's}}\right) \end{pmatrix} = \begin{pmatrix} \ln\left(\frac{h_{w'w'}^{ss'}}{\lambda^{ss'} f_{w'}^{s'} - h_{w'w'}^{ss'}}\right) + \ln\left(\frac{h_{w'w'}^{s's}}{\lambda^{s's} f_{w'}^{s} - h_{w'w'}^{s's}}\right) \\ \ln\left(\frac{h_{\tilde{w}\tilde{w}}^{ss'}}{\lambda^{ss'} f_{\tilde{w}}^{s'} - h_{\tilde{w}\tilde{w}}^{ss'}}\right) + \ln\left(\frac{h_{\tilde{w}\tilde{w}}^{s's}}{\lambda^{s's} f_{\tilde{w}}^{s} - h_{\tilde{w}\tilde{w}}^{s's}}\right) \end{pmatrix} \tag{A.1}$$

Note that now we exploit transitions across job types s and s', thus we are able to use the same wage in the old and new jobs. This nonlinear system of two equations and two unknowns—$\lambda^{ss'}$ and $\lambda^{s's}$—can be rewritten as follows:

$$\begin{pmatrix} B_{w'}\lambda^{ss'} + C_{w'}\lambda^{s's} - A_{w'}\lambda^{ss'}\lambda^{s's} \\ B_{\tilde{w}}\lambda^{ss'} + C_{\tilde{w}}\lambda^{s's} - A_{\tilde{w}}\lambda^{ss'}\lambda^{s's} \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \tag{A.2}$$

where the A, B, C coefficients are defined in Lemma 2 (ii). Assuming $A_{w'} \neq 0$ (Condition (a) from Lemma 2 (ii)) and replacing $\lambda^{ss'}\lambda^{s's}$ in the second equation by its expression from the first equation identifies the ratio of the arrival rates, with:

$$\lambda^{s's} = \left(\frac{B_{w'}A_{\tilde{w}} - B_{\tilde{w}}A_{w'}}{A_{w'}C_{\tilde{w}} - A_{\tilde{w}}C_{w'}}\right)\lambda^{ss'}$$

where $A_{w'}C_{\tilde{w}} - A_{\tilde{w}}C_{w'} \neq 0$ from Condition (c). Finally, substituting for $\lambda^{s's}$ in the first equation identifies, under Condition (b), $\lambda^{ss'}$ and then $\lambda^{s's}$, which admit the following closed-form expressions:

$$\lambda^{ss'} = \frac{B_{w'}C_{\tilde{w}} - B_{\tilde{w}}C_{w'}}{B_{w'}A_{\tilde{w}} - B_{\tilde{w}}A_{w'}} \quad \text{and} \quad \lambda^{s's} = \frac{B_{w'}C_{\tilde{w}} - B_{\tilde{w}}C_{w'}}{A_{w'}C_{\tilde{w}} - A_{\tilde{w}}C_{w'}} \tag{A.3}$$

Having identified the arrival rates $\lambda^{ss'}$ and the wage offer distribution f_w^s, identification of the CCPs $p_{ww'}^{ss'}$ follows. Then, we can identify $c^{ss'} + c^{s's}$, and together with the assumption that switching costs are symmetric (i.e., $c^{ss'} = c^{s's}$), $c^{ss'}$ is identified.

A.1.2 Proof of Lemma 3 (ii)–(iii)

(ii) Identification of CRRA preferences. We assume that workers are endowed with CRRA preferences, such that:

$$u(w) = \alpha \frac{w^{1-\theta}}{1-\theta}$$

From the prior identification result in Lemma 3 such that u_w is identified up to a constant, it follows that for $\tilde{w} > w' > w$, the following ratio is identified:

$$\frac{u_{w'} - u_w}{u_{\tilde{w}} - u_w} = \frac{w'^{1-\theta} - w^{1-\theta}}{\tilde{w}^{1-\theta} - w^{1-\theta}} \tag{A.4}$$

In order to establish identification of the risk aversion parameter θ, we show that the function $\theta \mapsto \frac{y^{1-\theta} - x^{1-\theta}}{z^{1-\theta} - y^{1-\theta}}$, where $z > y > x > 0$, is monotonically increasing on $(0, \infty)$.

$$f(\theta) = \frac{y^{1-\theta} - x^{1-\theta}}{z^{1-\theta} - y^{1-\theta}} \tag{A.5}$$

$$f'(\theta) = \left(z^{1-\theta} - y^{1-\theta}\right)^{-2} \cdot \Big[\left(x^{1-\theta} \ln x - y^{1-\theta} \ln y\right)\left(z^{\theta} - y^{\theta}\right) - \left(y^{1-\theta} - x^{1-\theta}\right)\left(y^{1-\theta} \ln y - z^{1-\theta} \ln z\right)\Big] \tag{A.6}$$

$$f'(\theta) > 0 \tag{A.7}$$

$$\Leftrightarrow \left(x^{1-\theta} \ln x - x^{1-\theta} \ln y\right)\left(z^{1-\theta} - y^{1-\theta}\right) + \left(x^{1-\theta} \ln y - y^{1-\theta} \ln y\right)\left(z^{1-\theta} - y^{1-\theta}\right) > \left(z^{1-\theta} \ln y - z^{1-\theta} \ln z\right)\left(y^{1-\theta} - x^{1-\theta}\right) + \left(y^{1-\theta} \ln y - z^{1-\theta} \ln y\right)\left(y^{1-\theta} - x^{1-\theta}\right) \tag{A.8}$$

$$\Leftrightarrow \left[x^{1-\theta} \ln(x/y)\right]\left(z^{1-\theta} - y^{1-\theta}\right) > \left[z^{1-\theta} \ln(y/z)\right]\left(y^{1-\theta} - x^{1-\theta}\right) \tag{A.9}$$

$$\Leftrightarrow \ln(y/x)\left[1 - (y/z)^{1-\theta}\right] < \ln(z/y)\left[(y/x)^{1-\theta} - 1\right] \tag{A.10}$$

$$\Leftrightarrow \quad (y/x)^{1-\theta} \ln(z/y) + \ln(y/x)(y/z)^{1-\theta} > \ln(y/x) + \ln(z/y) \tag{A.11}$$

The above condition holds if and only if $g(\theta) > g(1)$, where, for all $\theta > 0$, $g(\theta) \equiv (y/x)^{1-\theta}\ln(z/y) + (y/z)^{1-\theta}\ln(y/x)$. The derivative of $g(\cdot)$ is given by:

$$g'(\theta) = \ln(y/x)\ln(z/y)[(y/z)^{1-\theta} - (y/x)^{1-\theta}]$$

It follows that $g'(\theta) < 0$ on $(0,1)$ and $g'(\theta) > 0$ on $(1,\infty)$. Identification of θ follows.

Having identified θ, it follows that the utility coefficient α is identified and given by the following closed-form expression:

$$\alpha = \frac{u_{\tilde{w}} - u_w}{\tilde{w}^{1-\theta} - w^{1-\theta}} \tag{A.12}$$

which yields full identification of the flow utility of wages.

(iii) Identification of ϕ^s up to $V_0(0)$. We can express the log odds ratio in terms of the structural parameters using Equation (3.7):

$$\begin{aligned}
\ln\left(\frac{p_{w\tilde{w}}^{s\tilde{s}}}{1-p_{w\tilde{w}}^{s\tilde{s}}}\right) &= V_{\tilde{w}}^{\tilde{s}} - c^{s\tilde{s}} - V_w^s \\
&= \Big(u_{\tilde{w}} + \phi^{\tilde{s}} + \delta_0^{\tilde{s}}V_0(0) - \sum_{w'}\sum_{s'}\delta_{\tilde{w}w'}^{\tilde{s}s'}\left[c^{\tilde{s}s'} + \ln\left(p_{\tilde{w}w'}^{\tilde{s}s'}\right) - \ln\left(1-p_{\tilde{w}w'}^{\tilde{s}s'}\right)\right] \\
&\quad - \sum_{w'}\sum_{s'}\lambda^{\tilde{s}s'}f_{w'}^{s'}\ln\left(1-p_{\tilde{w}w'}^{\tilde{s}s'}\right)\Big)\Big/(\rho+\delta_0^{\tilde{s}}) \\
&\quad - \Big(u_w + \phi^s + \delta_0^s V_0(0) - \sum_{w'}\sum_{s'}\delta_{ww'}^{ss'}\left[c^{ss'} + \ln\left(p_{ww'}^{ss'}\right) - \ln\left(1-p_{ww'}^{ss'}\right)\right] \\
&\quad + \sum_{w'}\sum_{s'}\lambda^{ss'}f_{w'}^{s'}\ln\left(1-p_{ww'}^{ss'}\right)\Big)\Big/(\rho+\delta_0^s) - c^{s\tilde{s}}
\end{aligned} \tag{A.13}$$

Collecting all known terms on the left hand side, the equation can be rearranged as:

$$\kappa_{w\tilde{w}}^{s\tilde{s}} = \frac{1}{\rho+\delta_0^{\tilde{s}}}\phi^{\tilde{s}} - \frac{1}{\rho+\delta_0^s}\phi^s + \left(\frac{\delta_0^{\tilde{s}}}{\rho+\delta_0^{\tilde{s}}} - \frac{\delta_0^s}{\rho+\delta_0^s}\right)V_0(0) \tag{A.14}$$

where

$$
\begin{aligned}
\kappa_{w\tilde{w}}^{s\tilde{s}} &= \ln\left(\frac{p_{w\tilde{w}}^{s\tilde{s}}}{1-p_{w\tilde{w}}^{s\tilde{s}}}\right) + c^{s\tilde{s}} \\
&- \frac{u_{\tilde{w}} - \sum_{w'}\sum_{s'}\delta_{\tilde{w}w'}^{\tilde{s}s'}\left[c^{\tilde{s}s'} + \ln\left(p_{\tilde{w}w'}^{\tilde{s}s'}\right) - \ln\left(1-p_{\tilde{w}w'}^{\tilde{s}s'}\right)\right] - \sum_{w'}\sum_{s'}\lambda^{\tilde{s}s'} f_{w'}^{s'} \ln\left(1-p_{\tilde{w}w'}^{\tilde{s}s'}\right)}{\rho + \delta_0^{\tilde{s}}} \\
&+ \frac{u_{w} - \sum_{w'}\sum_{s'}\delta_{ww'}^{ss'}\left[c^{ss'} + \ln\left(p_{ww'}^{ss'}\right) - \ln\left(1-p_{ww'}^{ss'}\right)\right] - \sum_{w'}\sum_{s'}\lambda^{ss'} f_{w'}^{s'} \ln\left(1-p_{ww'}^{ss'}\right)}{\rho + \delta_0^{s}}
\end{aligned} \tag{A.15}
$$

Now, since $\phi^1 = 0$, writing Equation (A.14) for $s = 1$ yields:

$$
\tilde{\kappa}_{w\tilde{w}}^{1\tilde{s}} = \frac{1}{\rho + \delta_0^{\tilde{s}}}\,\phi^{\tilde{s}} + \left(\frac{\delta_0^{\tilde{s}}}{\rho + \delta_0^{\tilde{s}}} - \frac{\delta_0^{1}}{\rho + \delta_0^{1}}\right) V_0(0) \tag{A.16}
$$

Thus, we can write $\phi^{\tilde{s}}$ as a known linear function of $V_0(0)$. Furthermore, note that when the job destruction rates are not specific to job types, i.e., $\delta_0^s = \delta_0$ for all s, the non-pecuniary payoffs ϕ^s are directly identified from Equation (A.16).

A.2 Extension: aggregate shocks

One can extend our identification strategy to accommodate aggregate shocks. Specifically, consider the case where the market economy can be in one of K different states, where the job offer arrival rates, the job destruction rates, the rates of involuntary wage mobility, the offered wage distributions, and the flow payoff of unemployment are allowed to depend on the state of the economy. We further assume that the econometrician perfectly observes the state of the economy. We denote the rate at which the economy transitions from state k to k' by $q_{kk'}$, which is identified from the observed transition rates across market states.

On the employment side, identification of the state-specific offer arrival rates, destruction and involuntary wage mobility rates, offered wage distribution and conditional choice probabilities, along with the switching cost all follow directly from the baseline case, leaving the flow payoff of employment as the only unknown parameters. The value function of employment V^s_{wk} is given by:

$$\Big(\rho + \sum_{k'} q_{kk'} + \delta^s_{0k} + \sum_{s'} \lambda^{ss'}_k\Big) V^s_{wk} = u_w + \phi^s + \delta^s_{0k} V_{0k}(0) + \sum_{k'} q_{kk'} V^s_{wk'}$$
$$+ \sum_{w'} \sum_{s'} \delta^{ss'}_{ww'k} \left[V^{s'}_{w'k} - V^s_{wk}\right] + \sum_{s'} \lambda^{ss'}_k \sum_{w'} f^{s'}_{w'k} \ln\left(1 - p^{ss'}_{ww'k}\right) \tag{A.17}$$

where $V^{s'}_{w'k} - V^s_{wk} = \ln\left(p^{ss'}_{ww'k}\right) - \ln\left(1 - p^{ss'}_{ww'k}\right) + c^{ss'}$.

Subtracting off the corresponding expression for $V^s_{\tilde{w}k}$ (with $\tilde{w} \neq w$) yields:

$$\Big(\rho + \sum_{k'} q_{kk'} + \delta^s_{0k} + \sum_{s'} \lambda^{ss'}_k\Big) \left[V^s_{wk} - V^s_{\tilde{w}k}\right] = u_w - u_{\tilde{w}} + \sum_{k'} q_{kk'} \left[V^s_{wk'} - V^s_{\tilde{w}k'}\right]$$
$$+ \sum_{w'} \sum_{s'} \left(\delta^{ss'}_{ww'k} \left[V^{s'}_{w'k} - V^s_{wk}\right] - \delta^{ss'}_{\tilde{w}w'k} \left[V^{s'}_{w'k} - V^s_{\tilde{w}k}\right]\right)$$
$$+ \sum_{s'} \lambda^{ss'}_k \sum_{w'} f^{s'}_{w'k} \left(\ln\left(1 - p^{ss'}_{ww'k}\right) - \ln\left(1 - p^{ss'}_{\tilde{w}w'k}\right)\right) \tag{A.18}$$

where the difference in value functions on the left and right-hand sides are given by the sum of the log odds ratio and the switching cost. This identifies the wage component of the flow payoff up to a constant. Identification of the non-pecuniary components ϕ^s then proceeds in a similar fashion, using instead the job-to-job transitions across job types.

Identification of the unemployment-side parameters then follows from similar arguments as in Section 3.3. The same strategy applies to a context with aggregate shocks, after conditioning the hazard rates out of unemployment on the (observed) states of the economy.

B Data appendix

B.1 Sample creation

We define our analysis sample as follows:

1. Flip primary and secondary work arrangements (PWAs, SWAs)

    - In the raw data, PWA is defined as the arrangement with the highest earnings in the month. This setup may result in PWAs and SWAs flipping in the raw data, e.g. when a worker works only a few days in their PWA.

- *Solution:* Looping through all worker-months, we flip variables related to PWAs and SWAs as follows:

`month`	`firmid1`	`var1`	`firmid2`	`var2`		`month`	`firmid1`	`var1`	`firmid2`	`var2`
$t-1$	A	x_{t-1}	B	y_{t-1}	$\rightsquigarrow$	$t-1$	A	x_{t-1}	B	y_{t-1}
t	B	x_t	A	y_t		t	A	y_t	B	x_t

2. Calculate durations

   (a) Employed: we calculate or infer spell-year durations in PWA. See Appendix B.2 for details.

   (b) Unemployed: we observe daily unemployment durations in the raw data. For spells that end after October 2005 (the end date of our sample), we flag spells as right-censored and shorten their durations by the out-of-sample portion. Therefore, our analysis sample includes U spells that are censored earlier than 269 days.

3. Define EE, EU, UE, EN, NE transitions

4. Calculate wages

   (a) Calculate counterfactual minimum wage earnings: how much the worker would have earned in a day working full time in a minimum-wage job

   (b) Calculate daily wages as total earnings in a spell-year, divided by spell-year durations

   (c) Discretize wages: see Appendix B.3 for details

   (d) Calculate accepted wages

5. Define covariates for population probabilities

6. Save analysis sample

B.2 Correcting employment spell durations

The raw data on employment spells are recorded at a monthly frequency. In each month, the total number of days worked (`days`) and total earnings are known. Furthermore, days worked and earnings at PWAs and SWAs (`days_1`, `days_2`) are known if the arrangement was ongoing on the 15th of the month. We focus on PWAs only. Table 7 summarizes the possible ways in which EE transitions show up in the raw data when observations on PWAs are not missing. When `days` equals `days_1`, we know with certainty that the transition happened on the boundary of the month: we label this as a clean EE transition (see Panel a). When `days` does not equal `days_1`, we need to make some assumptions about the uncovered days: Panels b-d illustrate these cases that we label fuzzy. The bottom tables summarize our assumptions on the number of days worked in each PWA.

Table 7: EE scenarios in raw data, no missing PWAs

(a) Clean EE

days	days_1	firmid1
31	31	A
30	30	A
31	31	B

⇓

no assumption needed

(b) Fuzzy EE 1

days	days_1	firmid1
31	31	A
30	16	A
31	31	B

⇓

days_1	firmid1
31	A
16	A
14	B
31	B

(c) Fuzzy EE 2

days	days_1	firmid1
31	31	A
30	16	B
31	31	B

⇓

days_1	firmid1
31	A
14	A
16	B
31	B

(d) Fuzzy EE 3

days	days_1	firmid1
31	31	A
30	16	B
31	31	C

⇓

days_1	firmid1
31	A
$a < 14$	A
16	B
$30 - 16 - a$	C
31	C

Table 8 summarizes our assumptions when PWA data are missing.

Table 8: EE scenarios in raw data, missing PWAs

(a)

days	days_1	firmid1
31	31	A
25	.	.
31	31	A

⇓

days_1	firmid1
31	A
25	A
31	A

(b)

days	days_1	firmid1
31	31	A
25	.	.
31	31	B

⇓

days_1	firmid1
31	A
$d < 15$	A
$25 - d$	B
31	B

(c)

days	days_1	firmid1
31	31	A
10	.	.
7	.	.
30	30	B

⇓

days_1	firmid1
31	A
10	A
7	B
31	B

(d)

days	days_1	firmid1
31	31	A
20	.	.
25	.	.
31	31	B

⇓

days_1	firmid1
31	A
$a < 15$	A
$20 - a + 25 - b$	X
$b < 15$	B
31	B

Furthermore, we censor spells that spill over calendar years. We do so in order to track yearly wage changes observed in the raw data. Additionally, we censor spells at October 31st due to data limitations, as mentioned in the text. As an example, a continuous E spell from March 2003 until May 2005 that pays wage w and is followed by a EE transition to a job paying w' is represented as a right-censored spell of 8 months in w, a right-censored spell of 10 months in w, and a spell of 5 months with a EE transition from w to w'.

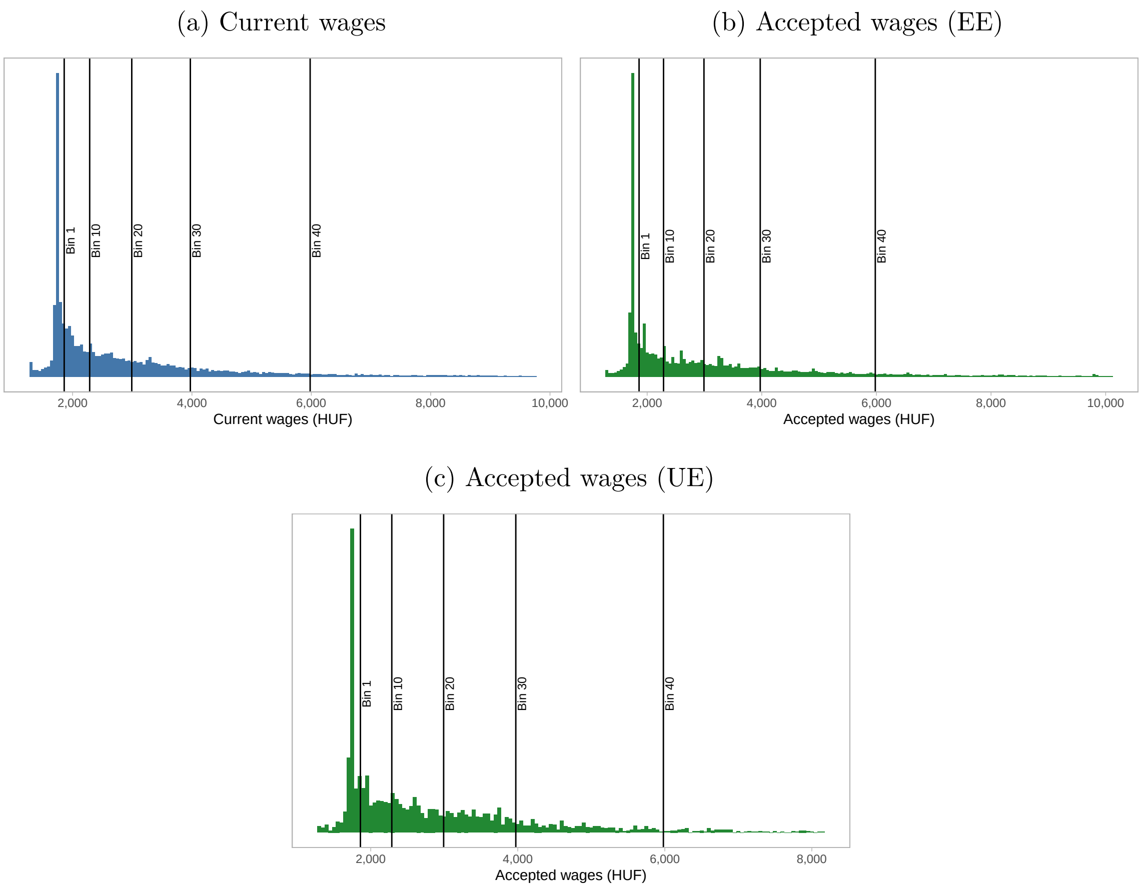
B.3 Discretizing wages

We discretize the continuously observed wages in the data into W bins, with $W = 50$ for our main results. First, we calculate the average daily wage for each worker in a given year across all months spent in employment. Then we categorize these continuous wages into discrete bins. The first bin contains wages between 75 and 107 percent of the effective minimum wage.[29] We drop wage observations below 75 percent of the effective minimum wage because we cannot distinguish between full-time and part-time earners in the data. Furthermore, we add a 7 percent padding to the right cutoff of the first bin to ensure that we include all minimum wage earners in the first bin. We then split the other wage observations, censored at the 99th percentile, evenly across the remaining $W-1$ bins. We repeat the same discretization procedure for each calendar year: Figure 6 demonstrates our discretization method for 2004 for various groups.

Figure 7 plots the resulting discrete distribution of current wages. Current wages for employment spells that lead to a job-to-job transition, on the left panel, have a mean of 3,428 HUF (percentiles: 25th 1,738 HUF; 50th 2,347 HUF; 75th 3,685 HUF). Current wages for all employment spells, on the right panel, have a mean of 3,670 HUF (percentiles: 25th 1,738 HUF; 50th 2,557 HUF; 75th 4,249 HUF). Similarly, Figure 8 plots the discrete distribution of accepted wages for job-to-job and unemployment-to-employment transitions. Accepted wages for job-to-job transitions have a mean of 3,657 HUF (percentiles: 25th 1,738 HUF; 50th 2,516 HUF; 75th 4,056 HUF). Accepted wages out of unemployment are more right-tailed than those for job-to-job

[29] During our sampling period, Hungary had a simple minimum wage policy: 50,000 HUF in 2003, 53,000 HUF in 2004, and 57,000 HUF in 2005 (200 HUF $\approx$ 1 USD in 2004).

Figure 6: Discretizing observed wages

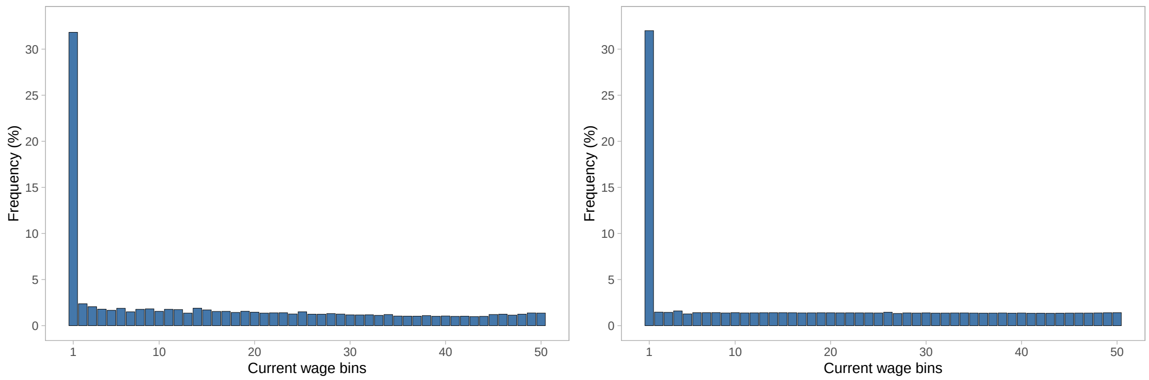


Notes: Histograms of daily wage rates in 2004 with 50 HUF bin width, truncated at the 95th percentile (200 HUF ≈ 1 USD in 2004). Vertical lines denote selected wage bin cutoffs. Panel (a): current daily wages for employment spells that lead to an EE transition. Panel (b): accepted daily wages for employment spells after an EE transition. Panel (c): accepted daily wages for unemployment spells after a UE transition.
Source: CERS-HAS, authors' own calculations.

Figure 7: Discrete distribution of current wages

(a) Spells leading to EE transitions

(b) All spells

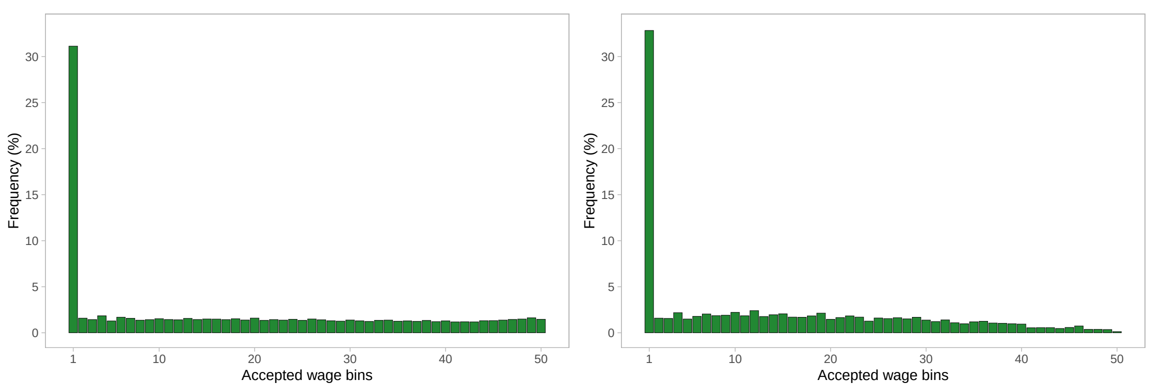


Notes: Panel (a): discrete distribution of current wages for employment spells that lead to an EE transition. Panel (b): discrete distribution of current wages for all employment spells.
Source: CERS-HAS, authors' own calculations.

Figure 8: Discrete distribution of accepted wages

(a) EE transitions

(b) UE transitions



Notes: Panel (a): discrete distribution of accepted wages for employment spells that lead to an EE transition. Panel (b): discrete distribution of accepted wages for unemployment spells that lead to an employment spell.
Source: CERS-HAS, authors' own calculations.

transitions, with a mean of 3,021 HUF (percentiles: 25th 1,802 HUF; 50th 2,427 HUF; 75th 3,543 HUF), in line with the notion that the unemployed tend to move to lower-paying jobs.

C Estimation appendix

This appendix details our estimation procedure, outlined in Section 5.

C.1 Posterior type distribution

Rather than imposing the structure of the model when classifying types, we instead choose a flexible functional form for the likelihood of job-to-job transitions. In particular, we obtain estimates of θ_r^I by maximizing an alternative objective function:

$$\sum_i \ln \left(\sum_r \pi_r \mathcal{L}_{ir}^I(\theta_r^I) \prod_{s=1}^{S_i} \tilde{\mathcal{L}}_{isr}^E(\tilde{\theta}_r^E) \right) \tag{C.1}$$

where $\mathcal{L}_{ir}^I(\theta_r^I)$ was defined in Equation (5.3) and we specify the reduced-form likelihood associated with employment spell s below.

We break the hazard of going from w to w' into two parts: (i) the hazard of leaving w-paying job for any other job, and (ii) the probability that the accepted job pays w'. These two parts are associated with the parameters $\tilde{\theta}_r^h$ and $\tilde{\theta}_r^w$, respectively. We specify the reduced-form hazard of leaving a w-paying job given the individual is of type-r as:

$$\tilde{h}_{wsr} = \exp(\tilde{\theta}_{1r}^h + \tilde{\theta}_{2r}^h \ln(w_s) + \tilde{\theta}_{3r}^h \mathbb{1}\{w_s = \underline{w}\} + \tilde{\theta}_{4r}^h \mathbb{1}\{y_s = 2004\} + \tilde{\theta}_{5r}^h \mathbb{1}\{y_s = 2005\}) \tag{C.2}$$

where y_s refers to the calendar year of spell s.

Conditional on moving to a new job, for the reduced form we model the accepted wage as a tobit like in Equation (5.3) but where one of the conditioning variables is the log of the current wage. Note that here we use the actual observed wage level in a given spell (unlike for the utility of wages where we use the mean wage in each bin). $\tilde{\mathcal{L}}_{isr}^E(\tilde{\theta}_r^E)$ is then given by:

$$\tilde{\mathcal{L}}^E_{isr}(\tilde{\theta}^E_r) = \left[\prod_w \tilde{h}_{wsr} \exp(-\tilde{h}_{wsr} t_s)\right]^{\mathbb{1}\{w_s = w\}} \tag{C.3}$$
$$\times \left[\Phi\left(\frac{\ln(\underline{w}) - \tilde{X}^w_s \tilde{\theta}^w_{xr}}{\tilde{\sigma}^w_r}\right)\right]^{\mathbb{1}\{w_{s+1} = \underline{w}\}} \cdot \left[\frac{1}{\tilde{\sigma}^w_r} \phi\left(\frac{\ln(w_{s+1}) - \tilde{X}^w_s \tilde{\theta}^w_{xr}}{\tilde{\sigma}^w_r}\right)\right]^{\mathbb{1}\{w_{s+1} > \underline{w}\}}$$

with $\tilde{\theta}^E_r = \left(\tilde{\theta}^h_r, \tilde{\theta}^w_{xr}, \tilde{\sigma}^w_r\right)'$, where $\tilde{X}^w_s \tilde{\theta}^w_{xr}$ is given by:

$$\tilde{X}^w_s \tilde{\theta}^w_{xr} = \tilde{\theta}^w_{1r} + \tilde{\theta}^w_2 \ln(w_s) + \tilde{\theta}^w_3 \mathbb{1}\{y_s = 2004\} + \tilde{\theta}^w_4 \mathbb{1}\{y_s = 2005\} \tag{C.4}$$

We then estimate the parameters $\left(\theta^I_r, \tilde{\theta}^E_r\right)$ using:

$$\max_{\theta^I_r, \tilde{\theta}^E_r} \sum_i \ln\left(\sum_r \pi_r \mathcal{L}^I_{ir}(\theta^I_r) \prod_{s=1}^{S_i} \tilde{\mathcal{L}}^E_{isr}(\tilde{\theta}^E_r)\right) \tag{C.5}$$

and recover the conditional type probabilities using:

$$q_{ir} = \frac{\pi_r \mathcal{L}^I_{ir}(\theta^I_r) \prod_{s=1}^{S_i} \tilde{\mathcal{L}}^E_{isr}(\tilde{\theta}^E_r)}{\sum_r \pi_r \mathcal{L}^I_{ir}(\theta^I_r) \prod_{s=1}^{S_i} \tilde{\mathcal{L}}^E_{isr}(\tilde{\theta}^E_r)} \tag{C.6}$$

C.2 Unemployed-side structural parameters

C.2.1 Optimization constraints for Type 1

The first set of constraints in Equation (5.27) simplify to the following nonlinear constraints:

$$p_{\underline{w}1}(t) \leq p_{\underline{w}1}(t+1) \tag{C.7}$$

$$\frac{h_{\underline{w}1}(t)}{\lambda_1(t)\, g_{\underline{w}1}(t)} \leq \frac{h_{\underline{w}1}(t+1)}{\lambda_1(t+1)\, g_{\underline{w}1}(t+1)} \tag{C.8}$$

$$\frac{\exp(X_{t+1}^{\lambda}\theta^{\lambda})}{\exp(X_t^{\lambda}\theta^{\lambda})} \frac{\Lambda\left(\beta_1\phi_{\underline{w}} + \gamma_{11} + \gamma_{21}\ln(t+1)\right)}{\Lambda\left(\beta_1\phi_{\underline{w}} + \gamma_{11} + \gamma_{21}\ln(t)\right)} \leq \frac{\exp(X_{t+1}^{h}\theta_1^{h})}{\exp(X_t^{h}\theta_1^{h})} \tag{C.9}$$

$$\begin{aligned} &\left(X_{t+1}^{\lambda} - X_t^{\lambda}\right)\theta^{\lambda} - \left(X_{t+1}^{h} - X_t^{h}\right)\theta_1^{h} \\ &+ \ln\left[1 + \exp\left(-\beta_1\phi_{\underline{w}} - \gamma_{11} - \gamma_{21}\ln(t)\right)\right] \\ &- \ln\left[1 + \exp\left(-\beta_1\phi_{\underline{w}} - \gamma_{11} - \gamma_{21}\ln(t+1)\right)\right] \leq 0 \end{aligned} \tag{C.10}$$

The second constraint simplifies to the following nonlinear constraint:

$$p_{\underline{w}1}(1) \geq \varepsilon \tag{C.11}$$

$$\frac{h_{\underline{w}1}(1)}{\lambda_1(1)\, g_{\underline{w}1}(1)} \geq \varepsilon \tag{C.12}$$

$$\frac{\exp(X_1^{h}\theta_1^{h})}{\exp(X_1^{\lambda}\theta^{\lambda})} \frac{1}{\Lambda\left(\beta_1\phi_{\underline{w}} + \gamma_{11}\right)} \geq \varepsilon \tag{C.13}$$

$$X_1^{h}\theta_1^{h} - X_1^{\lambda}\theta^{\lambda} - \ln\left[1 + \exp(-\beta_1\phi_{\underline{w}} - \gamma_{11})\right] \geq \ln(\varepsilon) \tag{C.14}$$

The third constraint simplifies as follows:

$$p_{\overline{w}1}(T) \leq 1 - \varepsilon \tag{C.15}$$

$$\frac{h_{\underline{w}1}(T)\exp(-\kappa_{\underline{w}\overline{w}1})}{\lambda_1(T)\, g_{\underline{w}1}(T) - h_{\underline{w}1}(T)[1 - \exp(-\kappa_{\underline{w}\overline{w}1})]} \leq 1 - \varepsilon \tag{C.16}$$

$$\exp(X_T^h \theta_1^h)\left[1 + \frac{\varepsilon}{1-\varepsilon}\exp(-\kappa_{\underline{w}\overline{w}1})\right] \leq \exp(X_T^\lambda \theta^\lambda)\,\Lambda\left(\beta_1 \phi_{\underline{w}} + \gamma_{11} + \gamma_{21}\ln(T)\right) \tag{C.17}$$

$$X_T^h \theta_1^h + \ln\left[1 + \frac{\varepsilon}{1-\varepsilon}\exp(-\kappa_{\underline{w}\overline{w}1})\right] \leq X_T^\lambda \theta^\lambda - \ln[1 + \exp(-\beta_1 \phi_{\underline{w}} - \gamma_{11} - \gamma_{21}\ln(T))] \tag{C.18}$$

C.2.2 Optimization constraints for Type $r = 2$

The first set of constraints in Equation (5.31) simplify to the following nonlinear constraints:

$$p_{\underline{w}2}(t) \leq p_{\underline{w}2}(t+1) \tag{C.19}$$

$$\frac{h_{\underline{w}2}(t)}{\lambda_2(t)\, g_{\underline{w}2}(t)} \leq \frac{h_{\underline{w}2}(t+1)}{\lambda_2(t+1)\, g_{\underline{w}2}(t+1)} \tag{C.20}$$

$$\frac{\exp(X_{t+1}^\lambda \theta^\lambda \nu_2^\lambda + \psi_2^\lambda)}{\exp(X_t^\lambda \theta^\lambda \nu_2^\lambda + \psi_2^\lambda)}\,\frac{\Lambda\left(\beta_2 \phi_{\underline{w}} + \gamma_{12} + \gamma_{22}\ln(t+1)\right)}{\Lambda\left(\beta_2 \phi_{\underline{w}} + \gamma_{12} + \gamma_{22}\ln(t)\right)} \leq \frac{\exp(X_{t+1}^h \theta_2^h)}{\exp(X_t^h \theta_2^h)} \tag{C.21}$$

$$\begin{aligned}&\left(X_{t+1}^\lambda - X_t^\lambda\right)\theta^\lambda \nu_2^\lambda - \left(X_{t+1}^h - X_t^h\right)\theta_2^h \\ &+ \ln\left[1 + \exp\left(-\beta_2 \phi_{\underline{w}} - \gamma_{12} - \gamma_{22}\ln(t)\right)\right] \\ &- \ln\left[1 + \exp\left(-\beta_2 \phi_{\underline{w}} - \gamma_{12} - \gamma_{22}\ln(t+1)\right)\right] \leq 0\end{aligned} \tag{C.22}$$

The second constraint simplifies as follows:

$$p_{\underline{w}2}(1) \geq \varepsilon \tag{C.23}$$

$$\frac{h_{\underline{w}2}(1)}{\lambda_2(1)\, g_{\underline{w}2}(1)} \geq \varepsilon \tag{C.24}$$

$$\frac{\exp(X_1^h \theta_2^h)}{\exp(X_1^\lambda \theta^\lambda \nu_2^\lambda + \psi_2^\lambda)}\,\frac{1}{\Lambda\left(\beta_2 \phi_{\underline{w}} + \gamma_{12}\right)} \geq \varepsilon \tag{C.25}$$

$$X_1^h \theta_2^h - X_1^\lambda \theta^\lambda \nu_2^\lambda - \psi_2^\lambda - \ln\left[1 + \exp(-\beta_2 \phi_{\underline{w}} - \gamma_{12})\right] \geq \ln(\varepsilon) \tag{C.26}$$

The third constraint which ensures that the CCPs are less than one simplifies to the following nonlinear constraint:

$$p_{\overline{w}2}(T) \leq 1 - \varepsilon \tag{C.27}$$

$$\frac{h_{\underline{w}2}(T)\exp(-\kappa_{\underline{w}\overline{w}2})}{\lambda_2(T)\, g_{\underline{w}2}(T) - h_{\underline{w}2}(T)[1-\exp(-\kappa_{\underline{w}\overline{w}2})]} \leq 1 - \varepsilon \tag{C.28}$$

$$\exp(X_T^h \theta_2^h)\left[1 + \frac{\varepsilon}{1-\varepsilon}\exp(-\kappa_{\underline{w}\overline{w}2})\right] \leq \exp(X_T^\lambda \theta^\lambda \nu_2^\lambda + \psi_2^\lambda)\,\Lambda\left(\beta_2\phi_{\underline{w}} + \gamma_{12} + \gamma_{22}\ln(T)\right) \tag{C.29}$$

$$X_T^h \theta_2^h + \ln\left[1 + \frac{\varepsilon}{1-\varepsilon}\exp(-\kappa_{\underline{w}\overline{w}2})\right] \leq X_T^\lambda \theta^\lambda \nu_2^\lambda + \psi_2^\lambda - \ln[1+\exp(-\beta_2\phi_{\underline{w}} - \gamma_{12} - \gamma_{22}\ln(T))] \tag{C.30}$$

Table 9: Computation time

Step	**Elapsed time**
Estimate posterior probabilities	24.13 min
Estimate job-to-job structural parameters	12.34 min
Estimate unemployment-to-job structural parameters	7.87 sec
Total	36.77 min

Notes: Computation time of the full three-step estimation procedure, using a random perturbation around the baseline estimates as starting values. Total includes, on top of the three estimation steps, reading in the data and estimating nonparametric unemployment-to-employment hazards. Benchmarked on a 32-core Intel® Xeon® Gold 6134 3.20GHz CPU with 96GB RAM, running MathWorks® MATLAB® R2018b (9.5.0.1033004).

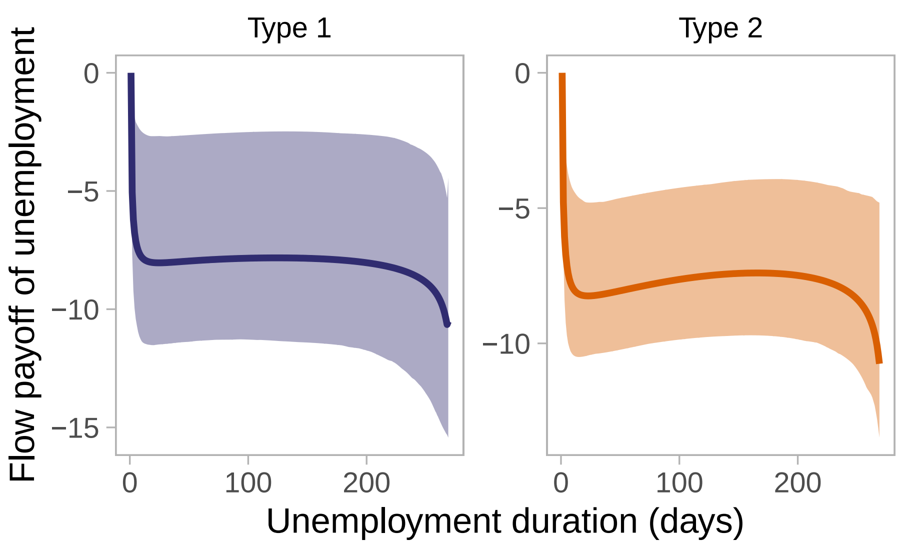
D Additional results

Table 10: Type probabilities

Initial wage bin	**Type probability**	
	Type 1	*Type 2*
1	99.8%	0.2%
	[99.8%, 99.8%]	[0.2%, 0.2%]
10	99.0%	1.0%
	[98.9%, 99.0%]	[1.0%, 1.1%]
20	96.2%	3.8%
	[95.9%, 96.4%]	[3.6%, 4.1%]
30	87.4%	12.6%
	[86.7%, 88.1%]	[11.9%, 13.3%]
40	61.8%	38.2%
	[60.0%, 63.0%]	[37.0%, 40.0%]
50	1.5%	98.5%
	[1.3%, 1.7%]	[98.3%, 98.7%]

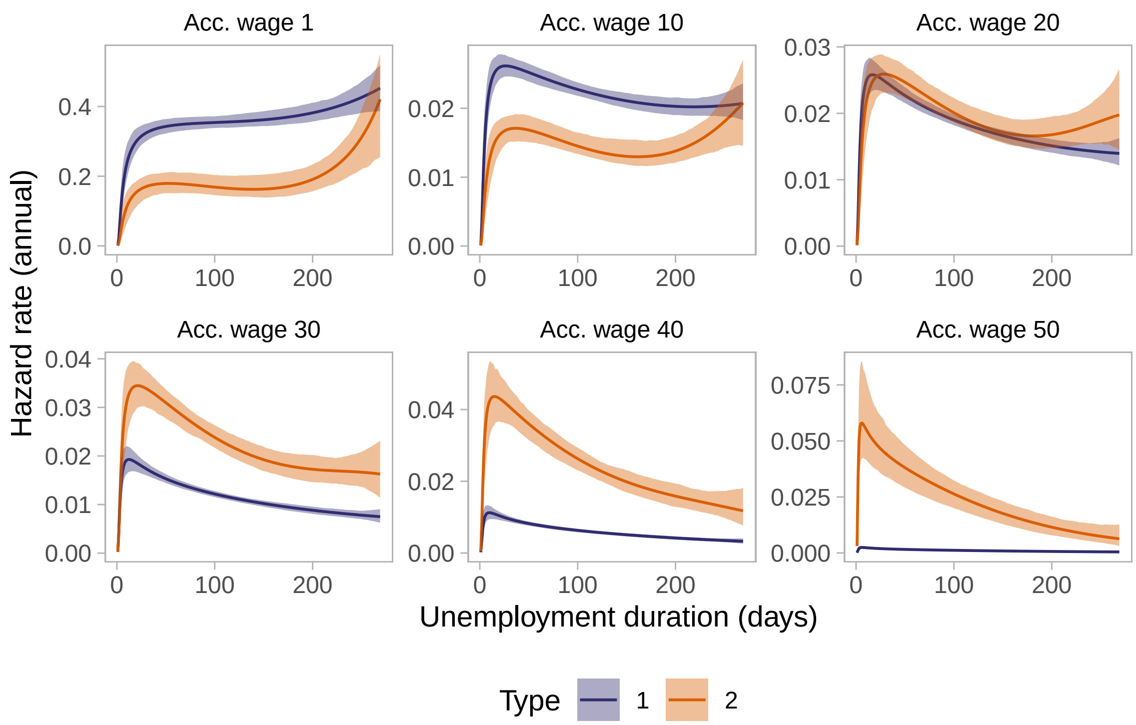
Notes: 95% bootstrap confidence intervals in brackets (500 replications).
Source: CERS-HAS, authors' own calculations.

Figure 9: Flow payoff of unemployment (normalized)



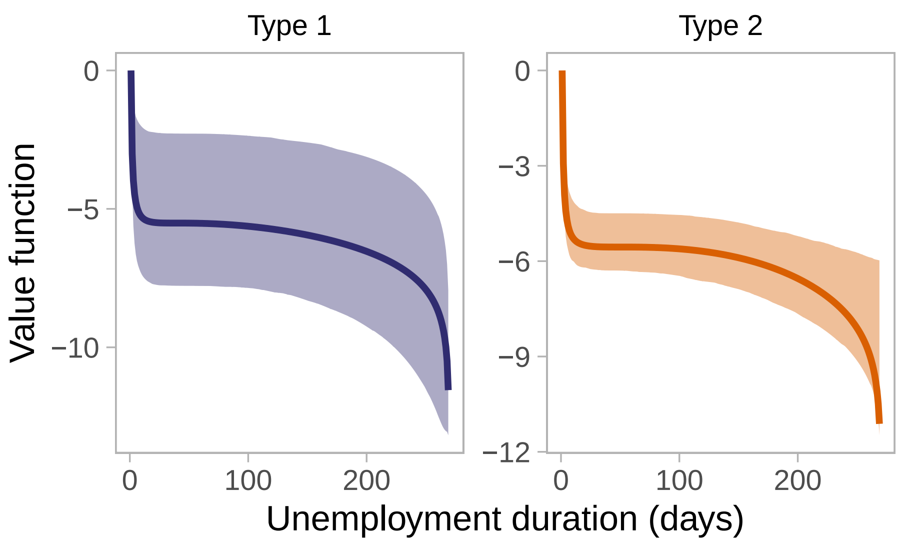
Notes: Flow payoff normalized w.r.t. $t = 0$ for each type. Shaded regions represent 95% bootstrap confidence band (500 replications).
Source: CERS-HAS, authors' own calculations.

Figure 10: Structural unemployment-to-employment hazards



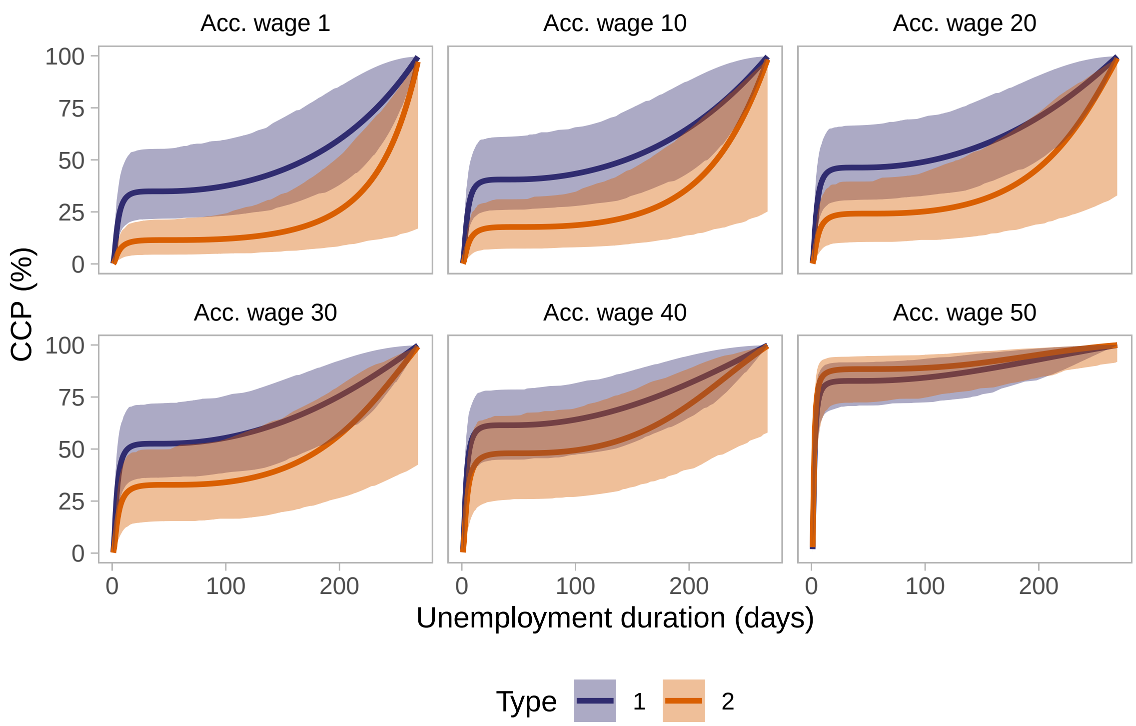
Notes: Annual hazard rates, conditional on exiting to a given wage bin. Shaded regions represent 95% bootstrap confidence band (500 replications).
Source: CERS-HAS, authors' own calculations.

Figure 11: Value function of unemployment (normalized)



Notes: Value function normalized w.r.t. the value of unemployment at $t = 0$ for each type. Shaded regions represent 95% bootstrap confidence band (500 replications).
Source: CERS-HAS, authors' own calculations.

Figure 12: CCPs, unemployment-to-employment transitions



Notes: Shaded regions represent 95% bootstrap confidence band (500 replications).
Source: CERS-HAS, authors' own calculations.