Reverse-engineering labor market flows

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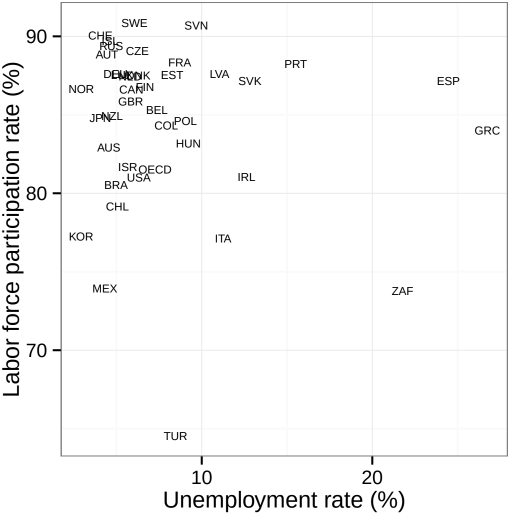
Motivation


Labor force participation rate (%)
Unemployment rate (%)
90
80
70
10
20
SWE
SVN
CHE
RUS
CZE
AUT
FRA
PRT
EST
LVA
SVK
ESP
NOR
CAN
FIN
GBR
BEL
JPN
NZL
POL
COL
GRC
AUS
HUN
ISR
OECD
USA
IRL
BRA
CHL
KOR
ITA
MEX
ZAF
TUR

Literature overview

- models for participation
  - frictionless, labor/leisure margin
  - Hansen (1985), Rogerson (1988), ...
- models for unemployment
  - frictional, driven by job finding and separation processes
  - Diamond-Mortensen-Pissarides model family
- synthesis 1:
  - Merz (1995), Andolfatto (1996), Gomes, Greenwood, and Rebelo (2001)
  - put frictions in the RBC model, no distinction between unemployment and inactivity
- synthesis 2:
  - Ljungqvist and Sargent (1998), Ljungqvist and Sargent (2007), Alvarez and Veracierto (2000), and Veracierto (2008)
  - account for stocks, but not gross flows
- synthesis 3:
  - Garibaldi and Wasmer (2005), Krusell et al. (2011), & their other papers
  - fully frictional, participation margin, target gross flows

Main question

Using matched CPS data,

$$P_{1\mathrm{m}} = \begin{array}{c c} & \begin{array}{ccc} E & U & I \end{array} \\ \begin{array}{c} E \\ U \\ I \end{array} & \begin{bmatrix} 0.980 & 0.009 & 0.010 \\ 0.286 & 0.569 & 0.145 \\ 0.078 & 0.039 & 0.883 \end{bmatrix} \end{array}$$

1. Can our models match these flows?
2. What are the necessary ingredients?
3. What do the flows identify?

Results

- reasonable benchmark model can only replicate a limited subset of the domain for short term flows
- data is outside this subset
- reason: $I \leftrightarrow U$ flows constrain processes

Results

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Extensions (✔: works, ✘: doesn't work)

- state-dependent separation rates ✘✘
- match-specific productivity ✘✘
- generalized productivity process ✘
- fluctuations in search cost ✘
- persistently inactive workers ✔
- skill loss for non-employed ✔
- skill gain for employed ✔✔
- generalized skill process ✔
- misclassification ✔

The benchmark model

- imposes structure on the labor market state process
- nests Garibaldi and Wasmer (2005)
- continuous time, linear utility, discount rate r
- partial equilibrium: only workers, exogenous
- passive search: costless, rate $\kappa\lambda$
- active search: costly, more effective, rate λ
- exogenous separation: rate σ
- state variables: employment status, general state x that determines productivity on the market $w(x)$ and at home $b(x)$
- change events arrive at rate γ, then x redrawn from a distribution $x \sim F(x)$ (IID in benchmark model, can be relaxed)

Value functions and HJB equations

$$rN(x) = b(x) + \max\{\overbrace{\lambda(W(x) - N(x))^+ - c}^{\text{active search}}, \overbrace{\kappa\lambda(W(x) - N(x))^+}^{\text{passive search}}\} + \overbrace{\gamma(E[N(x')] - N(x))}^{\text{change event}}$$

$$rW(x) = w(x) + \underbrace{\sigma(N(x) - W(x))}_{\text{exogenous separation}} + \underbrace{\gamma(\overbrace{E[N(x') \vee W(x')]}^{\text{possible endog. sep.}} - W(x))}_{\text{change event}}$$

Introduce the surplus value and the flow surplus

$$S(x) = W(x) - N(x) \qquad \text{and} \qquad s(x) = w(x) - b(x)$$

and subtract the two HJB equations to obtain

$$(r + \sigma + \gamma)S(x) = s(x) + \gamma E[S(x')^+] - \max\{\lambda S(x)^+ - c, \kappa\lambda S(x)^+\}$$

Solve for S, which determines the policy function (accept/reject, active/passive search).

Three regions

- low region: worker is not productive and would never accept a job (so won't pay for active search)

$$L = \{x : S(x) < 0\}$$

- middle or marginal region: would accept a job, but search passively

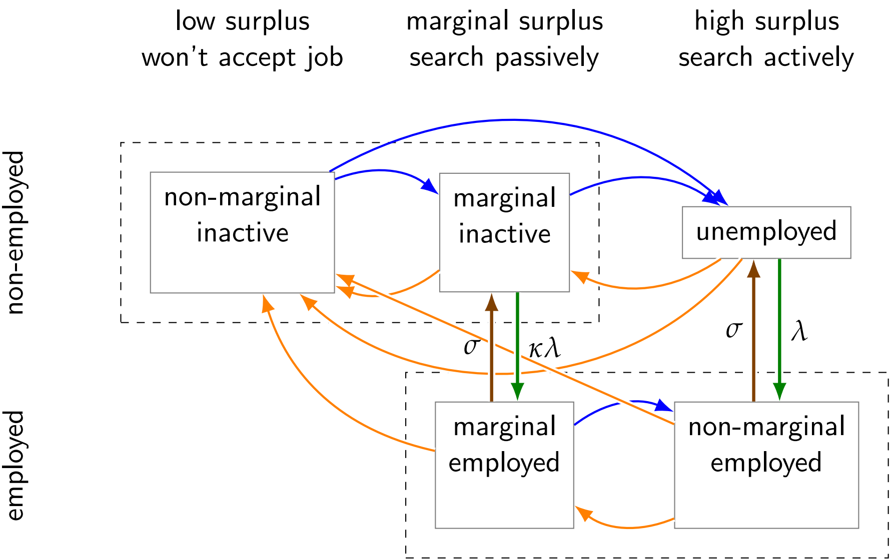
$$M = \left\{x : 0 \leq S(x) < \frac{c}{(1-\kappa)\lambda}\right\}$$

- high region: search actively (unemployed)

$$H = \left\{x : \frac{c}{(1-\kappa)\lambda} \leq S(x)\right\}$$

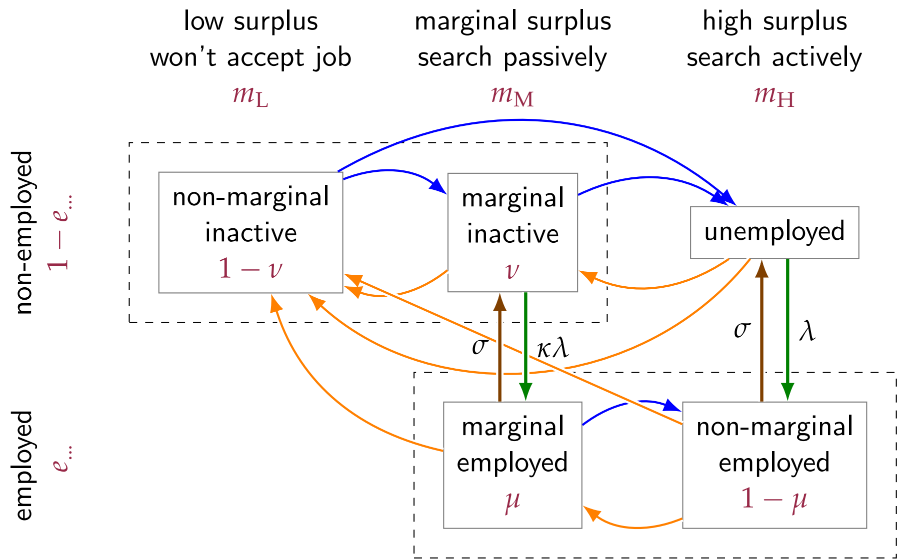
- choices for the nonemployed, but reflected in the state of the employed.

Flows



low surplus
won't accept job
marginal surplus
search passively
high surplus
search actively
non-employed
employed
non-marginal inactive
marginal inactive
unemployed
marginal employed
non-marginal employed
σ
κλ
σ
λ

Flows


low surplus
won't accept job
m_{L}
marginal surplus
search passively
m_{M}
high surplus
search actively
m_{H}
non-employed
$1 - e_{\dots}$
employed
$e_{\dots}$
non-marginal
inactive
$1 - \nu$
marginal
inactive
ν
unemployed
σ
$\kappa\lambda$
σ
λ
marginal
employed
μ
non-marginal
employed
$1 - \mu$

Notation: masses and ratios

- m_{L}, m_{M}, and m_{H} for all (employed + nonemployed) workers in each region, respectively
- employment rates e_{M} and e_{H}
- ratio of marginal inactives

$$\nu = \frac{\text{mass of marginal nonemployed}}{\text{mass of inactives}} = \frac{m_{\mathrm{M}}(1-e_{\mathrm{M}})}{m_{\mathrm{L}} + m_{\mathrm{M}}(1-e_{\mathrm{M}})}$$

- ratio of marginal employed

$$\mu = \frac{\text{mass of marginal employed}}{\text{mass of all employed}} = \frac{m_{\mathrm{M}}e_{\mathrm{M}}}{m_{\mathrm{M}}e_{\mathrm{M}} + m_{\mathrm{H}}e_{\mathrm{H}}}$$

- let p_{L}, p_{M}, p_{H} be the probabilities of drawing a state x in each region
- effective transition rates:

$$q_{\mathrm{L}} = \gamma \cdot p_{\mathrm{L}} \qquad q_{\mathrm{M}} = \gamma \cdot p_{\mathrm{M}} \qquad q_{\mathrm{H}} = \gamma \cdot p_{\mathrm{H}}$$

Observed flows

$$\lambda_{\mathrm{EI}} = \mu\sigma + q_{\mathrm{L}} \qquad \lambda_{\mathrm{UI}} = q_{\mathrm{L}} + q_{\mathrm{M}} \qquad \lambda_{\mathrm{IE}} = \nu\kappa\lambda$$
$$\lambda_{\mathrm{EU}} = (1-\mu)\sigma \qquad \lambda_{\mathrm{IU}} = q_{\mathrm{H}} \qquad \lambda_{\mathrm{UE}} = \lambda$$

Define

$$\lambda_{\mathrm{EA}} = \lambda_{\mathrm{EI}} + \lambda_{\mathrm{EU}} \quad \text{and} \quad \alpha = \frac{\lambda_{\mathrm{EI}}}{\lambda_{\mathrm{EA}}}$$

- match λ_{EA}, λ_{UI}, λ_{IU}, λ_{IE}, λ_{UE}, pinning down five parameters
- characterize α as a function of the free parameter q_{L}

$$\sigma = \lambda_{\mathrm{EA}} - q_{\mathrm{L}} \qquad \lambda = \lambda_{\mathrm{UE}} \qquad q_{\mathrm{M}} = \lambda_{\mathrm{UI}} - q_{\mathrm{L}} \qquad q_{\mathrm{H}} = \lambda_{\mathrm{IU}}$$

$$\begin{aligned}\alpha(q_{\mathrm{L}}) = \frac{\lambda_{\mathrm{EI}}}{\lambda_{\mathrm{EA}}} = \frac{\mu(q_{\mathrm{L}})\sigma + q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}} &= \frac{\mu(q_{\mathrm{L}})(\lambda_{\mathrm{EA}} - q_{\mathrm{L}}) + q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}} \\ &= \mu(q_{\mathrm{L}}) + (1-\mu(q_{\mathrm{L}}))\frac{q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}}\end{aligned}$$

Observed flows

$$\lambda_{\mathrm{EI}} = \mu\sigma + q_{\mathrm{L}} \qquad \lambda_{\mathrm{UI}} = q_{\mathrm{L}} + q_{\mathrm{M}} \qquad \lambda_{\mathrm{IE}} = \nu\kappa\lambda$$
$$\lambda_{\mathrm{EU}} = (1-\mu)\sigma \qquad \lambda_{\mathrm{IU}} = q_{\mathrm{H}} \qquad \lambda_{\mathrm{UE}} = \lambda$$

Define

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$$\alpha(q_{\mathrm{L}}) = \frac{\lambda_{\mathrm{EI}}}{\lambda_{\mathrm{EA}}} = \frac{\mu(q_{\mathrm{L}})\sigma + q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}} = \frac{\mu(q_{\mathrm{L}})(\lambda_{\mathrm{EA}} - q_{\mathrm{L}}) + q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}}$$
$$= \mu(q_{\mathrm{L}}) + (1-\mu(q_{\mathrm{L}}))\frac{q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}}$$

- direct (q_{L}) and composition ($\mu(q_{\mathrm{L}})$) effects

Flow balance equations

$$
\begin{aligned}
m_{\mathrm{L}} \cdot (q_{\mathrm{M}} + q_{\mathrm{H}}) &= (m_{\mathrm{M}} + m_{\mathrm{H}}) \cdot q_{\mathrm{L}} \\
m_{\mathrm{M}} \cdot (q_{\mathrm{L}} + q_{\mathrm{H}}) &= (m_{\mathrm{L}} + m_{\mathrm{H}}) \cdot q_{\mathrm{M}} \\
m_{\mathrm{H}} \cdot (q_{\mathrm{L}} + q_{\mathrm{M}}) &= (m_{\mathrm{L}} + m_{\mathrm{M}}) \cdot q_{\mathrm{H}} \\
m_{\mathrm{M}} e_{\mathrm{M}} \cdot (q_{\mathrm{L}} + \sigma + q_{\mathrm{H}}) &= m_{\mathrm{H}} e_{\mathrm{H}} \cdot q_{\mathrm{M}} + m_{\mathrm{M}}(1 - e_{\mathrm{M}}) \cdot \kappa\lambda \\
m_{\mathrm{H}} e_{\mathrm{H}} \cdot (q_{\mathrm{L}} + \sigma + q_{\mathrm{M}}) &= m_{\mathrm{M}} e_{\mathrm{M}} \cdot q_{\mathrm{H}} + m_{\mathrm{H}}(1 - e_{\mathrm{H}}) \cdot \lambda
\end{aligned}
$$

The solution to the first three and $m_{\mathrm{L}} + m_{\mathrm{M}} + m_{\mathrm{H}} = 1$ is simple,

$$
m_{\mathrm{L}} = \frac{q_{\mathrm{L}}}{q_{\mathrm{L}} + q_{\mathrm{M}} + q_{\mathrm{H}}} \qquad m_{\mathrm{M}} = \frac{q_{\mathrm{M}}}{q_{\mathrm{L}} + q_{\mathrm{M}} + q_{\mathrm{H}}} \qquad m_{\mathrm{H}} = \frac{q_{\mathrm{H}}}{q_{\mathrm{L}} + q_{\mathrm{M}} + q_{\mathrm{H}}}
$$

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m_{\mathrm{M}} e_{\mathrm{M}} \cdot (q_{\mathrm{L}} + \sigma + q_{\mathrm{H}}) &= m_{\mathrm{H}} e_{\mathrm{H}} \cdot q_{\mathrm{M}} + m_{\mathrm{M}}(1 - e_{\mathrm{M}}) \cdot \kappa\lambda \\
m_{\mathrm{H}} e_{\mathrm{H}} \cdot (q_{\mathrm{L}} + \sigma + q_{\mathrm{M}}) &= m_{\mathrm{M}} e_{\mathrm{M}} \cdot q_{\mathrm{H}} + m_{\mathrm{H}}(1 - e_{\mathrm{H}}) \cdot \lambda
\end{aligned}
$$

The solution to the first three and $m_{\mathrm{L}} + m_{\mathrm{M}} + m_{\mathrm{H}} = 1$ is simple,

$$
m_{\mathrm{L}} = \frac{q_{\mathrm{L}}}{q_{\mathrm{L}} + q_{\mathrm{M}} + q_{\mathrm{H}}} \qquad m_{\mathrm{M}} = \frac{q_{\mathrm{M}}}{q_{\mathrm{L}} + q_{\mathrm{M}} + q_{\mathrm{H}}} \qquad m_{\mathrm{H}} = \frac{q_{\mathrm{H}}}{q_{\mathrm{L}} + q_{\mathrm{M}} + q_{\mathrm{H}}}
$$

But solving for e_{M} and e_{H} is complicated, because of asymmetry.

Define

$$\zeta = \frac{q_\mathrm{H}}{q_\mathrm{L} + q_\mathrm{M} + q_\mathrm{H} + \lambda + \sigma} = \frac{\lambda_\mathrm{IU}}{\lambda_\mathrm{UE} + \lambda_\mathrm{IU} + \lambda_\mathrm{UI} + \lambda_\mathrm{EA} - q_\mathrm{L}}$$

If $\kappa \to 1$, then because of symmetry,

$$e_\mathrm{M} = e_\mathrm{H} = \frac{\lambda}{\lambda + \sigma + q_\mathrm{L}} = \frac{\lambda_\mathrm{UE}}{\lambda_\mathrm{UE} + \lambda_\mathrm{EA}}$$

In general,

$$\mu = \frac{q_\mathrm{M}}{q_\mathrm{M} + q_\mathrm{H} + (q_\mathrm{L} + \sigma)\frac{(1-\kappa)\zeta}{(1-\kappa)\zeta+\kappa}} = \frac{\lambda_\mathrm{UI} - q_\mathrm{L}}{\lambda_\mathrm{UI} - q_\mathrm{L} + \lambda_\mathrm{IU} + \lambda_\mathrm{EA}\underbrace{\frac{(1-\kappa)\zeta}{(1-\kappa)\zeta+\kappa}}_{\in[0,1]}}$$

Even though we can back out $\kappa \in [0,1]$ from λ_IE, leave it in as a free parameter for now. Then

$$\mu(q_\mathrm{L}, \kappa) \geq \underline{\mu}(q_\mathrm{L}) = \frac{\lambda_\mathrm{UI} - q_\mathrm{L}}{\lambda_\mathrm{EA} + \lambda_\mathrm{IU} + \lambda_\mathrm{UI} - q_\mathrm{L}}$$

Simple bounds for μ and α

Then, since $\lambda_{\mathrm{EA}} > q_{\mathrm{L}}$,

$$\alpha(q_{\mathrm{L}},\kappa) = (1-\mu(q_{\mathrm{L}},\kappa))\frac{q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}} + \mu(q_{\mathrm{L}},\kappa) \geq (1-\underline{\mu}(q_{\mathrm{L}}))\frac{q_{\mathrm{L}}}{\lambda_{\mathrm{EA}}} + \underline{\mu}(q_{\mathrm{L}}) \equiv \underline{\alpha}(q_{\mathrm{L}})$$

We can show that $\underline{\alpha}'(q_{\mathrm{L}}) > 0$, and consequently

$$\alpha(q_{\mathrm{L}},\kappa) \geq \underline{\alpha}(0) = \underline{\mu}(0) = \frac{\lambda_{\mathrm{UI}}}{\lambda_{\mathrm{EA}} + \lambda_{\mathrm{IU}} + \lambda_{\mathrm{UI}}}$$

Intuition

1. higher $q_{\mathrm{L}} \Rightarrow$ lower $\mu(q_{\mathrm{L}})$: composition effect, rather weak,
2. direct effect of q_{L} always dominates

General case: back out κ from $\lambda_{\mathrm{IE}} = \nu(\kappa, q_{\mathrm{L}})\kappa\lambda$, results are similar.

What we learn from the benchmark model

1. matching the other five moments, α is bounded from below
2. bound is obtained when $q_{\mathrm{L}} = 0$: all inactives are marginal, $\alpha = \mu$

Intuition: too many marginal employed.

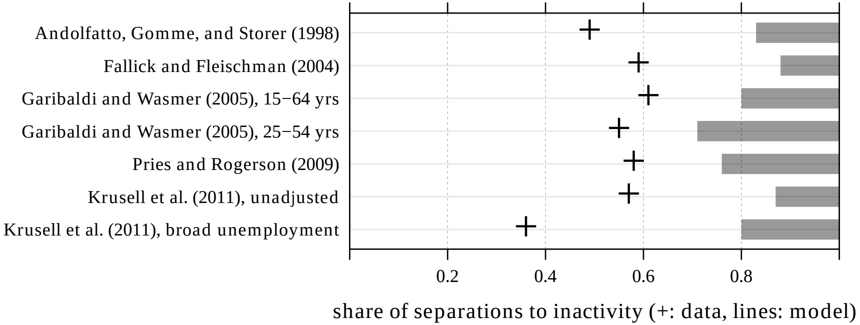
Typical magnitudes: lower bound

$$\underline{\alpha}(0) = \frac{\lambda_{\mathrm{UI}}}{\lambda_{\mathrm{EA}} + \lambda_{\mathrm{IU}} + \lambda_{\mathrm{UI}}} \approx \frac{\mathbf{0.33}}{0.044 + 0.035 + \mathbf{0.33}} \approx 0.81$$

but in the data

$$\alpha_{\mathsf{data}} = \frac{\lambda_{\mathrm{EI}}}{\lambda_{\mathrm{EA}}} = \frac{0.026}{0.044} \approx 0.60$$

Exact bounds for α, using data from various papers



Extensions that don't work ✘

- more general (non-IID process): same intuition, algebra hell
- state-dependent separation rates: σ higher for marginal employed
  1. composition effect: μ decreases
  2. direct effect: λ_{IE} increases relative to λ_{UE}, dominates, $\alpha \uparrow$
- match-specific productivity
  1. marginal matches dissolve with higher probability
  2. special case of state-dependent separation rates
- fluctuations in search cost: can be mapped to a benchmark model, same result

Permanently inactive workers — theory ✔

- fraction $\pi \in [0,1]$ of inactive workers be permanently inactive: they don't transition to any other state
- otherwise the model is the same as the benchmark model
- observed flows: mixture of the benchmark model ($'$) and permanently inactive (0)

$$\lambda_{\mathrm{IE}} = (1-\pi)\lambda'_{\mathrm{IE}} \qquad \lambda_{\mathrm{IU}} = (1-\pi)\lambda'_{\mathrm{IU}}$$
$$\lambda_{\mathrm{EU}} = \lambda'_{\mathrm{EU}} \qquad \lambda_{\mathrm{EI}} = \lambda'_{\mathrm{EI}}$$
$$\lambda_{\mathrm{UE}} = \lambda'_{\mathrm{UE}} \qquad \lambda_{\mathrm{UI}} = \lambda'_{\mathrm{UI}}$$

Intuition

$$\pi \uparrow \quad \Rightarrow \quad \lambda'_{\mathrm{IU}} = \frac{\lambda_{\mathrm{IU}}}{1-\pi} \uparrow \quad \Rightarrow \quad \alpha \downarrow$$

Permanently inactive workers — data ✔(?)

Lowest value of π for matching the flows:

	π
Andolfatto, Gomme, and Storer (1998)	0.86
Fallick and Fleischman (2004)	0.84
Garibaldi and Wasmer (2005) 15–64 yrs	0.66
Garibaldi and Wasmer (2005) 25–54 yrs	0.55
Pries and Rogerson (2009)	0.63
Krusell et al. (2011) unadjusted	0.84
Krusell et al. (2011) broad unemployment	0.89

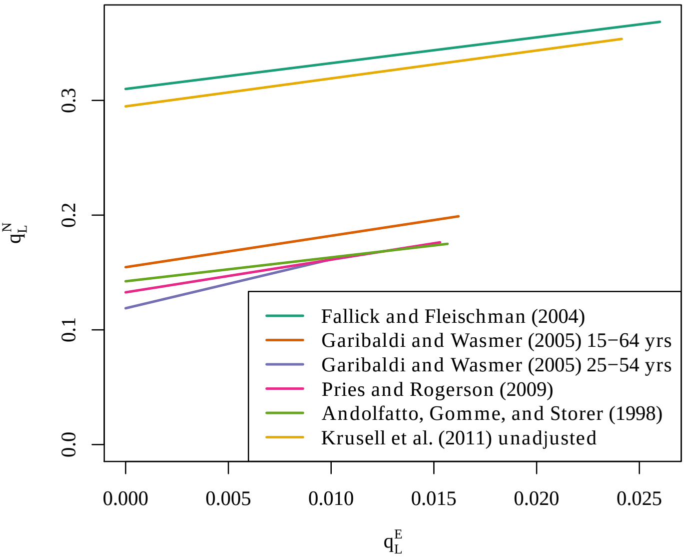
Not very plausible.

Different processes for employed and unemployed ✔

Key to breaking the result of the benchmark model: decouple processes for employed and nonemployed. Various possible parameterizations:

1. different q_{L}: non-employed transition to L with higher rate ("skill loss"), can obtain very low α
2. different q_{H}: employed transition to H with higher rate ("learning on the job"), can go to $\alpha = 0$ in the limit
3. richer processes, for example: non-employed draw from $N(0, 1)$, employed draw from $N(\bar{x}^E, 1)$
4. ...

Skill depreciation — locus for just matching α ✔



Learning on the job — locus for just matching α ✔

calibration ($q_{\mathrm{L}} = 0$)	q_{H}^{N}	q_{H}^{E}
Andolfatto, Gomme, and Storer (1998)	0.035	0.48
Fallick and Fleischman (2004)	0.035	0.40
Garibaldi and Wasmer (2005) 15–64 yrs	0.046	0.42
Garibaldi and Wasmer (2005) 25–54 yrs	0.038	0.38
Pries and Rogerson (2009)	0.022	0.26
Krusell et al. (2011) unadjusted	0.037	0.46
Krusell et al. (2011) broad unemployment	0.064	0.87

Misclassification

- impose consistency with observation error framework
- when questioned, marginal inactives respond that they are unemployed with probability ϕ_I
- similarly, unemployed respond that they are inactive with probability ϕ_U
- calculation:
  1. having observed U or I at $t-1$,
  2. conditional probability of actualy being I or U,
  3. conditional on that, use transition matrix to calculate state at t,
  4. conditional on that, draw observed state at t
- calibration: match monthly flows (✔)
- result: $\phi_I \approx 0.5$, ϕ_U not identified strongly (can be 0)

Long-term flows: data

$$P_{1\mathrm{m}} = \begin{array}{c c} & \begin{array}{ccc} E & U & I \end{array} \\ \begin{array}{c} E \\ U \\ I \end{array} & \begin{bmatrix} 0.980 & 0.009 & 0.010 \\ 0.286 & 0.569 & 0.145 \\ 0.078 & 0.039 & 0.883 \end{bmatrix} \end{array}$$

$$P_{12\mathrm{m}} = \begin{array}{c c} & \begin{array}{ccc} E & U & I \end{array} \\ \begin{array}{c} E \\ U \\ I \end{array} & \begin{bmatrix} 0.952 & 0.021 & 0.027 \\ 0.592 & 0.227 & 0.181 \\ 0.174 & 0.037 & 0.789 \end{bmatrix} \end{array} \qquad P_{1\mathrm{m}}^{12} = \begin{array}{c c} & \begin{array}{ccc} E & U & I \end{array} \\ \begin{array}{c} E \\ U \\ I \end{array} & \begin{bmatrix} 0.893 & 0.025 & 0.082 \\ 0.791 & 0.035 & 0.174 \\ 0.649 & 0.046 & 0.305 \end{bmatrix} \end{array}$$

- $P_{1\mathrm{m}}^{12} \neq P_{12\mathrm{m}}$, they are very different, in particular, $P_{1\mathrm{m}}^{12}[U, E]$ and $P_{1\mathrm{m}}^{12}[I, E]$ are too high (more on this later)
- implied stocks are close but not perfectly aligned with data, even after accounting for demographics, etc

Matching long-term flows: work in progress

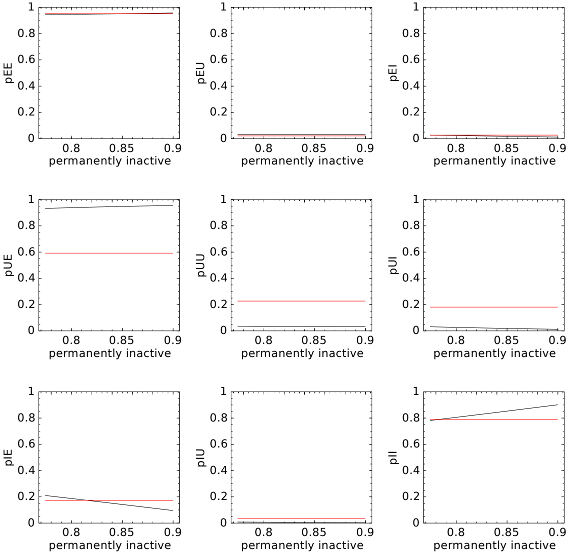
Exercise

- for any of the ✔ models before,
- match the short-term (1 month) flows,
- then calculate the long-term (12 month) flows.

Results so far

- UE and IE flows: much lower in the data
- rest: basically OK
- an ingredient is still missing

Permanently inactive workers — 12m flows (data, model)



Conclusion

- benchmark model cannot even match the short-term flows (impossibility result)
- neither can some plausible extensions
- promising: permanently inactive workers, decoupled processes, misclassification
- none of them come close for 12-month flows, especially difficult: UE and IE too high in the model
- next idea to explore: short term job volatility
- trade-off: makes short-term flows more difficult to match