Trends and Cycles in U.S. Job Mobility

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Summary

A study of job mobility in the USA in 1975–2017 with the *Annual Social and Economic* (ASEC) supplement to the *Current Population Survey* (CPS):

Long-Run Trends

Job-to-job mobility increasing from the 1970s to the 1990s.

Job-to-job mobility declining only since the turn of the millennium.

Business Cycles

Job-to-job mobility is highly cyclical over the 4+ cycles in 1975–2017.

Job-to-job mobility has a correlation of -0.86 with the unemployment rate at business-cycle frequencies.

Motivation

Productivity and Wages

Importance of the resource allocation across firms for aggregate productivity.

- If resource were as efficiently allocated as in the USA, aggregate TFP increase by 50% in China and 60% in India (Hsieh & Klenow, 2009).
- The resource reallocation from less to more productive firms accounts for >50% of aggregate growth in Denmark (Lentz & Mortensen, 2008).

Prominent role of firms in explaining the trends in wages.

- "It's Where You Work: Increases in Earnings Dispersion across Establishments and Individuals in the U.S." (Barth *et al.*, 2016)
- "Firming Up Inequality" (Song *et al.*, 2019)

A growing body of literature studies the sorting patterns among employees and employers in assignment and matching models (Chade *et al.*, 2017).

Motivation

Labor Mobility

The literature on long-run trends in worker mobility typically focuses on occupations, industries or regions (e.g., Kambourov & Manovskii, 2008).

Studies of U.S. job mobility in the sense of inter-firm mobility typically cover a limited time period only (Fallick & Fleischman, 2004).

In terms of methodology and data, this paper is most closely related to Blanchard & Diamond (1990) and Shimer (2005).

- Study of Blanchard & Diamond (1990) does not cover the last 3 decades.

  Shimer (2005) focuses on business-cycle patterns:
- Job-to-job transitions exhibit either a downward trend, no trend or an upward trend depending on the specific measure.

ASEC Data

The U.S. Bureau of the Census and of Labor Statistics conduct the *Current Population Survey* (CPS) jointly.

The CPS covers a nationally representative sample of more than 60,000 households, who are interviewed monthly.

I use the *Annual Social and Economic* (ASEC) data as provided by Flood *et al.* (2018), which is based on the march supplement of the CPS.

The march supplement of the CPS contains several questions relating to the respondent's employment in the preceding calendar year:

- number of weeks of employment and unemployment
- number of different employers (1+ employers simultaneously count as only 1 employer)

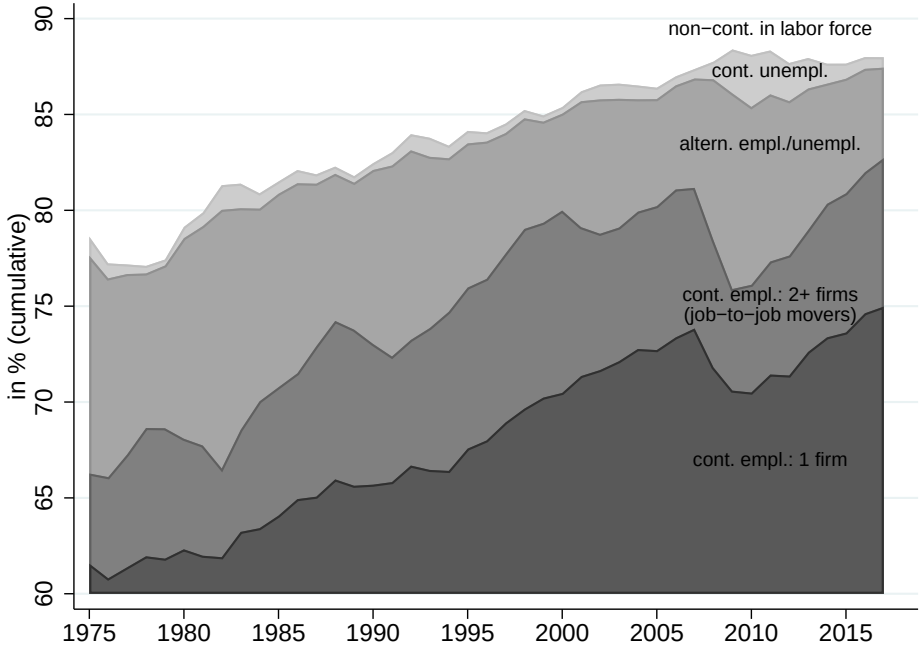
ASEC Data

Sample selection:

- survey participants ages 20–59, i.e., excluding survey participants in their early and late stages of working life
- labor-force participants, i.e., survey participants who have been employed, unemployed or looking for work for 1+ weeks during the year

I employ sampling weights in all calculations in order to obtain representative statistics.

I measure the aggregate economic activity by the aggregate unemployment rate that is computed by the Bureau of Labor Statistics (series ID: LNU04000000).



Job Mobility

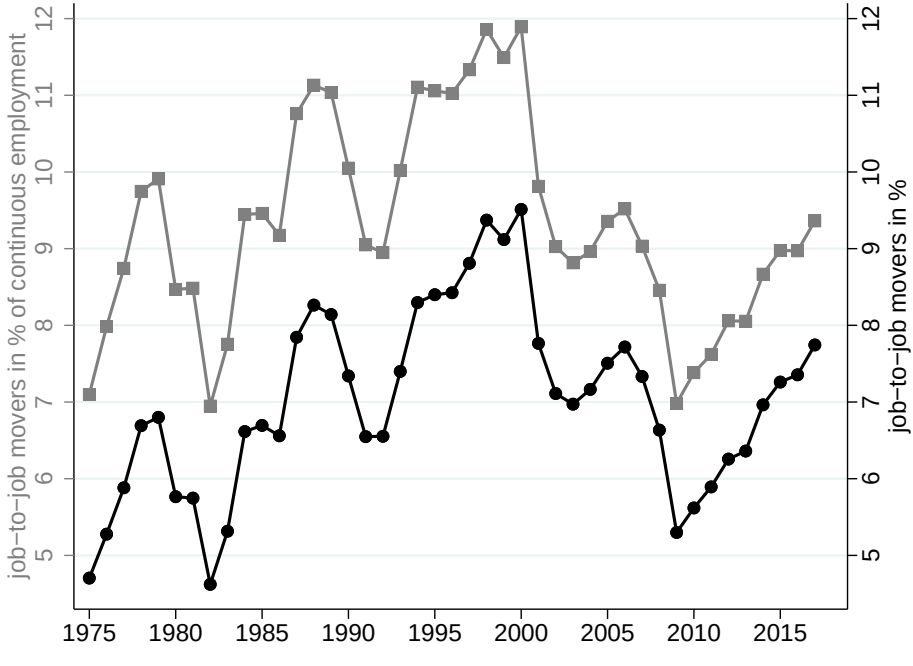
How to measure job mobility?

In this paper: share of continuously-employed job movers (individuals who were continuously employed over the year and had 2+ employers consecutively)

(Fairly) suitable for studying productive efficiency (e.g., Lentz & Mortensen, 2008) and the cyclical job ladder (e.g., Moscarini & Postel-Vinay, 2018).

- Lower bound on total job-to-job transitions, excluding multiple transitions of a single person and individuals with sizable non-employment spells.
- Such transitions are supposedly less likely to be associated with improvements in productive efficiency (e.g., Autor *et al.*, 2014, 2016)

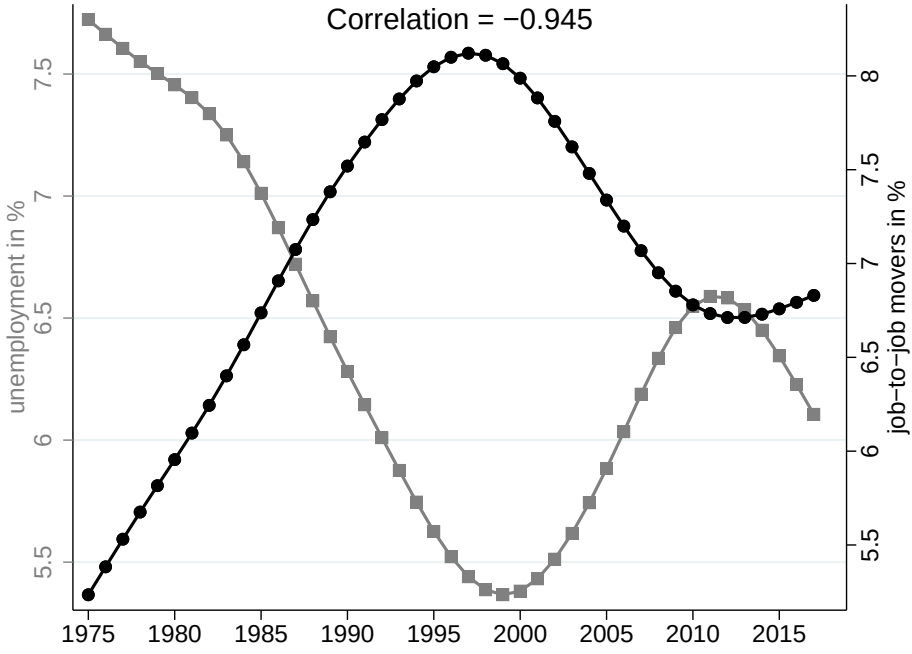
In order to validate the suitability of the measure, I also estimate the transition parameters of the random on-the-job search model.

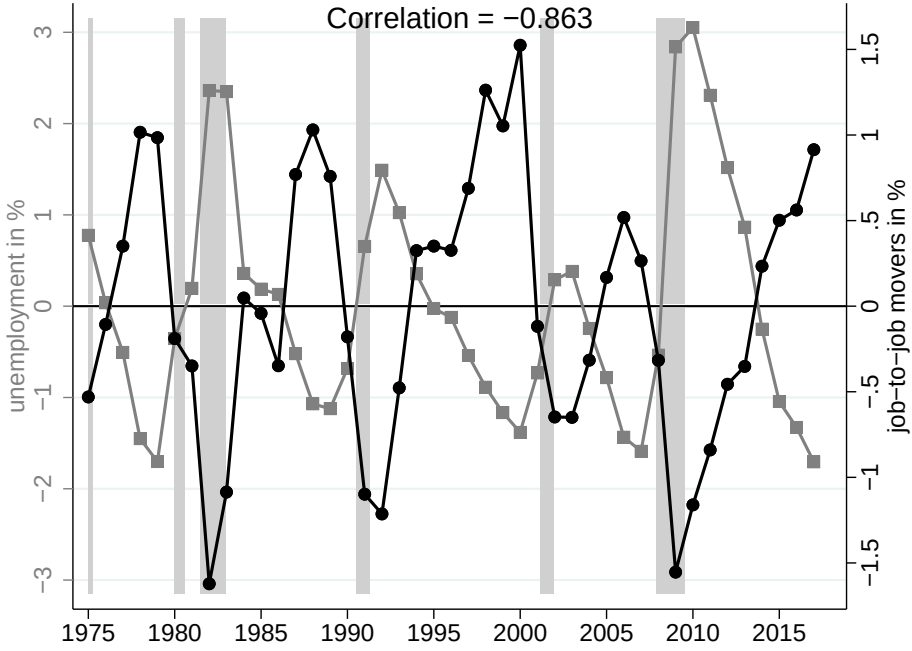


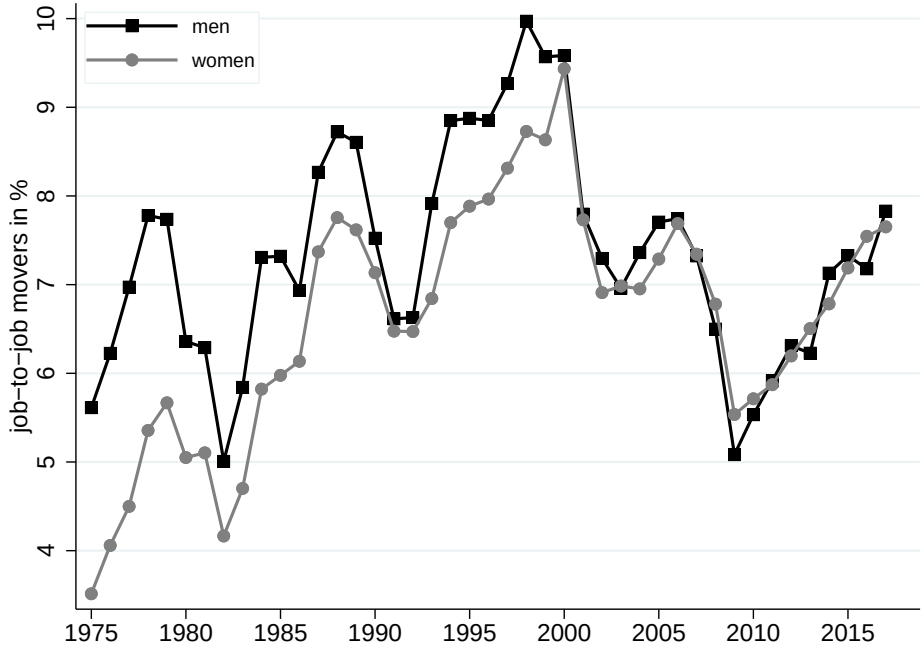
Trend and Cycle Components

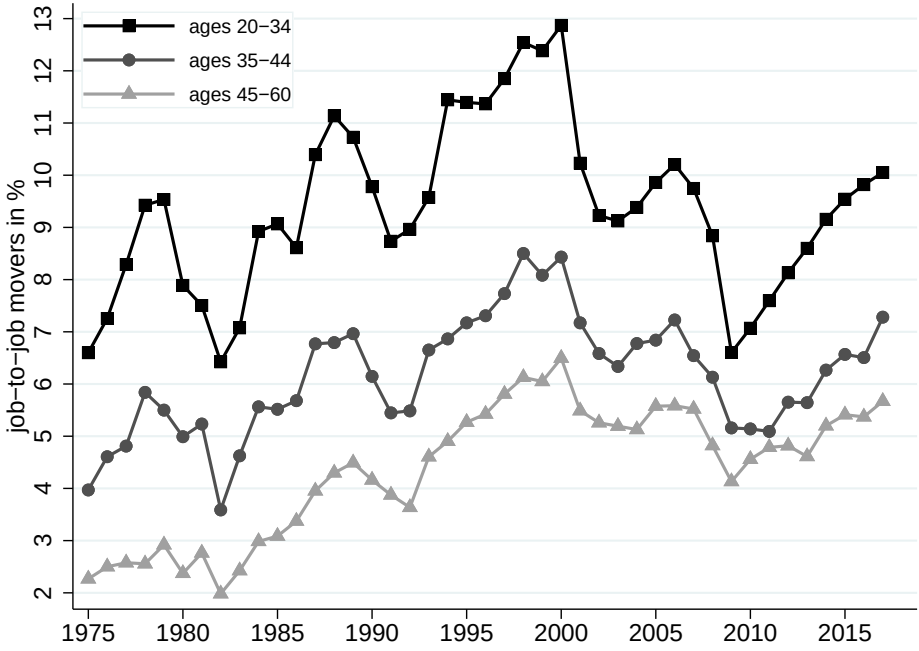
In order to extract the trend and cycle components from the time series, I make use of the Hodrick–Prescott filter.

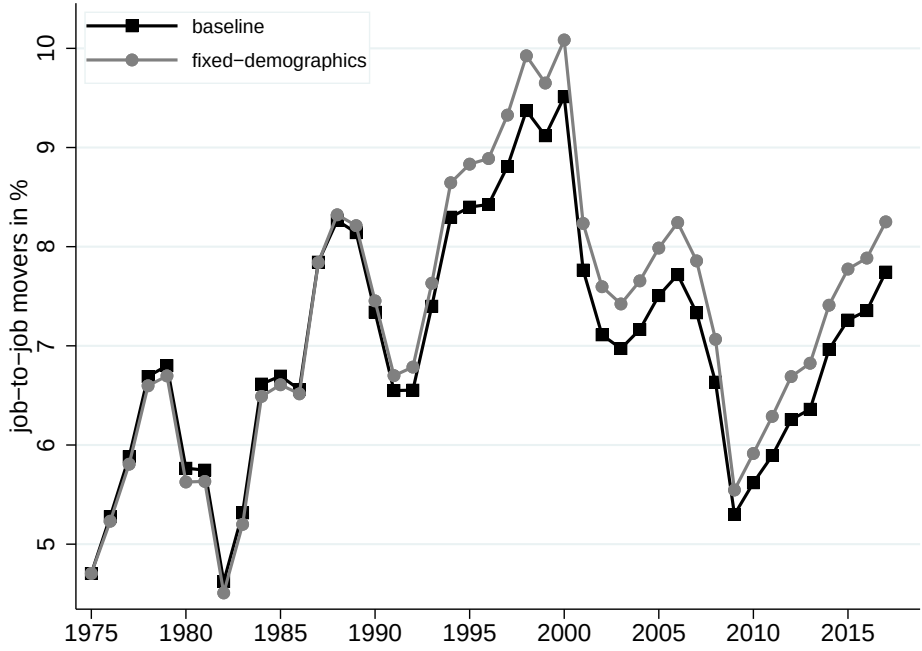
I choose a high smoothing parameter of 390.625 (in line with, e.g., Robin, 2011; Moscarini & Postel-Vinay, 2012; Shimer, 2012).











Structural Approach

In order to provide a formal economic interpretation, I rely on the canonical (random) on-the-job search model (see, e.g., Cahuc & Zylberberg, 2004; Burdett & Mortensen, 1998).

I tailor a likelihood function to the available survey questions with the Fokker–Planck formalism (Bayer & Wälde, 2010; Stijepic, 2020).

I estimate the transition parameters of the search model for the 4 fully-covered business cycles separately.

Structural Approach

On-the-Job Search Model

Model Description

Job offers are random draws from the wage-offer distribution $F(w)$.

Unemployed workers obtain job offers according to a Poisson process at rate μ.

Employed workers obtain job offers according to a Poisson process at rate λ.

Workers transition into unemployment according to a Poisson process at rate δ.

Workers exit and enter the labor force according to a Poisson process at rate ρ.

Structural Approach

On-the-Job Search Model

Law of Motion for a Person's State $s = (n, i, l, g)$

$$ds = \begin{cases} ((l^-, \omega, e^-, g) - s)\, dq_\mu + ((l^-, b, u^-, 2^+) - s)\, dq_\rho & \text{if } s = (n, b, u, g) \\ \mathbb{1}^*(\omega, s)\, ((l^-, \omega, e^-, g) - s)\, dq_\lambda & \\ \quad + ((l^-, b, u^-, g) - s)\, dq_\delta + ((l^-, \omega, e^-, 2^+) - s)\, dq_\rho & \text{if } s = (l^-, w, e^-, g) \\ \mathbb{1}^*(\omega, s)\, ((2^+, \omega, e^+, 1) - s)\, dq_\lambda & \\ \quad + ((l^-, b, u^-, 1) - s)\, dq_\delta + ((l^-, \omega, e^-, 2^+) - s)\, dq_\rho & \text{if } s = (n, w, e^+, 1) \end{cases}$$

q_x: Poisson process with arrival rate x
$\mathbb{1}^*(\omega, s)$: indicator function that equals 1 if $\omega > w$ and 0 otherwise, where $\omega \sim F$

Probabilities and the Probability Function

Let $P(s \in A)$ be the probability of $s \in A \subset \Omega$ with $p(s)$ as the associated density.

The probability at the future point in time dt is

$$P_{dt}(s \in A) = \int_A p_{dt}(s)ds$$

The probability function $p_{dt}(\cdot)$ is consistent with the stochastic process for the person's state $s_{dt}(\cdot)$ if the probability implied by the function coincides with that implied by the processes for any open set A (Stijepic, 2020).

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$$P_{dt}(s \in A) = \int_A p_{dt}(s)ds = \int_\Omega p_{dt}(s)\mathbb{1}_A(s)ds$$

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Structural Approach

Fokker–Planck

Probabilities and the Probability Function

Let $P(s \in A)$ be the probability of $s \in A \subset \Omega$ with $p(s)$ as the associated density.

The probability at the future point in time dt is

$$P_{dt}(s \in A) = \int_A p_{dt}(s)ds = \int_\Omega p_{dt}(s)\mathbb{1}_A(s)ds, \text{ or}$$
$$P_{dt}(s \in A) = \int_\Omega p(s)E\mathbb{1}_A(s_{dt}(s))ds.$$

The probability function $p_{dt}(\cdot)$ is consistent with the stochastic process for the person's state $s_{dt}(\cdot)$ if the probability implied by the function coincides with that implied by the processes for any open set A (Stijepic, 2020).

Structural Approach

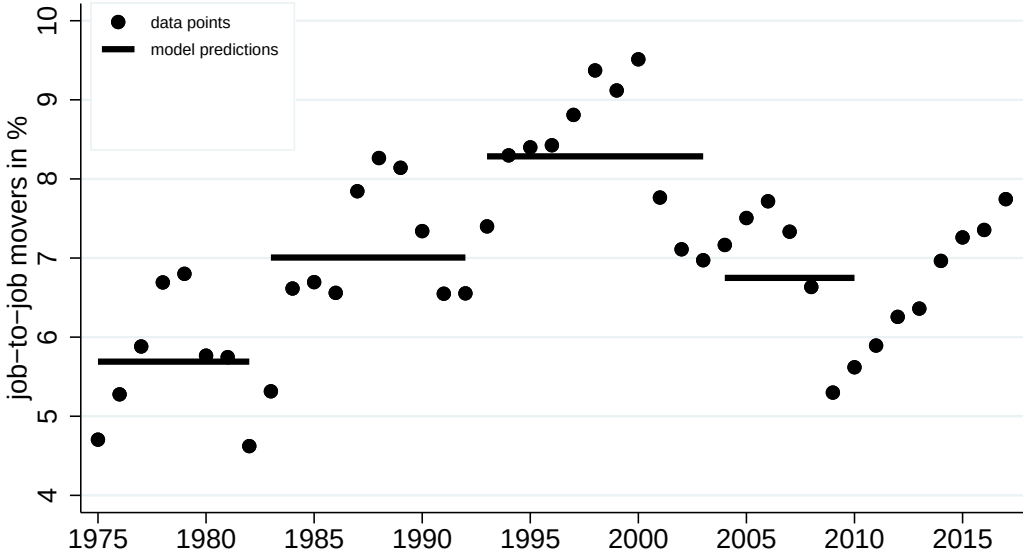
Likelihood

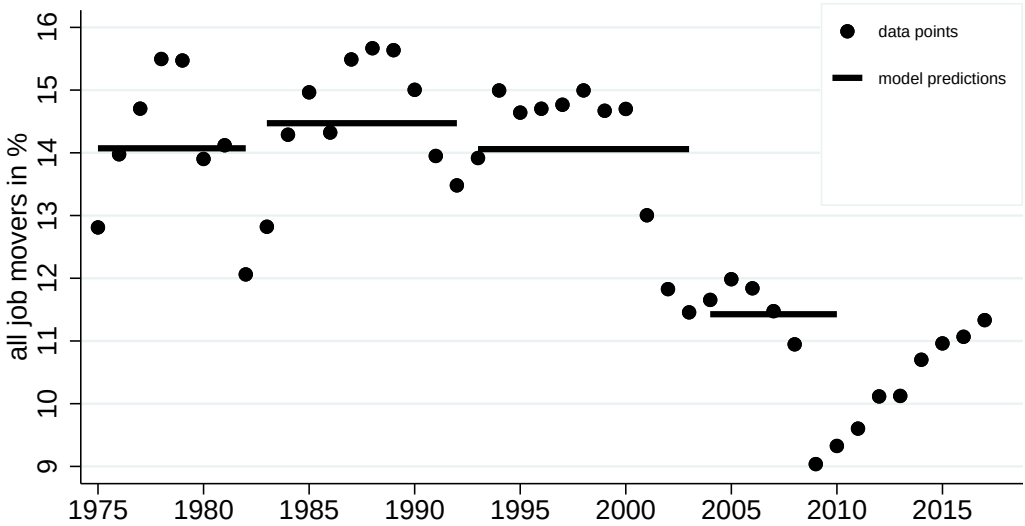
Likelihood Function $\mathcal{L}_{\rho,\mu,\delta,\lambda}$

$$\mathcal{L}_{\rho,\mu,\delta,\lambda} = \begin{cases} 1 - \mathrm{e}^{-\rho} & \text{if non-cont. in labor force} \\ \frac{\delta \mathrm{e}^{-(\rho+\mu)}}{(\delta+\mu)} & \text{if cont. unempl.} \\ \frac{\delta(\mathrm{e}^{-\rho} - \mathrm{e}^{-(\rho+\mu)})}{(\delta+\mu)} + \frac{\mu(\mathrm{e}^{-\rho} - \mathrm{e}^{-(\rho+\delta)})}{(\delta+\mu)} & \text{if altern. empl./unempl.} \\ \frac{\mu \mathrm{e}^{-(\rho+\delta)}}{(\delta+\mu)} \int_0^1 \frac{(\rho+\delta)(\rho+\delta+\lambda)\mathrm{e}^{-\lambda(1-x)}}{(\rho+\delta+\lambda(1-x))^2} dx & \text{if cont. empl.: 1 firm} \\ \frac{\mu \mathrm{e}^{-(\rho+\delta)}}{(\delta+\mu)} \int_0^1 1 - \frac{(\rho+\delta)(\rho+\delta+\lambda)\mathrm{e}^{-\lambda(1-x)}}{(\rho+\delta+\lambda(1-x))^2} dx & \text{if cont. empl.: 2+ firms} \end{cases}$$

	1975–1982	1983–1992	1993–2003	2004–2010
Spell durations				
$1/\rho$	4.1424*** (0.0124)	5.0893*** (0.0145)	6.1634*** (0.0176)	7.4038*** (0.0260)
$1/\delta$	10.1360*** (0.0486)	11.9151*** (0.0524)	17.9949*** (0.0855)	17.9974*** (0.0928)
$1/\mu$	0.5628*** (0.0038)	0.5684*** (0.0035)	0.6294*** (0.0040)	0.8374*** (0.0052)
$1/\lambda$	4.6554*** (0.0326)	3.7067*** (0.0220)	2.9900*** (0.0167)	3.9512*** (0.0264)
Further statistics				
μ/δ	18.0107*** (0.1082)	20.9618*** (0.1148)	28.5905*** (0.1617)	21.4912*** (0.1187)
$\lambda/(\rho+\delta)$	0.6317*** (0.0048)	0.9621*** (0.0064)	1.5355*** (0.0099)	1.3276*** (0.0102)
$\int_0^\infty \lambda(1-F(w))dG(w)$	0.0900*** (0.0005)	0.1050*** (0.0005)	0.1168*** (0.0005)	0.0917*** (0.0005)
Log-Likelihood	–557,611	–712,317	–788,066	–592,468
Observations	525,335	692,859	824,515	643,715

Table: Maximum-likelihood per-annum estimates of the transition parameters in the search model. Delta-method standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the ASEC data.





Conclusion

In line with the increase in mobility across occupations and industries over the last decades of the 20th century (Kambourov & Manovskii, 2008), I document a concurrent increase in job mobility, i.e., the share of continuously-employed job movers rises from 5.9% of the labor force in 1975–79 to 8.8% in 1995–99.

In line with the trend reversal in the demand for cognitive tasks and skills around the turn of the millennium (Beaudry *et al.*, 2016), I document a trend reversal in job mobility around the same time.

The cyclical fall in job mobility during the Great Recession is not exceptionally large in comparison to all the recessions according to the HP decomposition.

The particularity of the Great Recession is rather the concurrence of a pronounced cyclical fall and a pronounced overall downward trend in job mobility, which already starts around the turn of the millennium.

Conclusion

I also estimate the transition rates of the random on-the-job search for the 4 fully-covered business cycles.

All transition rates that govern the worker flows between employment and non-employment decrease over the last decades of the 20th century, implying a decline in the indirect labor reallocation across firms that is associated with intervening non-employment spells.

The job-finding rate on the job rises over the same period, implying an increase in the direct labor reallocation across firms that is not associated with intervening non-employment spells.

All the transition rates are decreasing since the turn of the millennium, implying a universal decline in the labor reallocation across firms.

Small Employers, Large Employers and the Skill Premium

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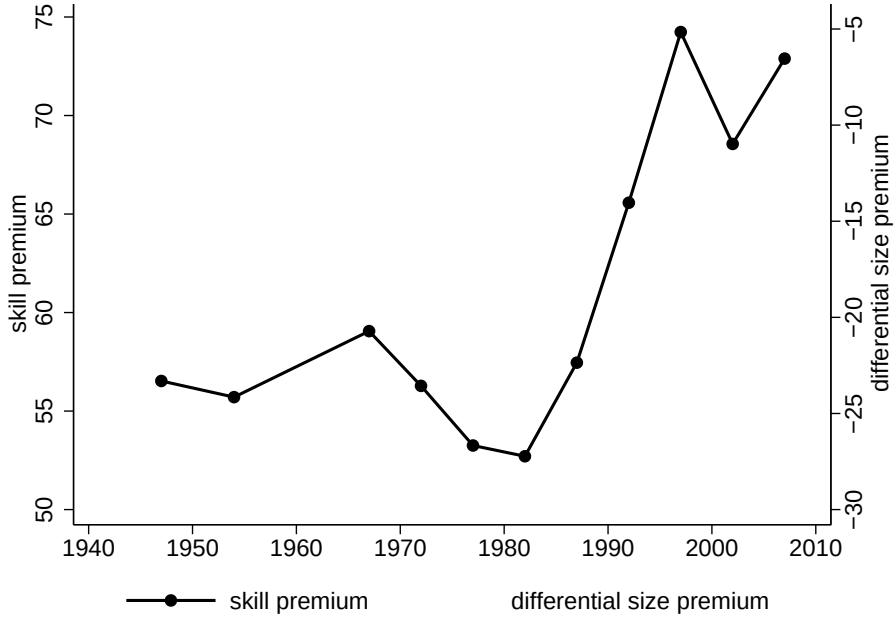

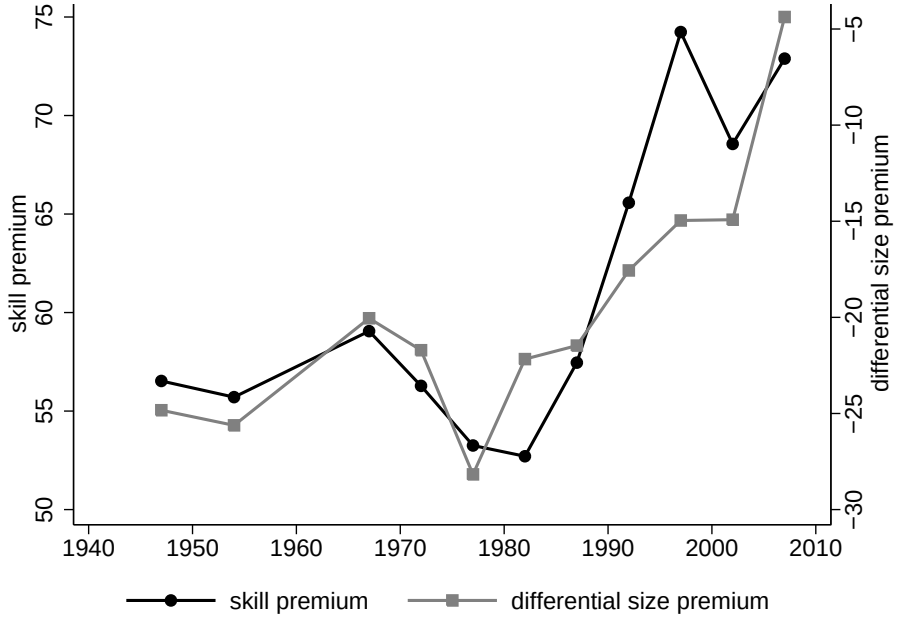

Differential Size Premium

"There has been a recurrence of doubts and fears for the future—aroused in this case by the protracted slowdown in productivity growth since the late 1960's, the seeming erosion of the competitiveness of U.S. industries in world markets, and the spectre of 'deindustrialization' and massive structural unemployment." (Baumol, 1986)

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