Educational Disparity in Job Mobility: The Great Trend Reversal

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Summary

The Rise and Fall in Job Mobility

turbulent changes in the pace of labor reallocation over the past half-century:

- surge in job-to-job mobility at the end of the 20th century
- collapse in job-to-job mobility at the start of the 21st century
- recent years at late-1970s levels—far below the peak late-1990s levels

rise and fall in mobility closely tied to skills:

- educated workers at the forefront of the boom in the 20th century
- educated workers at the center of the slowdown in the 21st century

Motivation

Productivity and Wages

importance of the resource allocation across firms for aggregate productivity:

- gains in aggregate TFP by 50% in China and 60% in India with U.S. efficiency levels (Hsieh & Klenow, 2009)
- >50% of aggregate growth in Denmark by reallocation from less to more productive firms (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)

growing body of literature on worker–firm sorting in assignment and matching models (Chade *et al.*, 2017)

Motivation

Labor Mobility

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

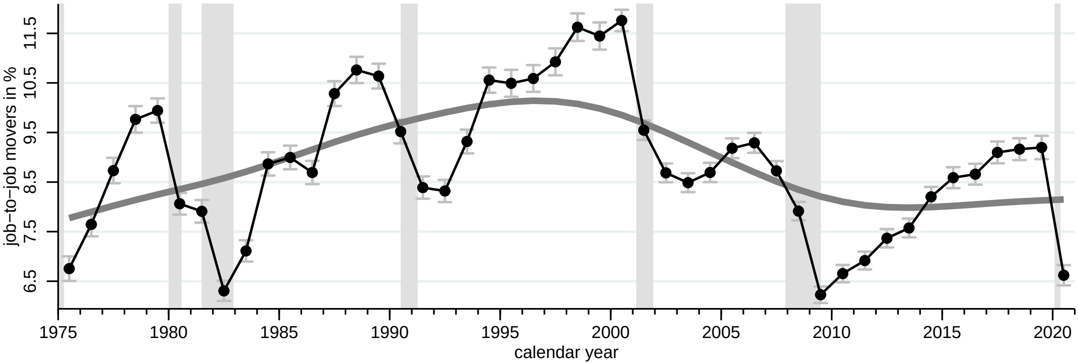
limited time frame of studies of U.S. job mobility in the sense of inter-firm mobility (Fallick & Fleischman, 2004)

related (methodology/data) to Blanchard & Diamond (1990) & Shimer (2005):

- Blanchard & Diamond (1990) without the last 3 decades
- focuse on business cycles in Shimer (2005)—downward, upward or no trend in transitions depending on measure

Motivation

Time Period



Time series on the share of job-to-job movers with 95-percent confidence bands (light gray) and Hodrick–Prescott filtered trend (dark gray). Sample restricted to active participants with at least 9 years of education and with less than 40 years of experience. Sampling weights employed in all calculations. Author's calculations based on the ASEC as provided by Flood *et al.* (2018). Shaded areas indicate NBER-dated contractions.

Motivation

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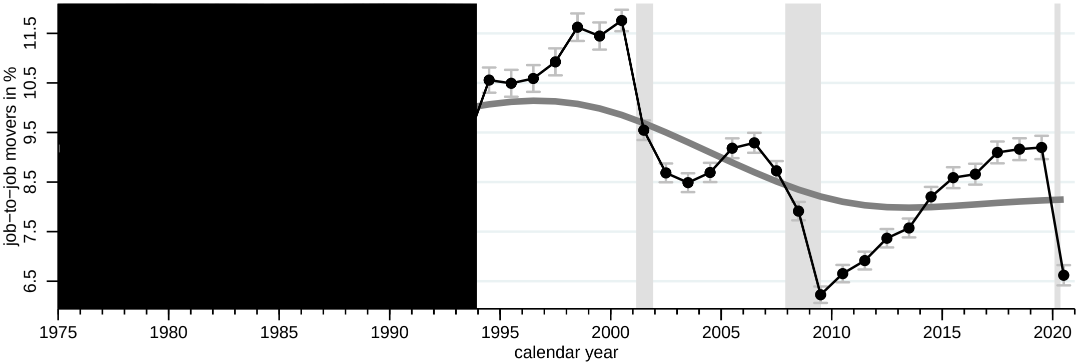

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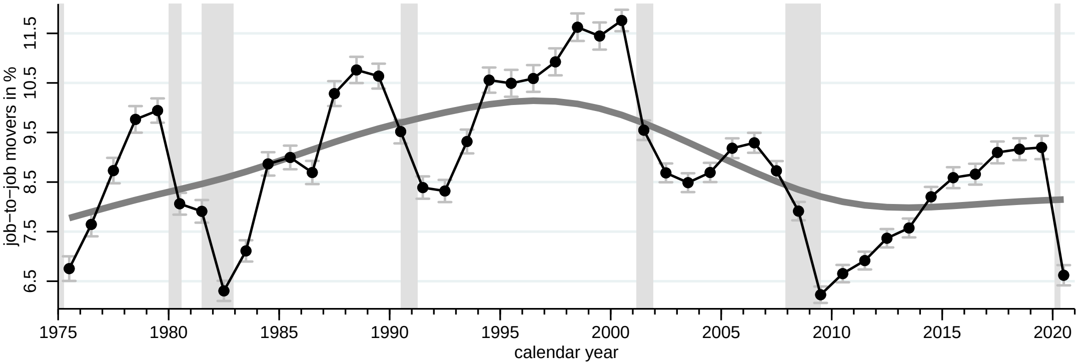
Motivation

Measurement



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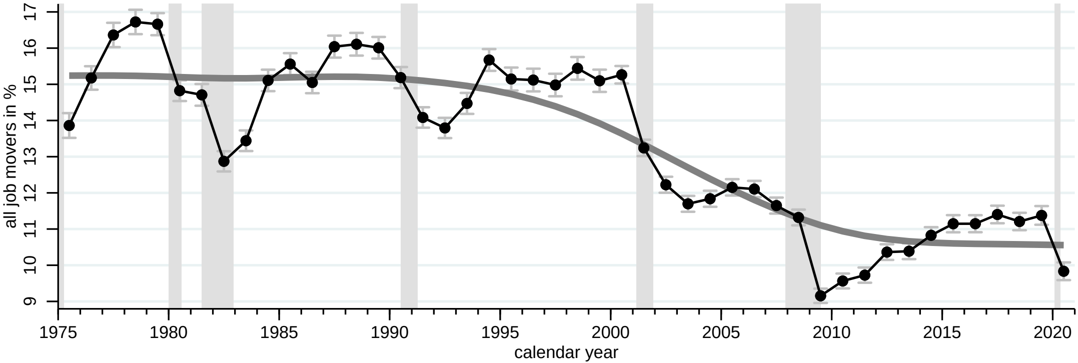

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Data & Stats

ASEC Data

Current Population Survey (CPS) by the U.S. Bureau of the Census and of Labor Statistics

nationally representative sample of >60,000 households with monthly interviews

here: *Annual Social and Economic* (ASEC) data (march supplement) as provided by Flood *et al.* (2018)

several questions relating to employment in the preceding calendar year:

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

Data & Stats

Sample

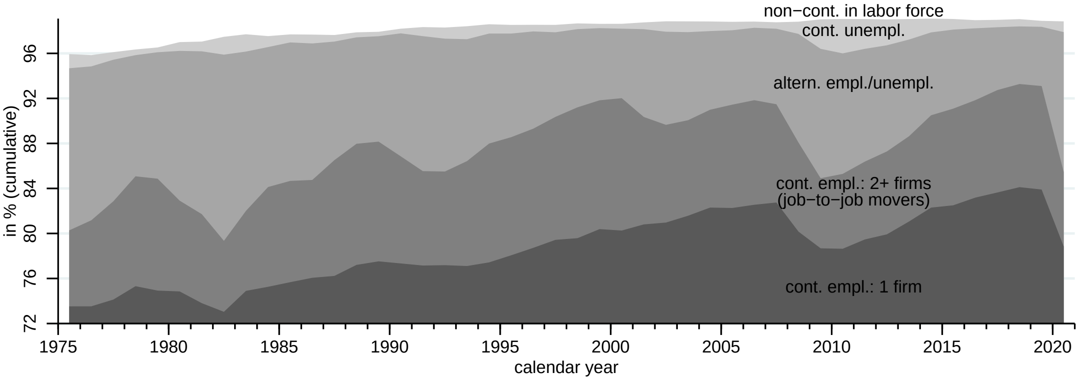
sample selection:

- at least 16 years old
- at least 9 years of education
- less than 40 years of (potential) experience
- at least 50 weeks of activity (early career workers: 12 weeks)

sampling weights in all calculations for representative statistics

Data & Stats

Categories



Decomposition into labor-force and mobility categories as defined in the main text. Sample restricted to active participants with at least 9 years of education and with less than 40 years of experience. Sampling weights employed in all calculations. Author's calculations based on the ASEC as provided by Flood *et al.* (2018).

Data & Stats

Measurement

How to measure job mobility?

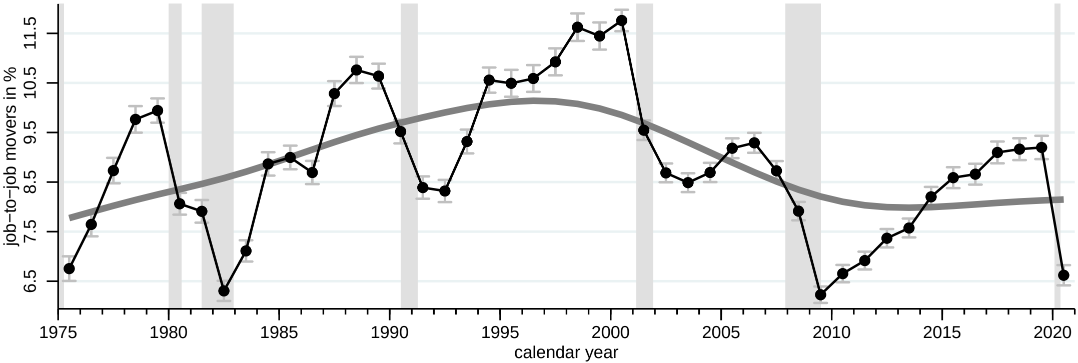
ad-hoc answer: share of continuously-employed job movers (individuals who were continuously employed over the year and had 2+ employers consecutively)

(fairly) suitable for the study of productive efficiency and related subjects:

- lower bound on total job-to-job transitions (excl. multiple transitions & individuals with sizable non-employment)
- excluded transitions less likely directional (e.g., Autor *et al.*, 2014, 2016)

Data & Stats

Job Mobility



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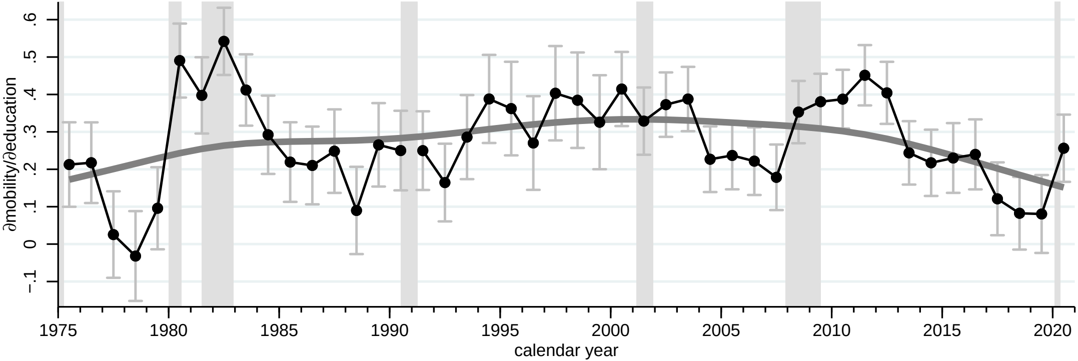
Data & Stats

Educational Gradient



Educational gradient in job-to-job mobility in percentage points with 95-percent confidence bands (light gray) and Hodrick–Prescott filtered trend (dark gray). Sample restricted to active participants with at least 9 years of education and with less than 40 years of experience. Sampling weights employed in all calculations. Author's calculations based on the ASEC as provided by Flood *et al.* (2018). Shaded areas indicate NBER-dated contractions.

Theoretical Background

Schumpeterian Growth Theory

new innovations replace older technologies (Grossman & Helpman, 1991; Aghion & Howitt, 1992; Klette & Kortum, 2004)

reallocation of resources central to this process of creative destruction (Lentz & Mortensen, 2008)

rich set of distinct (testable) predictions (Aghion *et al.*, 2014)

faster innovation-led growth associated with higher turnover rates

Theoretical Background

Labor Market

Labor Market: Indirect Job Mobility

Schumpeterian models incorporating search models of unemployment à la Pissarides (2000) (Aghion & Howitt, 1994; Mortensen & Pissarides, 1998):

- focus on indirect job mobility (job changes with intervening unemployment)
- search for new jobs only once unemployed

Creative destruction leads to displacement:

Jobs whose technology is fixed eventually become unprofitable, forcing the workers into unemployment until they find a new job.

Theoretical Background

Labor Market

Labor Market: Direct Job Mobility

Schumpeterian models incorporating on-the-job search models (Michau, 2013):

- prominent role of direct job mobility or job-to-job mobility (job changes without intervening unemployment)
- option of direct reallocation to new jobs without intervening unemployment

Creative destruction does not necessarily lead to displacement:

Rather a process of increasing job opportunities that workers have to seize, than a process of displacement and recurrent unemployment.

Theoretical Background

Labor Market

Labor Market: Reallocation to New-Technology Jobs

creative destruction potentially associated with vastly different experiences: increasing job opportunities vs. displacement & recurrent unemployment

related question: To what extent does job mobility reflect the reallocation from jobs with outdated technologies to jobs with new technologies?

Job mobility that is associated with recurrent displacement and protracted unemployment spells is less likely to be directional (e.g., Autor *et al.*, 2014, 2016).

Theoretical Background

Technology

General-Purpose Technology

General-purpose technologies are typically Schumpeterian:

- diffusion to all sectors eventually
- economy-wide abandonment of older technologies

General-purpose technologies typically lead to major transformations:

- uncertainty and novelties in early adoption stages
- familiar routines in later stages with widespread adoption

Theoretical Background

Skills

Skills and Adaptability

the key idea underlying the empirical study:

Skilled workers have an advantage in coping with the uncertainty and the novelties that are associated with a new technology in the early adoption stages (dates back to Nelson & Phelps, 1966).

related alternative concept: versatility (a broader set of skills)

Theoretical Background

Predictions

Main Premises/Hypotheses/Predictions for the Empirical Study

- churning pervasive in the labor market
- worker-level mobility necessary to sustain any aggregate labor allocation
- transition to a new technology
  - reallocation beyond the baseline turnover
  - build-up over time and decline eventually
- overall change in the educational gradient in mobility
  - adaptability advantage of skilled workers
  - extent of the excess turnover

Mobility and the educational gradient in mobility tend to have an inverted-‘U’ pattern over the technology adoption cycle.

Econometric Model

formal economic interpretation with on-the-job search model
(see, e.g., Cahuc & Zylberberg, 2004; Burdett & Mortensen, 1998)

likelihood function tailored to the available survey questions
(Kolmogorov forward/Fokker–Planck eqs: Bayer & Wälde, 2010; Stijepic, 2020)

variety of estimates:

- transition parameters in the search model
- relation between the parameters and selected covariates
- average marginal effects of the covariates on key model statistics

Econometric Model

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 λ_u.

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

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

Workers exit/enter the labor force according to a Poisson process at rate δ_g.

Econometric Model

On-the-Job Search Model

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

$$
ds = \begin{cases}
(0,0,0,dt) + ((l^-, \omega, e^-, y) - s)\, dq_{\lambda_u} \\
\quad + ((l^-, b, u^-, 0) - s)\, dq_{\delta_g} & \text{if } s = (n, b, u, y) \\
(0,0,0,dt) + \mathbb{1}^*(\omega, s)\, ((l^-, \omega, e^-, y) - s)\, dq_{\lambda_e} \\
\quad + ((l^-, b, u^-, y) - s)\, dq_{\delta_u} + ((l^-, \omega, e^-, 0) - s)\, dq_{\delta_g} & \text{if } s = (l^-, w, e^-, y) \\
(0,0,0,dt) + \mathbb{1}^*(\omega, s)\, ((2^+, \omega, e^+, y) - s)\, dq_{\lambda_e} \\
\quad + ((l^-, b, u^-, y) - s)\, dq_{\delta_u} + ((l^-, \omega, e^-, 0) - s)\, dq_{\delta_g} & \text{if } s = (n, w, e^+, y)
\end{cases}
$$

q_x: Poisson process with arrival rate x

$\mathbb{1}^*(\omega, s)$: indicator function that equals 1 if $\omega > w$ and 0 otherwise, where $\omega \sim F$

Econometric Model

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

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

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).

Econometric Model

Fokker–Planck

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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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Econometric Model

Fokker–Planck

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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).

Econometric Model

Likelihood

Likelihood Function $\mathcal{L}_t^{\delta_g,\delta_u,\lambda_u,\lambda_e}(n, l, y)$

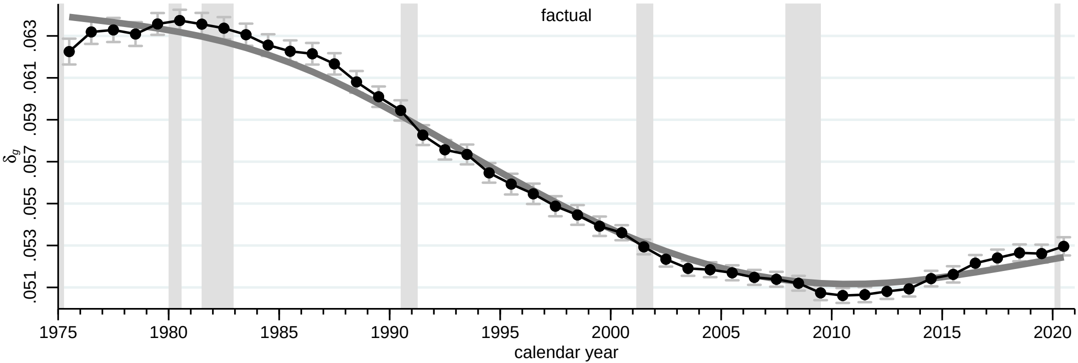
$$
\mathcal{L}_t = \begin{cases}
\delta_g \mathrm{e}^{-\delta_g y} & \text{if } y < t \\
\frac{\delta_u \delta_g \mathrm{e}^{-\delta_g y} \mathrm{e}^{-\lambda_u t}}{\lambda_u + \delta_u} & \text{if } l = u^+ \\
\frac{\delta_u \delta_g \mathrm{e}^{-\delta_g y}\left(1 - \mathrm{e}^{-\lambda_u t}\right)}{\lambda_u + \delta_u} + \frac{\lambda_u \delta_g \mathrm{e}^{-\delta_g y}\left(1 - \mathrm{e}^{-\delta_u t}\right)}{\lambda_u + \delta_u} & \text{if } l = l^- \wedge y \geq t \\
\frac{\lambda_u \delta_g \mathrm{e}^{-\delta_g y} \mathrm{e}^{-\delta_u t}}{\lambda_u + \delta_u} \int_0^1 \frac{\delta_u(\lambda_e + \delta_u) + \frac{\lambda_e((1+\lambda_e x(y-t))(1-x)(\lambda_e(1-x)+\delta_u) - \delta_u x)}{\mathrm{e}^{(\lambda_e(1-x)+\delta_u)(y-t)}}}{(\lambda_e(1-x)+\delta_u)^2 \mathrm{e}^{\lambda_e(1-x)t}} dx & \text{if } n = 1^- \wedge l = e^+ \\
\frac{\lambda_u \delta_g \mathrm{e}^{-\delta_g y} \mathrm{e}^{-\delta_u t}}{\lambda_u + \delta_u} \int_0^1 1 - \frac{\delta_u(\lambda_e + \delta_u) + \frac{\lambda_e((1+\lambda_e x(y-t))(1-x)(\lambda_e(1-x)+\delta_u) - \delta_u x)}{\mathrm{e}^{(\lambda_e(1-x)+\delta_u)(y-t)}}}{(\lambda_e(1-x)+\delta_u)^2 \mathrm{e}^{\lambda_e(1-x)t}} dx & \text{if } n = 2^+ \wedge l = e^+
\end{cases}
$$

	1975–1982	1983–1991	1992–2001	2002–2009	2010–2020
spell duration					
$1/\delta_g$	15.8031*** (0.0265)	16.3853*** (0.0231)	18.1336*** (0.0224)	19.3940*** (0.0254)	19.3418*** (0.0214)
$1/\delta_u$	10.2743*** (0.0544)	12.4720*** (0.0596)	17.2829*** (0.0796)	18.5984*** (0.0940)	19.0171*** (0.0812)
$1/(\delta_g + \delta_u)$	6.2263*** (0.0204)	7.0817*** (0.0197)	8.8490*** (0.0215)	9.4940*** (0.0252)	9.5890*** (0.0213)
$1/\lambda_u$	0.5862*** (0.0042)	0.5799*** (0.0038)	0.6296*** (0.0040)	0.7671*** (0.0049)	0.8835*** (0.0045)
$1/\lambda_e$	2.4990*** (0.0240)	1.8904*** (0.0166)	1.3286*** (0.0113)	2.1061*** (0.0187)	2.3384*** (0.0174)
further statistics					
λ_u/δ_u	17.5262*** (0.1138)	21.5066*** (0.1283)	27.4525*** (0.1581)	24.2457*** (0.1391)	21.5245*** (0.0990)
$\int \lambda_e(1 - F(w))dG(w)$	0.1208*** (0.0008)	0.1374*** (0.0007)	0.1516*** (0.0006)	0.1142*** (0.0006)	0.1071*** (0.0005)
$\lambda_e/(\delta_g + \delta_u)$	2.4915*** (0.0270)	3.7460*** (0.0371)	6.6604*** (0.0632)	4.5079*** (0.0444)	4.1006*** (0.0337)
$(1 - G(w_m))/G(w_m)$	3.4915*** (0.0270)	4.7460*** (0.0371)	7.6604*** (0.0632)	5.5079*** (0.0444)	5.1006*** (0.0337)

Maximum-likelihood estimates of the arrival rates in the on-the-job search model. Log-likelihood: $-13,225,674.4178$. Observations: $2,916,334$. Sampling weights employed in all calculations. 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 as provided by Flood *et al.* (2018).

Econometric Model

Estimates



Maximum-likelihood estimates with 95-percent confidence bands (light gray) and Hodrick–Prescott filtered trend (dark gray). Sample restricted to active participants with at least 9 years of education and with less than 40 years of experience. Sampling weights employed in all calculations. Author's calculations based on the ASEC as provided by Flood *et al.* (2018). Shaded areas indicate NBER-dated contractions.

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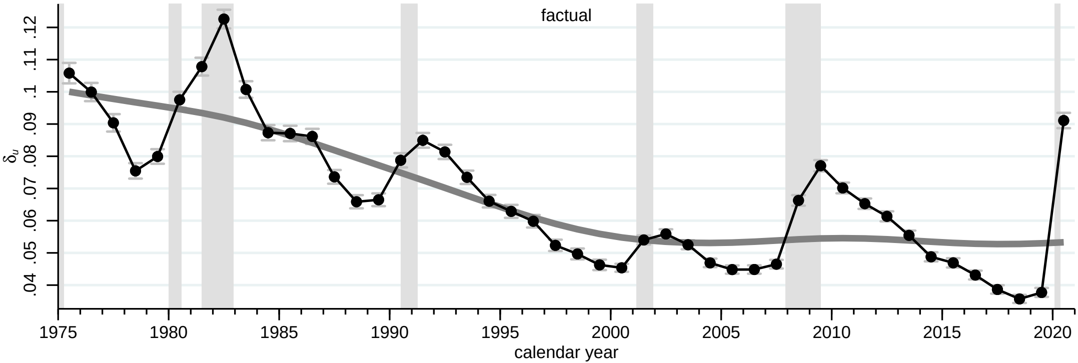

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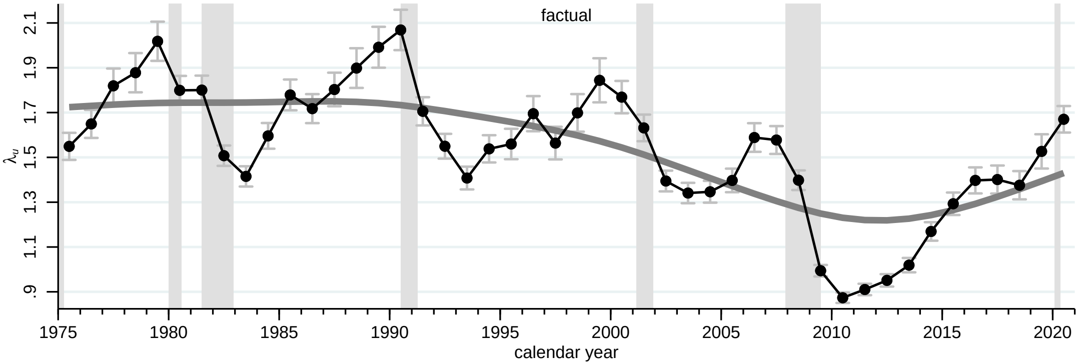

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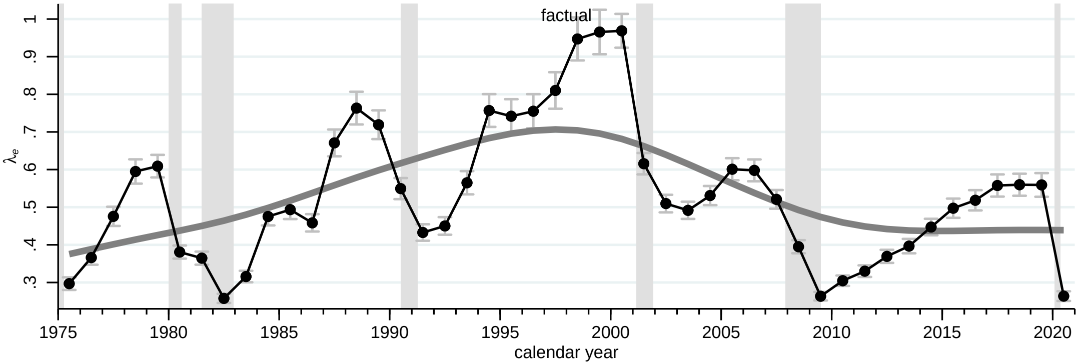

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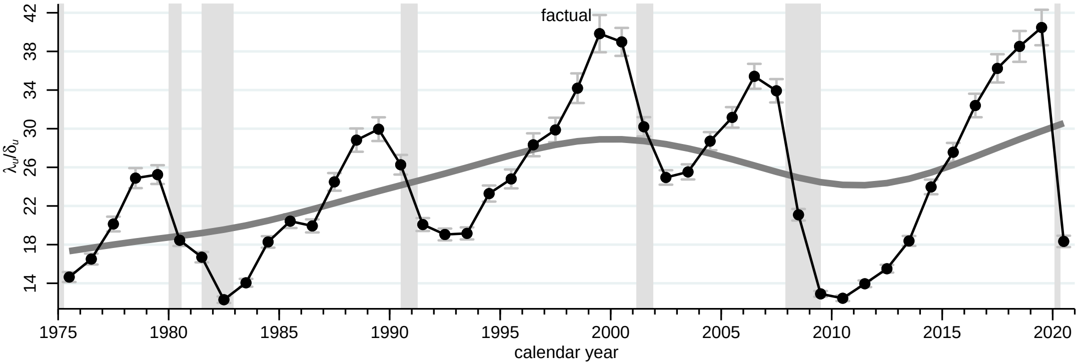

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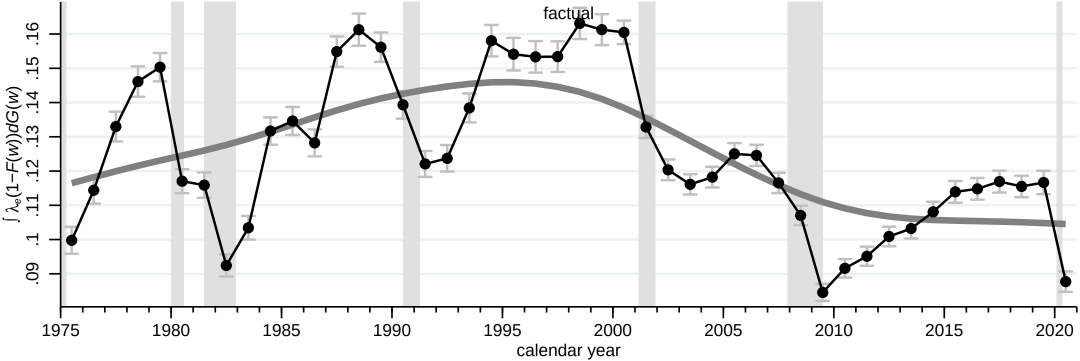

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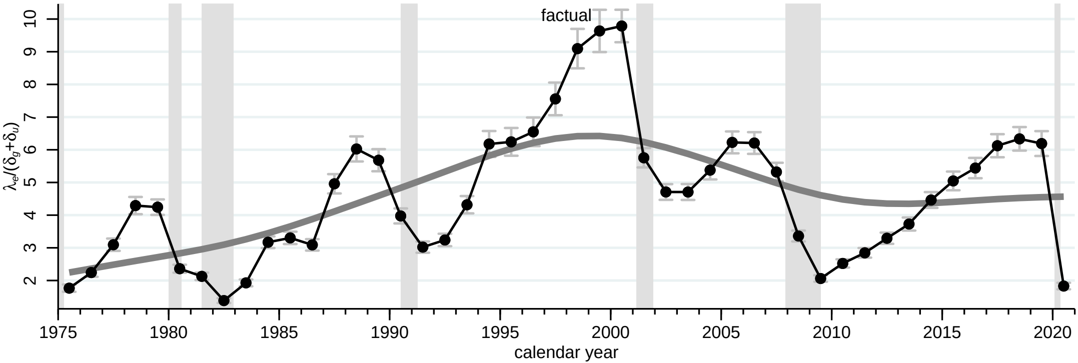

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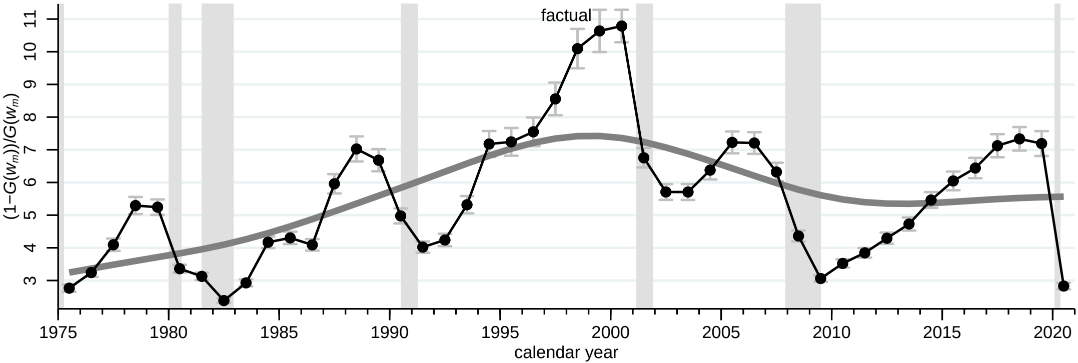

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Results

Assumptions

arrival rates are log-linear in the covariates x_j for $j \in \{1, ..., J\}$:

$$\delta_g = e^{\delta_g^0 + \sum_j \delta_g^j x_j}, \ \delta_u = e^{\delta_u^0 + \sum_j \delta_u^j x_j}, \ \lambda_u = e^{\lambda_u^0 + \sum_j \lambda_u^j x_j}, \ \lambda_e = e^{\lambda_e^0 + \sum_j \lambda_e^j x_j}$$

interpretation of coefficients: (logarithmized) risk ratios

	1975–1982	1983–1991	1992–2001	2002–2009	2010–2020
	$\ln(\delta_g)$ (log-risk of inactivity)				
constant	-2.9990^{***} (0.0121)	-2.8492^{***} (0.0108)	-2.7835^{***} (0.0103)	-2.8130^{***} (0.0110)	-2.9383^{***} (0.0094)
education (years)	0.0167^{***} (0.0009)	0.0029^{***} (0.0008)	-0.0088^{***} (0.0007)	-0.0113^{***} (0.0008)	-0.0022^{***} (0.0007)
woman	-0.4310^{***} (0.0204)	-0.4578^{***} (0.0172)	-0.3824^{***} (0.0158)	-0.3047^{***} (0.0166)	-0.1762^{***} (0.0140)
woman $\times$ education (years)	0.0376^{***} (0.0015)	0.0371^{***} (0.0013)	0.0291^{***} (0.0011)	0.0227^{***} (0.0012)	0.0134^{***} (0.0010)
	$\ln(\delta_u)$ (log-risk of unemployment)				
constant	0.6538^{***} (0.0409)	0.6573^{***} (0.0382)	-0.0284 (0.0403)	-0.3514^{***} (0.0432)	-0.3736^{***} (0.0373)
education (years)	-0.2281^{***} (0.0033)	-0.2347^{***} (0.0030)	-0.2064^{***} (0.0031)	-0.1838^{***} (0.0033)	-0.1836^{***} (0.0028)
woman	-1.2730^{***} (0.0717)	-1.3019^{***} (0.0647)	-1.1477^{***} (0.0635)	-0.8778^{***} (0.0678)	-0.5917^{***} (0.0561)
woman $\times$ education (years)	0.0885^{***} (0.0057)	0.0805^{***} (0.0050)	0.0752^{***} (0.0048)	0.0517^{***} (0.0051)	0.0395^{***} (0.0041)

Maximum-likelihood estimates of the effects of the displayed characteristics on the arrival rates in the on-the-job search model. Log-likelihood: $-13,195,574.0429$. Observations: $2,916,334$. Sampling weights employed in all calculations. 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 as provided by Flood *et al.* (2018).

	1975–1982	1983–1991	1992–2001	2002–2009	2010–2020
	$\ln(\lambda_u)$ (log-risk of employment)				
constant	0.3074^{***} (0.0582)	0.1916^{***} (0.0549)	-0.0042 (0.0566)	-0.1698^{***} (0.0552)	-0.2737^{***} (0.0452)
education (years)	0.0218^{***} (0.0047)	0.0307^{***} (0.0044)	0.0398^{***} (0.0044)	0.0352^{***} (0.0042)	0.0312^{***} (0.0034)
woman	-0.5239^{***} (0.1001)	-0.5160^{***} (0.0939)	-0.7232^{***} (0.0902)	-0.4248^{***} (0.0866)	-0.2986^{***} (0.0678)
woman × education (years)	0.0360^{***} (0.0081)	0.0379^{***} (0.0075)	0.0513^{***} (0.0070)	0.0297^{***} (0.0066)	0.0201^{***} (0.0050)
	$\ln(\lambda_e)$ (log-risk of outside contact on the job)				
constant	-2.0657^{***} (0.0767)	-2.0297^{***} (0.0744)	-2.3817^{***} (0.0843)	-2.3465^{***} (0.0821)	-2.3869^{***} (0.0688)
education (years)	0.0901^{***} (0.0059)	0.1012^{***} (0.0057)	0.1542^{***} (0.0065)	0.1112^{***} (0.0062)	0.1065^{***} (0.0050)
woman	-0.5221^{***} (0.1277)	-0.2103^{*} (0.1182)	0.2795^{**} (0.1228)	0.2093^{*} (0.1230)	0.4478^{***} (0.1003)
woman × education (years)	0.0368^{***} (0.0098)	0.0265^{***} (0.0090)	-0.0134 (0.0093)	-0.0010 (0.0091)	-0.0248^{***} (0.0072)

Maximum-likelihood estimates of the effects of the displayed characteristics on the arrival rates in the on-the-job search model (continued). Log-likelihood: $-13,195,574.0429$. Observations: $2,916,334$. Sampling weights employed in all calculations. 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 as provided by Flood *et al.* (2018).

Model Predictions

- various model statistics
- averages of the marginal effects of education in the estimation sample
- averages of the discrete gender differences in the estimation sample
- delta-method standard errors

	1977–1979	1987–1989	1994–2000	2005–2007	2014–2019
	$\ln(\delta_g)$ (log of labor-force turnover rate)				
education (years)	0.0337***	0.0188***	0.0047***	−0.0011	0.0043***
	(0.0012)	(0.0011)	(0.0007)	(0.0010)	(0.0007)
woman	0.0683***	0.0397***	0.0149***	0.0123***	0.0161***
	(0.0057)	(0.0049)	(0.0030)	(0.0043)	(0.0030)
	$\ln(\delta_u)$ (log of match destruction rate)				
education (years)	−0.1782***	−0.1991***	−0.1630***	−0.1654***	−0.1483***
	(0.0048)	(0.0044)	(0.0029)	(0.0044)	(0.0031)
woman	−0.0227	−0.1915***	−0.0703***	−0.0996***	−0.0348**
	(0.0207)	(0.0191)	(0.0119)	(0.0189)	(0.0136)
	$\ln(\lambda_u)$ (log of contact rate in unemployment)				
education (years)	0.0393***	0.0493***	0.0839***	0.0553***	0.0444***
	(0.0076)	(0.0073)	(0.0046)	(0.0062)	(0.0040)
woman	−0.0433	0.0505	0.0052	−0.0377	−0.0004
	(0.0327)	(0.0319)	(0.0191)	(0.0269)	(0.0182)
	$\ln(\lambda_e)$ (log of contact rate on the job)				
education (years)	0.0702***	0.1077***	0.1553***	0.1018***	0.0755***
	(0.0082)	(0.0077)	(0.0056)	(0.0076)	(0.0049)
woman	−0.1001***	0.1611***	0.0298	0.1922***	0.0632***
	(0.0339)	(0.0322)	(0.0218)	(0.0310)	(0.0211)

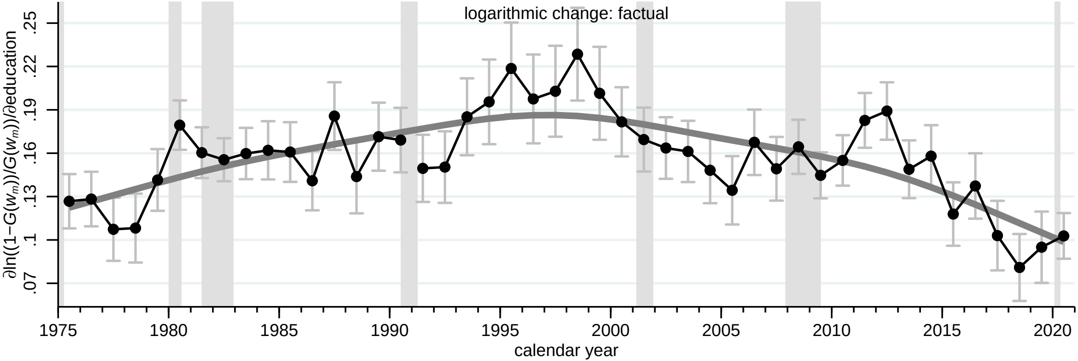
Averages of the marginal effects of education and of the discrete effects of gender on the displayed statistics. Sampling weights employed in all calculations. Delta-method standard errors in parentheses. Statistical significance at the 10, 5, and 1 percent level denoted by *, **, and ***, respectively. Author's calculations based on the ASEC data as provided by Flood *et al.* (2018).

	1977–1979	1987–1989	1994–2000	2005–2007	2014–2019
	$\ln(\lambda_u/\delta_u)$ (log-ratio of employment to unemployment)				
education (years)	0.2175***	0.2484***	0.2468***	0.2208***	0.1927***
	(0.0068)	(0.0065)	(0.0042)	(0.0057)	(0.0037)
woman	−0.0206	0.2420***	0.0755***	0.0619**	0.0344**
	(0.0291)	(0.0285)	(0.0174)	(0.0244)	(0.0165)
	$\ln(\int \lambda_e(1 - F(w))dG(w))$ (log of instantaneous job-to-job transition rate)				
education (years)	0.0094**	0.0179***	0.0391***	0.0198***	0.0136***
	(0.0048)	(0.0041)	(0.0027)	(0.0040)	(0.0026)
woman	−0.0523***	0.0523***	0.0080	0.0875***	0.0376***
	(0.0196)	(0.0165)	(0.0101)	(0.0157)	(0.0111)
	$\ln(\lambda_e/(\delta_g + \delta_u))$ (log of average number of outside contacts per employment spell)				
education (years)	0.1524***	0.2010***	0.2326***	0.1784***	0.1380***
	(0.0091)	(0.0085)	(0.0061)	(0.0083)	(0.0054)
woman	−0.1012***	0.2499***	0.0654***	0.2368***	0.0678***
	(0.0382)	(0.0357)	(0.0238)	(0.0339)	(0.0230)
	$\ln((1 - G(w_m))/G(w_m))$ (log of relative employment at above-median employers)				
education (years)	0.1194***	0.1669***	0.2036***	0.1505***	0.1151***
	(0.0071)	(0.0070)	(0.0053)	(0.0070)	(0.0045)
woman	−0.0875***	0.2053***	0.0494**	0.1964***	0.0522***
	(0.0303)	(0.0305)	(0.0213)	(0.0294)	(0.0196)

Averages of the marginal effects of education and of the discrete effects of gender on the displayed statistics (continued). Sampling weights employed in all calculations. 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 as provided by Flood *et al.* (2018).

Results

Average Effects



Average of the marginal effects of education with 95-percent confidence bands (light gray) and Hodrick–Prescott filtered trend (dark gray). Sample restricted to active participants with at least 9 years of education and with less than 40 years of experience. Sampling weights employed in all calculations. Author's calculations based on the ASEC as provided by Flood *et al.* (2018). Shaded areas indicate NBER-dated contractions.

Conclusion

The Rise and Fall in Job Mobility

turbulent changes in the pace of labor reallocation over the past half-century:

- surge in job-to-job mobility at the end of the 20th century
- collapse in job-to-job mobility at the start of the 21st century
- recent years at late-1970s levels—far below the peak late-1990s levels

rise and fall in mobility closely tied to skills:

- educated workers at the forefront of the boom in the 20th century
- educated workers at the center of the slowdown in the 21st century

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