Declining U.S. Labor Market Fluidity: A Long-term Perspective

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February 11, 2024

Abstract

We apply a prototypical 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 fall in EE mobility is associated with over one percentage point weaker annual wage growth today relative to the early 1980s. Third, the decline in mobility and its associated wage increases particularly impacted young workers, women, minorities, and those with less than a college degree.

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The views and opinions expressed are those of the authors and do not necessarily represent official positions of the Office of Financial Research or the U.S. Department of the Treasury.

1 Introduction

Shopping for jobs is an important part of workers' careers. Young workers enter the labor market poorly matched, and gradually relocate across firms to find a good match. Topel and Ward (1992) find that this process of *employer-to-employer* (EE) mobility accounts for a third of wage growth during the first 10 years of workers' careers. Moreover, macroeconomists have long emphasized the beneficial aspects of such reallocation for aggregate productivity growth. Yet, despite its importance both for micro and macroeconomic outcomes, little is known about long-run trends 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. Applied to publicly available data from the *Current Population Survey* (CPS), we find that such mobility halved between 1980 and 2020. Moreover, the decline is associated with over one percentage point weaker annual wage growth today than in the 1980s. Finally, the decline in wage growth was particularly pronounced among the young, women, minorities, and those without a college degree.

Our methodology is based on a prototypical job ladder model in the spirit of Burdett and Mortensen (1998), but with the wage offer distribution treated as exogenous. In each period, unemployed and employed workers receive job offers with some exogenous and potentially different probability. A job offer is a draw of a wage from some 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 unemployed.

According to the model, the wage distribution depends on the the separation rate to and the hiring rate from unemployment, the wage offer distribution, and the EE mobility rate. Knowledge of the other objects in this relationship hence allows us to recover the EE mobility rate. The logic is best illustrated by an example. Consider an economy in which 10 workers earn a wage below w at time t. Between time t and $t+1$, two of these workers separate to unemployment, while one worker is hired from unemployment by a job paying less than w. At time $t+1$, we again observe 10 workers earning less than w. Suppose that the only source of wage growth is EE mobility. 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 $t+1$ then solves

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

In our example, $x_t(w) = 0.1$. Knowledge of $x_t(w)$ as well as the share of workers employed at w for all w allows us to compute the EE mobility rate to higher paying jobs.

The logic breaks down if some workers move from a wage below w to a wage above w for some reason other than EE mobility. One obvious candidate is on-the-job wage growth. To address this issue, we flexibly residualize wages off a rich set of demographic controls that account for wage growth with experience, as well as aggregate, state-level trends. Furthermore, we incorporate on-the-job residual wage growth with tenure.

We compute the inputs required to estimate EE mobility using the CPS's basic monthly survey merged with its *Outgoing Rotation Groups* (ORG). Specifically, we record an individual's employment status in each month during a four month period, her hourly wage in the last of these fourth 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 record the share of workers earning less than residual wage w in months t and $t+1$, the share of hires from unemployment who earn a wage below w in month $t+1$, and the share of employed workers in month t who are unemployed in period $t+1$. Based on these objects, we recover the EE mobility rate in month t.

Our estimates highlight a sharp slowdown in EE mobility since the 1980s. The monthly EE mobility rate fell from over two percent in the 1980s to less than one percent today, with only a short-lived reversal in this trend during the Pandemic. Allowing for time-varying on-the-job growth in residual wages has only a small effect on our estimates, due to the fact that such wage growth is uniformly small over our period of study. Moreover, while as a benchmark we assume that the separation rate to unemployment is independent of the wage, we show that similar results hold if it is allowed to depend on the wage.

An appealing aspect of our methodology is that it does not require us to take a stance on the (unobserved) wage offer distribution of the employed. Nevertheless, if we additionally impose that they draw wage offers from the same distribution as the unemployed, 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. Hence, EE mobility does not appear to be lower today because workers are better matched with their existing jobs.

We find that EE mobility accounts for half of the sum of hires and separations—overall *worker reallocation*. Consequently, it is not surprising that overall worker reallocation declined with the fall in EE mobility. Flows in and out of employment, however, also decreased, further contributing to a precipitous decline in the overall worker reallocation rate from eight percent per month in 1980 to four 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 three 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 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. In contrast, the average wage gain conditional on an EE transition rose. The fact that the return to EE mobility did not fall provides further evidence that EE mobility did not decline because workers became better matched at their existing jobs.

Subsequently, we analyze changes in EE mobility within age, gender, race and education groups. While the decline in EE mobility was pervasive across all demographic groups, it was particularly large among young workers, women, and those without a college degree. These disproportionate declines in EE mobility are reflected in especially large declines in wage growth associated with EE mobility for these subpopulations. In addition, blacks experienced larger declines in wage growth due to EE mobility than whites, even though both groups saw similar declines in mobility.

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, 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, raw EE mobility includes all types of EE moves, regardless of whether they improve a worker's wage. In contrast, we identify only those EE transitions that move a worker toward higher paying jobs. From the perspective of macroeconomic performance, the latter may be more relevant.

That being said, our methodology relies on two strong assumptions. First, we assume that after taking out age-gender-race-education-year and state-date fixed effects, workers are ex ante fundamentally identical (even though they differ ex post). This assumption allows us to infer EE mobility from the gap between the overall distribution of wages and that among workers who were recently unemployed. Second, we ignore flows in and out of the labor force, even though such flows admittedly are large. It is natural to ask how our results are affected relaxing these two assumptions.

To address the first concern, we exploit the fact that wages are recorded twice in the ORG, with a twelve month gap. Alternatively, we obtain average wages during the previous calendar year from the *Annual Social and Economic Supplement* (ASEC) of the CPS. These data allow us to study the previous residual wage among those hired from unemployment. Consistent with the view that hires from unemployment are negatively selected in unobservable dimensions, we find that they had 5–15 percent lower residual wages 10–12 months earlier or in the previous calendar year. We find no evidence, however, that such selection worsened over time. To more formally account for the role of unobservable differences, we residualize a worker's current residual wage off her prior residual wage, at the cost of cutting the sample by more than half. While this lowers the *level* of EE mobility, it does not meaningfully change its *relative downward trend*.

To address the second concern, we alternatively count all non-employed individuals as unemployed. This has only a small effect on both the level of and change in EE mobility.

Literature. 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 theirs. 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 unemployment. 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.

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, are likely to understate EE mobility, since they are aggregated to a quarterly frequency. 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.

Our motivation is shared by Shimer (2012), who applies a parsimonious model of labor market flows to unemployment duration data to infer the separation and job finding rates 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 the estimated EE mobility rate and its associated wage growth (section 4). In section 5, we redo our analysis within demographic subpopulations. Section 6 contains additional robustness exercises, and section 7 concludes.

2 Theory

This section outlines a parsimonious partial equilibrium model of worker dynamics in the spirit of Burdett and Mortensen (1998), but with the wage offer distribution taken as exogenous. While stylized, an extensive literature finds that it provides a reasonably good explanation of labor market dynamics in the data.

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 unemployment.[1] Let e_t denote the employment rate at time t and u_t the unemployment rate.

At each point in time, unemployed 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 unemployed with support $w \in (-\infty, \infty)$. Let $f_{t+1}^u(w)$ denote its *probability density function* (pdf) and $F_{t+1}^u(w)$ its *cumulative distribution function* (cdf). We

[1] We abstract from growth in the workforce. Because labor market flows are an order of magnitude larger than growth in the workforce, this abstraction has little practical consequence.

assume that unemployed 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 $\lambda_t^e \in [0,1]$. Let $f_{t+1}^e(w)$ denote the pdf of this distribution and $F_{t+1}^e(w)$ 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 unemployment with exogenous probability $\delta_t \in [0,1]$. We require that these probabilities satisfy $\delta_t + \lambda_t^e \leq 1$.

2.2 Labor market flows

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

$$\begin{aligned} g_{t+1}(w)\, e_{t+1} &= g_t(w)e_t - \underbrace{\delta_t g_t(w)e_t}_{\text{separations to u.}} - \underbrace{\lambda_t^e \left(1 - F_{t+1}^e(w)\right) g_t(w)e_t}_{\text{EE separations}} \\ &+ \underbrace{\lambda_t^u f_{t+1}^u(w)(1-e_t)}_{\text{hires from u.}} + \underbrace{\lambda_t^e f_{t+1}^e(w) G_t(w) e_t}_{\text{EE hires}} \end{aligned} \tag{1}$$

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

$$G_{t+1}(w)\, e_{t+1} = \Big(1 - \delta_t - \lambda_t^e(1 - F_{t+1}^e(w))\Big) G_t(w)e_t + \lambda_t^u F_{t+1}^u(w)(1-e_t)$$

which we can rearrange as

$$\underbrace{\lambda_t^e\Big(1 - F_{t+1}^e(w)\Big)}_{sep_t^e(w) \equiv \text{poaching separation rate}} = 1 - \delta_t - \frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t} + \lambda_t^u \frac{F_{t+1}^u(w)}{G_t(w)}\frac{1-e_t}{e_t} \tag{2}$$

We discuss below how to measure $G_t(w)$, $G_{t+1}(w)$, $F_{t+1}^u(w)$, e_t, e_{t+1}, δ_t and λ_t^u in the CPS. Provided these objects, we can estimate the *poaching separation rate* at each wage w based on (2). We refer to (2) as the *simple model* to differentiate it from the extensions below.

The EE mobility rate is the probability that an employed worker receives a job offer

[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 unemployed workers.

[3] Integrating by parts the EE separations terms gives $\int_{-\infty}^{w}(1-F_{t+1}^e(\tilde{w}))g_t(\tilde{w})\, dw = (1-F_{t+1}^e(w))G_t(w) + \int_{-\infty}^{w} f_{t+1}^e(\tilde{w})G_t(\tilde{w})d\tilde{w}$. The last term cancel the integrated EE hires term in (1).

times the average probability that she accepts it, i.e. the average poaching separation rate

$$EE_t = \underbrace{\lambda_t^e}_{\text{job finding probability}} \underbrace{\int_{-\infty}^{\infty} \left(1 - F_{t+1}^e(w)\right) dG_t(w)}_{\text{acceptance probability}} = \int_{-\infty}^{\infty} sep_t^e(w) dG_t(w) \tag{3}$$

According to (3), a decrease in EE mobility can arise 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 (unobserved) wage offer distribution of the employed. This is not the case when decomposing the change in EE mobility into the two channels highlighted by (3). To conduct this decomposition, we follow the standard praxis in the literature to equate the wage offer distribution of the employed with that of the unemployed, $f_t^e(w) = f_t^u(w)$. This assumption allows us to recover the acceptance probability as $acceptance_t = \int_{-\infty}^{\infty}(1 - F_{t+1}^u(w))dG_t(w)$ and the job finding probability as $\lambda_t^e = EE_t / acceptance_t$.

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 unemployment, divided by employment

$$\underbrace{WR_t}_{\text{worker reallocation}} = \underbrace{2 \times EE_t}_{\text{poaching flows}} + \underbrace{\delta_t}_{\text{separations to unemployment}} + \underbrace{\lambda_t^u \frac{1 - e_t}{e_t}}_{\text{hires from unemployment}} \tag{4}$$

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

$$\underbrace{WR_t}_{\text{worker reallocation}} = \underbrace{JR_t}_{\text{job creation + job destruction}} + \underbrace{Churn_t}_{\text{replacement hiring}} \tag{5}$$

Worker reallocation is at least as large 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

$$\Delta w_t^{EE} = \lambda_t^e \int_{-\infty}^{\infty} \left(1 - F_{t+1}^e(w) \right) G_t(w) dw = \int_{-\infty}^{\infty} sep_t^e(w) G_t(w) dw \tag{6}$$

2.3 Extensions

Before we go to the data, we incorporate two extensions to the simple model. First, the simple 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]

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

[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 distribution $g(w,t)$ is characterized for all $t \geq 0$ by the partial equilibrium equation

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

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

Integrating this and rearranging

$$\underbrace{\lambda_t^e\Big(1-F_{t+1}^e(w)\Big)}_{\equiv sep_t^e(w)} \;=\; 1-\delta_t-\frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t}+\lambda_t^u\frac{F_{t+1}^u(w)}{G_t(w)}\frac{1-e_t}{e_t}-\frac{\xi_t g_t(w)}{G_t(w)} \tag{7}$$

We estimate the poaching separation rate $sep_t^e(w)$ at each wage w based on (7), and substitute it into (3) to obtain the EE mobility rate and into (6) to get the average wage gain due to EE mobility. We refer to (7) as the *OTJ model*.

Second, we incorporate a separation rate to unemployment 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 in (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 and rearranging

$$\begin{aligned} \underbrace{\lambda_t^e\Big(1-F_{t+1}^e(w)\Big)}_{\equiv sep_t^e(w)} &= 1-\delta_t(w)-\frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t}+\lambda_t^u\frac{F_{t+1}^u(w)}{G_t(w)}\frac{1-e_t}{e_t}-\frac{\xi_t g_t(w)}{G_t(w)} \\ &+ \frac{1}{G_t(w)}\int_{-\infty}^{w}\delta_t'(\tilde{w})G_t(\tilde{w})d\tilde{w} \end{aligned} \tag{8}$$

We estimate the poaching separation rate $sep_t^e(w)$ at each wage w based on (8), and substitute it into (3) to obtain the EE mobility rate and into (6) to get the average wage gain due to EE mobility. We refer to (8) as the *full model*.

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] At the time of writing, IPUMS has incorporated ORG data through March 2023. The CPS is the main U.S. labor force survey, serving as the go-to data set for labor market analyses.

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.

In January or February of 1983, 1987, and every other year since 1996, the CPS fielded the *Tenure Supplement*.[10] It asks employed respondents how long they have been working for their current employer, which we recode as years of tenure. We use this information to estimate residual wage growth on-the-job.

The basic monthly survey merged with the ORG does not allow us to observe the separation rate by an individual's wage, since the wage is collected in the month that an individual rotates out of the sample. To estimate this relationship, we add information 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.

[10]The supplement was fielded also in earlier years

average hourly wages in the previous year from the ASEC Supplement, which is fielded in March every year.

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 the IDs prevent linking individuals in the following breaks: June-July 1985, September-October 1985, and May-October 1995.

In our analysis of on-the-job wage growth using ORG and Tenure Supplement data, we restrict attention to those who are their second ORG month in the month that the Tenure Supplement is fielded, so that we can compute within-individual wage growth since their first ORG month.

In our analysis of the separation rate by the wage using the basic monthly survey merged with the Tenure Supplement and the ASEC, we focus on individuals with a valid March Supplement response, so that we can measure their average hourly wage in the previous calendar year. Additionally, we restrict attention to the Tenure Supplement month for those with a valid Tenure Supplement response, i.e. January or February. Finally, we require an individual to have at least 14 months of tenure with their current employer (since the latest the Tenure Supplement is fielded is February). Consequently, the average hourly wage reported by the ASEC refers to the job the individual currently holds. We use the employment status of these individuals in the subsequent month to estimate the separation rate by the 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 the basic monthly and Supplemental data using the consistent ID created by IPUMS (`CPSIDV`).[11] 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

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

and not in the labor force following standard practice. We estimate the separation rate δ_t as the share of employed individuals in month t who are unemployed in month $t+1$. We estimate the job finding rate of the unemployed λ_t^u as the share of unemployed individuals in month t who are 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 linearly interpolate the series across these breaks.

We construct the hourly wage as usual weekly earnings divided by usual weekly hours worked, and convert it to real 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 $F_{t,i}^u$ as the share of hires from unemployment at date t who earn a wage of at most b_i (again weighted by the survey weights), where we define a hire from unemployment at date t, $hire_{t,j}^u$, to be any individual j who was unemployed in month $t-1$

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

The overall 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 the rate of on-the-job wage growth, ξ_t, based on the merged ORG/Tenure Supplement data. Specifically, we condition on individuals who have been with their current employer more than a year, and compute the change in their residual wage between date t and $t-12$. We set ξ_t equal to (1/12 of) the mean of this at each Tenure Supplement date. Due to the inability to link individuals in the breaks mentioned above, we cannot compute on-the-job wage growth between June 1995, and September 1996. We linearly interpolate between Tenure Supplement dates as well as between these breaks.

We estimate the separation rate by the residual log hourly wage based on the merged basic monthly, Tenure Supplement and ASEC data. Specifically, we first residualize average log hourly wages in the previous calendar year following (9). Subsequently, we winsorize residual wages at each date at the bottom and top 0.5 percentiles. We bin residual log hourly wages $y_{i,t}$ into N bins as above, and compute the separation rate in each bin at each date of the Tenure Supplement data, $sep^u_{j,t}$. We also record the mean log residual hourly wage in each bin, $y_{j,t}$. Finally, we project the separation rate on a time dummy and time dummy interacted with a linear in the residual hourly wage

$$\ln sep^u_{j,t} = \delta^0_t + \delta^1_t y_{j,t}$$

We linearly interpolate the estimated coefficients δ^0_t and δ^1_t between Tenure Supplement dates, and assign the separation rate at date t for wage bin i as $\delta_{t,i} = e^{\delta^0_t + \delta^1_t w_i}$. We approximate the derivative of the separation rate with respect to the wage as $\delta'_{t,i} = \delta^1_t \delta_{t,i}$.

3.4 Estimating EE mobility

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 similar to a 23-month moving average. Specifically, merging the stocks and flows from the basic monthly CPS with the offer and wage distributions from the ORG, we construct

$$y_{\tau,i} = 1 - \delta_\tau - \frac{G_{\tau+1,i}}{G_{\tau,i}} \frac{e_{\tau+1}}{e_\tau} + \lambda^u_\tau \frac{F^u_{\tau+1,i}}{G_{\tau,i}} \frac{1 - e_\tau}{e_\tau} \tag{10}$$

Subsequently, we project this on a set of dummies

$$y_{\tau,i} = sep^e_{t,i} + \varepsilon_{\tau,i} \tag{11}$$

Based on the estimated poaching separation rate, we approximate based on (3)

$$EE_t = \sum_{i=1}^{N} sep^e_{t,i} g_{t,i} dw_i \tag{12}$$

and average wage growth due to EE mobility based on (6) as

$$\Delta w_t = \sum_{i=1}^{N} sep^e_{t,i} G_{t,i} dw_i \tag{13}$$

To estimate the *OTJ model* with on-the-job wage growth, we augment (10) as

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

We estimate (11) with this alternative definition of the dependent variable, and construct the EE mobility rate based on (12) and the average wage gain based on (13).

To estimate the *full model* that incorporates both on-the-job wage growth and a separation rate that depends on the wage, we augment (10) as

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

We estimate (11) with this alternative definition of the dependent variable, and construct the EE mobility rate based on (12) and the average wage gain based on (13).

4 A Historical Account of Worker Flows

This section presents a complete historical account of gross worker flows in the U.S. since 1979, highlighting in particular the evolution of the EE mobility rate.

4.1 Labor market flows

Figure 1 plots the EE mobility rate for each of the three models introduced above. According to the *simple model*, over two percent of workers made an EE transition toward a higher paying job in the 1980s. The *OTJ model*, which includes on-the-job wage growth, indicates a somewhat lower level of EE mobility, because it does not attribute all positive wage changes to EE moves. The *full model* shows an even lower level of EE mobility. The reason is that, in this model, the rate at which workers separate into unemployment is higher at the bottom of the wage distribution. *Ceteris paribus*, this feature leads to an upward shift in the wage distribution relative to the offer distribution even in the absence of EE mobility. Consequently, the level of EE mobility required to generate a given rightward shift in the wage distribution relative to the offer distribution is lower.

All three models indicate a pronounced decline in EE mobility since the 1980s. For instance, according to the simple model, EE mobility rate fell by 50 percent from 1980 to 2020. The decline was particularly pronounced during the 1990s, and briefly reverted after the Pandemic, but has since started to decrease again.

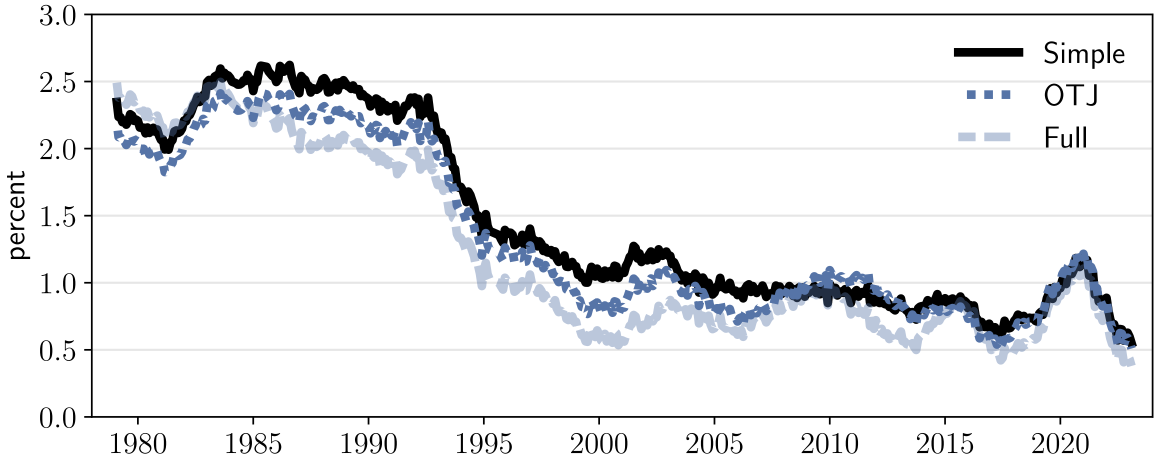


Figure 1: Estimated EE mobility rate in the simple model (black), the OTJ model with on-the-job wage growth (dark blue dotted), and the full model (light blue dashed).

Figure 2 compares our estimate of EE mobility with raw data. Since all three models deliver similar results, for brevity we focus on the *simple model* (solid black). The raw series from the CPS shows a a pronounced decline in EE mobility during the early 2000s (dashed light blue). Fujita, Moscarini and Postel-Vinay (2023) argue, however, that changes in non-response rates bias this series toward finding an excessively large decline. Consistent with this view, the decline in EE mobility according to the SIPP is less pronounced (dotted dark blue). Contrasting our structural estimate with the SIPP, it is evident that a large share of EE mobility is *not* to higher paying jobs. This conclusion is validated by the *SIPP (up)* series, which plots the monthly EE mobility rate to higher wage 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.

Figure 3 decomposes the change in the EE mobility rate in the *simple model* into the probability that a worker receives an outside job offer versus the probability that she accepts it. This decomposition requires the assumption that the employed sample from the same offer distribution as the unemployed. Since the mid-1980s, the decline in EE mobility is entirely due to a lower probability that an employed worker receives a job

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

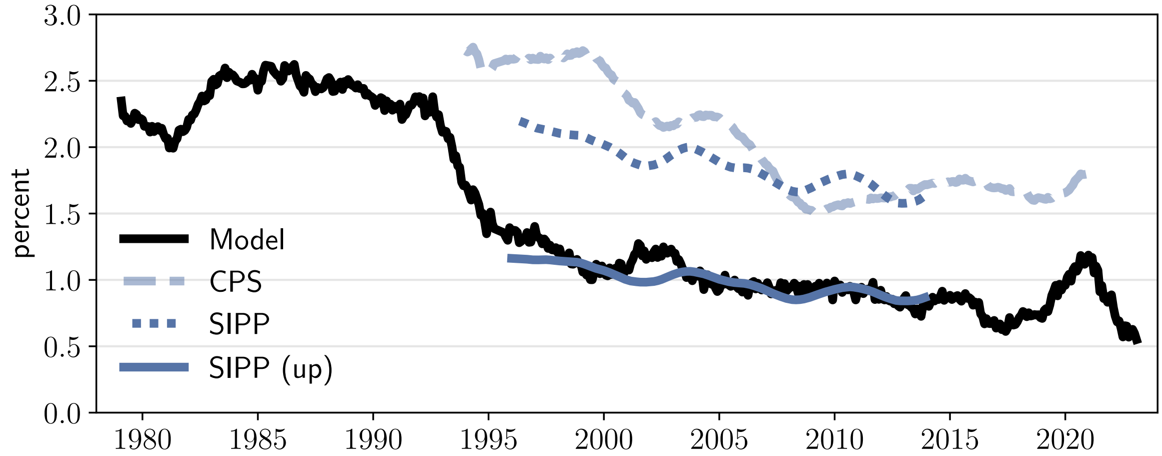


Figure 2: Comparison between the EE mobility rate implied by the simple model (black), the raw overall EE mobility rate in the CPS (dashed light blue) and the SIPP (dotted dark blue), and the raw EE mobility rate towards higher-paying jobs in SIPP (solid dark blue).

offer. In contrast, workers have become more likely to accept an extended offer.

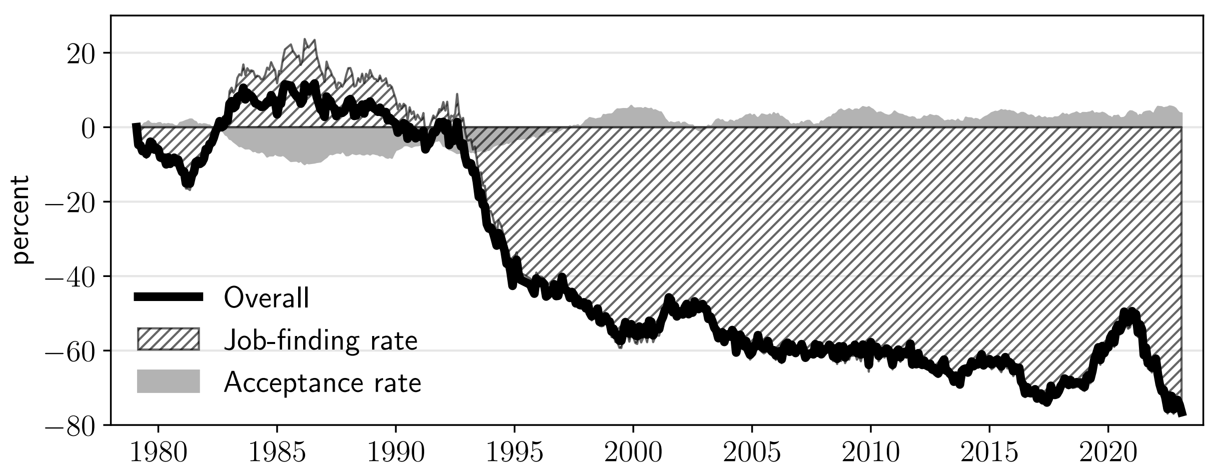
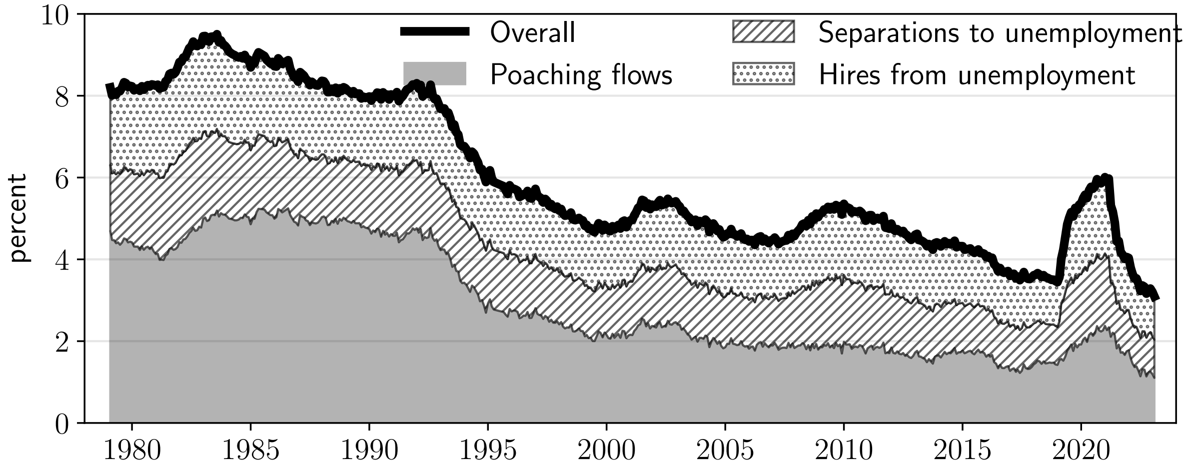
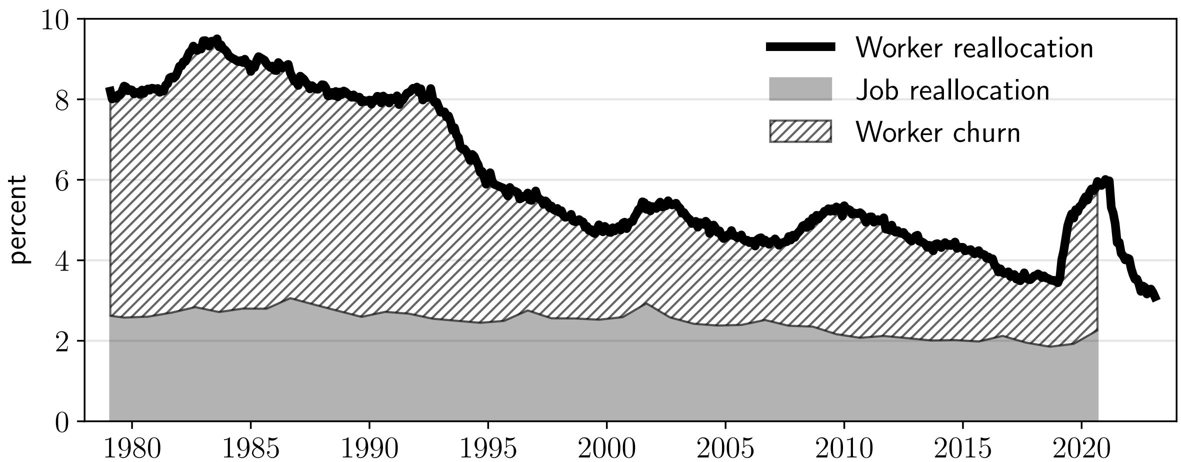


Figure 3: Decomposition of EE mobility decline into the job-finding probability and the acceptance probability.

Figure 4 illustrates the implications for overall worker mobility, focusing again on the *simple model*. Roughly half of worker flows take the form of EE transitions toward higher paying jobs (panel a). Moreover, lower EE mobility accounts for 62 percent of the overall decline in worker reallocation, with reallocation through unemployment responsible for the remaining decrease. Since the latter also declined, the overall worker reallocation rate fell precipitously from over eight percent of employment per month in the 1980s to four percent prior to the Pandemic. 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 4: Worker relocation broken down as stated in equations (4) and (5).

4.2 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

[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.

wage growth. Figure 6 quantifies this effect based on equation (6) 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 (6) and on-the-job wage growth, ξ. 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 this result, we compare this model-implied measure to wage growth due to EE moves to higher paying jobs in the SIPP (solid blue). 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.

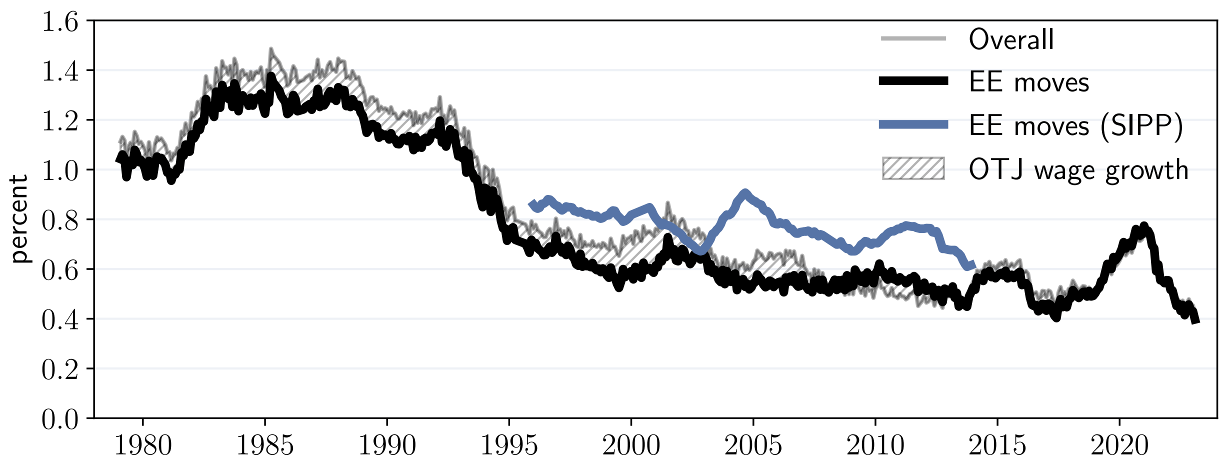


Figure 5: Average wage growth associated with EE mobility in the OTJ model and in the SIPP.

Figure 6 shows average wage gains *conditional* on making an EE transition in the model as well as in the SIPP data. The latter are for workers moving to higher paying jobs.[14] Both the structural model and the raw SIPP data indicate substantial wage growth associated with EE mobility toward higher paying jobs. According to both the structural model and the SIPP, the average wage gain conditional on moving to a higher paying job increased over time. The fact that returns to mobility rose suggests that the decline in EE mobility is not the result of workers being better matched with their current jobs.

[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.

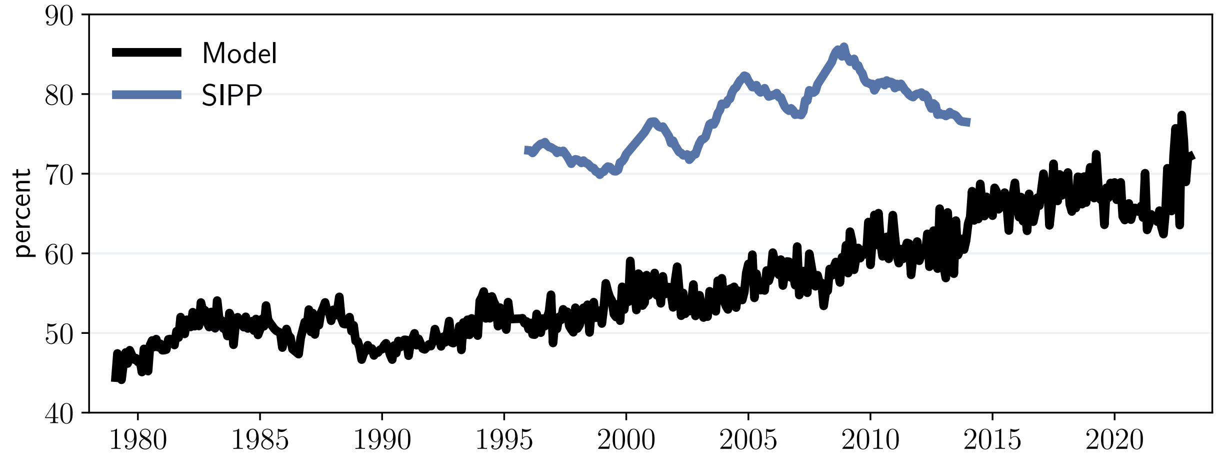


Figure 6: Wage growth conditional on switching to a higher-paying employer in model (black) and in the SIPP (blue).

5 Results by subgroups

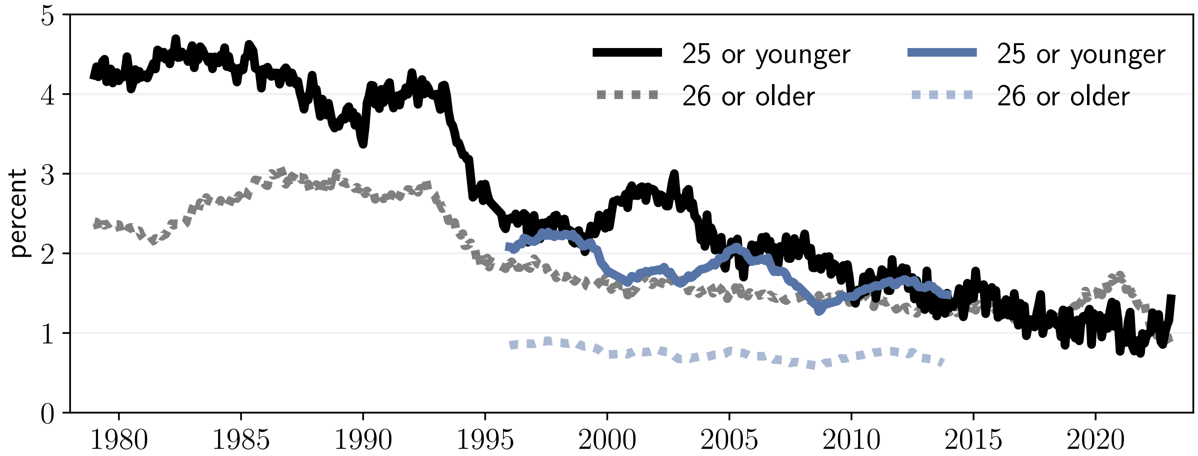
In this section, we study trends in EE mobility and wage growth within age, race, gender, and education subpopulations. To that end, we restrict attention to a particular subpopulation and replicate the methodology of sections 2–3 for that subpopulation only.

5.1 By age

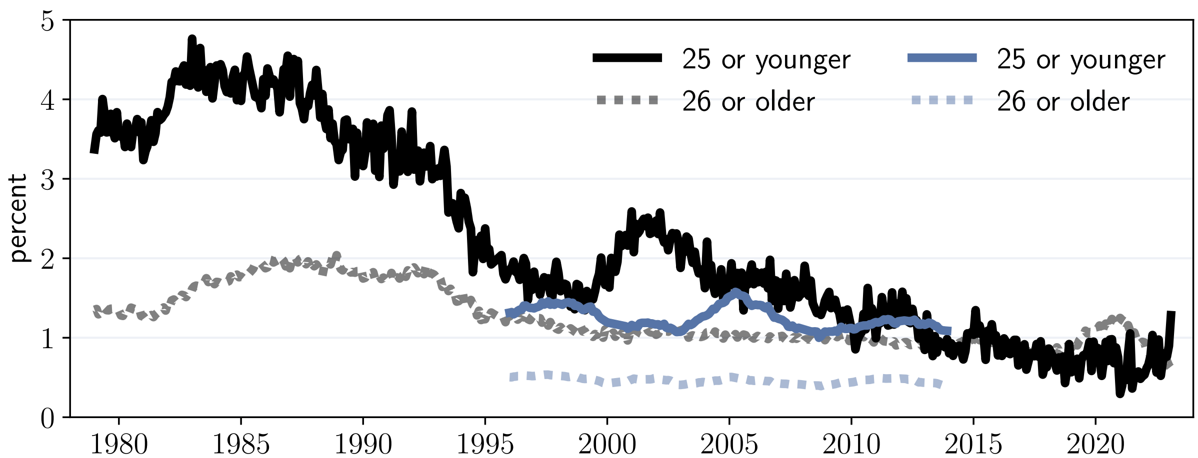
Figure 7 shows results for workers 25 and younger (solid black) and workers 26 and older (dotted gray). We include in blue also the corresponding moments from the raw SIPP data. While younger workers are more mobile, they experienced a larger decline in EE mobility over the past 40 years (panel a). These 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).

5.2 By gender

EE mobility and the associated wage growth were larger for women than men in the 1980s, a period when women made rapid advancements in the labor market (Figure 8). However, both measures fell more rapidly for women over time, at the same time as the gender pay gap stopped to converge (Goldin, 2014).



(a) EE mobility rate.

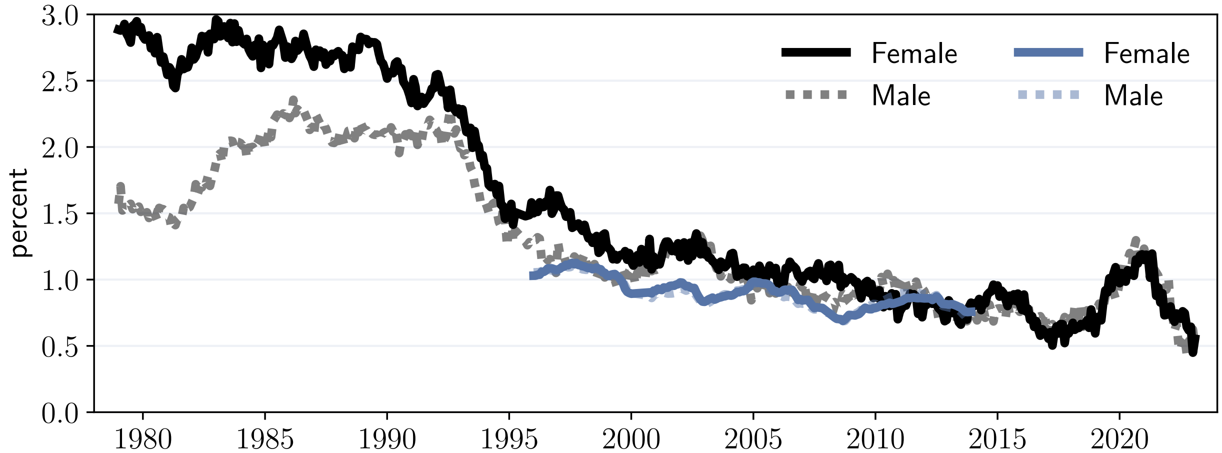


(b) Average wage growth associated with EE mobility.

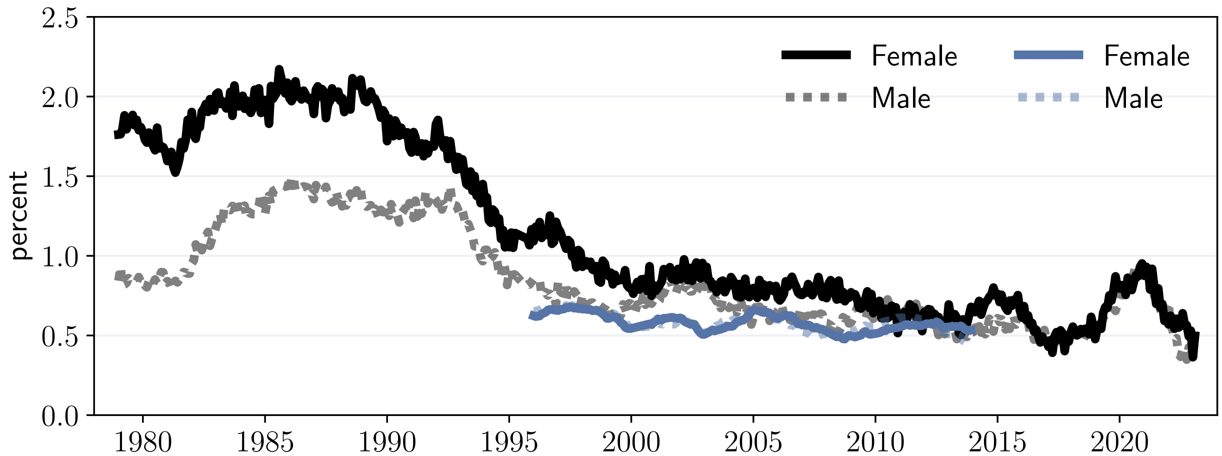
Figure 7: EE mobility and associated wage growth by age in the model (black) and SIPP (blue). All mobility is to higher-paying jobs.

5.3 By race

According to Figure 9, the level of and the change in EE mobility over the past 45 years is broadly comparable for whites and blacks (panel a). In terms of the wage growth associated with mobility, however, blacks experienced higher associated wage growth in the 1980s, which was a period of a closing white-black wage gap. That is, blacks experienced higher wage growth conditional on making an EE transition in the 1980s. Over time, however, wage growth due to EE mobility declined particularly for blacks (panel b).



(a) EE mobility rate.

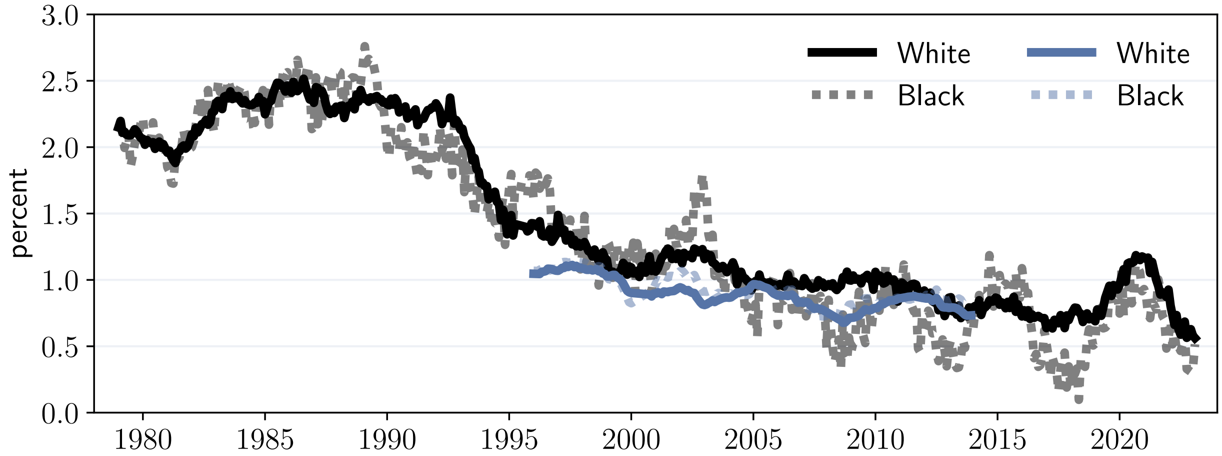


(b) Average wage growth associated with EE mobility.

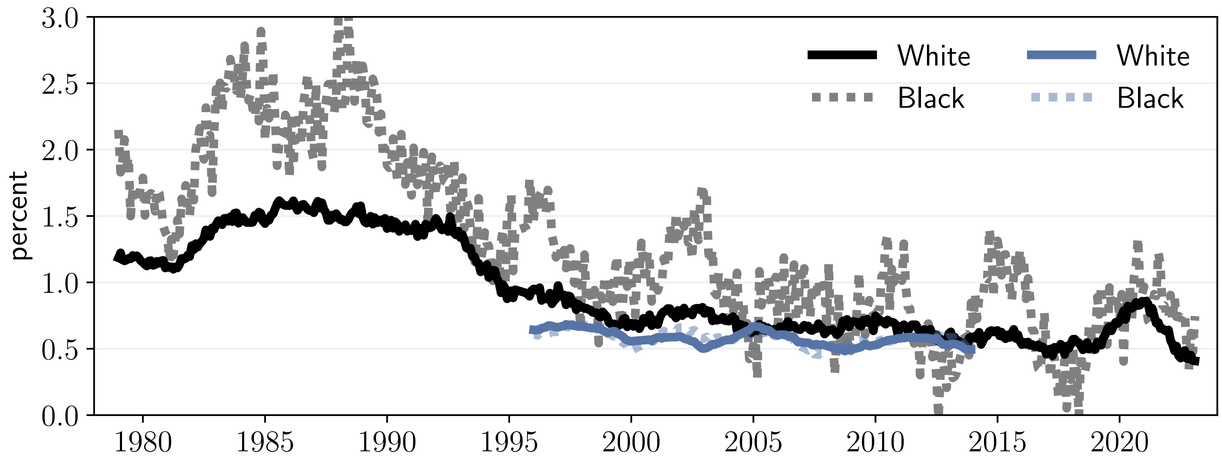
Figure 8: EE mobility and associated wage growth by gender in the model (black) and SIPP (blue). All mobility is to higher-paying jobs.

5.4 By education

Figure 10 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 pattern flipped, so that today those with a degree are more likely to make an EE transition toward a higher paying job. The pattern for the wage growth due to EE mobility is even starker—those with a degree always experienced greater wage growth due to EE mobility, and the gap further widened over time (panel b).



(a) EE mobility rate.



(b) Average wage growth associated with EE mobility.

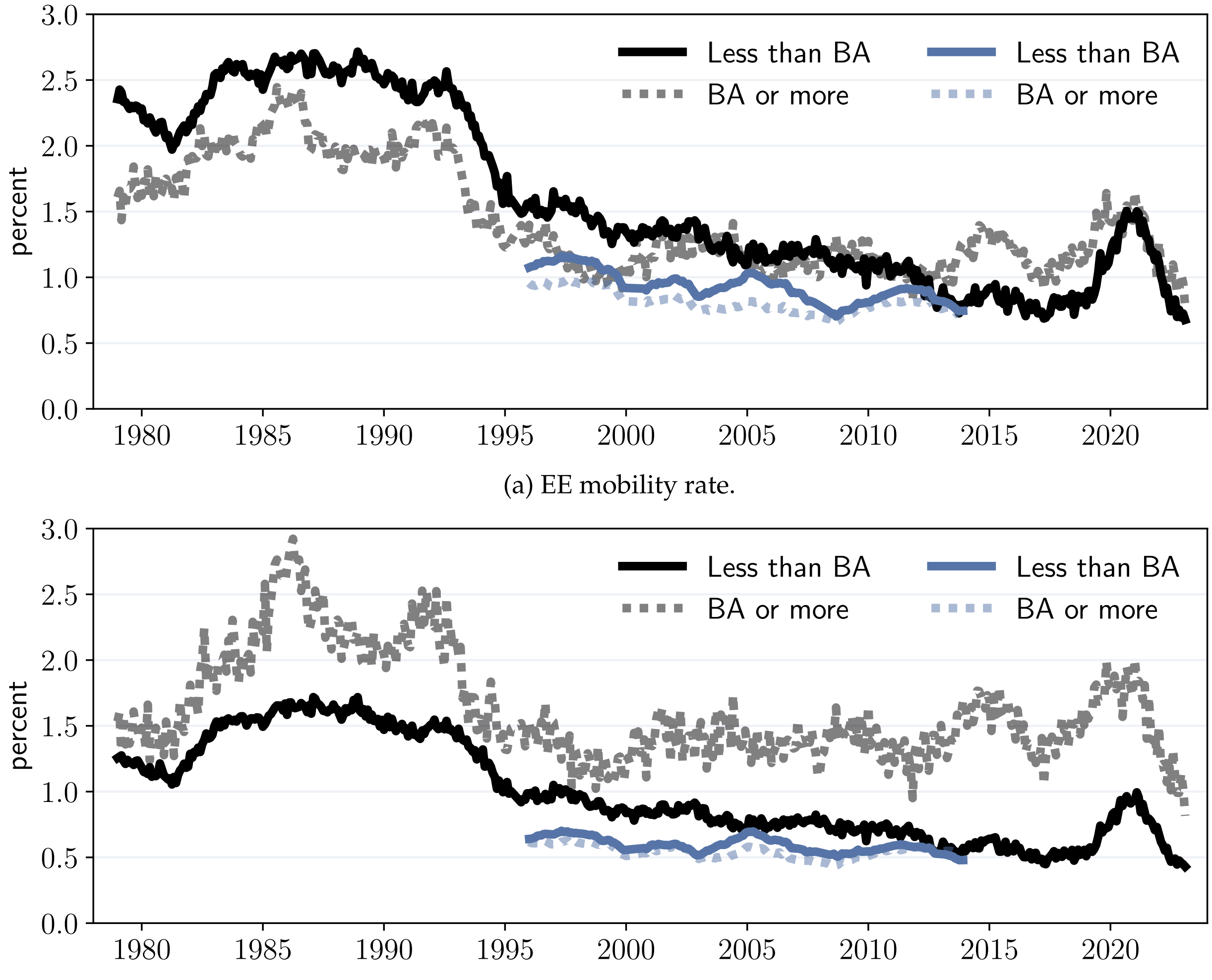
Figure 9: EE mobility and associated wage growth by race in the model (black) and SIPP (blue). All mobility is to higher-paying jobs.

6 Robustness

This section turns to two robustness exercises. First, we address concerns about the pool of recently unemployed workers being different in unobservable dimensions from the overall pool of employed. Second, we show that we obtain similar results if we instead include as unemployed all non-employed workers.

6.1 Unobservable heterogeneity

Although we control for observable demographic characteristics, recently unemployed workers might differ in unobservable dimensions from their identical-looking peers who



(a) EE mobility rate.

(b) Average wage growth associated with EE mobility.

Figure 10: EE mobility and associated wage growth by education in the model (black) and SIPP (blue). All mobility is to higher-paying jobs.

were not. 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 wages at a prior date. Specifically, the ORG provides two wage observations, allowing us to assess how the pool of hires from unemployment differ from the overall pool of workers by their residual wage 10–12 months earlier.[15] Alternatively, we use the ASEC, based on which we can construct the average residual log hourly wage in the previous year of hires from unem-

[15]We observe prior wages in survey month 4, and we can classify individuals as hires from unemployment in survey months 6, 7 and 8 (since one lagged month of data is required to indicate prior employment status). Hence, in survey month 6, prior wages refer to wages 10 months earlier, in survey month 7 they refer to wages 11 months earlier, and in survey month 8 to wages 12 months earlier.

ployment relative to all workers. The advantage of the latter is that it does not condition on employment 10–12 months earlier (wages in the ORG are only recorded for those who are currently in wage employment), but only some work history in the previous year. Its drawback is that it is smaller, since it requires the respondent to be in the survey in March.

Figure 11 plots the average previous residual log wage of hires from unemployment relative to all workers. Hires from unemployment earned 5–15 percent lower residual wages in the past, suggesting that they are worse in unobservable dimensions. Alternatively, this pattern would arise in the *full model* in which low paid jobs are more likely to terminate. We stress, however, that neither series displays any pronounced time trend. Consequently, while our estimated EE mobility series may be biased in levels, it is less clear why such unobserved heterogeneity would bias the estimated *changes*.

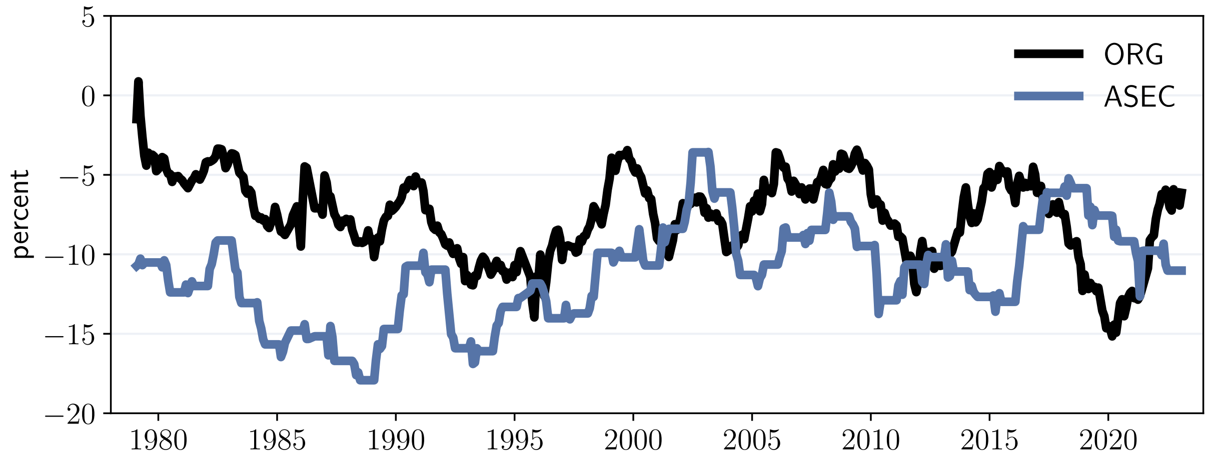


Figure 11: Previous residual log wages of hires from unemployment relative to all workers measured 10–12 months earlier in the ORG (black) or in the previous calendar year in the ASEC (blue).

To more formally adjust for selection, we further residualize a worker's current residual wage off her prior residual wage. 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 (we focus on the ORG since it is larger than the ASEC). Moreover, non-random attrition from the sample has an independent effect on our estimates by changing the sample. To separate the role of changes in the sample versus selection on unobservables, we also present results without unobservable controls, but with the sample restricted to those in their second ORG month with a valid wage in their first ORG month. We refer to this as the *restricted model*.

6.2 Non-employed versus unemployed

In our benchmark, we include in the pool of unemployed only those who are unemployed following the standard definition. We refer to this as the *u-specification*. Flows in and out of non-participation are, however, sizeable (Krusell et al., 2017). To assess the robustness of our results to this assumption, we consider the polar opposite assumption of labeling all non-employed as unemployed. We refer to this as the *n-specification*.

6.3 Results

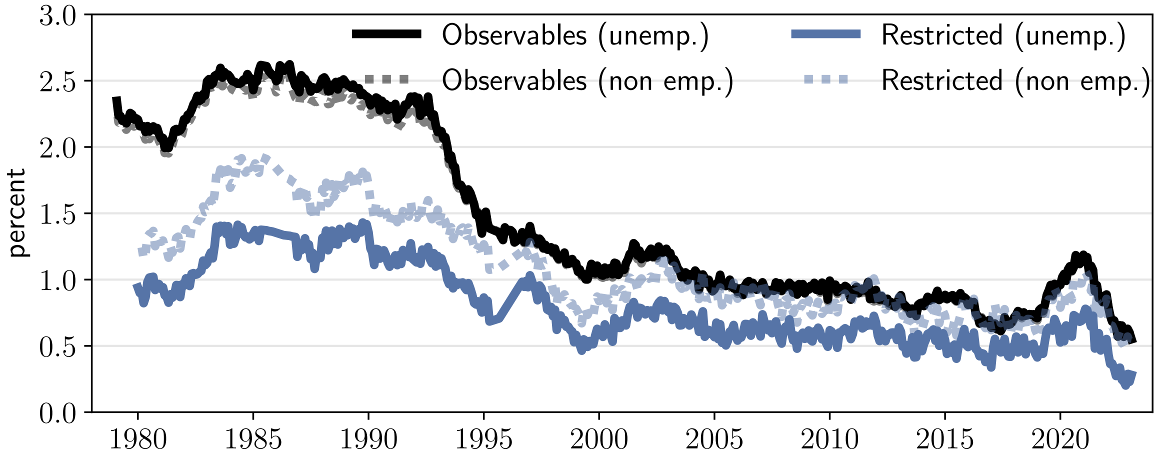
Figure 12 shows the results from these robustness exercises for EE mobility. To separate the impact of changes in the sample versus unobservable controls, we show in panel a the baseline *observables model* and the *restricted model*. In panel b, we show the *restricted model* and the restricted model with current residualized wages further residualized off the previous residual wage, which we refer to as the *unobservables model*. We focus throughout on the *simple model*, and include both the *u specification* and *n specification*.

The level of EE mobility is lower according to the *restricted model*, suggesting that by requiring employment 12 months earlier, we drop some highly mobile workers. In contrast, the addition of controls for the prior wage only marginally affects our estimates, despite the fact that hires from unemployment have lower prior residual wages. The reason is that these differences are small relative to overall wage dispersion. Counting all non-employed as unemployed has little effect on EE mobility in the *observables model*, while it increases our estimate somewhat in the *restricted model*. All robustness specifications, however, indicate a significant decline in EE mobility since the 1980s.

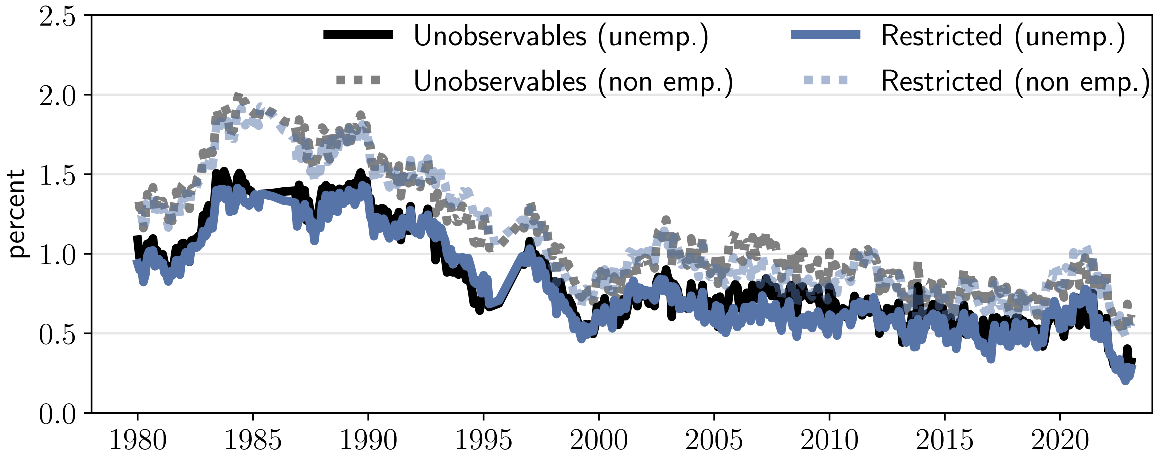
Figure 13 presents results for wage growth associated with EE mobility under these alternative specifications. As for EE mobility, the *restricted model* indicates lower wage growth due to EE mobility than the *observables model*, which is unsurprising given that mobility is lower (panel a). Further residualizing current wages off previous wages has only a small effect on estimated wage growth due to EE mobility (panel b). Again, all specifications point to a substantial decline in wage growth due to the fall in 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. Our



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

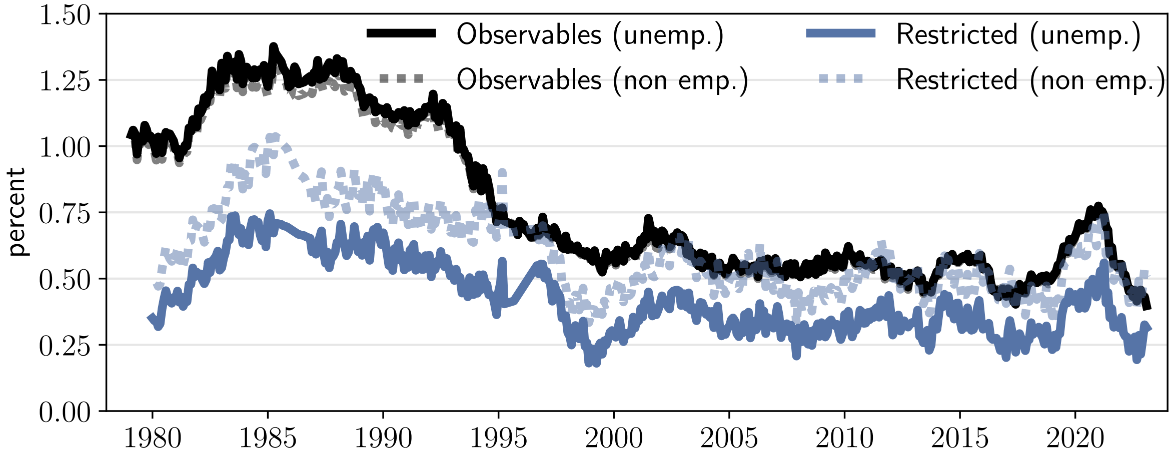


(b) EE mobility in the unobservables (black) and restricted (blue) models.

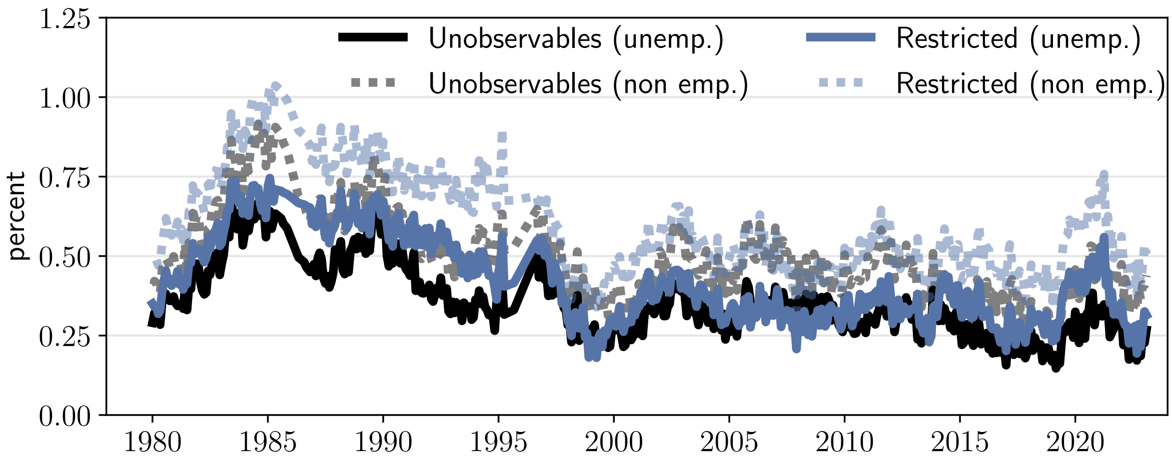
Figure 12: EE mobility rate in robustness specifications.

methodology has the advantage that it allows us to measure worker flows during a period of rapid changes in the labor market, it sidesteps issues associated with sample non-response in the CPS, and it isolates the component of overall 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, minorities, and those without a college degree experienced a particularly large decline in wage growth due to less EE mobility over this period. Future work should investigate further the causes behind the declines in U.S. labor market fluidity and whether policy can play a role in fostering a more dynamic labor market.



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



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

Figure 13: Average wage growth associated with EE mobility in robustness specifications.

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