Unemployment Insurance and Worker-Firm Sorting

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10 November 2023

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Motivation

Introduction

- Recessions have an **ambiguous** impact on the allocation of workers across jobs
  - Lower productivity matches **'cleansed'**, slower reallocation (**'sullying'**)
  - Available empirical evidence suggests cleansing effect **marginally dominates**

    Haltiwanger et al. (2022), Crane et al. (2022), Baley et al. (2023)

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- In United States unemployment insurance (UI) becomes **more generous** during recessions
  - Max. duration **extended** above usual 26 weeks (systematic + discretionary component)
  - Matters for **search behaviour** Marinescu and Skaldalis (2020), **job creation** Hagedorn et al. (2019)
  - **This paper:** ...**sorting** of workers across jobs?

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Research questions

1. How does cyclical UI policy affect worker-firm sorting? Are these effects large?
2. Are cyclical changes in UI generosity desirable?

Preview of Results

1. **Model:** Random search with **ex ante heterogeneous** workers & jobs
   - $\rightarrow$ **Complementarities** between worker-firm types
   - $\rightarrow$ Heterogeneity in **unemployment risk**
   - $\rightarrow$ **On-the-job** search, employed use **outside offers** in wage bargain

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2. **Empirics:** Document facts using micro-data to discipline model
   - $\rightarrow$ Low-type workers face **higher** unemployment risk, driven by **separations**
   - $\rightarrow$ $\uparrow$ **UI generosity** associated with $\downarrow$ **job finding rate**, separations essentially **flat**
   - $\rightarrow$ Wages sensitivity depends on recent **employment history**

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   - → ↑ **UI generosity** associated with ↓ **job finding rate**, separations essentially **flat**
   - → Wages sensitivity depends on recent **employment history**

3. **Quantitative:**
   - → Countercyclical UI strengthens **both** cleansing and sullying effects of recessions
   - → ↑ **Sorting** during recessions **stronger** (corr. w/ GDP -0.3 compared to -0.01)
   - → Macro effects & welfare gains from cyclical UI policy are **quantitatively small**
   - → Workers benefit **relatively more** from countercyclical UI, firms from procyclical UI

Literature review

- Worker-firm sorting: Lise and Robin (2017); Lise and Postel-Vinay (2020); Baley et al. (2023)
  - **Contribution:** Study interaction of **cyclical** UI policy with **worker-firm sorting**
- Effects of UI: Chodorow-Reich et al. (2019); Jäger et al. (2020)
  - **Contribution:** Estimate effects of UI shocks using **panel data**
    1. New estimates on effects of UI on transition rates and wages
    2. Novel evidence that wage effects depend on worker's labour market history
- Cyclical design of UI: Mitman and Rabinovich (2015); Jung and Kuester (2015); Landais et al. (2018)
  - **Contribution:** Model with heterogeneous workers & jobs consistent with **microdata**
    - Countercyclical UI can deliver **welfare gains** by improving worker-firm sorting

Road map

1. Motivation
2. A Model of Sorting
3. Empirical evidence
4. Bringing the Model to the Data
5. The Anatomy of Sorting
6. Welfare
7. Conclusion

A Model of Sorting

Model overview

- Random search model with **two-sided** heterogeneity: e.g. Lise and Robin (2017)
  - Production complementarities
  - On-the-job search
  - Endogenous vacancy creation
  - Firms compete for workers (à la Bertrand)
  - Aggregate shocks

Model primitives

Agents.

- Risk-neutral, discount future at rate r
- Worker and jobs are **ex ante** heterogeneous
  - Workers indexed by ability $x \in \mathcal{X}$, drawn from distribution $\mathcal{L}(x)$
  - Continuum of firms, $y \in \mathcal{Y}$ endogenously chosen at job creation
- Measures of unemployed and employed denoted as $u(x)$ and $e(x, y)$, where

$$u(x) + \int e(x, y) dy = \mathcal{L}(x)$$

Model primitives

Production.

- Worker-firm matches produce value-added according to $p(x, y, z)$
  - Allow for worker-firm **complementarities** (i.e. $p_{xy} \geq 0$)
  - Productivity depends on **quality** of worker-firm match

- Aggregate productivity indexed by $z \in \mathcal{Z}$
  - Evolves according to Markov transition probability $\pi(z, z')$

Model primitives

UI policy.

- Workers receive UI income $b(x, z)$ when unemployed, given by

$$b(x, z) = \Psi(z) \times p(x, y^*(x, 1), 1)$$

  where $y^*(x, 1)$ is **optimal choice** of firm type for worker x when $z = 1$

- $\Psi(z)$ function controls the **design** of UI policy (i.e. generosity, cyclicality)

Labour market

Search.

- All unemployed workers search, employed workers search with intensity s
- Aggregate search effort: $L = \int u(x)dx + s \int \int e(x,y)dydx$

Jobs.

- Measure of type-y opportunities given by $v(y)$, posted with per-period cost $c(v)$
- Aggregate vacancies given by $V = \int v(y)dy$

Matching.

- Workers and firms meet via aggregate matching function

$$M_t = M(V_t, L_t)$$

- $f_t = M_t/L_t$ is unemployed worker contact rate, $s \cdot f_t$ for employed
- $q_t = M_t/V_t$ is firm contact rate

Labour market

Upon matching.

- **Unemployed**: Firms make take it or leave it offer, unemployed always accept
- **Employed**: Firms engage in Bertrand competition, worker goes to firm with highest value

Contracts.

- Unemployed workers begin match with **zero** surplus share
- Force renegotiation upon receipt of **credible** alternative job offer

Separations.

- **Endogenous** due to changes in z, or worker being poached by another firm
- **Exogenous** with probability $\delta \in (0, 1)$

Match surplus

Proposition 1. Lise and Robin (2017)

The surplus of match (x, y) at time t does not depend on the distribution of vacancies, unemployed, or worker-firm pairs. Specifically, $S_t(x, y) \equiv S(x, y, z)$ such that

$$S(x,y,z) = s(x,y,z) + \frac{1-\delta}{1+r} \int S(x,y,z')^+ \pi(z,z') dz'$$

where $s(x, y, z) = p(x, y, z) - b(x, z)$ and $x^+ = \max\{x, 0\}$.

- $S(x, y, z)$ fully summarises all separation & mobility decisions
- Remaining equilibrium conditions are identities and laws of motion for distributions

Vacancy creation

- **Free entry.** Value of an unfilled vacancy in equilibrium is equal to zero
- Job creation equates marginal cost to marginal return:

$$c'(v_t(y)) = q_t J_t(y)$$

where $J_t(y)$ is the expected value of a new match:

$$\begin{aligned} J_t(y) &= \int \frac{u_{t+}(x)}{L_t} \max\{S_t(x,y),0\}dx \\ &+ \int\int \frac{s \cdot e_{t+}(x,y)}{L_t} \max\{S_t(x,y) - S_t(x,y'),0\}dxdy' \end{aligned}$$

Wage distribution

- Framework does not require us to explicitly solve for wages
- Assume wage contract is commitment by firms to deliver fraction $\sigma \in (0,1)$ of match surplus to worker:
$$W_t(\sigma, x, y) = U_t(x) + \sigma S_t(x, y)$$
- σ for worker x at firm y depends on individual worker **job offer history**
- Contract σ will be equal to:

$$\sigma = \begin{cases} 0 & \text{if hired from unemployed} \\ S(x,y')/S(x,y) & \text{Bertrand competition between } y \text{ and } y', \text{ with } S(x,y) \geq S(x,y') \\ S(x,y)/S(x,y') & \text{Bertrand competition between } y \text{ and } y', \text{ with } S(x,y) < S(x,y') \end{cases}$$

- σ remains constant until next credible job offer, i.e. $S(x, y') > \sigma S(x, y)$

Wage distribution

- Wage given by:

$$w_t(\sigma, x, y) = \sigma p_t(x, y) + (1 - \sigma) b_t(x) - \Delta$$

where Δ is a discount for (expected) future renegotiation opportunities:

$$\Delta = (1-\delta)\beta \mathbb{E}_t \left[\mathbb{1}\{S_{t+1}(x, y) \geq 0\} s f_{t+1} \int \left[I_{t+1}(\sigma, x, y, y') - \sigma S_{t+1}(x, y) \right] \frac{v_{t+1}(y')}{V_{t+1}} dy' \right]$$

and where

$$I_{t+1}(\sigma, x, y, y') = \begin{cases} S_{t+1}(x, y) & \text{if } S_{t+1}(x, y') > S_{t+1}(x, y), \\ S_{t+1}(x, y') & \text{if } \sigma S_{t+1}(x, y) < S_{t+1}(x, y') \leq S_{t+1}(x, y), \\ \sigma S_{t+1}(x, y) & \text{if } S_{t+1}(x, y') \leq \sigma S_{t+1}(x, y) \end{cases}$$

Timing

Within period timing is as follows:

1. Aggregate productivity shock z is drawn from $\pi(z|z_{-1})$
2. Separations occur.
3. Firms decide which vacancies to post, $v_t(y)$
4. Vacancies and searchers meet according to $M(V_t, L_t)$
5. Matches decide whether to proceed, bargain over wages
6. Production takes place, wages are paid

Laws of motion for distributions

- Worker measures after realization of aggregate/idiosyncratic shocks given by $u_{t+}(x)$, $e_{t+}(x,y)$, i.e.
$$e_{t+}(x,y) = (1-\delta)\mathbb{1}\{S(x,y,z_t) \geq 0\}e_t(x,y)$$
- Measures are then updated according to:

$$u_{t+1}(x) = u_{t+}(x)\left[1 - \int f_t \frac{v_t(y)}{V_t}\mathbb{1}\{S(x,y,z_t) \geq 0\}dy\right]$$

$$\begin{aligned} e_{t+1}(x,y) &= e_{t+}(x,y)\left[1 - \int sf_t \frac{v_t(y)}{V_t}\mathbb{1}\{S(x,y',z_t) \geq S(x,y,z_t)\}dy'\right] \\ &\quad + \int e_{t+}(x,y')sf_t \frac{v_t(y)}{V_t}\mathbb{1}\{S(x,y,z_t) \geq S(x,y',z_t)\}dy' \\ &\quad + u_{t+}(x)f_t \frac{v_t(y)}{V_t}\mathbb{1}\{S(x,y,z_t) \geq 0\} \end{aligned}$$

Computation of stochastic search equilibrium

Algorithm

1. Solve for surplus function $S(x, y, z)$ independently of realization of aggregate productivity shocks z
2. Given initial distributions $u_0(x)$ and $e_0(x, y)$, we simulate a sequence of productivity shocks $\{z_0, \ldots, z_T\}$ for a cohort of N workers and solve for the sequence of measures for vacancies, unemployed workers and worker-firm matches, $\{v_t(y), u_{t+1}(x), e_{t+1}(x, y)\}_{t=0}^{T}$, as well as the distribution of workers over wage contracts $\{\mathcal{W}_{t+1}(\sigma, x, y)\}_{t=0}^{T}$

How does UI affect worker-firm sorting?

Changes in $\Psi(z)$ can **strengthen** sorting by contracting matching space towards optimum...

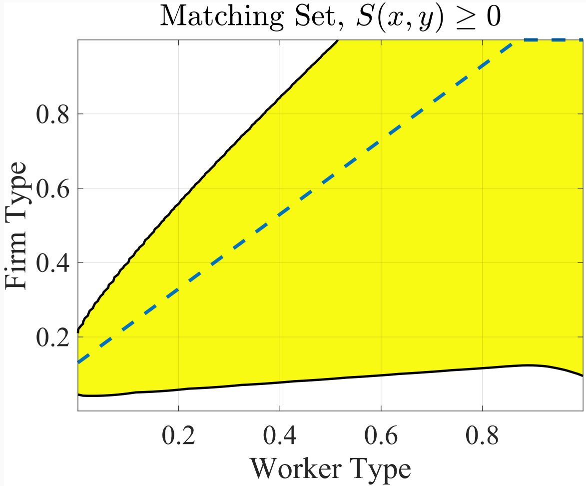

Figure (1) Feasible matching set

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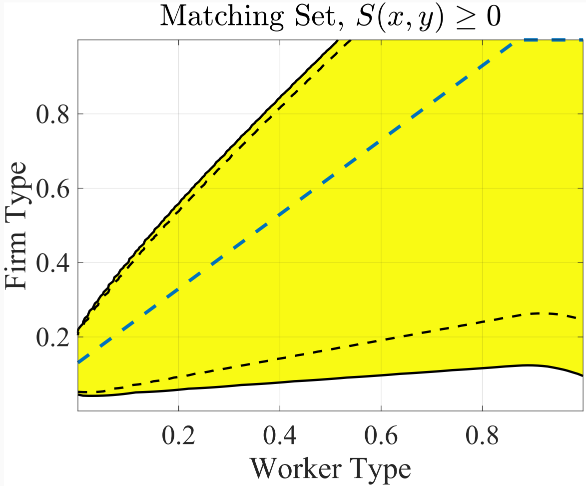
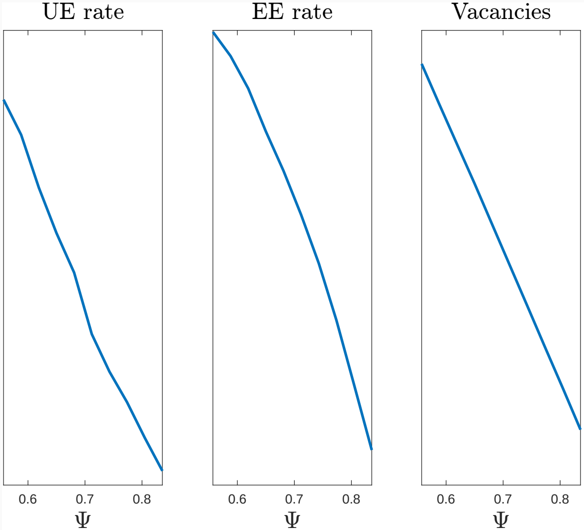


Figure (2) Feasible matching set

How does UI affect worker-firm sorting?

...but can also **weaken** sorting by reducing the speed of worker reallocation in equilibrium



Empirical evidence

Panel data

Document micro-level evidence which we use to discipline model:

1. **Unemployment risk** by worker rank
2. Effects of UI shocks, both in **aggregate** and **across workers**

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Panel data: Survey of Income and Programme Participation (SIPP)

- Participants interviewed every 4 months, up to 12 times
- Variables: earnings, employment, demographics, industry, occupation, assets/liabilities
- Unbalanced panel for 1996-2013, individuals observed for 30 months on average
- Final sample: 67,561 individuals aged 25-65. **1,442,645** total observations.
- Deflate nominal variables using PCE price index

Ranking workers

- Worker 'rank' is **unobservable**
  - How do we rank workers in the data?

- Use two different methods informed by theory:
  1. **Non-employment time**
     → Higher-type workers are productive at more firm types, spend less time out of employment
  2. **Earnings**
     → Higher-type workers in more productive matches, paid higher wages

  Both methods used in sorting literature e.g. Bagger and Lentz (2019), Crane et al. (2020)

- Worker rank correlated with wealth, but not other characteristics (e.g. education, occupation etc.)

Unemployment risk by worker rank

How does **unemployment risk** vary with worker rank?

Unemployment risk determined by:

1. **Separation risk**, i.e. employment-unemployment (EU) rate
2. **Job finding rate**, i.e. unemployment-employment (UE) rate

Table (1) Unemployment risk by worker rank

	Average (%)	Ranking #1			Ranking #2		
		Low	Mid	High	Low	Mid	High
EU	0.10	1.32	0.91	0.72	1.48	0.77	0.97
UE	27.10	1.08	1.01	0.93	0.94	0.93	0.71

Notes: The first column displays the average flow rates in the SIPP data in our sample from 1996-2013. The remaining columns present ratios of transition rate by rank to the average transition rate.

Estimating the Effects of UI

Impulse responses: Panel version of Jordà (2005) LPs

- Labour market flows (job finding rate, separation rate)
- Wages

$$w = \sigma \overbrace{p}^{\text{Productivity}} + (1-\sigma) \overbrace{\Omega}^{\text{Outside option}}$$

  - UI affects outside option (Ω), potentially **heterogeneous** across workers
  - Worker bargaining power σ will also vary, e.g. due to job offer history

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UI shocks: Chodorow-Reich, Coglianese & Karabarbounis (2019 *QJE*)

- State-monthly shocks to UI duration covering sample period
- **Identification**: Real-time measurement error in state-level unemployment rate UI shocks

Estimating the Effects of UI: Empirical specification

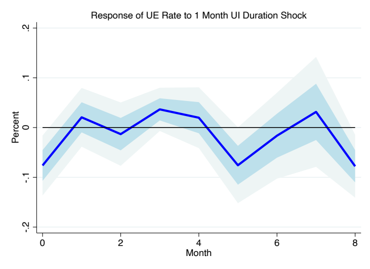
General empirical specification: Estimate the following regression for time horizon $h \geq 0$:

$$(\Delta_h) y_{i,s,t+h} = \left(\sum_{k=-\kappa}^{h} \gamma_h \varepsilon_{s,t+k}^{UI} \right) \times \mathbb{1}_{i \in \mathcal{I}^x} + \sum_{j=1}^{L} \delta_{\mathbf{h}}' \mathbf{X}_{\mathbf{i},\mathbf{s},\mathbf{t}-\mathbf{j}} + \phi_{i,h} + \phi_{s,h} + \phi_{t,h} + \nu_{i,t+h}$$

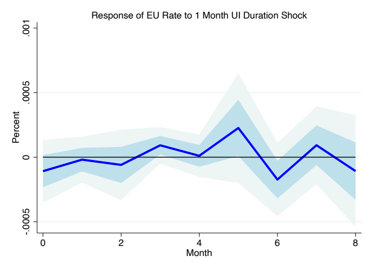
- $(\Delta_h) y_{i,s,t+h}$ is the (cumulative change in) worker-level variable of interest
- $\varepsilon_{s,t}^{UI}$ is the UI shock in state s and time t
- $\mathcal{I}^x$ is a sub-sample based on worker characteristic x (e.g. $<$ 10th earnings pct.)
- $\mathbf{X}_{\mathbf{i},\mathbf{s},\mathbf{t}}$ is a vector of individual and state-level controls
- $\phi_{i,h}$, $\phi_{s,t}$ and $\phi_{t,h}$ are individual, state and time fixed effects respectively

where $\{\gamma_h\}_{h=0}^{H}$ are the coefficients of interest

Estimating the Effects of UI: Labour Market Flows



(a) UE Rate



(b) EU Rate

Figure (4) Estimated responses of job finding and separation rates

- Job finding (UE) rate falls on impact, unwinds thereafter
- Separation (EU) rate essentially flat
- **Robustness:** (i) Individual-level controls, (ii) lagged & future shocks, (iii) seasonality, & (iv) cumulative change vs. levels

Estimating the Effects of UI: Wages

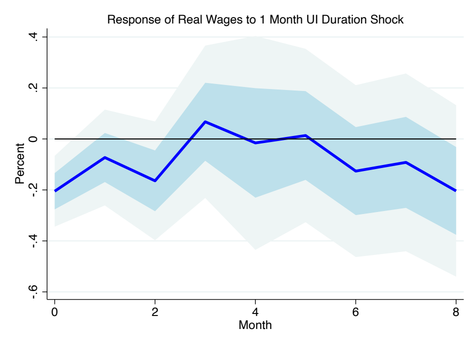
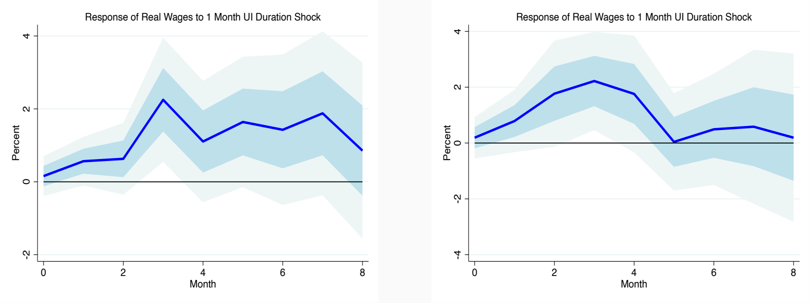


Figure (5) Impulse Responses of (Log) Real Wages

- Wages insensitive on average to changes in UI
- **Robustness:** (i) Individual-level controls, (ii) lagged & future shocks, (iii) seasonality, & (iv) cumulative change vs. levels

Heterogeneous Effects of UI: Wages



(a) UI Recipients

(b) Unemployed

Figure (6) Wage effects by labour market experience

- Higher wage sensitivity for workers who spend time in unemployment
- Consistent with Postel-Vinay and Robin (2002) wage protocol
- Limited evidence that other characteristics matter Income/wealth Demographics

Empirical evidence: Summary

1. **Unemployment risk**
   - **Significant heterogeneity** in unemployment risk by worker rank
   - Key driver is differences in **separation risk**
   - Differences in job finding rate less important

2. **What are the effects of UI policy changes?**
   - Job finding rate **falls** in response to $\uparrow$ UI generosity
   - Separations almost **flat** in response to UI policy changes
   - Wages highly **insensitive** on average, but sensitive for **recently unemployed**

$\Longrightarrow$ Consistent with Postel-Vinay and Robin (2002) wage determination

Next: Bring model to the data

Bringing the Model to the Data

Functional forms

- **Value-added:** $p(x, y, z) = z(p_1 x + p_2 y - p_3 \min\{x - y, 0\}^2)$

  e.g. Lise and Postel-Vinay (2020)

  - p_1 captures return to higher-type workers
  - p_2 captures return to higher-type firms
  - p_3 controls costs associated with worker-firm mismatch

- **Unemployment insurance:** $\Psi(z) = b_0 \cdot z^{b_1}$

  - b_0 controls average replacement rate
  - b_1 controls the cyclicality of generosity with respect to the aggregate state, z

Functional forms

- **Type distributions:** $x \sim \text{Beta}(\beta_1, \beta_2) \in [0,1], \quad y \in [0,1]$
- **Matching function:**

$$M(L_t, V_t) = \frac{\alpha L_t V_t}{(L_t^\omega + V_t^\omega)^{1/\omega}}, \quad \alpha > 0,\ \omega > 0$$

- **Vacancy costs:**

$$c(v) = \frac{c_0 v^{1+c_1}}{1+c_1}, \quad c_0 > 0,\ c_1 > 0$$

- **Aggregate shocks:** $z \sim \pi(z|z_{-1})$ modelled as Gaussian copula with lognormal marginals

Calibration (preliminary)

Fixed parameters.

- Fix r to give 5% ann. interest rate (weekly freq.)
- Set ω to match elasticity of substitution between vacancies-searchers equal to 0.7
- Set $\{\rho, \sigma\}$ to mimic cyclical properties of US labor productivity

Strategy. Calibrate remaining parameters to match salient features of the data

- Identify $\{\alpha, s, \delta\}$ by targeting average labour market flows
- Identify worker heterogeneity $\{\beta_1, \beta_2\}$ by targeting unemployment level + concentration
- Identify $\{c_0, c_1\}$ by targeting volatility and cyclicality of vacancies
- Set UI policy parameters $\{b_0, b_1\}$ to match level and cyclicality of replacement rate

Identifying $p(x, y, z)$

How do we identify the shape of the production function, $p(x, y, z)$?

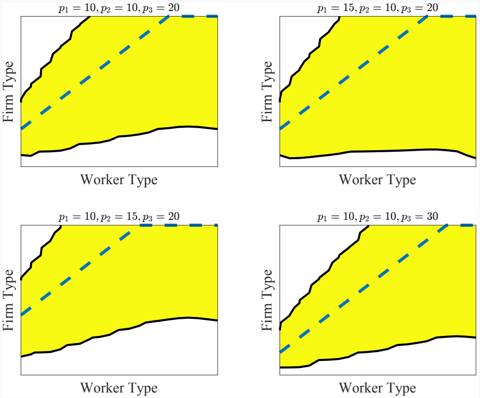


Figure (7) Production function and matching set

- Target wage dispersion $\sigma(w)$, + estimated elasticity of flow rates $\epsilon_{UE}, \epsilon_{EU}$

Model fit (preliminary)

Table (2) Targeted moments

Fitted moments	Data	Model	Origin
$\mathbb{E}[UE]$	0.421	0.376	BLS
$\mathbb{E}[EE]$	0.025	0.024	BLS
$\mathbb{E}[EU]$	0.025	0.022	BLS
sd$[V]$	0.206	0.224	BLS
corr$[V, VA]$	0.721	0.568	BLS
$\mathbb{E}[U]$	0.058	0.051	BLS
$\%U$ acc. by top 10	0.660	0.444	Morchio (2020)
$\mathbb{E}[b/w]$	0.470	0.593	SIPP
corr$[b/w, VA]$	-0.462	-0.442	Landais et al. (2018)
$\mathbb{E}$[sd wages]	0.420	0.538	SIPP
$\epsilon_{UE,UI}$	-0.075	-0.059	SIPP
$\epsilon_{EU,UI}$	0.0003	0.0003	SIPP

Parameter estimates (preliminary)

Table (3) Summary of parameters

Parameter	Value	Description
Assigned:		
r	log(1.05)/52	Weekly interest rate
ω	0.429	Matching function
σ	0.148	Dispersion of aggregate shock
ρ	0.992	Persistence of aggregate shock
Calibrated:		
α	0.554	Match efficiency
s	0.070	Relative search intensity of employed
δ	0.008	Exogenous separation rate
c_0	0.651	Vacancy cost scale
c_1	0.184	Vacancy cost convexity
b_0	0.696	UI constant
b_1	-0.984	UI elasticity
β_1	2.01	Worker shape 1
β_2	1.540	Worker shape 2
p_1	16.277	Returns to worker type
p_2	11.561	Returns to firm type
p_3	45.188	Mismatch cost

Feasible matching sets

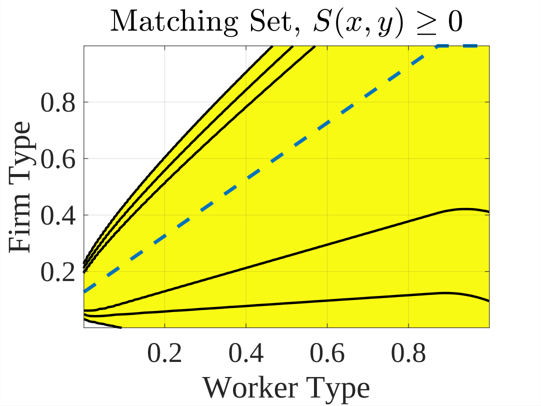


Figure (8) Feasible matching sets, $S_t(x, y) \geq 0$

Worker and firm distributions

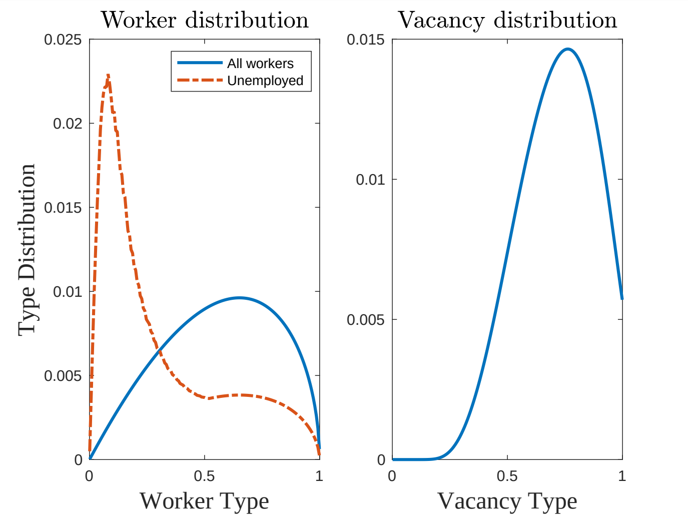
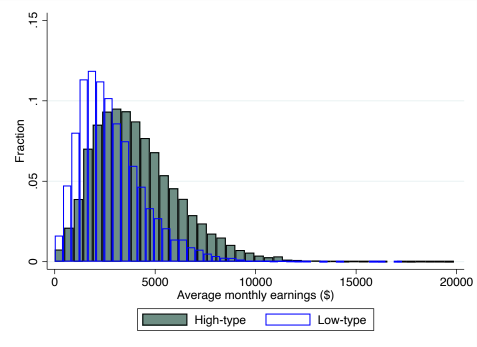
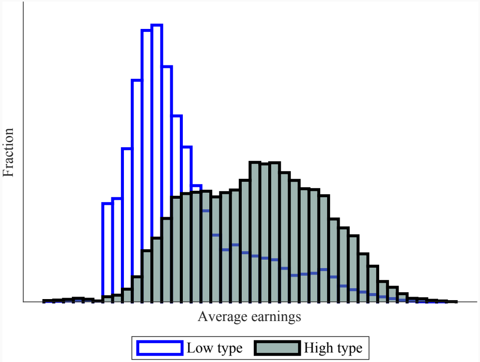


Figure (9) Worker and firm distributions $\mathcal{L}(x)$, $u(x)$ and $v(y)$

Untargeted: Earnings distribution by worker rank



(a) Data



(b) Model

Figure (10) Earnings distribution by rank: Data vs. Model

- Qualitatively generates correct pattern in earnings distribution
- Matches shape of low-rank earnings distribution, not high-rank

Untargeted: Unemployment risk by worker rank

Table (4) Unemployment risk: Model vs. Data

	Data			Model		
	Low	Mid	High	Low	Mid	High
EU	1.32	0.91	0.72	1.26	1.02	0.75
UE	1.08	1.01	0.93	0.55	1.87	2.30

Notes: Table presents ratios of worker transition rates to average transition rate by rank, where average EU and UE rates are targeted moments.

- Model captures heterogeneity in separation risk by worker rank fairly well
- Job finding rate strongly increasing in rank, at odds with data

The Anatomy of Sorting

Sorting: Model vs Data

Questions:

- How do workers and firms sort in the model? How does this compare to the data?
- How does the design of UI affect sorting patterns in the model?

Empirical evidence: Crane et al. (2020)

- LEHD data, 1994-2014
- Rank workers by employment time, firms by poaching share
- Document cyclicality of employment shares by worker/firm rank

Policy counterfactual: Acyclical UI, i.e. $b_2 = 0$

Sorting: Worker and firm distributions

Table (5) Changes in worker and firm employment shares

Tercile	Data	Baseline	Acyclical
Workers:			
Low	-44.9	-10.65	-9.74
High	31.6	11.74	9.35
Firms:			
Low	12.0	17.13	12.0
High	-8.9	-7.31	-2.13

Notes: Table presents percentage change in employment shares in response to a 1 percent increase in unemployment rate. This is computed by regressing changes in employment shares on the first-difference of the unemployment rate.

- UI strengthens both worker cleansing and firm sullying

Sorting: Joint distribution

Table (6) Changes in joint composition

Tercile	Data	Baseline	Acyclical
High-type workers &:			
Low-type firms	9.80	-1.69	0.50
High-type firms	11.0	13.41	10.49
Low-type workers &:			
Low-type firms	-8.30	-3.47	-1.56
High-type firms	-18.1	1.99	-0.66

Notes: Table presents percentage change in employment shares in response to a 1 percent increase in unemployment rate. This is computed by regressing changes in employment shares on the first-difference of the unemployment rate.

- Model not consistent with 'off-diagonals'
- Reduces high-worker/low-firm matches, but increases low-worker/high-firm matches

Sorting and UI: Macro implications

Is the overall effect on sorting significant? Does this matter at the macro level?

Sorting index: $\rho_{x,y} = \text{corr}(x, y)$

Table (7) Cyclical behaviour of sorting: Baseline vs. Acyclical

Moment	Baseline	Acyclical
Sorting:		
$\text{sd}[\rho_{x,y}]$	0.039	0.046
$\text{corr}[\rho_{x,y}, VA]$	-0.338	-0.011
Others:		
$\text{sd}[U]$	0.178	0.125
sd[VA]	0.092	0.089

Sorting and UI: A recession experiment

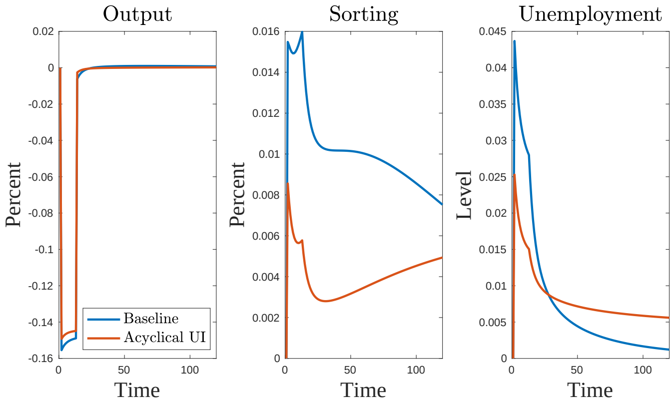


Figure (11) Recession under alternative UI policies

- Improved sorting comes at cost of more unemployment, larger initial fall in output
- Overall relatively small macro effects ($\approx 1\%$ on output, 2% on unemployment)

Welfare

Welfare quantification

- Is cyclicality in UI generosity desirable?

- **Social welfare:**

$$\Omega = \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \left\{ \int p(x,y,z) de_t(x,y) + \int b(x,z) du_t(x) - \int c(v) dv_t(y) \right\}$$

- **Exercise:** Evaluate social welfare at ergodic distribution over range for b_2
  - Compare welfare (as % annual GDP) to acyclical UI case

Social welfare and UI cyclicality

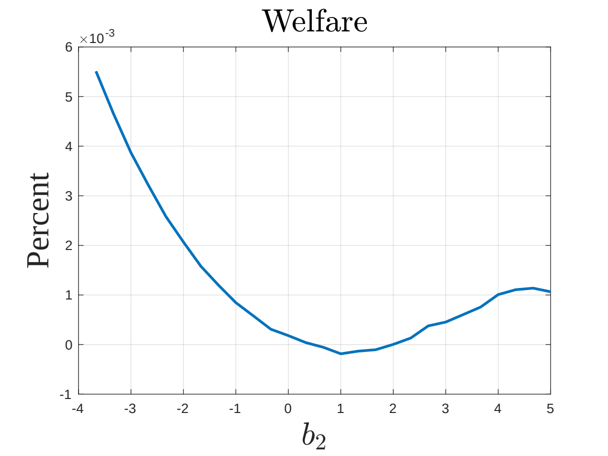


Figure (12) Social welfare and UI cyclicality

Decomposing social welfare

- How are welfare gains from UI policy distributed?

- Social welfare can be decomposed into workers consumption and firm profits:

Workers:

$$\Omega^w = \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \left\{ \int w(\sigma, x, y) d\mathcal{W}_t(\sigma, x, y) + \int b(x, z) du_t(x) \right\}$$

Firms:

$$\Omega^f = \mathbb{E}_0 \sum_{t=0}^{\infty} \left(\frac{1}{1+r}\right)^t \left\{ \int (p(x, y, z) - w(\sigma, x, y)) d\mathcal{W}_t(\sigma, x, y) - \int c(v) dv_t(y) \right\}$$

Decomposing social welfare

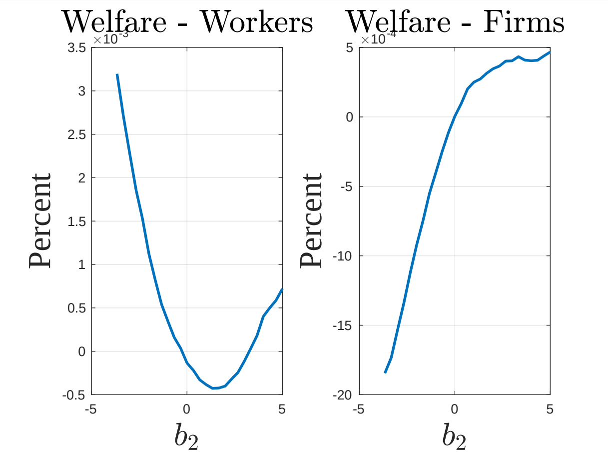


Figure (13) Distribution of welfare gains: Workers vs. firms

Welfare: A recession experiment

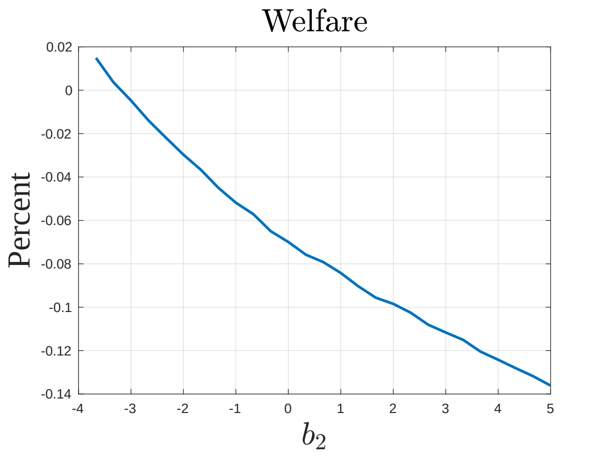


Figure (14) Social welfare under different UI policies in recession

- Countercyclical UI delivers small welfare gains relative to acyclical UI ($< 0.1\%$)

Conclusion

Conclusion

- In this project:

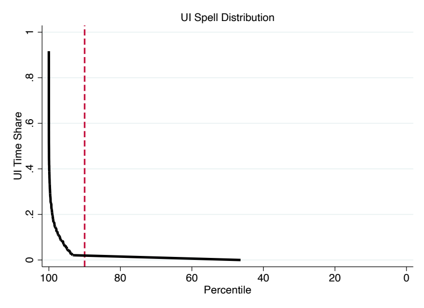
1. Outline a model of worker-firm sorting over the business cycle disciplined with **micro data**
    - Document **heterogeneity** in unemployment risk
    - Novel finding that UI effects **depend** on labour market experience

2. Cyclicality UI policy has **significant effects** on sorting
    - Counteryclical UI **strengthens** both cleansing & sullying effect
    - Effect on cleansing effect dominates, increasing countercyclicality in sorting

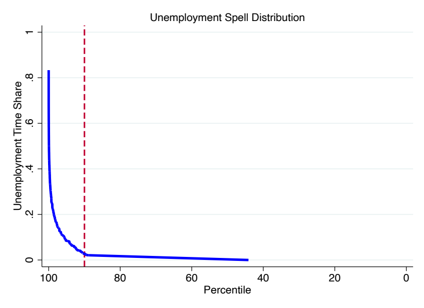
3. Interaction between cyclical UI policy and sorting has **small** macroeconomic effects

Appendix

Who Claims UI?



(a) UI Time Distribution



(b) Unemployment Time Distribution

Figure (15) Labour force status: Distributions by time

- UI receipts even more concentrated than unemployment
- **Birinci and See (2023):** $\approx 40\%$ eligible workers don't claim UI

Who Claims UI?

Table (8) Fraction of time in unemployment or receiving UI: SIPP 1996-2013

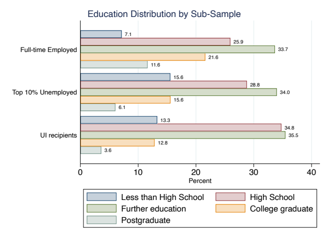
	Unemployment	UI Recipient
Avg. % time	1.8	1.0
Avg. % time, excluding top 5%	0.65	0.14
% never	85.2	91.6

Notes: Table presents statistics summarising labour market experiences of workers in the SIPP sample during the period 1996-2013. Column (1) refers to being in unemployed, which includes unemployed worker receiving UI but also those who do not. Column (2) refers only to workers receiving UI.

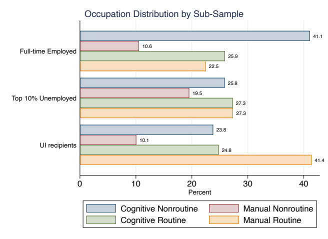
- Majority never experience unemployment (85%) or claim for UI (92%)
- Top 5% by time receiving UI account for 85% total UI spells

UI Recipients: Demographics

(a) Gender



(b) Education



(c) Occupation

Figure (16) Worker characteristics by sub-sample

- No large differences in gender, education between UI recipients and rest of sample
- UI recipients skewed towards manual routine occupations

UI Recipients: Earnings & Wealth

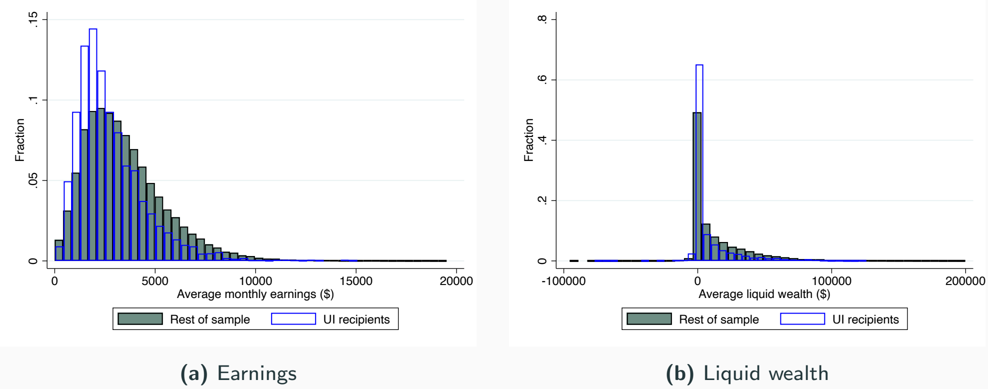


Figure (17) Average earnings & wealth distributions: UI recipients vs. Rest of sample

- On average UI recipients work in lower paid jobs & hold less liquid wealth

UI Recipients: Unemployment Risk

Table (9) Transition rates by group: SIPP 1996-2013

Transition rate	Aggregate (%)	Gender		Education		Occupation		Earnings		Wealth	
		Male	Female	>College	<College	Cognitive	Manual	<50th pct.	> 50pct	<50th pct.	>50th pct.
E-U	0.10	1.13	0.79	0.24	1.21	0.92	1.22	1.87	0.42	1.50	0.62
U-E	27.10	0.94	0.96	1.08	0.94	1.02	1.02	1.04	1.04	1.10	0.85

Notes: Table presents transition rates between employment and unemployment. Transition rates are computed as the average transition rate by group across the full sample period 1996m1-2013m11. The table reports the average transitions rates across the whole sample, and then reports ratios of transition rates for sub-groups over the whole sample.

- Separation risk varies strongly with education, occupation, earnings & wealth
- Job finding rates only really correlared with education & wealth
- Doesn't account for heterogeneity in eligibility & take-up

UI Recipient: Which Characteristics Matter?

Table (10) Effects of worker-level observables on UI receipt status

Logit: Receives $\text{UI}_i = \gamma + \beta' \mathbf{X}_i + \varepsilon_i$	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-2.602***	-2.199***	-2.707***	-2.171***	-2.085***	-3.141***
Age	0.00223	0.000414	0.00103	-0.000587	0.000985	0.00697***
Experience	-0.00146***	-0.00121***	-0.00124***	-0.000111	-4.20e-05	0.000331*
Education						
High school		-0.159***	-0.115**	0.0246	0.0292	0.179***
Some further		-0.352***	-0.217***	-5.97e-05	0.00247	0.177***
College		-0.870***	-0.588***	-0.240***	-0.225***	-0.0369
>College		-1.367***	-1.042***	-0.619***	-0.593***	-0.447***
Occupation						
Manual Nonroutine			-0.150***	-0.411***	-0.422***	-0.414***
Cognitive routine			0.113***	-0.0425	-0.0407	-0.0483
Manual routine			0.671***	0.524***	0.521***	0.568***
Earnings & wealth						
Earnings percentile				-0.0160***	-0.0151***	-0.00794***
Liquid wealth percentile					-0.00429***	-0.00404***
% Unemp						13.31***
Standard controls	X	X	X	X	X	X
Observations	67,561	67,561	67,561	67,561	67,561	67,561

Notes: Standard additional controls for each logit model include gender, race & state of residence. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ using robust standard errors.

- Education & occupation most strongly correlated when controlling for UI take-up

UI Recipients: Which Characteristics Matter?

Table (11) Accounting for fraction (%) time receiving UI

Regression: Time Share $\text{UI}_i = \gamma + \beta' \cdot \mathbf{X}_i + \varepsilon_i$	(1)	(2)	(3)	(4)	(5)
Constant	0.0798***	0.0938***	0.0868***	0.0917***	0.0923***
Age	0.000517***	0.000503***	0.000549***	0.000539***	0.000547***
Experience	2.60e-05	2.73e-05	2.23e-05	2.93e-05*	2.97e-05*
Education					
High school		-0.0125**	-0.0125**	-0.0116**	-0.0116**
Some further		-0.0175***	-0.0168***	-0.0156***	-0.0157***
College		-0.0185***	-0.0167**	-0.0143**	-0.0141**
$>$College		-0.0200**	-0.0186**	-0.0152*	-0.0150*
Occupation					
Manual Nonroutine			-0.0183***	-0.0208***	-0.0209***
Cognitive routine			-0.00392	-0.00548	-0.00552
Manual routine			0.00978**	0.00810*	0.00805
Earnings & wealth					
Earnings percentile				-0.000126**	-0.000121*
Liquid wealth percentile					-2.68e-05
Standard controls	X	X	X	X	X
R^2	0.022	0.023	0.027	0.030	0.031
Observations	3,885	3,885	3,885	3,885	3,885

Notes: Standard controls for each regression model include gender, race & state of residence. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ using robust standard errors.

- Worker observables do not explain cross-sectional variation in UI claim duration

Worker rankings: Earnings & wealth

Worker rankings: Education & occupation

Chodorow-Reich et al. (2019) UI shocks

Main idea: Exploit *ex post* mistakes in UI duration extensions due to measurement error

- Extensions based on *real-time* estimates of state-level unemployment rate $u_{s,t}$
- $u^*_{s,t}$ is a noisy real-time measure of $u_{s,t}$, which is subject to revisions

Actual UI duration $T^*_{s,t}$ given by:

$$T^*_{s,t} = T_{s,t} + \hat{T}_{s,t}$$

where $T_{s,t} = f(u_{s,t-1})$ is the 'correct' UI duration and $\hat{T}_{s,t}$ is a UI error.

Challenge: UI errors $\hat{T}_{s,t}$ are serially correlated

$\rightarrow$ Define structural innovation $\epsilon_{s,t}$ as unexpected component of UI error:

$$\epsilon_{s,t} = \hat{T}_{s,t} - \mathbb{E}_{t-1}\hat{T}_{s,t}$$

Identifying assumption: $\mathrm{Cov}(\mathbb{E}_{t-1}\hat{T}_{s,t}, \epsilon_{s,t}) = \mathrm{Cov}(T^*_{s,t+j}, \epsilon_{s,t}) = 0, \quad \forall\, j < 0$ Data

Transition rates

Table (12) Transition rates by group: SIPP 1996-2013

Transition rate (%)	Aggregate	Gender		Education		Occupation		Earnings		Wealth	
		Male	Female	>College	<College	Cognitive	Manual	<50th pct.	> 50pct	<50th pct.	>50th pct.
E-U	0.11	0.98	0.99	0.57	1.10	0.89	1.32	1.81	0.37	1.37	0.67
E-N	1.56	0.75	1.15	0.94	1.07	0.92	1.06	1.60	0.45	1.26	0.63
U-E	27.10	1.15	1.01	1.12	0.96	1.07	1.05	0.96	1.32	1.08	0.95
U-N	7.25	1.1	0.98	1.03	0.98	1.02	0.9	0.99	0.84	1.11	0.89
N-E	37.50	1.1	0.97	1.04	0.94	1.11	0.94	0.96	1.25	1.04	1.0
N-U	7.62	1.4	0.85	1.0	1.08	0.97	1.06	1.05	0.97	1.09	0.78

Notes: Table presents transition rates between employment, unemployment and non-participation. Transition rates are computed as the average transition rate by group across the full sample period 1996m1-2013m11. The table reports the average transitions rates for the aggregates, and then reports ratios of transition rates to these averages.

Which workers spending time in unemployment?

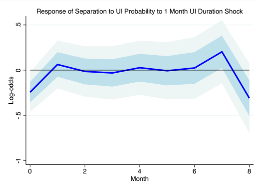
Regression: $\text{Time Share Unemp.}_i = \gamma + \beta' \cdot \mathbf{X}_i + \varepsilon_i$

Table (13) Accounting for share (%) time unemployed

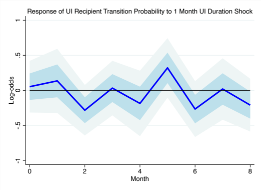
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0806***	0.101***	0.0961***	0.104***	0.103***	0.102***
Age	0.000412***	0.000391***	0.000398***	0.000386***	0.000371***	1.72e-05
Experience	-3.58e-05***	-3.13e-05***	-3.22e-05***	-1.78e-05	-1.83e-05	-3.79e-05***
Education						
High school		-0.0150***	-0.0150***	-0.0134***	-0.0134***	-0.0131***
Some further		-0.0254***	-0.0246***	-0.0226***	-0.0225***	-0.0210***
College		-0.0371***	-0.0351***	-0.0309***	-0.0310***	-0.0262***
>College		-0.0370***	-0.0351***	-0.0298***	-0.0301***	-0.0193***
Occupation						
Manual Nonroutine			-0.00686*	-0.0110***	-0.0109***	-0.000130
Cognitive routine			0.000320	-0.00257	-0.00253	-0.000898
Manual routine			0.00820**	0.00545	0.00548	0.000639
Earnings & wealth						
Earnings percentile				-0.000233***	-0.000241***	-0.000328***
Liquid wealth percentile					4.32e-05	4.79e-05
% time UI						0.507***
Standard controls	X	X	X	X	X	X
R^2	0.022	0.032	0.034	0.037	0.037	0.186
Observations	10,030	10,030	10,030	10,030	10,030	10,030

Notes: Standard controls for each regression model include gender, race & state of residence. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ using robust standard errors.

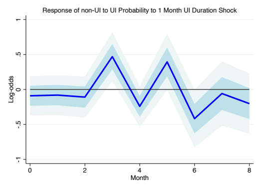
Worker-level Transition: Average effects



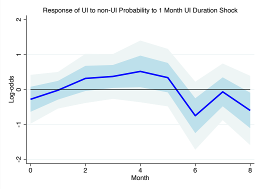
(a) E-UI Transition



(b) UI-E Transition



(c) N-UI Transition



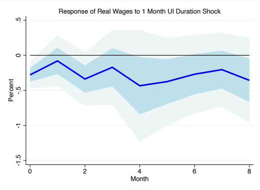
(d) UI-N Transition

Figure (18) Impulse responses of transition probabilities

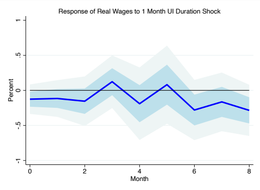
- Dynamic logit estimates for individual-level transition probabilities also very small

▸ Transition rates

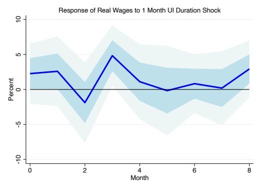
Wage effects by income and wealth



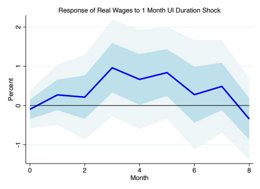
(a) < Median earnings



(b) < Median wealth



(c) < 10th earnings pct.



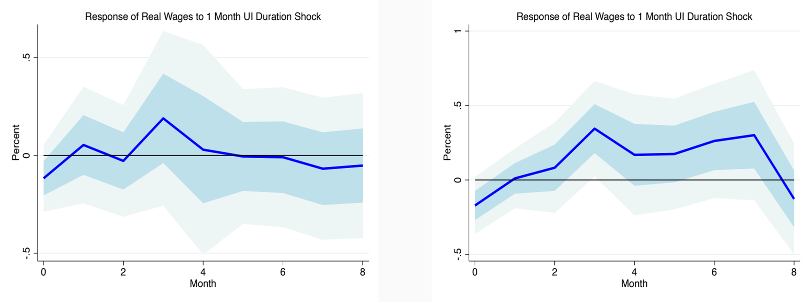
(d) < 10th wealth pct.

Figure (19) Wage effects by earnings & wealth percentile

- Small effects even for workers below median of earnings/wealth distribution(s)
- . . . but start to see some evidence of positive wage effects for very lowest earners/poorest

▸ Wage effects

Wage effects by demographics



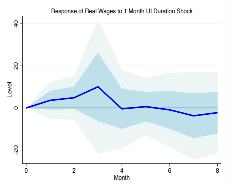
(a) < College

(b) Male

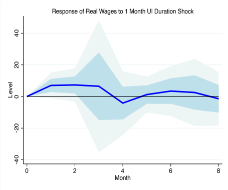
Figure (20) Impulse Responses of (Log) Real Wages by Worker Demographics

▸ Wage effects

Re-employment wage effects by worker characteristics

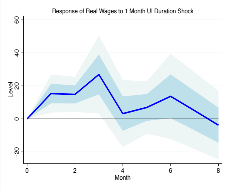


(a) < Median earnings



(b) < Median wealth

(c) < College



(d) Male

Figure (21) Re-employment Wages by Worker Characteristic

- Characteristics such as education and gender more important than earnings/wealth for