The Long-term Decline of the U.S. Job Ladder

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Abstract

We apply a parsimonious job ladder model to publicly available microdata from the *Current Population Survey* to obtain a consistent estimate of *employer-to-employer* (EE) mobility toward higher paying jobs over the past half century in the U.S. Three findings stand out. First, EE mobility toward higher paying jobs halved between 1980 and 2020. Second, the decline was particularly pronounced among young workers, women, and those with less than a college degree. Third, all else equal, the fall in EE mobility accounts for over one percentage point weaker annual wage growth today relative to the early 1980s.

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1 Introduction

Shopping for jobs is an integral part of workers' careers. Young workers enter the labor market poorly matched, and gradually relocate across firms to find better matches. Topel and Ward (1992) find that this process of *employer-to-employer* (EE) mobility accounts for a third of workers' wage growth during the first ten years of their careers. More recently, macroeconomists have stressed that such mobility also plays a critical role for aggregate economic performance, by reallocating workers from less to more productive firms (Moscarini and Postel-Vinay, 2017; Bilal et al., 2022). Yet, despite its importance for both micro and macroeconomic outcomes, little is known about the long-run trend in EE mobility in the U.S.

This paper proposes a framework to consistently estimate EE mobility toward higher paying jobs over the past half century in the U.S., overcoming data limitations that so far have prevented a long-run historical analysis. Applied to publicly available data from the *Current Population Survey* (CPS), we find that such mobility halved between 1980 and 2020. Moreover, the decline was particularly pronounced among young workers, women, and those without a college degree. All else equal, we estimate that the decline in EE mobility is associated with over one percentage point weaker annual wage growth today than in the 1980s.

Our methodology is based on a prototypical job ladder model in the spirit of Burdett and Mortensen (1998). In the baseline version, the only source of wage growth is EE mobility. In each period, nonemployed and employed workers receive job offers with some exogenous and potentially different probability. A job offer is a draw of a wage from an exogenous wage offer distribution, which may also vary by employment status. If the worker accepts the job, she supplies a unit of labor at the specified wage until either she finds a new job offering a higher wage or her job exogenously terminates and she becomes nonemployed.

The model predicts that the number of workers earning at most a wage w in period $t+1$ depends on the number of workers paid at most w in period t, the number of these workers who separate to either nonemployment or to new jobs paying more than w, and the number of nonemployed workers in period t who find a job paying at most w in period $t+1$. Knowledge of all the other objects in this relationship allows us to recover the number of workers earning at most wage w in period t who made an EE transition to a job paying more than w in period $t+1$.

The logic is best illustrated by an example. Consider an economy in which 10 workers earn a wage below w in period t. Suppose that between periods t and $t+1$, we observe one of these workers separate to nonemployment, while two workers are hired from nonemployment by jobs paying less than w. In period $t+1$, we again record 10 workers earning less than w. Then the fraction $x_t(w)$ of workers employed at a wage less than w in period t that made an EE transition to jobs paying more than w in period $t+1$ solves

$$\underbrace{10}_{\text{earning} \leq w \text{ at } t} - \underbrace{1}_{\text{employment outflows}} + \underbrace{2}_{\text{employment inflows}} - \underbrace{10x(w)}_{\text{EE moves from} \leq w \text{ to} > w} = \underbrace{10}_{\text{earning} \leq w \text{ at } t+1}$$

Hence in our example, $x_t(w) = 10\%$ of workers earning less than w in period t made an EE transition to jobs paying more than w in period $t+1$. Knowledge of this share as well as the share of all workers paid w for each wage w in period t allows us to compute the overall EE transition probability to higher paying jobs in period t.

The logic breaks down if workers move from a wage below w to a wage above w for reasons other than EE mobility. One obvious candidate is on-the-job wage growth. To address this possibility, our baseline specification residualizes wages off a rich set of demographic controls that account for wage growth with experience, as well as aggregate trends. Furthermore, we provide an extension that incorporates on-the-job residual wage growth with tenure.

Our structural approach to estimating EE mobility features three advantages over computing EE mobility as the fraction of workers at different employers in two consecutive months—what we refer to as *raw EE mobility*. First, it allows us to document worker flows from 1979 to 1994,[1] a period of significant economic change in the U.S for which the raw series is not available. Second, it overcomes data challenges such as the bias introduced by changes to the CPS over time (Fujita, Moscarini and Postel-Vinay, 2023) as well as *seam bias*, the tendency to report changes occurring between interview blocks rather than within them (Polivka and Rothgeb, 1993). Third, our methodology identifies only those EE transitions that move a worker toward higher paying jobs, whereras a substantial share of EE moves in raw data are toward lower paying jobs (see Sorkin, 2018). From the perspective of macroeconomic performance, the former may be more relevant.

To compute the inputs required to estimate EE mobility, we use the basic monthly survey and the *Outgoing Rotation Groups* (ORG) of the CPS. Specifically, we record an individual's employment status in each month during a four month period, her hourly wage in the last of these four months, and demographic characteristics. We compute residual wages controlling flexibly for age-gender-race-education-year as well as state-date fixed effects. Subsequently, we measure the share of workers earning less than (residual) wage w in months t and $t+1$, the share of hires from nonemployment who earn a wage below w in month $t+1$, and the share of employed workers in month t who are nonemployed in period $t+1$. Through the lens of our theory, these objects are sufficient to recover the EE transition probability in month t.

Our estimates highlight a sharp slowdown in EE mobility since the 1980s. The monthly EE transition probability fell from 1.5 percent in the 1980s to less than one percent today, with only a short-lived reversal during the Pandemic. Allowing for time-varying on-the-job growth in residual wages with tenure has only a small effect on our estimates, due to the fact that such wage

[1] Although we have not yet attempted to do so, it should be possible to extend our analysis back to 1976.

growth is uniformly small over our period of study. Moreover, while as a benchmark we assume that the separation probability to nonemployment is independent of the wage, we show that similar results hold if it is allowed to depend on the wage.

Our methodology does not require us to take a stance on the (unobserved) wage offer distribution of the employed. If, however, we are willing to additionally impose that they receive wage offers from the same distribution as the nonemployed, we can decompose the change in EE mobility into the role of a lower arrival probability of offers versus a lower probability that an employed worker accepts the offer. We find that the entire decline in EE mobility is accounted for by a lower probability that a worker receives a job offer. In contrast, workers today are (slightly) more likely to accept an extended offer than they were in the 1980s. This appears at odds with the view espoused in Mercan (2017) and Pries and Rogerson (2022) that EE mobility is lower because workers are better matched with their existing jobs. Molloy et al. (2016) draw a similar conclusion to ours based on the lack of a long-run trend in starting wages.

We find that EE mobility toward higher paying jobs constitutes over a quarter of total worker reallocation in the 1980s, with reallocation through unemployment contributing another 30 percent of total worker flows. The remainder takes place through non-participation. Over time, poaching flows declined significantly as a share of total worker flows to roughly 15 percent today. Reallocation through unemployment also fell, but by less, reaching a quarter of total worker flows today. Hence, the relative importance of reallocation through non-participation grew.

Combining these forces, the overall worker reallocation rate fell from 12 percent per month in the early 1980s—i.e. 12 percent of workers were either hired or separated in a month—to eight percent today. While this result mirrors the well-known decline in job reallocation over this period (Davis and Haltiwanger, 2014), we nevertheless argue that it does not follow mechanically from the latter. The reason is that worker reallocation is four times as large as job reallocation in levels, and most of its decline is accounted for by a fall in worker flows over and above what is strictly necessary to reallocate jobs. In other words, replacement hiring decreased over this period.

We proceed to quantify the implications of lower EE mobility for wage growth. We find that, all else equal, it is associated with a more than one percentage point decline in annual wage growth. Furthermore, the decline is accounted for entirely by the declining frequency of EE transitions. By contrast, the average wage gain conditional on an EE transition rose over this period. We interpret this as further evidence that EE mobility is not lower today because workers are better matched.

Subsequently, we analyze changes in EE mobility and its associated wage growth within age, gender, race and education groups. While the decline in EE mobility was pervasive, it was particularly large among young workers, women, and those without a college degree. These disproportionate declines are reflected in especially large declines in wage growth associated with EE mobility for these subgroups.

Our methodology relies on the assumption that conditional on age-gender-race-education-year and state-date fixed effects, workers are ex ante identical. To address the concern that recently nonemployed workers might be different in unobservable dimensions, we exploit the fact that wages are recorded twice in the ORG (with a 12 month gap). Alternatively, we use average wages during the previous calendar year from the *Annual Social and Economic Supplement* (ASEC). These data sources allow us to study the *previous* residual wage among hires from nonemployment.

Consistent with the view that hires from nonemployment are negatively selected in unobservable dimensions, we find that they had 5–15 percent lower residual wages in the recent past. There is no evidence, however, that such selection worsened over time, with some indicators in fact suggesting that it became less pronounced. If so, our estimated decline *understates* the true decline. More formally, we account for the role of unobservable differences by residualizing a worker's current residual wage also off her prior residual wage, at the cost of cutting the sample by more than half. It only has a modest effect on both the level and trend in EE mobility.

Literature. This paper relates closely to the large literature studying declining "economic dynamism". Davis and Haltiwanger (2014) document a long-run decline in job reallocation since the 1980s—a measure of *net* worker reallocation. Three reasons lead us to view our findings for *gross* worker reallocation as more than a simple corollary of their finding. First, as we demonstrate below, gross flows are three times as large as net flows. Moreover, a majority of the decline in gross flows is not accounted for by the fall in net flows. Pries and Rogerson (2005) stress further the importance of differentiating gross from net flows, showing that while net flows are similar across countries, gross flows differ substantially. Consequently, it is important to separately document trends in gross flows. Second, even if the correlation between changes in net and gross flows were perfect, worker reallocation could be achieved either through EE mobility or reallocation through nonemployment. Since these forms of reallocation have vastly different implications for workers, it is important to dissect the nature of the changes in worker flows. Third, in this spirit, we quantify the implications of the decline in EE mobility for wage growth.

Our paper fits in the large literature that measures EE transitions. Unlike these papers, we use a structural approach to quantify EE mobility. Hyatt and Spletzer (2013) and Haltiwanger et al. (2018) study trends in EE mobility using matched employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD) program starting in 1998. These data, however, likely understate EE mobility due to their quarterly frequency. Pries and Rogerson (2022) use the publicly available version of the LEHD, the Quarterly Workforce Indicators, to document a particularly pronounced decline in short employment spells since 1999. They interpret this to suggest that workers and firms became more selective in terms of what matches they opt to form. Fallick and Fleischman (2004) construct a raw measure of EE mobility in the CPS starting with its redesign in 1994, while Nagypal (2008) documents trends in EE mobility using the Survey of Income and Program Participation (SIPP) starting in 1996. She finds a consistently lower level of EE mobility in the SIPP than the CPS. Fujita, Moscarini and Postel-Vinay (2023) show that changes in non-response rates bias the raw measure in the CPS toward an excessively large decline in EE mobility over time, which our structural approach confirms. Molloy et al. (2016) use a variety of data sources to document a decline in U.S. labor market dynamics over the past 40 years, but are forced to proxy for EE mobility with the fraction of employed workers that had more than one employer in the previous year.

Another literature studies EE mobility over the business cycle (Krusell et al., 2017). Moscarini and Postel-Vinay (2022) point to the impact of EE transitions on inflation dynamics (other papers that include EE mobility in models with nominal rigidities include Gertler, Huckfeldt and Trigari, 2020 and Fukui, 2020). Caratelli (2022) finds that differences in EE mobility across workers helps explain heterogenous labor market outcomes after recessions.

Our motivation is shared by Shimer (2012), who applies a parsimonious model of labor market flows to unemployment duration data to infer the separation rate to and job finding rate from unemployment starting in 1948. Jolivet, Postel-Vinay and Robin (2006) discipline a partial equilibrium search model using cross-country micro data on wages and labor market flows, finding that such data allow an estimate of on-the-job search.

We start by outlining a partial equilibrium job ladder model of the labor market in section 2. Section 3 discusses the data and our estimation procedure. We then display and analyze the long-term trends in EE mobility and its associated wage growth in section 4. In section 5, we redo our analysis within demographic subgroups, while section 6 adjusts for selection on unobservables. Finally, section 7 concludes.

2 Theory

This section outlines a parsimonious partial equilibrium model of worker dynamics in the spirit of Burdett and Mortensen (1998) set in discrete time. The job finding probabilities, the separation probabilities, and the wage offer distribution are all treated as exogenous. While stylized, an extensive literature finds that this framework is remarkably successful at matching empirical labor market dynamics (Jolivet, Postel-Vinay and Robin, 2006).

2.1 Environment

Time $t \geq 0$ is discrete and infinite. A unit mass of ex-ante identical, infinitely lived workers move across jobs as well as between employment and nonemployment. Let e_t denote the employment rate at time t and u_t the nonemployment rate.

At each point in time, nonemployed workers receive job offers with exogenous probability $\lambda_t^u \in [0,1]$. A job offer is a draw of a (log) wage w from an exogenously given wage offer distribution of the nonemployed with support $w \in (-\infty, \infty)$. Let $f_{t+1}^u(w)$ denote its *probability density* *function* (pdf) and $F^u_{t+1}(w)$ its *cumulative distribution function* (cdf). We assume that nonemployed workers accept any job offer they receive.[2]

Workers also search on-the-job. Specifically, they receive outside offers from a wage offer distribution of the employed with probability $\lambda^e_t \in [0,1]$. Let $f^e_{t+1}(w)$ denote the pdf of this distribution and $F^e_{t+1}(w)$ its corresponding cdf. Since workers choose whether to accept an offer, they only switch to jobs that offer higher wages.

Finally, employed workers separate to nonemployment with exogenous probability $\delta_t \in [0,1]$. We require that these probabilities satisfy $\delta_t + \lambda^e_t \leq 1$.

2.2 Labor market flows

The mass of workers earning wage w at time t, $g_t(w)e_t$, evolves according to

$$\begin{aligned} g_{t+1}(w)\, e_{t+1} \;&=\; g_t(w)e_t - \underbrace{\delta_t g_t(w)e_t}_{\text{separations to u.}} - \underbrace{\lambda^e_t\left(1-F^e_{t+1}(w)\right)g_t(w)e_t}_{\text{EE separations}} \\ &+ \underbrace{\lambda^u_t f^u_{t+1}(w)(1-e_t)}_{\text{hires from u.}} + \underbrace{\lambda^e_t f^e_{t+1}(w) G_t(w) e_t}_{\text{EE hires}} \end{aligned} \tag{1}$$

Integrating (1), applying integration by parts, gives[3]

$$G_{t+1}(w)\, e_{t+1} \;=\; \Big(1-\delta_t-\lambda^e_t(1-F^e_{t+1}(w))\Big)G_t(w)e_t + \lambda^u_t F^u_{t+1}(w)(1-e_t)$$

which we can rearrange as

$$\underbrace{\lambda^e_t\Big(1-F^e_{t+1}(w)\Big)}_{sep^e_t(w)\equiv\text{poaching separation probability}} \;=\; 1 \;-\; \frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t} \;+\; \lambda^u_t\frac{F^u_{t+1}(w)}{G_t(w)}\frac{1-e_t}{e_t} \;-\; \delta_t \tag{2}$$

We discuss below how to measure $G_t(w)$, $G_{t+1}(w)$, $F^u_{t+1}(w)$, e_t, e_{t+1}, λ^u_t and δ_t in the CPS. Provided these objects, we can estimate the *poaching separation probability* at each wage w based on (2). We refer to (2) as the *baseline model*.

The EE transition probability is the product of the probability that an employed worker receives a job offer and the probability that she accepts it

$$EE_t \;=\; \underbrace{\lambda^e_t}_{\text{job finding probability}} \underbrace{\int_{-\infty}^{\infty}\Big(1-F^e_{t+1}(w)\Big)dG_t(w)}_{\text{acceptance probability}} \;=\; \int_{-\infty}^{\infty} sep^e_t(w)dG_t(w) \tag{3}$$

[2]This assumption can be motivated by the fact that no firm would advertise a job paying less than the reservation wage common to all nonemployed workers.

[3]Integrating by parts the EE separations term in (1) gives $\int_{-\infty}^{w}(1-F^e_{t+1}(\tilde{w}))g_t(\tilde{w})\;d\tilde{w} = (1-F^e_{t+1}(w))G_t(w) + \int_{-\infty}^{w} f^e_{t+1}(\tilde{w})G_t(\tilde{w})d\tilde{w}$. The last term cancel the integrated EE hires term.

Hence, EE mobility can fall either because workers are less likely to receive job offers or because they are less likely to accept them.

An appealing aspect of our methodology is that it does not require us to take a stance on the wage offer distribution of the employed in order to infer EE mobility. To implement the decomposition in (3), however, requires us to separately measure the unobserved wage offer distribution of the employed. We follow the literature to assume that the employed sample jobs from the same distribution as the nonemployed, $f_t^e(w) = f_t^u(w)$. Under this assumption, the acceptance probability is

$$acceptance_t \quad = \quad \int_{-\infty}^{\infty} (1 - F_{t+1}^u(w)) dG_t(w)$$

and the job finding probability of the employed is $\lambda_t^e = EE_t / acceptance_t$.

In steady-state, outflows from and inflows into employment coincide, $\lambda_t^u(1 - e_t) = \delta_t e_t$. Hence, if we assume that the labor market at date t is in steady-state, the law of motion (2) simplifies to

$$\lambda_t^e \Big(1 - F_{t+1}^e(w)\Big) \quad = \quad \lambda_t^u \frac{F_{t+1}^u(w)}{G_t(w)} \frac{1 - e_t}{e_t} - \delta_t \quad = \quad \delta_t \frac{F_{t+1}^u(w) - G_t(w)}{G_t(w)} \tag{4}$$

Integrating (4) against the distribution of employment and taking logs gives

$$\ln \Big(EE_t\Big) \quad = \quad \ln \Big(\delta_t\Big) \; + \; \ln \left(\int_{-\infty}^{\infty} \frac{F_{t+1}^u(w) - G_t(w)}{G_t(w)} dG_t(w) \right) \tag{5}$$

Hence under the assumption that the economy is in steady-state, two factors contribute to us inferring a change in the EE transition probability: a change in the separation probability to unemployment and a change in the average gap between the offer and the wage distribution. We stress that this decomposition should be interpreted in a purely statistical sense— according to the model, a change in δ_t would result in a change in the distribution of employment, $g_t(w)$.

The overall worker reallocation rate—the sum of hiring and separation rates—is the sum of separations to and hires from other jobs (which by construction are the same), and separations to and hires from nonemployment, divided by employment

$$\underbrace{WR_t}_{\text{worker reallocation}} \quad = \quad \underbrace{2 \times EE_t}_{\text{poaching flows}} + \underbrace{\delta_t}_{\text{separations to nonemployment}} + \underbrace{\lambda_t^u \frac{1 - e_t}{e_t}}_{\text{hires from nonemployment}} \tag{6}$$

Alternatively, worker reallocation can be written as the sum of *job reallocation* and *worker churn*—

worker flows over and above what is necessary to reallocate jobs

$$\underbrace{WR_t}_{\text{worker reallocation}} = \underbrace{JR_t}_{\text{job creation + job destruction}} + \underbrace{Churn_t}_{\text{replacement hiring}} \tag{7}$$

Worker reallocation is at least as large as job reallocation, since whenever a job is reallocated across firms, a worker necessarily switches employer. It may be higher because a job may stay with the firm when a worker who switches to a new employer is replaced.

Wage growth due to EE mobility is the average wage gain across all accepted job offers

$$\Delta w_t^{EE} = \lambda_t^e \int_{-\infty}^{\infty} \int_{w}^{\infty} \left(\tilde{w} - w\right) dF_{t+1}^e(\tilde{w}) dG_t(w) = \lambda_t^e \int_{-\infty}^{\infty} \int_{-\infty}^{w} \left(w - \tilde{w}\right) dG_t(\tilde{w})\, dF_{t+1}^e(w)$$

Integrating first the inner integral by parts

$$\begin{aligned}
\Delta w_t^{EE} &= \lambda_t^e \int_{-\infty}^{\infty} \left(\left[\left(w - \tilde{w}\right) G_t(\tilde{w}) \right]_{\tilde{w}=-\infty}^{w} + \int_{-\infty}^{w} G_t(\tilde{w}) d\tilde{w} \right) dF_{t+1}^e(w) \\
&= \lambda_t^e \int_{-\infty}^{\infty} \int_{-\infty}^{w} G_t(\tilde{w}) d\tilde{w} dF_{t+1}^e(w)
\end{aligned}$$

Integrating the outer integral by parts

$$\Delta w_t^{EE} = \lambda_t^e \left(\left[\int_{-\infty}^{w} G_t(\tilde{w}) d\tilde{w} F_{t+1}^e(w) \right]_{w=-\infty}^{\infty} - \int_{-\infty}^{\infty} G_t(w) F_{t+1}^e(w) dw \right)$$

Since $\lim_{w\to\infty} F_{t+1}^e(w) = 1$, we have

$$\Delta w_t^{EE} = \lambda_t^e \int_{-\infty}^{\infty} \left(1 - F_{t+1}^e(w)\right) G_t(w) dw = \int_{-\infty}^{\infty} sep_t^e(w) G_t(w) dw \tag{8}$$

2.3 Extensions

Before we go to the data, we incorporate two extensions to the baseline model. First, the baseline model abstracts from on-the-job growth in wages, which could arise if, for instance, workers accumulated skills with tenure at an employer. Suppose that wages grow on the job at rate ξ_t. Then the law of motion for the wage distribution (1) becomes[4]

$$\begin{aligned} g_{t+1}(w)\, e_{t+1} &= g_t(w)e_t - \delta_t g_t(w)e_t - \lambda_t^e \left(1 - F_{t+1}^e(w)\right) g_t(w)e_t \\ &+ \lambda_t^u f_{t+1}^u(w)(1-e_t) + \lambda_t^e f_{t+1}^e(w) G_t(w)e_t - \xi_t g_t'(w)e_t \end{aligned}$$

Integrating this and rearranging

$$\underbrace{\lambda_t^e\Big(1 - F_{t+1}^e(w)\Big)}_{\equiv sep_t^e(w)} = 1 - \frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t} + \lambda_t^u \frac{F_{t+1}^u(w)}{G_t(w)}\frac{1-e_t}{e_t} - \delta_t - \frac{\xi_t g_t(w)}{G_t(w)}$$

We estimate the poaching separation probability $sep_t^e(w)$ and substitute it into (3) to obtain the EE transition probability and into (8) to get the average wage gain due to EE mobility. We refer to this as the *OTJ model* to distinguish it from the *baseline model* above.

Second, we incorporate a separation probability to nonemployment that varies with the wage, $\delta_t(w)$. For instance, low wage jobs might be more likely to terminate in response to adverse productivity shocks. Then the law of motion (1) becomes

$$\begin{aligned} g_{t+1}(w)\, e_{t+1} &= g_t(w)e_t - \delta_t(w) g_t(w)e_t - \lambda_t^e \left(1 - F_{t+1}^e(w)\right) g_t(w)e_t \\ &+ \lambda_t^u f_{t+1}^u(w)(1-e_t) + \lambda_t^e f_{t+1}^e(w) G_t(w)e_t - \xi_t g_t'(w)e_t \end{aligned}$$

Integrating this under the empirically plausible assumption that $\delta_t(w) = \delta_t^0 + \delta_t^1 w$

$$\underbrace{\lambda_t^e\Big(1 - F_{t+1}^e(w)\Big)}_{\equiv sep_t^e(w)} = 1 - \frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t} + \lambda_t^u \frac{F_{t+1}^u(w)}{G_t(w)}\frac{1-e_t}{e_t} - \delta_t(w) - \frac{\xi_t g_t(w)}{G_t(w)} + \frac{\delta_t^1 \mathcal{G}_t(w)}{G_t(w)}$$

where $\mathcal{G}_t(w) = \int_{-\infty}^{w} G_t(\tilde{w})d\tilde{w}$ is the *super-cumulative distribution function*. We estimate the poaching separation probability $sep_t^e(w)$ at each wage w and substitute it into (3) to obtain the EE transition probability and into (8) to get the average wage gain due to EE mobility. We refer to this as the *full model* to distinguish it from the OTJ and baseline models above.

[4]This is a discrete time approximation to a continuous time model in which (log) wages drift at rate $\xi(t)$, i.e. the evolution of the pdf $g(w,t)$ is characterized by the *Fokker-Planck* partial differential equation

$$\begin{aligned} \frac{\partial g(w,t)}{\partial t} &= -\left(\delta(t) + \lambda^e(t)\left(1 - F^e(w,t)\right) + \frac{\dot{e}(t)}{e(t)}\right) g(w,t) \\ &+ \lambda^u(t) f^u(w,t)\frac{1-e(t)}{e(t)} + \lambda^e(t) f^e(w,t) G(w,t) - \xi(t)\frac{\partial g(w,t)}{\partial w} \end{aligned}$$

for all $t \geq 0$, subject to initial value $g(w,0) = g_0(w)$ for all w and $\int_{-\infty}^{\infty} g(w,t)dw = 1$ for all t.

3 Estimation

We now discuss how to bring the model to the data in order to estimate EE mobility.

3.1 Data sources

We use publicly available data from the CPS from 1979 to 2023 conducted by the *Bureau of Labor Statistics* (BLS) and made available by the *Integrated Public Use Microdata Series* (IPUMS) and the *National Bureau of Economic Research* (NBER).[5] The CPS is the main U.S. labor force survey, serving as the benchmark data set for labor market analyses. At the time of writing, IPUMS has incorporated ORG data through March 2023.

Every month, the CPS surveys roughly 60,000 households using a rotating panel design. Specifically, a household responds to the basic monthly survey in each month for four consecutive months, rotates out of the survey for eight months, and finally returns to answer the basic monthly survey in each month for another four consecutive months. We refer to the first four months as survey months 1–4 and the latter four months as survey months 5–8. While the CPS is designed to be representative of the U.S. population, non-random attrition necessitates the use of survey weights, which we use throughout.

For a reference week in each month,[6] the CPS records the employment status of each household member aged 15 and older,[7] as well as usual weekly hours for those who are employed and job search activities during the four weeks leading up to the reference week for those who are not employed.[8] Usual weekly hours are top-coded at 99 hours. In addition, basic demographic characteristics of the household member are collected.[9]

In the final month before a household either temporarily or permanently leaves the sample—i.e. in survey months 4 and 8—respondents are asked about usual weekly wage and salary earnings. Earnings are before taxes and other deductions and include overtime pay, commissions and tips. For multiple jobholders, the data reflect earnings at their main job. Earnings are top-coded at thresholds that vary throughout the sample. We refer to the first (second) wage observation month as the first (second) ORG month.

Either in January or February of 1983, 1987, and every other year since 1996, the CPS fielded the *Tenure Supplement*. It asks employed respondents how long they have been working at their current employer. We use information from the Tenure Supplement to estimate wage growth on-

[5] It should be possible to extend our analysis back to 1976 using wage data from the May Supplements (the ORG started in 1979), but we have not yet attempted to do so.

[6] The reference week is typically the Sunday–Saturday that covers the 12th of the month. Prior to the redesign of the CPS in 1994, the reference week was not defined to respondents.

[7] Prior to 1989, household members aged 14 and older were included.

[8] Prior to 1994, usual weekly hours are only recorded in the ORG.

[9] Starting in 1994, households with varying hours do not report usual weekly hours on the main job. We replace these with actual hours worked on the main job.

the-job as well as how the separation probability to nonemployment varies with the wage.

3.2 Sample selection

We restrict attention to individuals aged 16 and older who have non-missing age, race, gender and education, and who live in one of the 50 U.S. states plus Washington D.C. We drop self-employed individuals, since weekly earnings are only recorded for wage and salary employees. Changes to individual identifiers prevent linking individuals in the following breaks: June-July 1985, September-October 1985, and May-October 1995, at which point our results are linearly interpolated.

Our analysis of on-the-job wage growth using ORG and Tenure Supplement data is restricted to those who are in their second ORG month when the Tenure Supplement is fielded, so that we can compute within-individual wage growth since their first ORG month. Furthermore, we condition on more than 12 months of tenure with the current employer, so that within-individual wage growth coincides with within-job wage growth.

In our analysis of how the separation probability to nonemployment varies with the wage using basic monthly, ORG and Tenure Supplement data, we restrict attention to individuals in their Tenure Supplement month and drop those who are simultaneously in their ORG months. The latter is necessary since we need to observe employment status in the subsequent month. We record wages in the previous ORG month as well as the number of months lapsed since the previous ORG month, and keep only those with a valid prior wage and whose tenure with their current employer exceeds the number of months since their previous ORG month. We focus on workers who remained with the same employer since their last ORG month, in order to be able to plausibly proxy the current wage with the previous ORG wage.

3.3 Variable construction

We aggregate race to white, black and other, and education to less than high school, a high-school diploma, some college, a bachelor's degree, and more than a bachelor's degree. We top-code age at 65 years. We multiply top-coded weekly earnings by 1.5.

We link individuals across survey months as well as between the basic monthly/ORG and Tenure Supplement files using the consistent ID created by IPUMS (`CPSIDV`).[10] It links individuals based on household identifiers, person identifiers, age, sex, and race.

We classify individuals in each month as wage employed, self-employed, unemployed and not in the labor force following standard practice. Since it is not clear how to conceptually distinguish unemployment from being outside the labor force—in particular given that flows between employment and not in the labor force are larger than flows between employment and

[10] See https://assets.ipums.org/_files/ipums/working_papers/ipums_wp_2023-01.pdf.

unemployment—we count both the unemployed and those not in the labor force as unemployed.[11]

We estimate the separation probability to nonemployment δ_t as the share of wage employed individuals in month t who are nonemployed in month $t+1$. We estimate the job finding probability of the nonemployed λ_t^u as the share of nonemployed individuals in month t who are wage employed in month $t+1$. Due to inability to link individuals in the breaks mentioned above, we cannot compute these flow rates in June 1985, September 1985, and May-September 1995.

We construct the hourly real wage as usual weekly earnings divided by usual weekly hours worked, converted to 2022 USD using the CPI. We then project log hourly real wages on age-race-gender-education-year dummies and state-date fixed effects

$$w_{it} = \xi_{argey} + \xi_{st} + \varepsilon_{it} \tag{9}$$

We compute residual wages as the residuals from (9). Subsequently, to limit the impact of a few outliers, we winsorize residual wages at each date at the bottom and top 0.5 percentiles. Finally, we compute N cutoffs b_i such that a share i/N of observations in the pooled 1979–2023 sample fall below b_i (weighted by the survey weights). We assign $b_0 = \underline{w}$, $dw_i = b_i - b_{i-1}$ and $w_i = (b_i + b_{i-1})/2$. In practice, we set $N = 50$.

We estimate the cdf of the wage offer distribution of the nonemployed $F_{t,i}^u$ as the share of hires from nonemployment at date t who earn a wage of at most b_i (again weighted by the survey weights), where we define a hire from nonemployment at date t, $hire_{t,j}^u$, to be any individual j who was nonemployed in month $t-1$ and employed in month t

$$\begin{aligned}\widehat{F}_{t,i}^u &= \sum_j \mathbb{1}_{w_{t,j} \leq b_i} * \mathbb{1}_{hire_{t,j}^u = 1} * weight_{t,j} \\ F_{t,i}^u &= \widehat{F}_{t,i}^u / F_{t,N}^u\end{aligned}$$

The cdf of the wage distribution is simply $G_{t,i} = i/N$. We approximate the densities as

$$\begin{aligned}g_{t,i} &= \frac{G_{t,i} - G_{t,i-1}}{dw_i} \\ f_{t,i}^u &= \frac{F_{t,i}^u - F_{t,i-1}^u}{dw_i}\end{aligned}$$

where $G_{i,0} = 0$ and $F_{i,0}^u = 0$.

We estimate on-the-job wage growth, ξ_t, as the change in residual wages between month t and $t-12$ among workers who remain with the same employer. Since we cannot link individuals in the breaks mentioned above, we cannot compute wage growth between June 1995, and September 1996. We set ξ_t equal to (1/12 of) the mean of this at each Tenure Supplement date, and linearly

[11] We have confirmed that we get a similarly large decline in EE mobility over time if we alternatively restrict attention to only those who are formally unemployed.

interpolate between Tenure Supplement dates as well as between these breaks to get ξ_t for all t.

Because wages are only collected in the month before an individual rotates out of the CPS, we cannot measure the separation probability to nonemployment and the wage simultaneously. To estimate how the separation probability to nonemployment varies with the wage, we incorporate information from the Tenure Supplement. Specifically, we first residualize and winsorize wages in the full ORG following (9). We then focus on individuals who are in their Tenure Supplement month and who remained with the same employer since their previous ORG month. We proxy a worker's wage in her Tenure Supplement month with her residual wage in her previous ORG month, and map this into the N bins constructed above. At each Tenure Supplement date and for each bin, we compute the separation probability to nonemployment as the fraction of workers earning a wage in bin i in month t who are nonemployed in month $t+1$. We project this on a time dummy interacted with a constant and a linear in the residual hourly wage

$$sep^u_{i,t} \quad = \quad \delta^0_t + \delta^1_t y_i + \varepsilon_{i,t} \tag{10}$$

where y_i is the average wage in bin i. Let $\delta_{i,t}$ be the predicted values based on (10). We linearly interpolate $\delta_{i,t}$ between Tenure Supplement dates. Finally, we normalize them such that the (weighted) average at date t coincides with δ_t.

3.4 Estimating the EE transition probability

To improve the precision of our estimates of EE mobility at date t, we pool months $t-T$ to $t+T$. In our benchmark, we set $T = 12$, so that we obtain something akin to a 23-month centered moving average. Specifically, merging the stocks and flows from the basic monthly CPS with the offer and wage distributions from the ORG, we construct

$$y_{\tau,i} \quad = \quad 1 - \delta_\tau - \frac{G_{\tau+1,i}}{G_{\tau,i}}\frac{e_{\tau+1}}{e_\tau} + \lambda^u_\tau \frac{F^u_{\tau+1,i}}{G_{\tau,i}}\frac{1-e_\tau}{e_\tau} \tag{11}$$

We project $y_{\tau,i}$ on a set of dummies using OLS

$$y_{\tau,i} \quad = \quad sep^e_{t,i} \quad + \quad \varepsilon_{\tau,i} \tag{12}$$

Based on the estimated dummies, we compute the EE transition probability based on (3) as

$$EE_t \quad = \quad \sum_{i=1}^{N} sep^e_{t,i} g_{t,i} dw_i \tag{13}$$

and average wage growth due to EE mobility based on (8) as

$$\Delta w_t \quad = \quad \sum_{i=1}^{N} sep^e_{t,i} G_{t,i} dw_i \tag{14}$$

To estimate the OTJ model with on-the-job wage growth, we augment (11) as

$$y_{\tau,i} \quad = \quad 1 - \delta_\tau - \frac{G_{\tau+1,i}}{G_{\tau,i}} \frac{e_{\tau+1}}{e_\tau} + \lambda^u_\tau \frac{F^u_{\tau+1,i}}{G_{\tau,i}} \frac{1-e_\tau}{e_\tau} - \xi_\tau \frac{g_{\tau,i}}{G_{\tau,i}}$$

We estimate (12) with this alternative definition of the dependent variable, and construct the EE transition probability based on (13) and the average wage gain based on (14).

To estimate the full model that incorporates both on-the-job wage growth and a separation probability to nonemployment that depends on the wage, we augment (11) as

$$y_{\tau,i} \quad = \quad 1 - \delta_{\tau,i} - \frac{G_{\tau+1,i}}{G_{\tau,i}} \frac{e_{\tau+1}}{e_\tau} + \lambda^u_\tau \frac{F^u_{\tau+1,i}}{G_{\tau,i}} \frac{1-e_\tau}{e_\tau} - \xi_\tau \frac{g_{\tau,i}}{G_{\tau,i}} + \frac{\delta^1_\tau \sum_{j=1}^{i} G_{\tau,j} dw_j}{G_{\tau,i}}$$

We estimate (12) with this alternative definition of the dependent variable, and construct the EE transition probability based on (13) and the average wage gain based on (14).

4 A Historical Account of EE mobility

This section presents a complete historical account of gross worker flows in the U.S. between 1979 and 2023, highlighting in particular the evolution of the EE transition probability.

4.1 EE mobility

According to the baseline model in Figure 1, 1.5 percent of workers made an EE transition toward a higher paying job per month in the 1980s. The OTJ model, which allows for on-the-job growth in residual wages, indicates a somewhat lower level of EE mobility, because it does not attribute all positive wage changes to EE moves. The difference, however, is modest, driven by the fact that on-the-job residual wage growth with tenure is small. The full model that also allows the separation probability to nonemployment to depend on the wage implies an even lower level of EE mobility. The reason is that the separation probability to nonemployment is higher at the bottom of the wage distribution. All else fixed, this leads to an upward shift in the wage distribution relative to the offer distribution. Consequently, once we allow for this, a given gap between the wage and wage offer distributions implies a lower EE transition probability.

All three models indicate a secular decline in EE mobility over the past decades. For instance, the baseline model implies a 50 percent fall in the EE transition probability from 1980 to 2020.

According to the baseline and OTJ models, the decline was particularly pronounced between 1985 and 2000, while the full model indicates a sharp decline also in the first years of the sample. We caution, however, that the full model requires extrapolating how the separation probability to nonemployment varies with the wage prior to the first available Tenure Supplement data in 1983. All models indicate a brief reversal in the recovery after the Pandemic. Since then, however, EE mobility continued its decline.

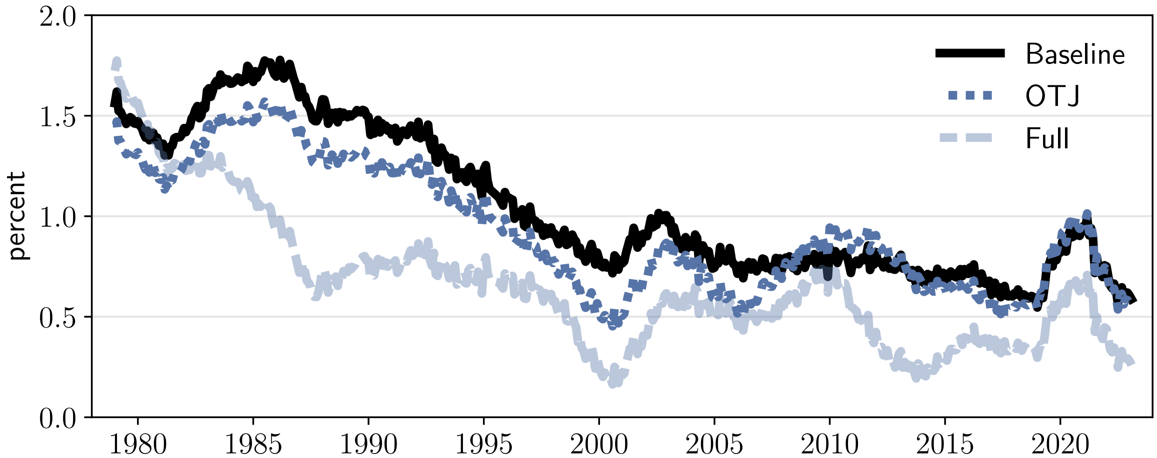


Figure 1: Estimated EE transition probability in the baseline model (black), the OTJ model with on-the-job wage growth (dark blue dotted), and the full model with on-the-job wage growth and a separation probability to nonemployment that varies with the wage (light blue dashed).

Figure 2 contrasts our structural estimate of EE mobility with the fraction of employed workers in month t that is employed with a different employer in month $t+1$. For brevity, we focus on the structural estimate in the baseline model (solid black). The raw series from the CPS shows a pronounced decline in EE mobility during the 2000s (dashed light blue). Fujita, Moscarini and Postel-Vinay (2023) argue, however, that changes in non-response rates in the 2000s bias the raw CPS series toward an excessively large decline. Consistent with this view, our structural estimate as well as the raw series from the SIPP (dotted dark blue) shows a more moderate decline in EE mobility during the 2000s.

Contrasting our structural estimate with the SIPP, it is evident that a large share of EE mobility is *not* to higher paying jobs (see also Sorkin, 2018). This conclusion is validated by the *SIPP (up)* series, which plots the monthly EE transition probability to higher paying jobs in the SIPP (solid dark blue).[12] It is reassuringly similar to our estimated EE series, both in levels and changes during the years for which the SIPP is available.

Recall from (3) that the EE transition probability can be decomposed into the probability that

[12] Because it does not collect wages in consecutive months, we cannot construct this outcome in the CPS.

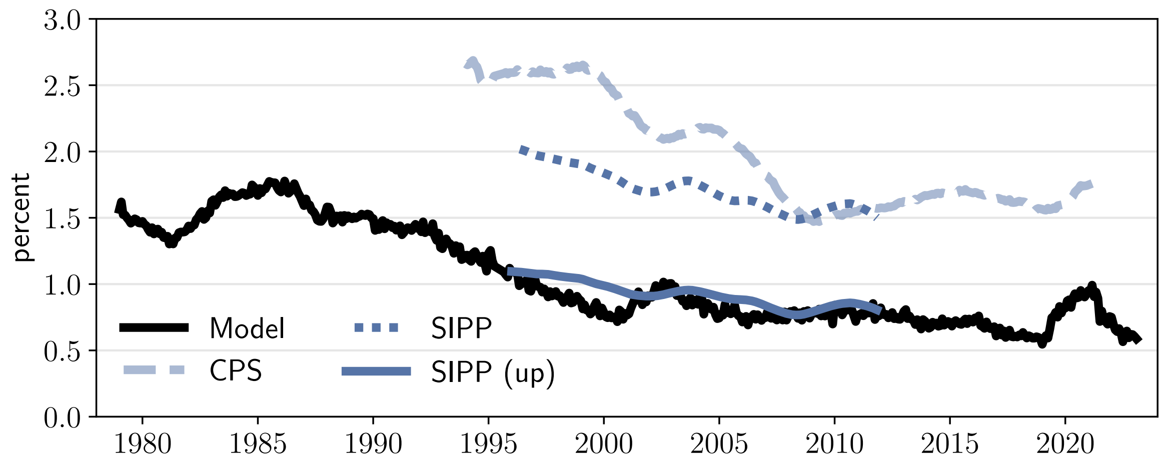


Figure 2: Comparison between the EE transition probability implied by the baseline model (black), the raw overall EE transition probability in the CPS (dashed light blue) and the SIPP (dotted dark blue), and the raw EE transition probability towards higher-paying jobs in SIPP (solid dark blue).

a worker receives an outside job offer versus the probability that she accepts it

$$\ln EE_t = \underbrace{\ln\left(\lambda_t^e\right)}_{\text{job finding probability}} + \underbrace{\ln\left(\int_{-\infty}^{\infty}\left(1 - F_{t+1}^e(w)\right)dG_t(w)\right)}_{\text{acceptance probability}} \tag{15}$$

Figure 3 implements (15) under the assumption that the employed receive job offers from the same distribution as the nonemployed. Since the mid-1980s, the decline in EE mobility is entirely due to a lower probability that an employed worker receives a job offer. In contrast, workers have become slightly *more* likely to accept extended offers. We interpret this as suggesting that EE mobility is not lower today because workers are better matched with their existing jobs. Molloy et al. (2016) draw a similar conclusion based on the lack of a long-run trend in starting wages.

Figure 4 implements the steady-state decomposition (5) of the EE transition probability into changes in the separation probability to nonemployment and changes in the average gap between the offer and wage distributions. Although this incorrectly assumes that the economy is in steady-state, in practice it seems to matter little. While we find this decomposition useful to highlight what features of the data lead us to infer the change in EE mobility that we observe, we stress that it should not be given a structural interpretation. In particular, it should *not* be interpreted to suggest that a change in δ_t *resulted* in a change in EE mobility. Holding fixed the offer and wage distributions, the decline in the separation probability to nonemployment implies that the EE transition probability must have declined. Conversely, holding fixed the separation probability to unemployment, the shrinking gap between the offer and wage distributions also implies that EE mobility must have declined. In a purely statistical sense, a shrinking gap between the offer and wage distributions is the most important reason why we infer a decline in EE mobility.

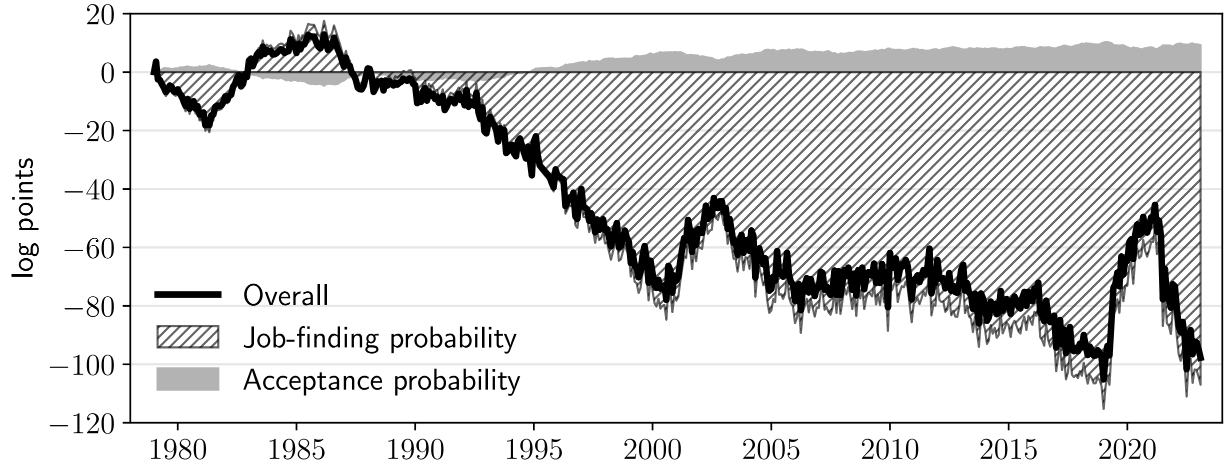


Figure 3: Decomposition of log-EE mobility decline into the job-finding probability and the acceptance probability.

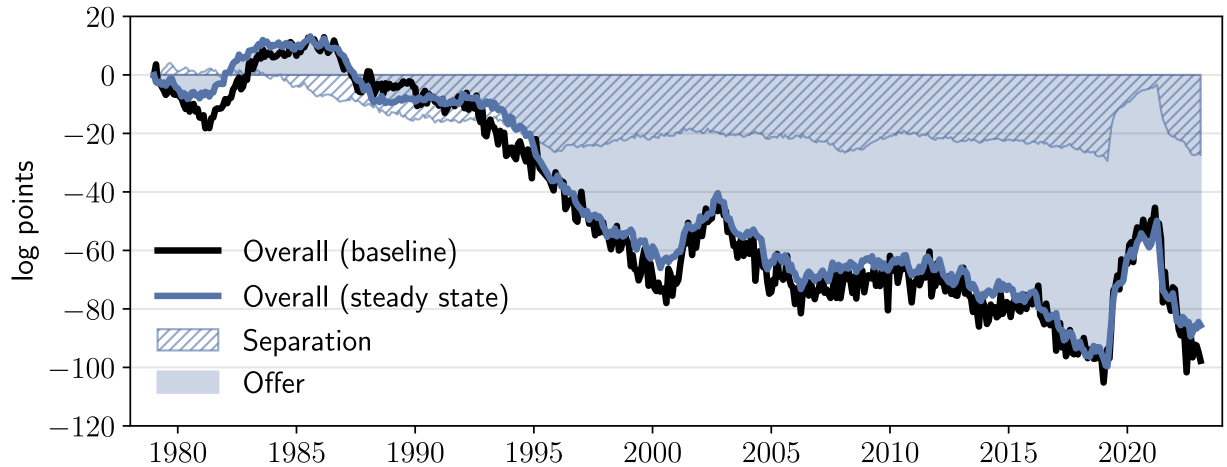


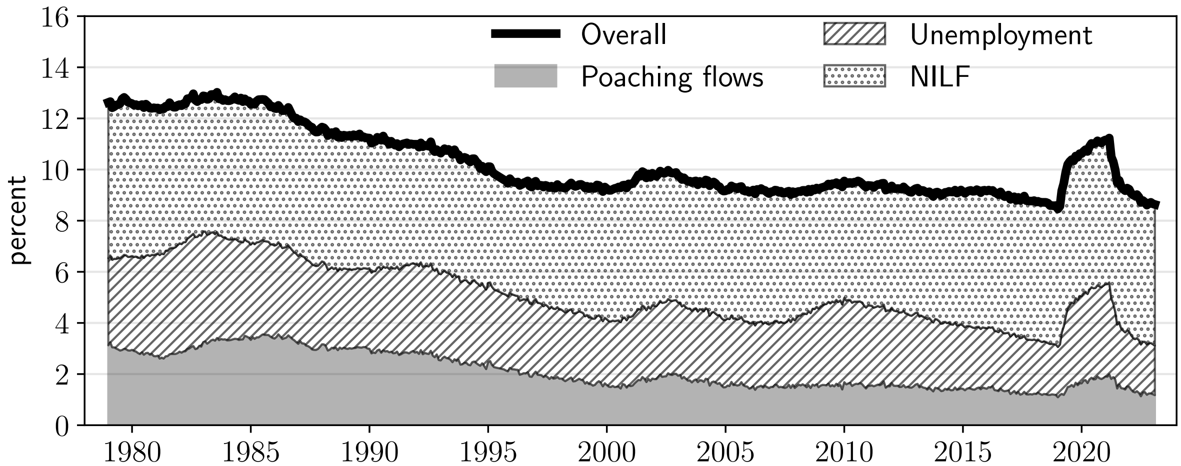
Figure 4: Decomposition of log-EE mobility decline into the separation probability to nonemployment and the average gap between the offer and wage distributions.

4.2 Implications for overall worker flows

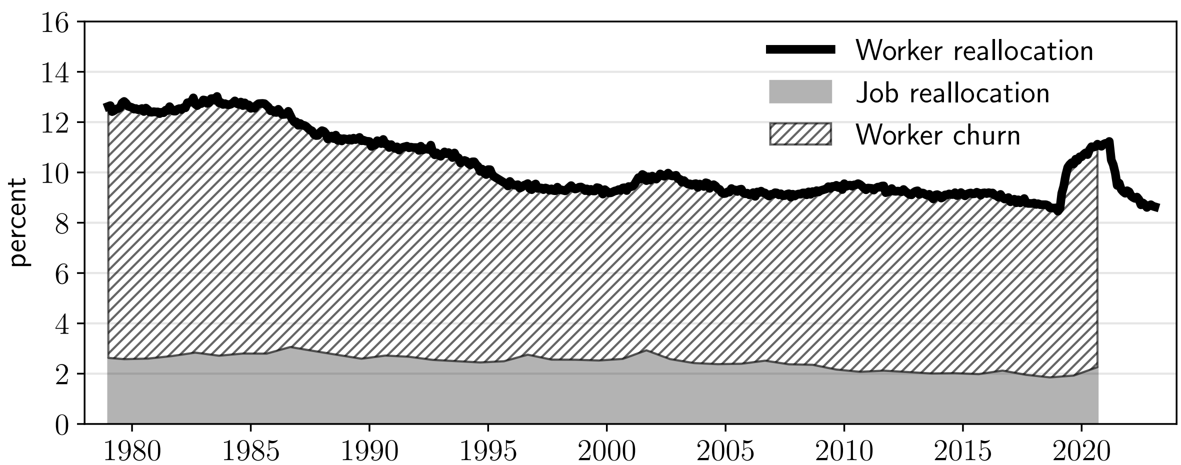
Figure 5 illustrates the implications for overall worker mobility (using the baseline model). During the 1980s, EE mobility toward higher paying jobs constituted roughly a quarter of overall worker flows (panel a). Flows in and out of unemployment accounted for about 30 percent of overall flows, with the remainder of worker reallocation taking place through non-participation. Because we do not adjust for recalls, which are a significant share of flows into and out of nonemployment (Fujita and Moscarini, 2017), this likely understates the role of EE mobility for overall worker reallocation. Moreover, the CPS is known to suffer from labor force status classification error, which inflates gross flows between employment and nonemployment (Abowd and Zellner, 1985).

Poaching flows declined substantially as a share of total worker flows over the past 45 years, reaching an all time low of about 15 percent today. Flows in and out of unemployment also fell, while flows in and out of non-participation are at about the same level today as they were in 1980. Combining these trends, the overall worker reallocation rate fell from over 12 percent of employment per month in the 1980s to nine percent today, with poaching flows responsible for almost half of this decline.

Panel b shows that worker reallocation is substantially larger than job reallocation.[13] Consequently, although some of the fall in worker reallocation is accounted for by the well-documented decline in job reallocation (Davis and Haltiwanger, 2014), most of the decline is accounted for by decreasing worker churn.



(a) Worker reallocation and its components in extended models compared to reallocation in benchmark model (black).



(b) Worker reallocation decomposed in job reallocation and churn. Monthly job reallocation here is the annual rate divided by 12 (available from the Census Bureau's *Business Dynamics Statistics* until 2021).

Figure 5: Worker relocation broken down as stated in equations (6) and (7).

[13]The BDS reports in year t the job reallocation between March in year $t-1$ and March in year t. We divide this by 12 to get a proxy for the job reallocation rate in September in year $t-1$, and linearly interpolate for the months in between September in year $t-1$ and year t.

4.3 Implications for wage growth

Workers use EE mobility to move to higher-paying jobs (Topel and Ward, 1992). Consequently, all else equal we would expect the decline in EE mobility to contribute to weaker wage growth. Figure 6 quantifies this effect based on equation (8) using the OTJ model that allows also for on-the-job growth in residual wages. It shows a stark decline in aggregate wage growth among continuously employed workers, i.e. the sum of wage growth among EE switchers computed based on (8) and on-the-job wage growth, ξ_t. Monthly growth in residual log wages among continuously employed workers fell from over one percent in the 1980s to just 0.4 percent in 2019. Most of this decline is due to the fall in EE mobility, as opposed to weaker residual wage growth on-the-job.

To validate our structural estimate, we compare it to wage growth upon EE transitions to higher paying jobs in the SIPP. That is, the solid blue line plots the product of the average percent change in wages between month $t+1$ and t for workers who made an EE transition in month t times the average EE transition probability in month t. The data and model are, once again, in line both in levels and in their downward trend over the 1996–2013 period for which SIPP data are available.

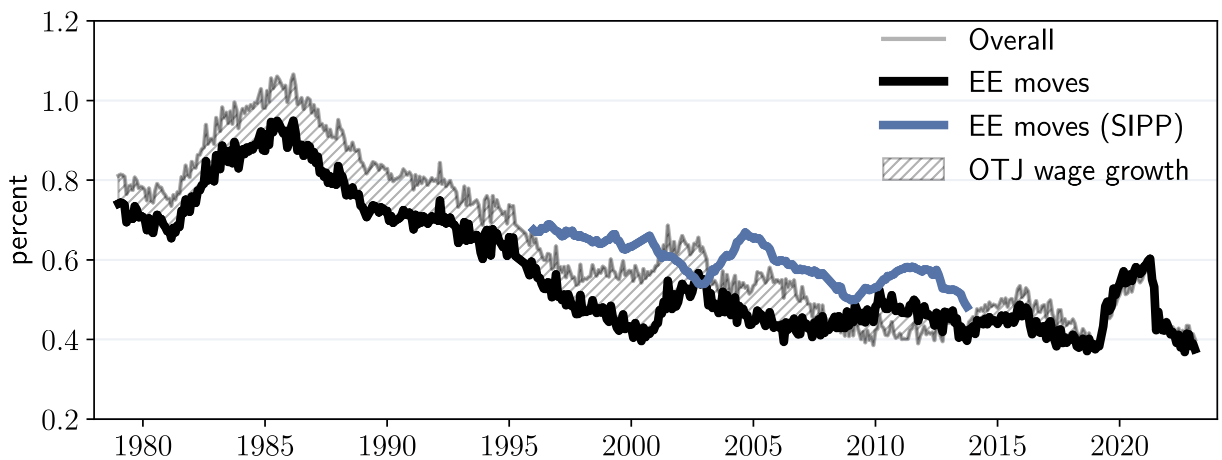


Figure 6: Monthly growth in residual wages associated with EE mobility in the OTJ model and in the SIPP.

Figure 7 shows the average wage gain *conditional* on making an EE transition in the model as well as in the SIPP data. The latter is for workers moving to higher paying jobs.[14] Both the structural estimate and the raw SIPP measure indicate substantial wage growth associated with EE mobility toward higher paying jobs. According to both, the average wage gain conditional on moving to a higher paying job increased over time. We interpret the fact that returns to mobility rose as further evidence that the decline in EE mobility is not the result of workers being better

[14]We impose exactly the same sample selection criteria and construct variables identically in the SIPP as in the CPS. This includes residualizing wages off demographic characteristics the same way as above, and subsequently winsorizing wages at the bottom and top 0.5 percentiles.

matched with their current employers.

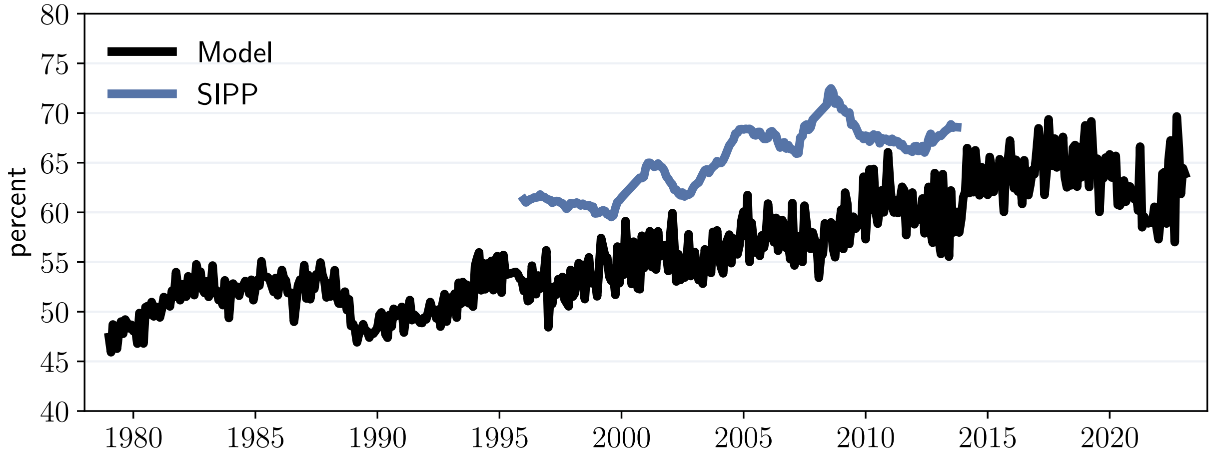


Figure 7: Wage growth conditional on switching to a higher-paying employer in model (black) and in the SIPP (blue).

5 Results by subgroups

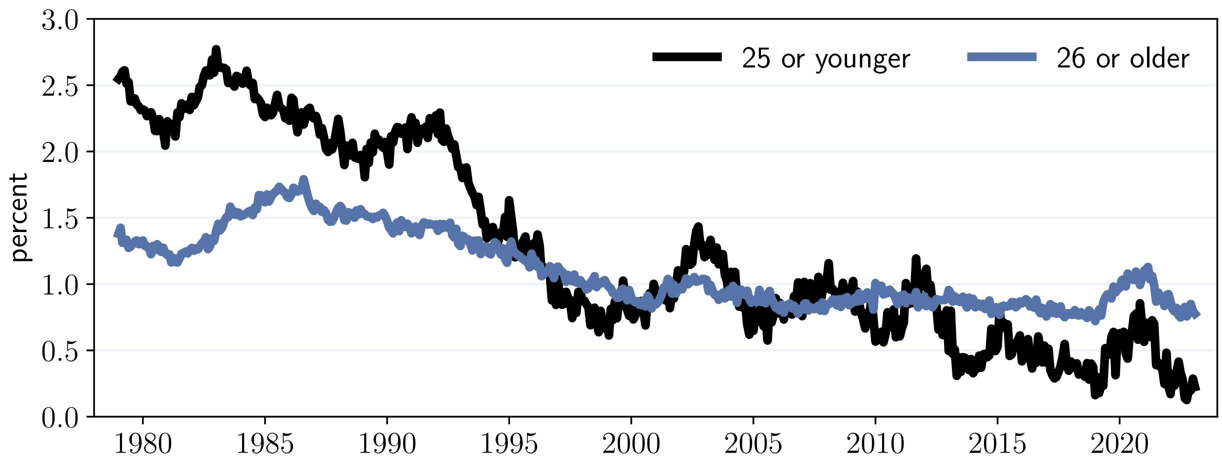
In this section, we analyze EE mobility and its associated wage growth within subgroups defined by age, race, gender and education. To that end, we restrict attention to a particular subgroup and replicate the methodology of Sections 2–3 using the baseline model.

5.1 By age

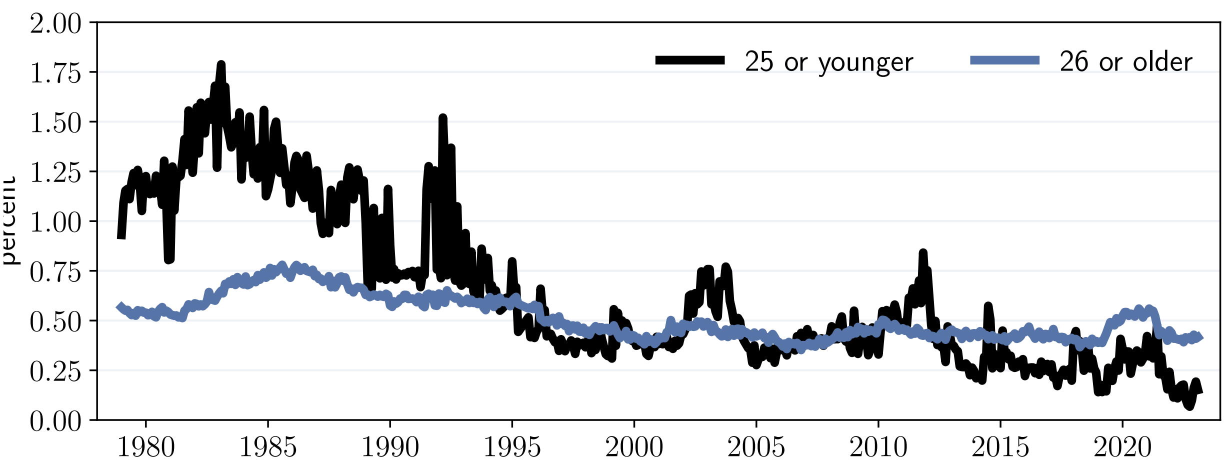
Figure 8 shows results for workers 25 and younger (solid black) and workers 26 and older (solid blue). While younger workers are more mobile, they experienced a larger decline in EE mobility over the past 40 years (panel a). These results point to worsening labor market prospects for young workers, which is also confirmed by the steeper decline in wage growth due to EE mobility for young workers over this period (panel b) (Beaudry, Green and Sand, 2014).

5.2 By gender

Figure 9 shows that EE mobility and the associated wage growth were larger for women than men throughout most of this period, which coincided with a period when women made rapid advancements in the labor market (Goldin, 2014). However, both measures fell by more for women over time, *ceteris paribus* contributing to a lack of full convergence in the gender pay gap (Blau and Kahn, 2006; Blair and Posmanick, 2023).



(a) EE mobility rate.



(b) Average wage growth associated with EE mobility.

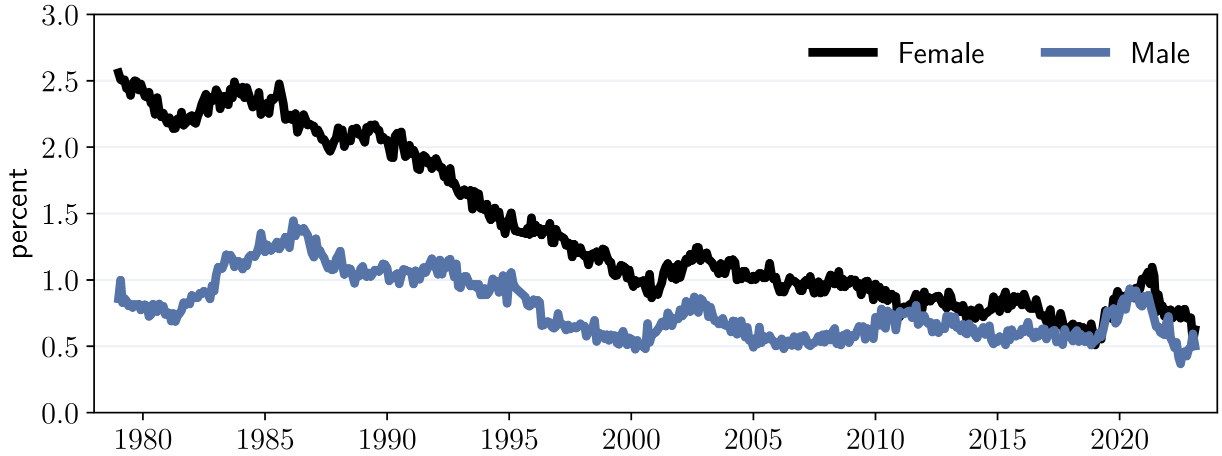
Figure 8: EE mobility and associated wage growth by age. All mobility is to higher-paying jobs.

5.3 By race

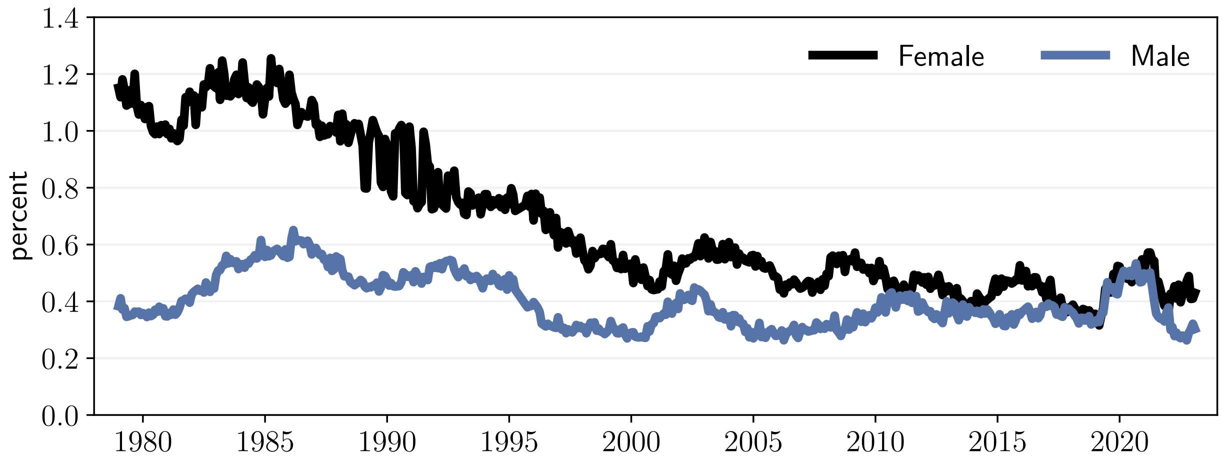
According to Figure 10, the level of and the change in EE mobility over the past 45 years is broadly similar for whites and blacks (panel a). Similarly, wage growth associated with EE mobility has decreased but not differentially for the two groups (panel b).

5.4 By education

Figure 11 illustrates that workers without a college degree were *more* likely than their peers with a degree to make an EE transition toward a higher paying job in the 1980s. Over time, however, the two groups converged, so that today those without a degree are no more likely to make an EE transition toward a higher paying job than those with a degree. A similar pattern holds for wage growth associated with EE mobility (panel b).



(a) EE mobility rate.



(b) Average wage growth associated with EE mobility.

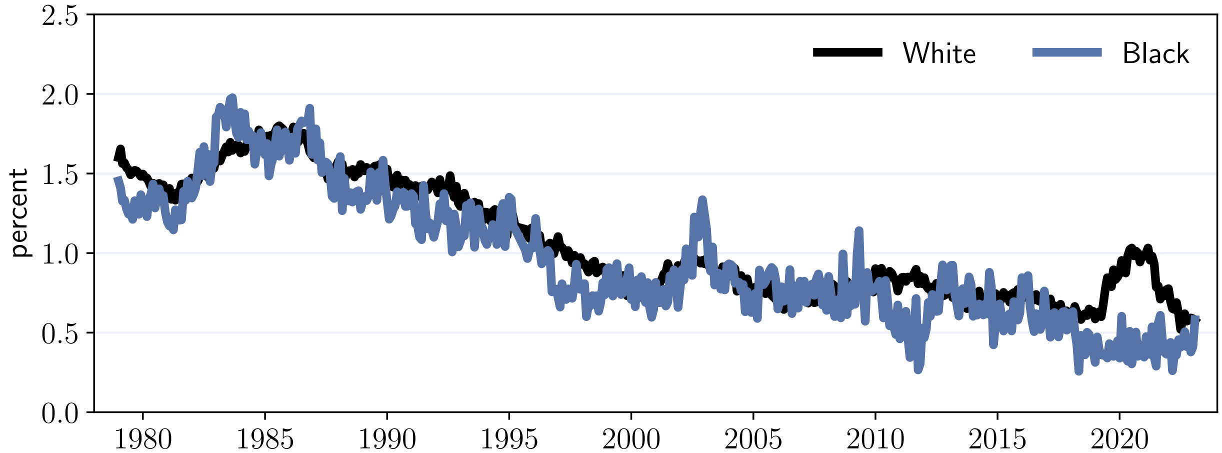
Figure 9: EE mobility and associated wage growth by gender. All mobility is to higher-paying jobs.

6 Unobserved heterogeneity

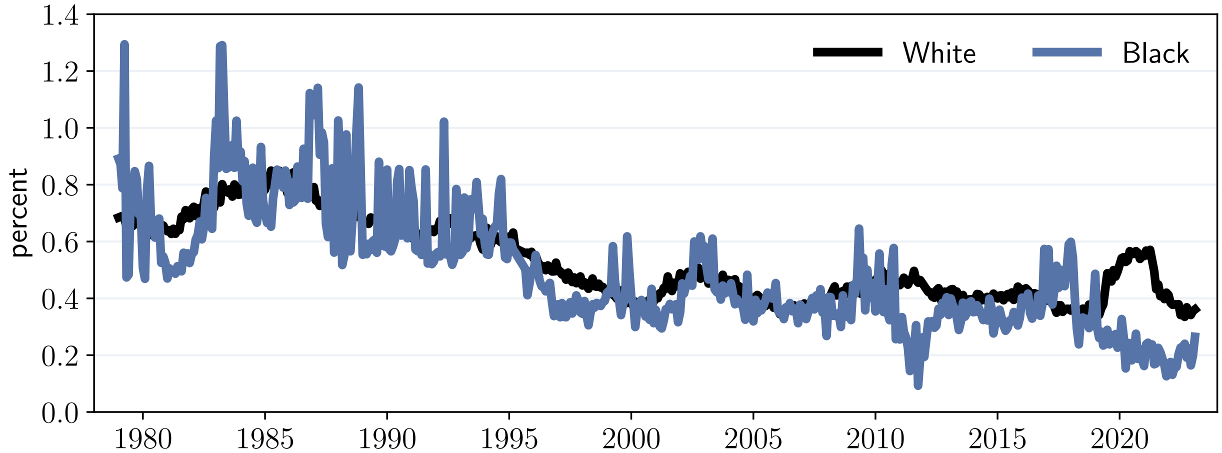
Although we control for observable demographic characteristics, hires from nonemployment might differ in unobservable dimensions from their identical-looking peers who did not recently experience nonemployment. To the extent that they generically earn less, we would overstate EE mobility, because we attribute the entire gap between the wage and offer distributions to EE mobility.

To address this concern, we exploit the fact that we can observe prior wages. Specifically, the basic monthly survey merged with the ORG allows us to link hires from nonemployment in survey month 6–8 to their lagged residual wage in survey month four, i.e. 10–12 months earlier. We compute the lagged residual wage of hires from nonemployment relative to those not hired from nonemployment.[15] Note that we do not know an individual's prior employment status in

[15] Although we residualize wages in survey month four controlling for time effects, we do this prior to restricting



(a) EE mobility rate.



(b) Average wage growth associated with EE mobility.

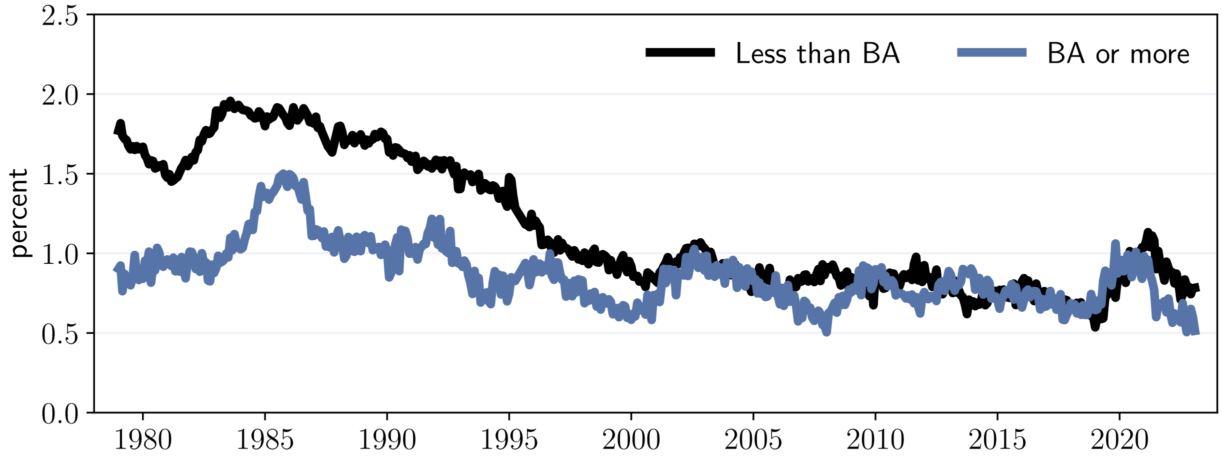
Figure 10: EE mobility and associated wage growth by race. All mobility is to higher-paying jobs.

survey month five, hence its exclusion.

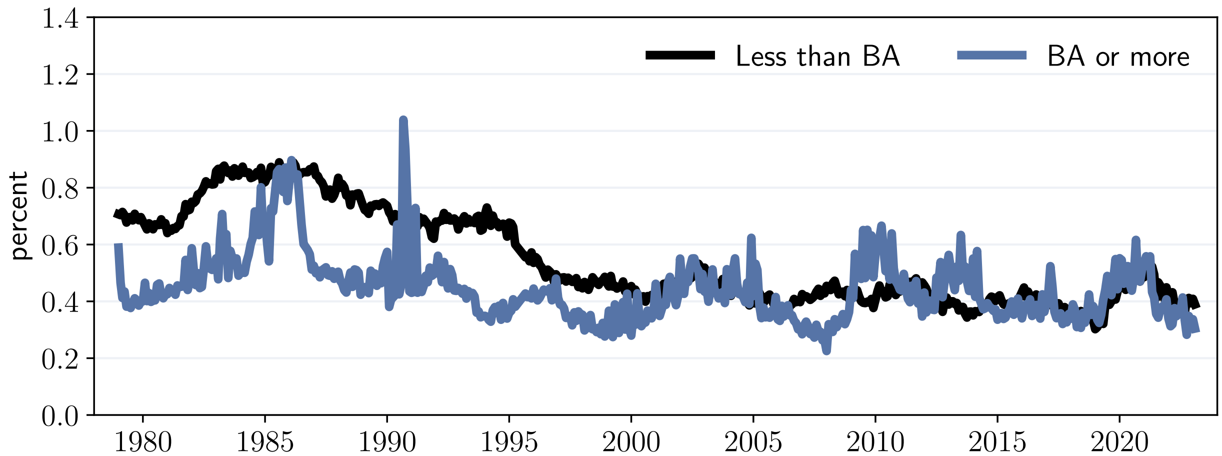
A drawback of this approach is that it conditions on wage employment at the time of the first ORG survey. An alternative is to use wages in the previous calendar year from the ASEC, which only imposes that the respondent worked for pay at some point in the previous calendar year. To implement this approach, we first construct residual log average hourly wages in the previous calendar year using the same observable controls as in the ORG. Subsequently, we focus on January-June, since we require one prior month in order to classify hires and the respondent has to be in the March Supplement.

Figure 12 plots the average previous residual log wage of hires from nonemployment relative to all workers. Hires from nonemployment earned 5–15 percent lower residual wages 10–12

attention to those with valid wage employment in survey months 6–8. Non-random attrition necessitates expressing lagged residual wages of hires from nonemployment in survey months 6–8 relative to lagged residual wage of all workers in survey months 6–8.



(a) EE mobility rate.



(b) Average wage growth associated with EE mobility.

Figure 11: EE mobility and associated wage growth by education. All mobility is to higher-paying jobs.

months earlier or in the previous calendar year. This pattern is consistent with hires from nonemployment being negatively selected in unobservable dimensions. It would also arise in the full model, in which low paid jobs are more likely to terminate. In any case, the ORG series does not display much of a time trend, suggesting that such selection did not change. Moreover, the ASEC series if anything indicates that selection on unobservables become *less* pronounced over time, such that our estimated fall in the EE transition probability over the past 40 years *understates* the magnitude of the true decline.

To more formally adjust for selection, we further residualize a worker's current residual wage off her prior residual wage. We refer to this as the *unobservables model*. The main drawback of this is that it cuts the sample by roughly 60 percent, since it requires respondents to be employed in both the first and second ORG month. For this reason, we focus on the ORG since it is larger than the ASEC.

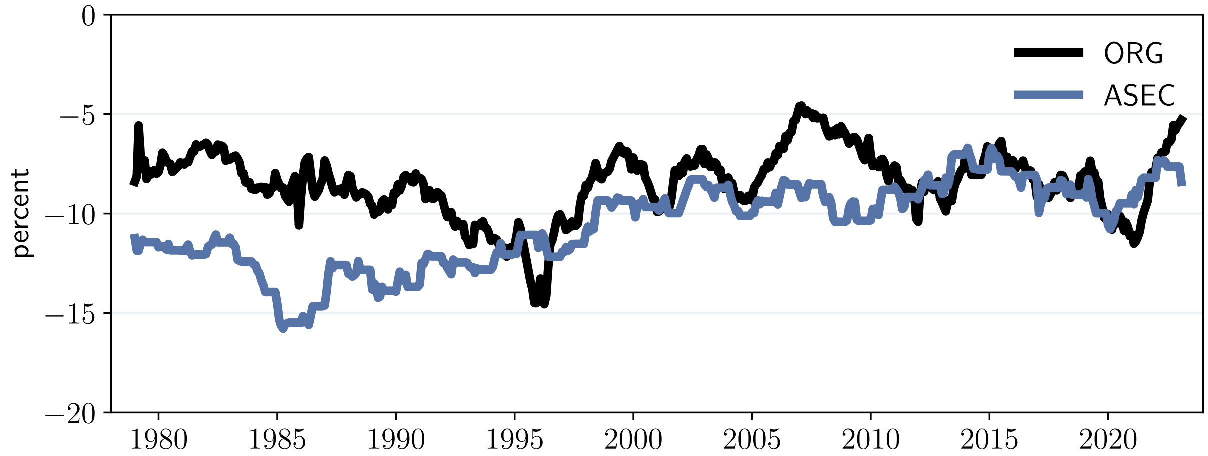


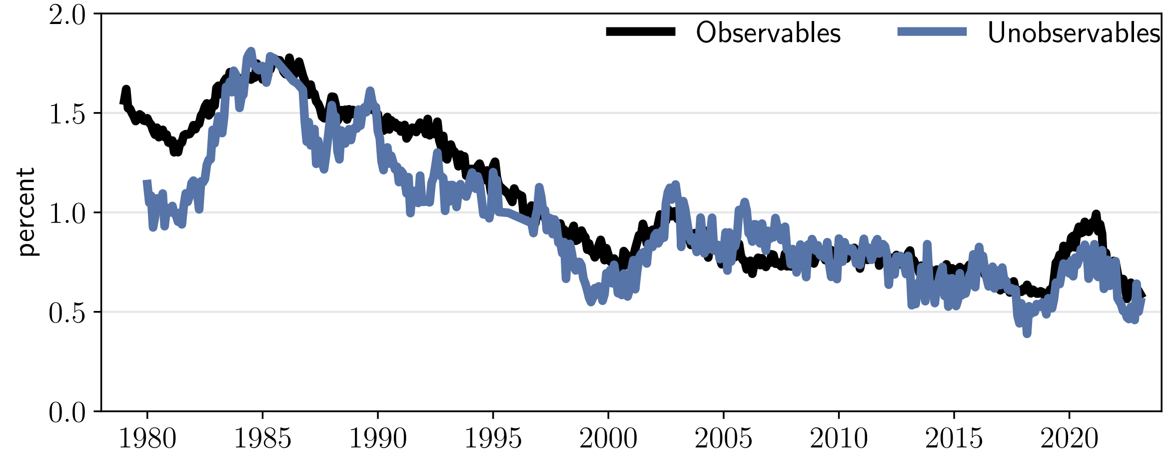
Figure 12: Previous residual log wages of hires from nonemployment relative to all workers measured 10–12 months earlier in the ORG (black) or in the previous calendar year in the ASEC (blue).

Figure 13 shows the results from this robustness exercises for EE mobility (panel a) and its associated wage growth (panel b). We focus throughout on the baseline model. The level of EE mobility is somewhat lower once we control for unobservable differences, but the difference is relatively small. The reason is that although hires from nonemployment have lower prior residual wages, these differences are small relative to overall wage dispersion. Moreover, it does little to the estimated decline in EE mobility over time. The same is true for wage growth associated with EE mobility.

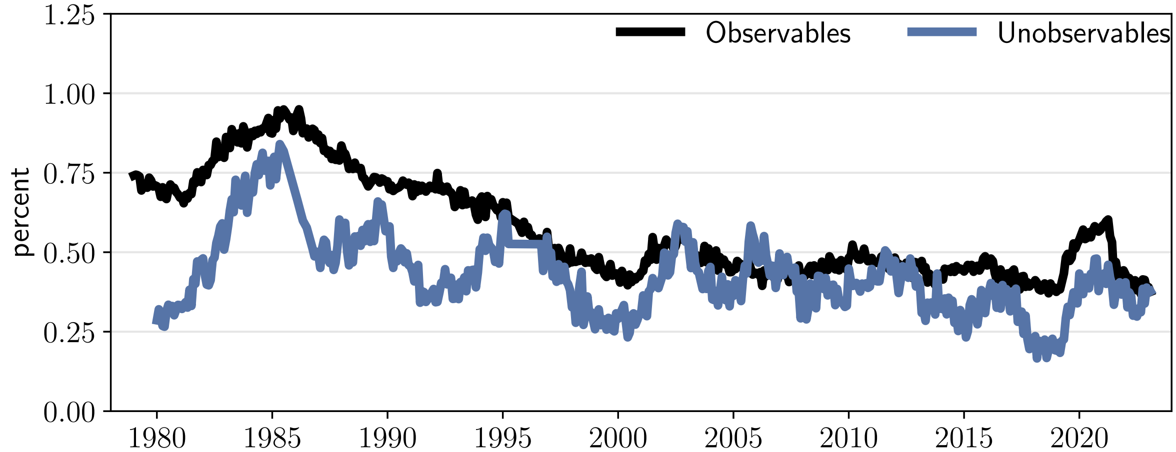
7 Conclusion

We estimate a large decline in EE mobility toward higher paying jobs since the 1980s in the U.S., using a prototypical job ladder model and publicly available micro data. This methodology allows us to measure EE mobility during a period of rapid changes in the U.S. labor market, but for which data limitations have prevented the construction of direct EE mobility measures. Moreover, our methodology overcomes issues associated with non-random attrition, and it isolates the component of EE mobility that is directed toward higher paying jobs. It can easily be extended to incorporate more data over time.

Although there could be benign aspects of the decline in EE mobility, we view it as a worrying sign. In particular, EE mobility plays a crucial role for wage growth, so that its decline is associated with over one percentage point weaker annual wage growth. Moreover, young workers, women, and those without a college degree experienced a particularly large decline in EE mobility toward higher paying jobs over the past 40 years. Future work should further investigate the causes behind the decline in U.S. labor market fluidity and whether policy can play a role in fostering a more dynamic, inclusive labor market.



(a) EE mobility in the observables (black) and unobservables (blue) models.



(b) Wage growth associated with EE mobility in the observables (black) and unobservables (blue) models.

Figure 13: EE transition probability and average wage growth associated with EE mobility in model with unobservable controls.

References

Abowd, John M., and Arnold Zellner. 1985. "Estimating Gross Labor-Force Flows." *Journal of Business and Economic Statistics*, 3: 254–283.

Beaudry, Paul, David A. Green, and Benjamin M. Sand. 2014. "The Declining Fortunes of the Young since 2000." *American Economic Review*, 104(5): 381–86.

Bilal, Adrien, Niklas Engbom, Simon Mongey, and Giovanni L Violante. 2022. "Firm and Worker Dynamics in a Frictional Labor Market." *Econometrica*, 90: 1425–1462.

Blair, Peter Q, and Benjamin Posmanick. 2023. "Why Did Gender Wage Convergence in the United States Stall?" National Bureau of Economic Research Working Paper 30821.

Blau, Francine D., and Lawrence M. Kahn. 2006. "The U.S. Gender Pay Gap in the 1990s: Slowing Convergence." *Industrial and Labor Relations Review*, 60(1): 45–66.

Burdett, Kenneth, and Dale T Mortensen. 1998. "Wage differentials, employer size, and unemployment." *International Economic Review*, 257–273.

Caratelli, Daniele. 2022. "Labor Market Recoveries Across the Wealth Distribution." Working Paper.

Davis, Steven J, and John Haltiwanger. 2014. "Labor Market Fluidity and Economic Performance." National Bureau of Economic Research Working Paper 20479.

Fallick, Bruce, and Charles A Fleischman. 2004. "Employer-to-employer flows in the US labor market: The complete picture of gross worker flows." *Federal Reserve Board Finance and Economics Discussion Series 2004-34*.

Fujita, Shigeru, and Giuseppe Moscarini. 2017. "Recall and Unemployment." *American Economic Review*, 107(12): 3875–3916.

Fujita, Shigeru, Giuseppe Moscarini, and Fabien Postel-Vinay. 2023. "Measuring employer-to-employer reallocation." American Economic Journal: Macroeconomics.

Fukui, Masao. 2020. "A theory of wage rigidity and unemployment fluctuations with on-the-job search." *Job Market Paper, Massachusetts Institute of Technology*.

Gertler, Mark, Christopher Huckfeldt, and Antonella Trigari. 2020. "Unemployment fluctuations, match quality, and the wage cyclicality of new hires." *The Review of Economic Studies*, 87(4): 1876–1914.

Goldin, Claudia. 2014. "A grand gender convergence: Its last chapter." *American economic review*, 104(4): 1091–1119.

Haltiwanger, John C, Henry R Hyatt, Lisa B Kahn, and Erika McEntarfer. 2018. "Cyclical job ladders by firm size and firm wage." *American Economic Journal: Macroeconomics*, 10(2): 52–85.

Hyatt, Henry R, and James R Spletzer. 2013. "The recent decline in employment dynamics." *IZA Journal of Labor Economics*, 2(1): 1–21.

Jolivet, Gregory, Fabien Postel-Vinay, and Jean-Marc Robin. 2006. "The empirical content of the job search model: Labor mobility and wage distributions in Europe and the US." *Contributions to Economic Analysis*, 275: 269–308.

Krusell, Per, Toshihiko Mukoyama, Richard Rogerson, and Ayşegül Şahin. 2017. "Gross worker flows over the business cycle." *American Economic Review*, 107(11): 3447–3476.

Mercan, A. Yusuf. 2017. "Fewer but Better: The Decline in Job Mobility and the Information Channel." University of Melbourne Mimeo.

Molloy, Raven, Christopher L. Smith, Riccardo Trezzi, and Abigail Wozniak. 2016. "Understanding Declining Fluidity in the U.S. Labor Market." *Brookings Papers on Economic Activity*, 46(1): 183–237.

Moscarini, Giuseppe, and Fabien Postel-Vinay. 2017. "The relative power of employment-to-employment reallocation and unemployment exits in predicting wage growth." *American Economic Review*, 107(5): 364–68.

Moscarini, Giuseppe, and Fabien Postel-Vinay. 2022. "The job ladder: Inflation vs. reallocation." *Draft, Yale University*.

Nagypal, Eva. 2008. "Worker reallocation over the business cycle: the important of employer-to-employer transitions."

Polivka, Anne E, and Jennifer M Rothgeb. 1993. "Redesigning the CPS questionnaire." *Monthly Labor Review*, 116(9): 10–28.

Pries, Michael, and Richard Rogerson. 2005. "Hiring Policies, Labor Market Institutions, and Labor Market Flows." *Journal of Political Economy*, 113(4): 811–839.

Pries, Michael, and Richard Rogerson. 2022. "Declining Worker Turnover: The Role of Short-Duration Employment Spells." *American Economic Journal: Macroeconomics*, 14(1): 260–300.

Shimer, Robert. 2012. "Reassessing the ins and outs of unemployment." *Review of Economic Dynamics*, 15(2): 127–148.

Sorkin, Isaac. 2018. "Ranking firms using revealed preference." *The Quarterly Journal of Economics*, 133(3): 1331–1393.

Topel, Robert H, and Michael P Ward. 1992. "Job mobility and the careers of young men." *The Quarterly Journal of Economics*, 107(2): 439–479.