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

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March 22, 2024

Abstract

We develop a methodology to consistently estimate *employer-to-employer* (EE) mobility toward higher paying jobs based on publicly available microdata from the *Current Population Survey*, and use it to document three trends over the past half century. First, such EE mobility fell by half between 1979 and 2023. Second, its decline reduced annual wage growth by over one percentage point. Third, the decline was particularly pronounced for women, those without a college degree, and new cohorts. We find little support for the notion that the decline resulted from workers being better matched with their current jobs or the labor market being worse at matching workers and firms. Instead, based on long-run variation across U.S. states, we present evidence consistent with the view that greater labor market concentration reduced workers' opportunities to transition toward higher paying employers.

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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. We thank Sadhika Bagga, Katarina Borovickova, Ricardo Lagos, Claudia Macaluso and Venky Venkateswaran for useful comments.

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) reallocation toward higher paying jobs accounts for a third of workers' wage growth during the first 10 years of their careers. More recently, macroeconomists have stressed that such reallocation also plays a critical role for aggregate economic performance, by reallocating workers from less to more productive firms (Lentz and Mortensen, 2012; Moscarini and Postel-Vinay, 2017). Yet, despite its importance for both micro and macroeconomic outcomes, little is known about long-run trends in such reallocation.

The reason is twofold. First, the data required to measure the frequency at which workers move from one employer to another without an intervening spell of nonemployment are only available since the mid-1990s. Furthermore, the series available from the main labor force survey in the U.S., the *Current Population Survey* (CPS), suffers from bias arising from changes in survey methodology and non-response over time (Fujita, Moscarini and Postel-Vinay, Forthcoming).[1] Second, many EE transitions in the raw data are toward lower paying jobs (Tjaden and Wellschmied, 2014; Sorkin, 2018). Of particular interest for macroeconomic performance, however, is EE mobility toward higher paying, more productive jobs—what we henceforth refer to as *allocative EE mobility* (Bilal et al., 2022; Elsby and Gottfries, 2022).[2]

This paper proposes a methodology that overcomes these dual challenges, and uses it to document three trends in allocative EE mobility over the past half century in the U.S. based on publicly available micro data from the CPS. First, allocative EE mobility fell in half between 1979 and 2023. Second, *ceteris paribus* the decline reduced annual wage growth by over one percentage point. Third, the fall was particularly pronounced for women, those without a college degree, and recent cohorts. In terms of potential explanations, we find little support for the notion that allocative EE mobility is lower today because workers are better matched with their current employers (Mercan, 2017; Pries and Rogerson, 2022) or the labor market is worse at matching workers and firms. Instead, based on long-run variation across U.S. states, we provide evidence consistent with the view that greater labor market concentration reduced workers' opportunities to transition toward higher paying employers (Bagga, 2023; Berger et al., 2023; Jarosch, Nimczik and Sorkin, 2024).

Our point of departure is a prototypical job ladder model in the spirit of Burdett and Mortensen (1998). In each period, non-employed 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 (Faberman et al., 2022). If the worker accepts the job, she supplies a unit of labor at the specified wage until either she finds a

[1] An alternative, arguably superior, series is available from the *Survey of Income and Program Participation* (SIPP), but high-quality data are only available for 1996–2013.

[2] We borrow this terminology from the literature, but caution that it should be interpreted from the perspective of a social planner who does not face any frictions and who aims to maximize aggregate output.

new job offering a higher wage or her job exogenously terminates and she becomes non-employed.

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 separated to non-employment between periods t and $t+1$, the number of non-employed workers in period t who found a job paying at most w in period $t+1$, and the fraction who made an EE transition to a job paying more than w between t and $t+1$. Knowledge of all the other objects in this relationship allows us to recover the EE transition probability.

The logic is best explained via the example in Figure 1. Consider a labor market in steady-state in which eight workers earn a wage below w in each period t. Suppose that between periods t and $t+1$, one of these workers separates to non-employment, while two workers are hired from non-employment into jobs paying less than w. We are interested in what fraction $x(w)$ of workers employed at a wage less than w that made an EE transition to jobs paying more than w. It solves

$$\underbrace{8}_{\text{earning} \leq w \text{ at } t} - \underbrace{1}_{\text{employment outflows}} + \underbrace{2}_{\text{employment inflows}} - \underbrace{8x(w)}_{\text{EE moves from} \leq w \text{ to} > w} = \underbrace{8}_{\text{earning} \leq w \text{ at } t+1}$$

In this example $x(w) = 12.5\%$. That is, 12.5 percent of workers earning less than w made an EE transition to a job paying more than w. Knowledge of this share as well as the share of all workers who are paid w for each wage w allows us to compute the overall EE transition probability to higher paying jobs. In fact, the example easily generalizes to an economy away from steady-state.

While our methodology allows us to provide new evidence on long-run trends in allocative EE mobility, it is subject to at least three critiques. First, we assume that after taking out the effect of observable characteristics such as experience, residual wage growth is driven by EE mobility. Although this assumption is consistent with recent work highlighting the central role of EE mobility for wage dynamics (Karahan et al., 2017; Moscarini and Postel-Vinay, 2017; Ozkan, Song and Karahan, 2023; Tanaka, Warren and Wiczer, 2023), wages may also grow on-the-job with tenure. To speak to this possibility, we extend the model to allow for residual wage growth with tenure. Second, we abstract from unobserved heterogeneity, which a recent literature stresses as an important determinant of worker flows (Hall and Kudlyak, 2019; Morchio, 2020; Gregory, Menzio and Wiczer, 2021; Ahn, Hobijn and Şahin, 2023).[3] To address this issue, we use the fact that we can observe wages twice to residualize a worker's current wage also off her previous wage as a control for unobservable characteristics. Third, while allocative EE mobility may be the most relevant for macroeconomic performance, many EE transitions are associated with wage cuts. To quantify its importance and assess whether abstracting from it biases our estimate of allocative EE mobility, we incorporate *undirected* EE mobility following Jolivet, Postel-Vinay and Robin (2006).

To measure the inputs required to estimate allocative EE mobility, we use data from the basic monthly survey and the *Outgoing Rotation Group* (ORG) of the CPS. Specifically, we record an

[3] Clark and Summers (1979) originally stressed the importance of unobserved heterogeneity for labor market flows.

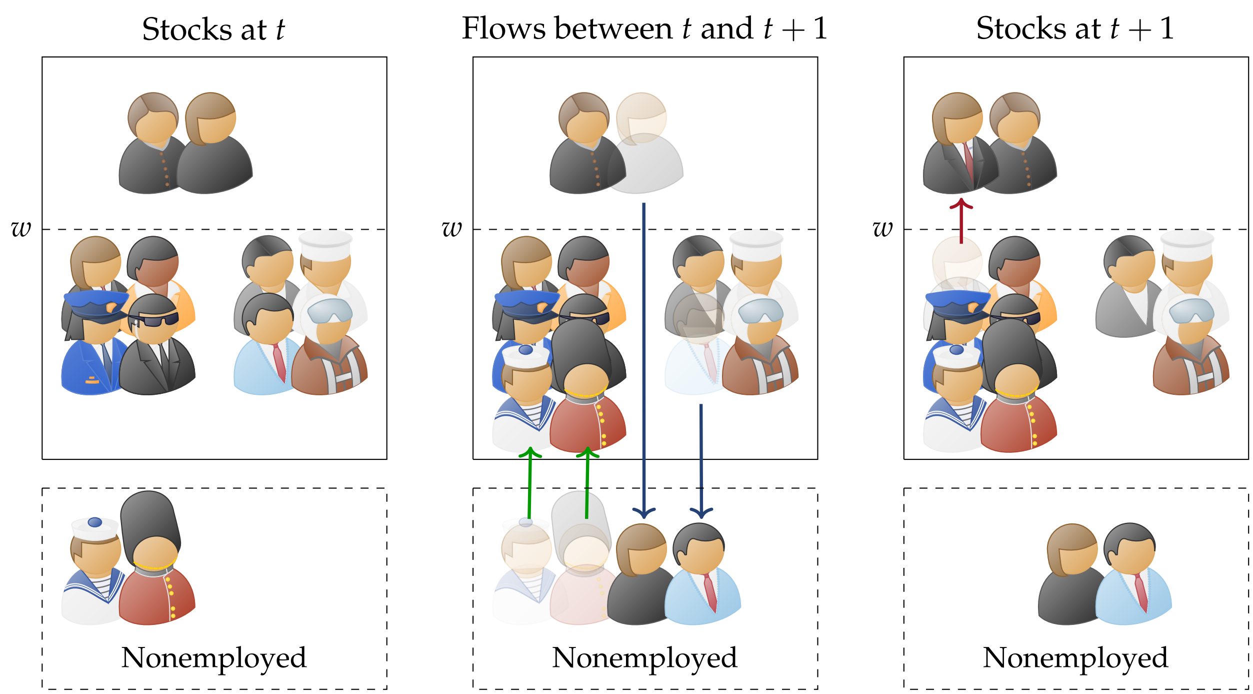

Figure 1: Identifying EE mobility using microdata. Eight individuals earn less than or equal to w in each period t. Between date t and $t+1$, we observe two individuals entering employment at a wage less than or equal to w from nonemployment (green arrows), and we observe one individual earning at most w and another earning more than w separate into nonemployment (blue arrows). We conclude (red arrow) that one individual must have moved to a new job at a wage higher than w, corresponding to 12.5% of workers employed at a wage of at most w making an EE transition up the job ladder to a higher wage.

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. Since our model assumes that all wage growth is due to EE mobility, we residualize wages on a rich set of demographic controls that account for wage growth with experience as well as for the impact of aggregate trends. Subsequently, we measure the share of workers earning less than (residual) wage w in months t and $t+1$, the share of hires from non-employment who earn a wage below w in month $t+1$, and the share of employed workers in month t who are non-employed in period $t+1$. Through the lens of our theory, these objects are sufficient to recover allocative EE mobility in month t.

We contrast our measure of allocative EE mobility to raw EE mobility in the CPS since 1994 and in the SIPP between 1996 and 2013. We find that raw EE mobility is higher in the CPS than in the SIPP, which in turn is higher than allocative EE mobility. Raw EE mobility *toward a higher paying job* in the SIPP is, however, close to our estimate of allocative EE mobility. Furthermore, consistent with evidence that changes in non-response rates in the CPS bias raw EE mobility toward an excessively large decline (Fujita, Moscarini and Postel-Vinay, Forthcoming) as well as the time trend in both raw EE mobility and EE mobility toward higher paying jobs in the SIPP, allocative EE mobility shows a smaller decline since the early 2000s.

Having validated our methodology, we use it to establish three trends in allocative EE mobility in the U.S. over the past half century. First, allocative EE mobility declined sharply since the mid-1980s, falling from 1.5 percent per month 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 minor effect on our estimates, due to the fact that such wage growth is uniformly small (see Molloy et al., 2016, for similar evidence). Furthermore, although hires from non-employment earned 5–15 percent lower residual wages in their previous job, such negative selection on unobservables did not change over time. Consequently, controlling for it does not affect our finding of a large decline in allocative EE mobility over the past decades. Finally, while undirected EE mobility is quite common, it did not change systematically over the last 30 years (when we can measure it). Moreover, allowing for it does not change our conclusion that allocative EE mobility declined substantially over the past decades.

Second, *ceteris paribus* the fall in allocative EE mobility is associated with a sizeable decline in wage growth, as workers climbed the job ladder less. Our estimates imply that allocative EE mobility contributed over three percentage points to annual real wage growth in the 1980s. As such mobility declined, so did the wage gains associated with it. In fact, despite an increase in the average wage gain conditional on an allocative EE transition, the declining frequency of such transitions contributed to over one percentage point weaker annual wage growth today.

Third, although the decline in allocative EE mobility and its associated wage growth were pervasive across demographic groups, it was particularly pronounced for women, workers without a college degree, and young workers. Furthermore, under the assumption that mobility is flat with age later in life—as predicted by prototypical job ladder models—we can decompose the change in allocative EE mobility over time into a time, age and cohort effect (Heckman, Lochner and Taber, 1998; Lagakos et al., 2018). We find an important role for cohort effects in accounting for the aggregate decline in allocative EE mobility. That is, recent cohorts are less mobile than older ones, controlling for factors that affect mobility of all cohorts.

Having established these long-run trends in allocative EE mobility and its associated wage growth, we proceed to evaluate three prominent potential explanations for them. One possibility is that workers today are better matched in the labor market, so that they are less likely to accept an outside job offer (Mercan, 2017; Pries and Rogerson, 2022). Under the standard assumption that the non-employed and employed sample wage offers from the same distribution, we show that we can separately identify the job finding probability of the employed and the probability that they accept an extended offer. We estimate that the acceptance probability modestly *rose* over time.[4] Hence, the decline in allocative EE mobility is entirely accounted for by a lower probability that an employed worker receives an outside job offer. Molloy et al. (2016) draw a similar conclusion that workers are not better matched today based on the lack of a long-run trend in starting wages.

[4]We stress that this refers to the acceptance probability of the *employed*, not the acceptance probability of the *non-employed*, which Birinci, See and Wee (2023) find has declined.

Second, the decline in the job finding probability of the employed could, for instance, be the result of changes in the efficiency with which the labor market matches workers and firms. Alternatively, firms might advertise fewer job openings today. Benchmark equilibrium theories of the labor market predict that such forces *proportionately* reduce the job finding probability of the employed and non-employed. In contrast, we find that the job finding probability of the employed declined by much more than that of the non-employed, suggesting that the decline in EE mobility was not primarily the result of changes in matching efficiency or firms' recruitment efforts.

Our results instead point to factors that particularly impacted the job finding prospects of the employed. Two hypotheses consistent with this pattern are the increased use of non-compete agreements that may discourage on-the-job search (Gottfries and Jarosch, 2023) or greater labor market concentration which limits workers' outside options (Bagga, 2023; Berger et al., 2023; Jarosch, Nimczik and Sorkin, 2024). In line with the latter view, we document that the job finding probability of the employed declined disproportionately in U.S. states that saw larger increases in labor market concentration. Specifically, we replicate our analysis for each state plus Washington D.C., and merge the resulting data set with measures of the number of firms per worker and the prevalence of large firms from the U.S. Census *Business Dynamic Statistics* (BDS). We project the job finding probability of the employed at the state-5-year period level on various measures of labor market concentration, controlling for state and time fixed effects. Our results reveal that labor market concentration is strongly negatively correlated with the job finding probability of the employed, but only weakly so with that of the non-employed. Indeed, the point estimate would imply that the increase in labor market concentration observed at the national level between 1979 and today accounts for more than 40 percent of the fall in allocative EE mobility over this period.

Literature. This paper contributes to a literature studying the decline in economic "dynamism" in the U.S. over the past fifty years. Following Steve Davis' and John Haltiwanger's pioneering work, several papers document large declines in the rates of job creation and destruction in the U.S. since the early 1980s (Davis and Haltiwanger, 2014; Decker et al., 2016). Due to data limitations, however, less is known about long-run trends in worker flows, in particular EE mobility.

Fallick and Fleischman (2004) is the first paper to use the introduction of "dependent interviewing" techniques to the CPS to estimate EE mobility back to 1994. Fujita, Moscarini and Postel-Vinay (Forthcoming) note that selective non-response biases the CPS toward showing an excessively large decline in EE mobility, and propose a corrected version that displays a more muted decline. Hyatt and Spletzer (2013), Hyatt (2015) 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. Several papers proxy the EE transition probability using the number of employers a respondent had in the previous calendar year (Blanchard and Diamond, 1990; Shimer, 2005; Diamond and Şahin, 2016; Molloy et al., 2016), but this is an imperfect proxy because it risks misclassifying, for instance, employment-unemployment-employment transitions as EE transitions. Hyatt and Spletzer (2016, 2017) and Molloy, Smith and Wozniak (2024) infer changes in worker mobility based on the tenure distribution. In addition to allowing us to consistently estimate EE mobility starting in 1979, an advantage of our methodology is that it isolates the component of EE mobility that is toward higher paying jobs. Jolivet, Postel-Vinay and Robin (2006) apply a job ladder model similar to ours to cross-country data in order to infer the rate at which workers move up the job ladder. Our motivation is shared by Shimer (2012), who uses a parsimonious model of labor market flows to unemployment duration data to infer the separation probability to and job finding probability from unemployment starting in 1948.

Our paper is also related to a rapidly growing literature that studies the impact of labor market power on wages and employment (Macaluso, Hershbein and Yeh, 2019; Azar et al., 2020; Prager and Schmitt, 2021; Azar, Marinescu and Steinbaum, 2022; Berger, Herkenhoff and Mongey, 2022; Benmelech, Bergman and Kim, 2022; Handwerker and Dey, 2022; Rinz, 2022; Caldwell and Danieli, 2024). Most closely related, Bagga (2023) finds a positive correlation between EE mobility and the ratio of firms to workers across U.S. local labor markets. Due to data limitations, however, she is restricted to analyze the cross-sectional relationship, as opposed to the within-state patterns that we study. While both papers lack a credible identification strategy to obtain a causal estimate, within-region variation arguably reduces concerns about third factors driving the correlation. Berger et al. (2023) correlate measures of market concentration with worker flows both across and within local labor markets in Norway between 2006 and 2018. Consistent with our result, they find a negative relationship between the two. Our result complements their finding by offering a longer time series and by providing evidence from the U.S., whose institutional setting may differ in important dimensions from Norway's.

We start by outlining our partial equilibrium job ladder model in section 2. Section 3 discusses the data and our estimation procedure. In section 4, we present three new facts on long-term trends in EE mobility and its associated wage growth. Section 5 evaluates three prominent explanations for the decline in EE mobility. Finally, section 6 concludes.

2 A Prototypical Job Ladder Model

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 probability, and the wage offer distribution are all taken as exogenous. While stylized, an extensive literature finds that this framework is quite 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 in and out of employment. Let e_t denote the employment rate at time t.

Non-employed workers receive job offers with exogenous probability $\lambda_t^n \in [0,1]$. A job offer is a draw of a (log) wage w from an exogenous *wage offer distribution* of the non-employed. Let $f_{t+1}^n(w)$ denote its probability density function (pdf) and $F_{t+1}^n(w)$ its cumulative distribution function (cdf), with support $w \in (-\infty, \infty)$. We assume that non-employed workers accept any job offer they receive.[5] The wage remains fixed for the duration of the match.

With exogenous probability $\lambda_t^e \in [0,1]$, an employed worker receives an outside offer from a wage offer distribution of the employed, whose pdf (cdf) we denote $f_{t+1}^e(w)$ ($F_{t+1}^e(w)$). Since workers choose whether to accept an offer, they only switch to jobs that offer higher wages. We refer to the resulting mobility toward higher paying jobs as *allocative EE mobility*.

Finally, employed workers separate to non-employment 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 number of workers earning wage w at time t, $g_t(w)e_t$, evolves according to

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

Integrating (1) from $-\infty$ to w, applying integration by parts, gives[6]

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

which we can rearrange as

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

We discuss below how to measure $G_t(w)$, $G_{t+1}(w)$, $F_{t+1}^n(w)$, e_t, e_{t+1}, λ_t^n and δ_t in the CPS. Provided these objects, we can estimate the *poaching separation probability* at each wage w based on (2). The

[5]This assumption can be motivated by the fact that no firm would find it optimal to advertise a job paying less than the reservation wage common to all non-employed workers.

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

EE transition probability is then the average poaching separation rate

$$EE_t \quad = \quad \lambda_t^e \int_{-\infty}^{\infty} \Big(1 - F_{t+1}^e(w)\Big) dG_t(w) \quad = \quad \int_{-\infty}^{\infty} sep_t^e(w) dG_t(w) \tag{3}$$

The EE transition probability can be written as the product of the probability that an employed worker receives a job offer and the average probability of the worker accepting the offer

$$EE_t \quad = \quad \underbrace{\lambda_t^e}_{\text{job finding probability}} \underbrace{\int_{-\infty}^{\infty} \Big(1 - F_{t+1}^e\left(w\right)\Big) dG_t\left(w\right)}_{\text{acceptance probability}} \tag{4}$$

Hence, EE mobility can fall either because workers are less likely to receive job offers or because they are less likely to accept them. While we do not need to measure the wage offer distribution of the employed to estimate overall EE mobility (3), the decomposition (4) requires it. Since it is fundamentally unobserved,[7] to implement (4) we follow much of the literature in assuming that the employed sample jobs from the same distribution as the non-employed, $f_t^e(w) = f_t^n(w)$.

2.3 Wage growth due to EE mobility

Wage growth due to EE mobility is the fraction of workers who receive a job offer times the average wage gain conditional on accepting it

$$\Delta w_t^{EE} \quad = \quad \lambda_t^e \int_{-\infty}^{\infty} \int_{w}^{\infty} \Big(\tilde{w} - w\Big) dF_{t+1}^e(\tilde{w}) dG_t(w) \quad = \quad \lambda_t^e \int_{-\infty}^{\infty} \int_{-\infty}^{w} \Big(w - \tilde{w}\Big) dG_t(\tilde{w}) \; dF_{t+1}^e(w)$$

Integrating by parts and using the fact that $\lim_{w \to \infty} F_{t+1}^e(w) = 1$, we have

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

[7] Although the wage distribution of new hires from employment can be inferred in the CPS since 1994, it is not the same as the wage *offer* distribution of the employed, since employed workers reject some wage offers.

$$= \int_{-\infty}^{\infty} sep_t^e(w) G_t(w) dw \tag{5}$$

2.4 Identification

To highlight what aspects of the data inform the level of EE mobility, we note that in steady-state, outflows from and inflows into employment coincide, $\lambda_t^n(1-e_t) = \delta_t e_t$. Hence, if the labor market at date t is in steady-state, the law of motion for the wage distribution (2) simplifies to

$$\lambda_t^e \left(1 - F_{t+1}^e(w)\right) = \lambda_t^n \frac{F_{t+1}^n(w)}{G_t(w)} \frac{1-e_t}{e_t} - \delta_t = \delta_t \frac{F_{t+1}^n(w) - G_t(w)}{G_t(w)} \tag{6}$$

Integrating (6) over all wages from $-\infty$ to ∞ delivers

$$EE_t = \underbrace{\delta_t}_{\text{separation probability channel}} \times \underbrace{\int_{-\infty}^{\infty} \frac{F_{t+1}^n(w) - G_t(w)}{G_t(w)} dG_t(w)}_{\text{offer channel}} \tag{7}$$

Ceteris paribus, we will infer a higher EE transition probability if either the separation probability to non-employment, δ_t, or the average deviation between the wage and wage offer distribution is larger. Figure 2 illustrates the intuition by plotting the wage offer and wage distributions based on the data constructed in the next section pooled across all years. The wage distribution first-order stochastically dominates the wage offer distribution, consistent with EE mobility gradually relocating workers toward higher paying jobs. All else equal, more frequent EE transitions increase the gap between the two distributions. That being said, this pattern could also be the result of other forces. We incorporate below extensions to the baseline model that address what we view as the three most plausible alternative explanations of this empirical pattern.

2.5 Three extensions

We now incorporate three extensions of the baseline model above.

On-the-job wage growth. An alternative explanation of the fact that the wage distribution first-order stochastically dominates the wage offer distribution is on-the-job growth in wages. Although our empirical implementation residualizes wages off a rich set of demographic characteristics that capture wage growth with experience (separately by gender-race-education-year) as well as with aggregate factors (state-date fixed effects), residual wages may still grow with tenure at an employer. Such wage growth may, for instance, arise if employers backload wages (Balke and Lamadon, 2022) or counter outside job offers (Postel-Vinay and Robin, 2002). Suppose that

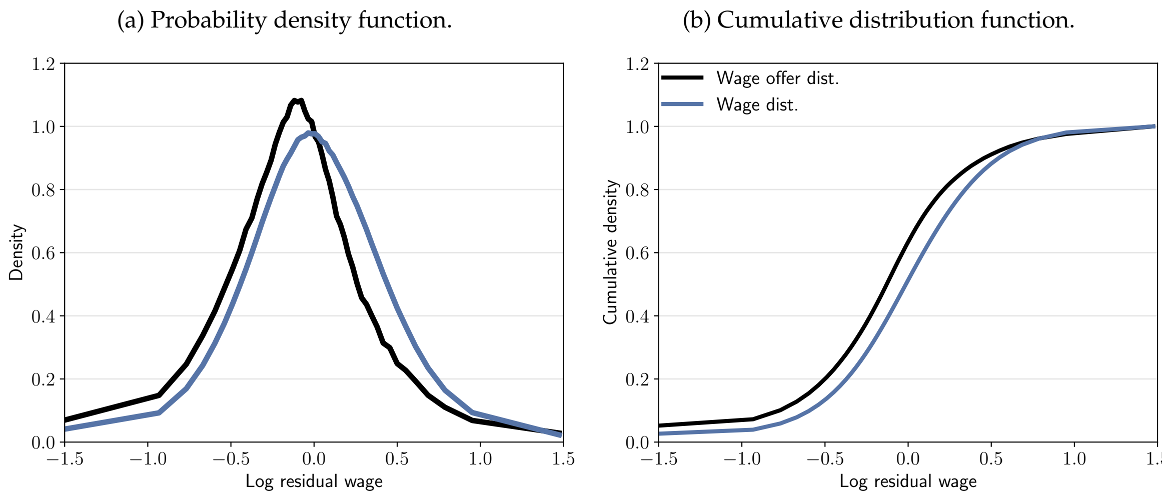

Figure 2: Wage and wage offer distributions in the pooled CPS 1979–2023.

wages grow on the job at rate ξ_t. Then the law of motion for the wage distribution (1) becomes[8]

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

Integrating this from $-\infty$ to w and rearranging

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

We estimate the poaching separation probability $sep_t^e(w)$ and substitute it into (3) to obtain the EE transition probability and into (5) to get the associated wage growth. We refer to this as the *OTJ model* to distinguish it from the *baseline model* above.

Unobserved heterogeneity. A second reason why the wage distribution may dominate the wage offer distribution is if recent hires from non-employment disproportionately consist of workers who generically earn less across all jobs. In this case, the gap between the wage and the wage offer distribution partly reflects observable or unobservable permanent worker heterogeneity.

[8] 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

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

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

As we noted above, we control for a rich set of observable demographic characteristics in our empirical implementation. Yet workers may also differ in unobservable dimensions. To address this, we exploit the fact that we observe wages twice in the ORG, with a 12 month gap. We add a worker's prior wage when we residualize current wages. The main drawback 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 refer to this as the *unobservables model*.

EE mobility with wage cuts. Our model so far does not allow for EE mobility with wage cuts, which is common in the data (Tjaden and Wellschmied, 2014; Sorkin, 2018). To allow for this, we follow Jolivet, Postel-Vinay and Robin (2006) to assume that workers receive an outside job offer that they have to accept with probability λ_t^g, drawn from the wage offer distribution $F_{t+1}^g(w)$.[9] We refer to such mobility as *undirected* EE mobility to differentiate it from the concept of allocative EE mobility discussed above. Then the law of motion (1) becomes

$$\begin{aligned} g_{t+1}(w)\, e_{t+1} \;&=\; g_t(w)e_t - \delta_t g_t(w)e_t - \lambda_t^e\left(1 - F_{t+1}^e(w)\right) g_t(w)e_t - \lambda_t^g g_t(w)e_t \\ &+\; \lambda_t^n f_{t+1}^n(w)(1-e_t) + \lambda_t^e f_{t+1}^e(w)G_t(w)e_t + \lambda_t^g f_{t+1}^g(w)e_t \end{aligned}$$

Integrating this from $-\infty$ to w, applying integration by parts, gives

$$\begin{aligned} G_{t+1}(w)\, e_{t+1} \;&=\; \Big(1 - \delta_t - \lambda_t^e(1 - F_{t+1}^e(w))\Big) G_t(w)e_t + \lambda_t^n F_{t+1}^n(w)(1-e_t) \\ &+\; \lambda_t^g \Big(F_{t+1}^g(w) - G_t(w)\Big) e_t \end{aligned}$$

which we can rearrange as

$$\lambda_t^e\Big(1 - F_{t+1}^e(w)\Big) \;=\; 1 - \frac{G_{t+1}(w)}{G_t(w)}\frac{e_{t+1}}{e_t} + \lambda_t^n \frac{F_{t+1}^n(w)}{G_t(w)}\frac{1-e_t}{e_t} - \delta_t + \lambda_t^g \frac{F_{t+1}^g(w) - G_t(w)}{G_t(w)} \tag{8}$$

Suppose first that such wage offers are drawn from the overall wage distribution at time t, $F_{t+1}^g(w) = G_t(w)$. One microfoundation is if employed workers learn about outside offers from meeting with other employed workers (during conferences, through supplier networks, etc).[10] In this case, the last term in (8) cancels, i.e. such undirected mobility leaves the wage offer distribution unaffected. Consequently, to construct allocative EE mobility, we can proceed identically to the baseline model to compute the poaching separation probability based on (15) and the allocative EE transition probability from (3). The undirected EE transition probability is the difference

[9] One can view this as a reduced form way of modeling amenities as in Hall and Mueller (2018).

[10] Since our methodology to infer allocative EE mobility does not require an assumption on $F_t^e(w)$, we are free to also set $F_{t+1}^e(w) = G_t(w)$ to be consistent with our assumption regarding undirected mobility.

between overall EE mobility and allocative EE mobility

$$\underbrace{\lambda_t^g}_{\text{undirected EE mobility, } EE_t^g} = \underbrace{EE_t^T}_{\text{overall EE mobility}} - \underbrace{EE_t}_{\text{directed EE mobility}} \tag{9}$$

While we can continue to infer allocative EE mobility since 1979 as above, we can only estimate undirected EE mobility since 1994 (when the overall EE transition probability became available in the CPS). We refer to this as the *1st godfather* model (Jolivet, Postel-Vinay and Robin, 2006).

Alternatively, suppose that such job offers are drawn from the distribution of wage offers of the non-employed, $F_t^g(w) = F_t^n(w)$. Using this in (8), the poaching separation probability becomes

$$sep_t^e(w) = 1 - \frac{G_{t+1}(w)}{G_t(w)} \frac{e_{t+1}}{e_t} + \left(\lambda_t^n \frac{1-e_t}{e_t} + \lambda_t^g\right) \frac{F_{t+1}^n(w)}{G_t(w)} - \left(\delta_t + \lambda_t^g\right) \tag{10}$$

Allocative EE mobility is given by (3), while overall EE mobility (9) is

$$\begin{aligned} EE_t^T &= \int_{-\infty}^{\infty} \left(1 - \frac{G_{t+1}(w)}{G_t(w)} \frac{e_{t+1}}{e_t} + \left(\lambda_t^n \frac{1-e_t}{e_t} + \lambda_t^g\right) \frac{F_{t+1}^n(w)}{G_t(w)} - \left(\delta_t + \lambda_t^g\right)\right) dG_t(w) + \lambda_t^g \\ &= \int_{-\infty}^{\infty} \left(1 - \frac{G_{t+1}(w)}{G_t(w)} \frac{e_{t+1}}{e_t} + \lambda_t^n \frac{1-e_t}{e_t} \frac{F_{t+1}^n(w)}{G_t(w)} - \delta_t\right) dG_t(w) + \lambda_t^g \int_{-\infty}^{\infty} \frac{F_{t+1}^n(w)}{G_t(w)} dG_t(w) \end{aligned}$$

Using the overall EE transition probability available since 1994 in the CPS, we recover λ_t^g from

$$\lambda_t^g = \frac{EE_t^T - \int_{-\infty}^{\infty} \left(1 - \frac{G_{t+1}(w)}{G_t(w)} \frac{e_{t+1}}{e_t} + \lambda_t^n \frac{1-e_t}{e_t} \frac{F_{t+1}^n(w)}{G_t(w)} - \delta_t\right) dG_t(w)}{\int_{-\infty}^{\infty} \frac{F_{t+1}^n(w)}{G_t(w)} dG_t(w)} \tag{11}$$

We substitute the estimated λ_t^g into (10) to recover the poaching separation probability, and use this in (3) to construct the allocative EE transition probability. We refer to this as the *2nd godfather* model.

3 Estimation

We now discuss how to bring the model to the data in order to estimate allocative 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).[11] 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, the CPS records the employment status of each household member aged 15 and older, 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.[12] Usual weekly hours are top-coded at 99 hours. In addition, basic demographic characteristics of the household member are collected.[13]

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*.[14] It asks employed respondents how long they have been with their current employer. We use information from the Tenure Supplement to estimate wage growth on-the-job.

[11] The ORG started in 1979, but we are currently in the process of extending our analysis back to 1976 using the May Supplements.

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

[13] 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.

[14] Microdata from the Tenure Supplement exist also for 1979 and 1981, while aggregate tabulations of tenure exist back to the 1960s. Prior to 1983, however, respondents were asked for tenure on their current *job*, while after 1983 they were asked for tenure with their current *employer*. For this reason, we focus on the post-1983 data.

3.2 Sample selection and variable construction

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 or 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.

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.

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 75 years. Occupations are recoded to the 2010 classification. We multiply top-coded weekly earnings by 1.5 following standard praxis.

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`).[15] 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 at least Clark and Summers (1979), it has been recognized that the distinction between unemployment and not in the labor force is fuzzy. Consequently, we classify all unemployed and not in the labor force as non-employed.[16]

We estimate the separation probability to non-employment δ_t as the share of wage employed individuals in month t who are non-employed in month $t+1$. We estimate the job finding probability of the non-employed λ_t^n as the share of non-employed 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. To account for the fact that different workers experience different job-ladder dynamics (Ozkan, Song and Karahan, 2023), we project log hourly real wages off age-race-gender-education-year dummies and state-date fixed effects

$$w_{i,t} \quad = \quad \xi_{a,r,g,e,y} + \xi_{s,t} + \varepsilon_{i,t} \tag{12}$$

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

[16]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.

We compute residual wages $\widehat{w}_{i,t}$ as the residuals from (12). We also present results adding 3-digit occupation-year fixed effects to (12). To estimate the unobservables model, we additionally include a worker's wage 12 months earlier in (12).

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 earn a residual wage below b_i (weighted by the survey weights). We construct these thresholds based on the baseline model, and use the same thresholds consistently in all models to avoid any differences being driven by changes in the binning. 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 $N = 50$.[17]

We estimate the wage offer distribution of the non-employed at time t, $f^n_{t,i}$, as the (weighted) share of hires from non-employment who earns a residual wage greater than b_{i-1} but less than b_i

$$f^n_{t,i} \quad = \quad \frac{1}{dw_i} \frac{\sum_j \mathbb{1}_{b_{i-1} \leq \widehat{w}_{t,j} < b_i} * \mathbb{1}_{hire^n_{t,j}=1} * weight_{t,j}}{\sum_j \mathbb{1}_{hire^n_{t,j}=1} * weight_{t,j}} \tag{13}$$

where we define a hire from non-employment at date t, $hire^n_{t,j}$, as any employed individual j at time t who was non-employed in month $t-1$. We estimate the wage distribution at time t, $g_{t,i}$, as the (weighted) share of employment who earns a residual wage greater than b_{i-1} but less than b_i

$$g_{t,i} \quad = \quad \frac{1}{dw_i} \frac{\sum_j \mathbb{1}_{b_{i-1} \leq \widehat{w}_{t,j} < b_i} * weight_{t,j}}{\sum_j weight_{t,j}} \tag{14}$$

We subsequently construct the cdfs of the wage offer and wage distributions in the obvious way.

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

3.3 Estimating EE mobility and its associated wage growth

To improve the precision of our estimates of EE mobility at date t, we pool months $t-T$ to $t+T$, where in our benchmark we set $T = 12$. That is, we obtain a 23-month centered moving average. Specifically, we first assign for each outcome $y_{\tau,i} = \{G_{\tau,i}, G_{\tau+1,i}, F_{\tau+1,i}, g_{\tau,i}\}$ and $x_\tau =$

[17] While the level of EE mobility changes modestly if we change the number of grid points—we have experimented with $N = 10$, $N = 20$, $N = 100$ or $N = 500$—the time trend is virtually identical. These results are available on request (or can easily be reproduced by changing one global setting in the code we plan to make available for public use).

$\{e_\tau, e_{\tau+1}, \lambda^n_\tau, \delta_\tau\}$ in period t the average outcome between $t-T$ and $t+T$

$$\begin{aligned} \overline{y}_{t,i} &= \frac{1}{2T+1}\sum_{\tau=t-T}^{t+T} y_{\tau,i} \\ \overline{x}_t &= \frac{1}{2T+1}\sum_{\tau=t-T}^{t+T} x_\tau \end{aligned}$$

We set the poaching separation rate in period t as

$$sep^e_{t,i} = 1 - \overline{\delta}_t - \frac{\overline{G}_{t+1,i}}{\overline{G}_{t,i}}\frac{\overline{e}_{t+1}}{\overline{e}_t} + \overline{\lambda}^n_t \frac{\overline{F}^n_{t+1,i}}{\overline{G}_{t,i}}\frac{1-\overline{e}_t}{\overline{e}_t} \tag{15}$$

Based on (3), we estimate the EE transition probability in period t as

$$EE_t = \sum_{i=1}^{N} sep^e_{t,i}\overline{g}_{t,i}dw_i \tag{16}$$

Based on (5), we estimate average wage growth due to EE mobility as

$$\Delta w_t = \sum_{i=1}^{N} sep^e_{t,i}\overline{G}_{t,i}dw_i \tag{17}$$

To implement the decomposition (4) of the EE transition probability into the job finding probability versus the acceptance probability (which requires the assumption that $f^e_t = f^n_t$), we estimate the job finding probability of the employed and the acceptance probability as

$$\begin{aligned} x_{t,i} &= \left(1 - \overline{\delta}_t - \frac{\overline{G}_{t+1,i}}{\overline{G}_{t,i}}\frac{\overline{e}_{t+1}}{\overline{e}_t} + \overline{\lambda}^n_t \frac{\overline{F}^n_{t+1,i}}{\overline{G}_{t,i}}\frac{1-\overline{e}_t}{\overline{e}_t}\right) \Big/ \left(1 - \overline{F}^n_{t+1,i}\right) \\ \lambda^e_t &= \sum_{i=1}^{N} x_{t,i}\overline{g}_{t,i}dw_i \\ acceptance_t &= \frac{EE_t}{\lambda^e_t} \end{aligned}$$

To estimate the OTJ model with on-the-job wage growth, we augment (15) as

$$sep^e_{t,i} = 1 - \overline{\delta}_t - \frac{\overline{G}_{t+1,i}}{\overline{G}_{t,i}}\frac{\overline{e}_{t+1}}{\overline{e}_t} + \overline{\lambda}^n_t \frac{\overline{F}^n_{t+1,i}}{\overline{G}_{t,i}}\frac{1-\overline{e}_t}{\overline{e}_t} - \overline{\xi}_t\frac{\overline{g}_{t,i}}{\overline{G}_{t,i}}$$

We construct the EE transition probability based on (16) and the average wage gain based on (17).

To estimate the unobservables model, we proceed identically to above but instead using wages residualized also off the previous wage to construct the wage offer and wage distributions.

To estimate the 1st godfather model, we use allocative EE mobility as estimated in the baseline model, and infer undirected EE mobility as the difference between overall EE mobility in the CPS and allocative EE mobility. In theory, this can be measured since the redesign of the CPS in 1994, but since the series provided by Fujita, Moscarini and Postel-Vinay (Forthcoming) starts in September 1995, we start then. To estimate the 2nd godfather model, we first construct the undirected arrival probability of offers (11) as

$$\lambda_t^g \quad = \quad \frac{\overline{EE}_t^T - \sum_{i=1}^N \left(1 - \frac{\overline{G}_{t+1,i}}{\overline{G}_{t,i}} \frac{\overline{e}_{t+1}}{\overline{e}_t} + \overline{\lambda}_t^n \frac{1-\overline{e}_t}{\overline{e}_t} \frac{\overline{F}_{t+1,i}^n}{\overline{G}_{t,i}} - \overline{\delta}_t\right) \overline{g}_{t,i} dw_i}{\sum_{i=1}^N \frac{\overline{F}_{t+1,i}^n}{\overline{G}_{t,i}} \overline{g}_{i,t} dw_i}$$

where $\overline{EE}_t^T$ is the overall EE transition probability as measured by Fujita, Moscarini and Postel-Vinay (Forthcoming) (averaged between $t-T$ and $t+T$). Given an estimate of the arrival probability of godfather shocks λ_t^g, we construct the poaching separation probability (10) as

$$sep_{t,i}^e \quad = \quad 1 - \overline{\delta}_t - \lambda_t^g - \frac{\overline{G}_{t+1,i}}{\overline{G}_{t,i}} \frac{\overline{e}_{t+1}}{\overline{e}_t} + \left(\overline{\lambda}_t^n \frac{1-\overline{e}_t}{\overline{e}_t} + \lambda_t^g\right) \frac{\overline{F}_{t+1,i}^n}{\overline{G}_{t,i}} - \overline{\xi}_t \frac{\overline{g}_{t,i}}{\overline{G}_{t,i}}$$

We substitute this alternative poaching separation probability into (16) to estimate the allocative EE transition probability.

3.4 Validation

Before we use our methodology to evaluate long-run trends in allocative EE mobility, we pause to contrast it with EE mobility available in the raw data over a shorter time period. Figure 3 contrasts allocative EE mobility (under the baseline model) with various raw measures. Specifically, the CPS and SIPP measures plot the fraction of employed workers in month t who are employed with a different employer in month $t+1$, while the SIPP (up) measure additionally conditions on those who experienced a wage gain associated with their transition.[18] The FMP series shows the raw EE series provided by Fujita, Moscarini and Postel-Vinay (Forthcoming) that adjusts the bias that they identify. All series are smoothed with a 23-month centered moving average.

The raw series from the CPS declined by more during the 2000s than both allocative EE mobility and the raw measure in the SIPP. Fujita, Moscarini and Postel-Vinay (Forthcoming) argue that this is due to changes in non-response rates that bias the raw CPS series toward showing an excessively large decline since the early 2000s. Allocative EE mobility is substantially lower than raw EE mobility in both the CPS and SIPP, consistent with large EE flows toward lower paying jobs (Tjaden and Wellschmied, 2014; Sorkin, 2018). Once we condition on those who experienced a wage gain during their transition, raw EE mobility toward higher paying jobs is reassuringly similar in both level and changes to allocative EE mobility.

[18]Consistent SIPP data are available from 1996 to 2013. We impose exactly the same sample selection criteria in the SIPP as in the CPS.

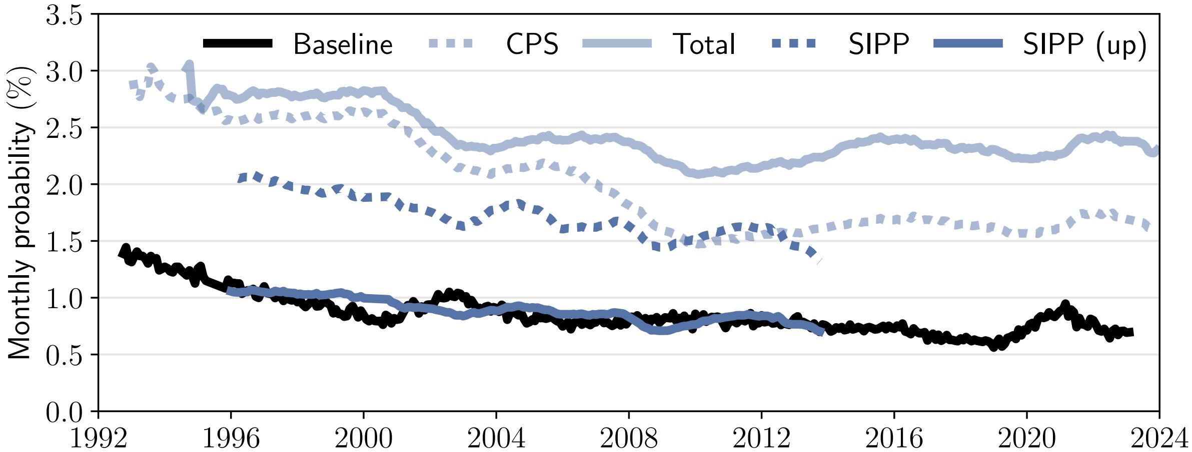

Figure 3: Comparison between the EE transition probability implied by the baseline model (black), the raw overall EE transition probability in the CPS (dotted light blue), the Fujita, Moscarini and Postel-Vinay (Forthcoming) series (solid light blue), the SIPP (dotted dark blue), and the EE transition probability towards higher-paying jobs in SIPP (solid dark blue) over time.

Our theory predicts that wages of hires from non-employment should converge over time to the average wage among all workers. Figure 4 validates this prediction by plotting the progression of average wages for workers hired in month 0 from non-employment as well as the average wage of all workers. All series are residualized off the demographic characteristics in the baseline model, and normalized relative to initial residual wages in month 0 for hires from non-employment. Note that we do not condition on continuous employment—i.e. some workers experience subsequent non-employment spells. Since we are only able to follow workers for a relatively short period of time in the CPS, we exploit also the longer panel of the SIPP.

Wages grow somewhat more with time since non-employment in the SIPP than the CPS, consistent with a larger gap between the offer distribution and wage distribution in the former. Both data sources, however, paint the same picture of gradual convergence, as predicted by our theory. That being said, convergence remains incomplete (but continuing) 60 months later.

Figure 29 uses the panel structure of the SIPP to decompose subsequent wage growth into that among workers who remain with the same employer between two consecutive months, those who make an EE transition toward a higher paying job, and those who make a move toward a lower paying job, including the effect of some workers separating to non-employment and others entering from non-employment.[19] The evolution of wages of recent hires from non-employment in Figure 4 is primarily the result of job ladder dynamics, as opposed to wage changes on-the-job, consistent with the assumptions of our theory.

In Appendix 7.1, we further validate our measure by contrasting both levels of and changes in EE mobility by age and education groups with the raw measures from the CPS and SIPP.

[19]Because the employment rate of hires at time $t = 0$ varies as time progresses, the decomposition is not exact. We lump the residual with the falling off the job ladder component, but note that it is small.

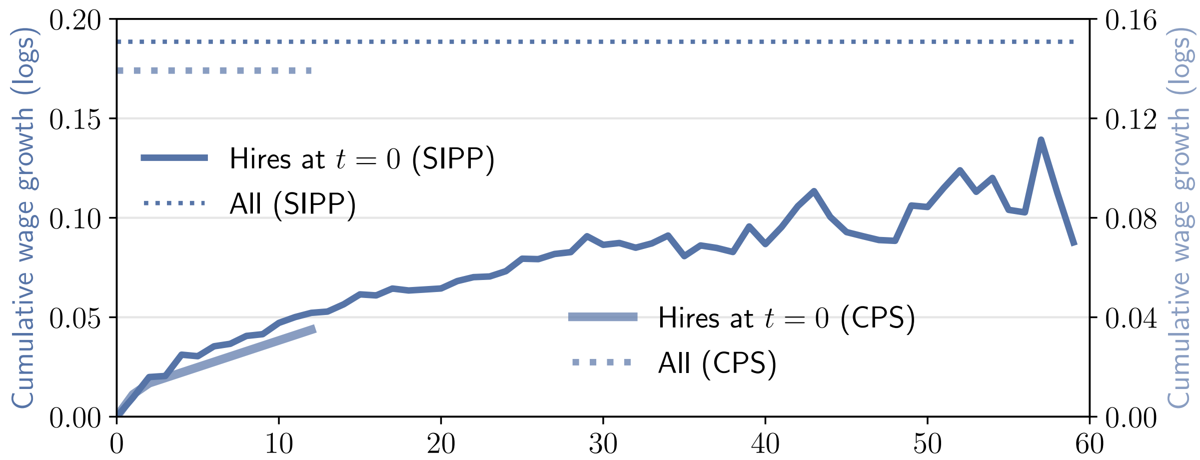

Figure 4: Convergence in average residual wages of workers after they leave non-employment ($t = 0$) toward economy-wide average residual wage. Both series are expressed in log deviations to average wages of hires from non-employment in the month they enter employment. SIPP (dark blue) over 60 months and CPS (light blue) over 12 months following employment entry.

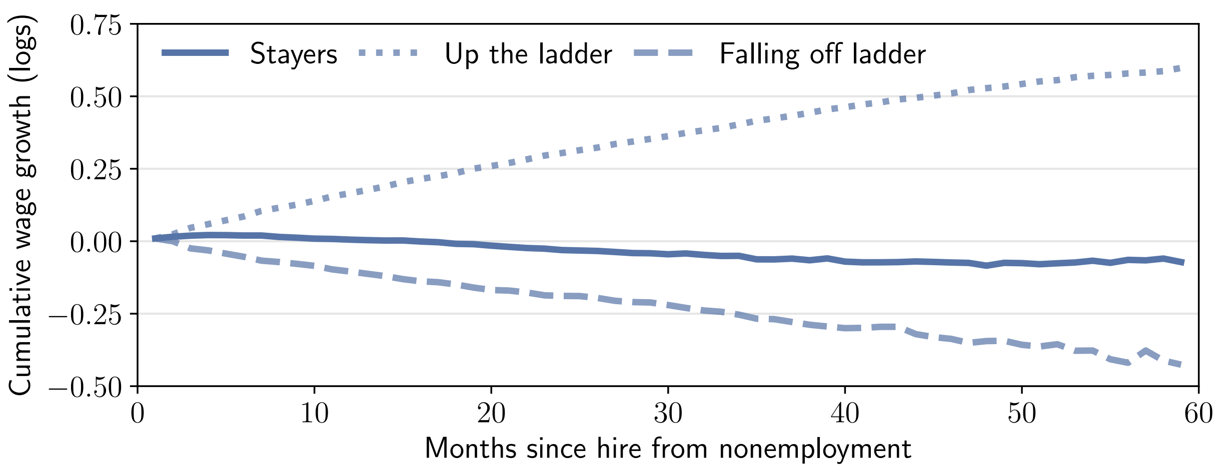

Figure 5: Decomposition of overall cumulated wage growth (black) for workers exiting nonemployment at $t = 0$ in contribution due to moves up the ladder (dotted), falling off the ladder (dashed), and non-movers (solid).

4 Three trends in EE mobility over the past half century

Having validated our approach, we now use it to establish three trends in EE mobility in the U.S. over the past half century.

4.1 Fact I: Allocative EE mobility fell by half since 1979

According to the baseline model in Figure 6, 1.5 percent of workers made an EE transition toward a higher paying job per month in the 1980s. Over time, however, allocative EE mobility declined substantially, falling by roughly 50 percent from 1979 to 2023. The decline was particularly pronounced between 1985 and 2000. Our estimate also indicates a brief reversal in the decline during the early years of the pandemic (Birinci et al., 2022; Caratelli, 2022) and the recovery that followed, but that the allocative EE transition probability continued to decline since then.

In Appendix 7.2 we discuss the implications of our estimate of allocative EE mobility for overall worker flows, finding that allocative EE mobility contributed to almost half of the decline in worker reallocation since 1980. Moreover, we show that worker flows are roughly four times as large as job flows, and that most of the decline in worker reallocation over the past 40 years is accounted for by a fall in worker churn, not job reallocation.

Allowing for on-the-job wage growth. The OTJ model that allows for on-the-job growth in residual wages indicates a slightly lower level of allocative EE mobility than the baseline model, because it does not attribute all positive wage changes to EE moves. The difference, however, is small, driven by the fact that on-the-job residual wage growth with tenure is second-order.

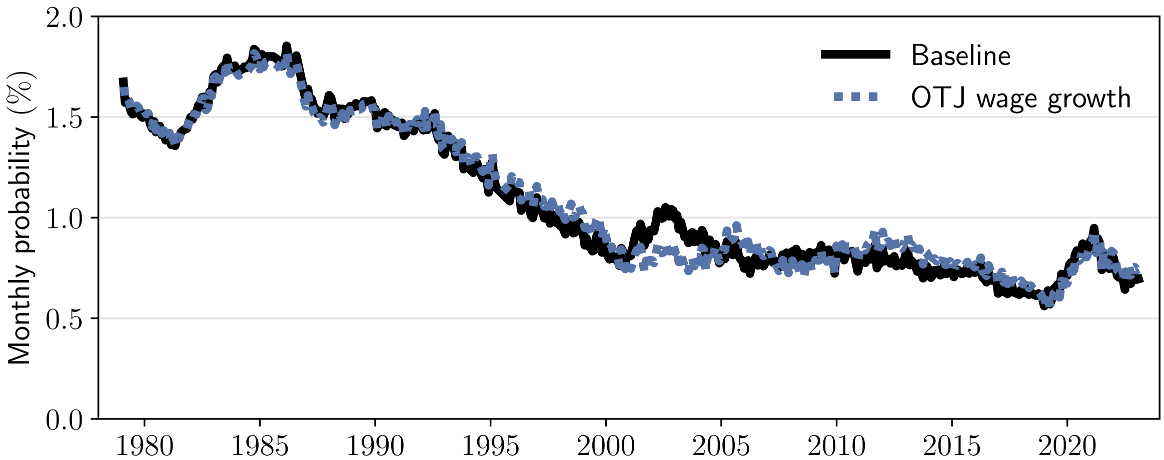

Figure 6: Estimated EE transition probability in the baseline model (black), the OTJ model with on-the-job wage growth (dark blue dotted).

Observed and unobserved heterogeneity. Figure 7 illustrates the role of observable and unobservable heterogeneity. Specifically, the "raw" series plots the EE transition probability we would infer if we did not residualize wages off *any* demographic characteristics. It is substantially higher than our baseline estimate, because recent hires are more likely to come from lower earning demographic subpopulations. Consequently, the gap between the wage offer and wage distribution is larger, leading us to infer a higher level of EE mobility. If we additionally include three digit occupation-year fixed effects in the residualization of wages, we infer an even lower level of EE mobility. If EE transitions are associated with occupational upgrading, however, one might not want to control for detailed occupation. In any case, the *relative* decline over time is of a similar magnitude with and without detailed occupation-year controls. In contrast, it matters relatively less if we also control for unobservable characteristics via the prior wage 12 months earlier.

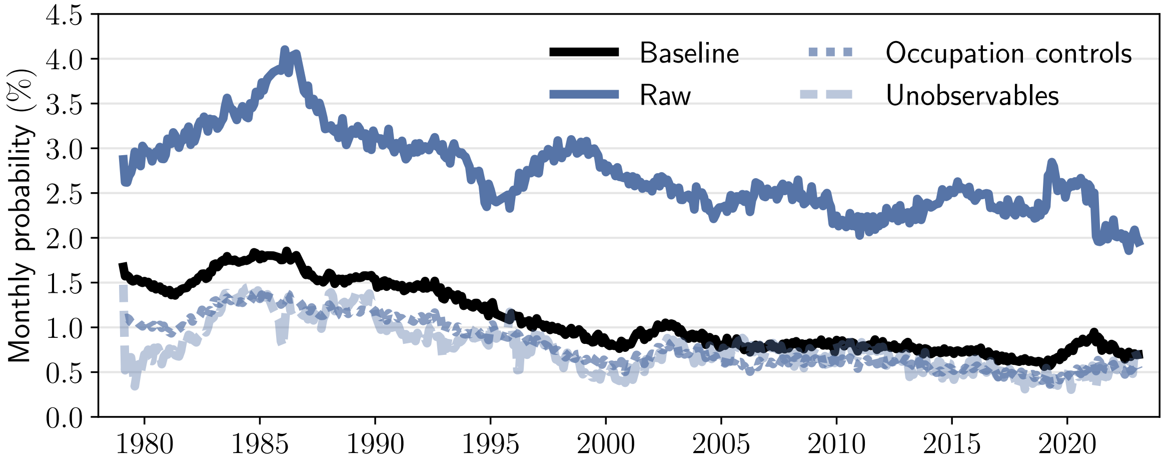

Figure 7: Estimated EE transition probability in the baseline model with age-gender-race-education year and state-date controls (black), the model that additionally adds three digit occupation-year controls (dotted light blue), the "unobservables" model that also includes the prior wage 12 months earlier (dashed light blue), and the model with no controls (solid blue).

Incorporating godfather shocks. Figure 8 shows allocative and undirected EE mobility according to the 1st and 2nd godfather models. Allocative EE mobility is higher according to the latter, because it assumes that undirected EE job offers are drawn from the wage offer distribution of the non-employed instead of the overall wage distribution. Consequently, undirected EE mobility tends to move workers down the job ladder according to the 2nd godfather model. To counter this force, allocative EE mobility must be higher to be consistent with a given gap between the wage offer and wage distributions. The relative decline in allocative EE mobility is, however, similar according to both models. While both models indicate a substantial amound of undirected EE mobility, neither shows a pronounced secular trend. Although we cannot estimate allocative EE mobility according to the 2nd godfather model prior to 1994, we speculate based on the close similarity in the time trends across models that it declined since the mid-1980s.

Why do we infer a decline? To illustrate why we infer that allocative EE mobility declined, Figure 9 implements the steady-state decomposition (7) of the EE transition probability into changes in the separation probability to non-employment and changes in the 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, in the sense that the estimated overall change in EE mobility is similar whether we use the full dynamic model (solid black) or impose the steady-state assumption (solid blue). For a fixed average gap between the wage and offer distributions, the observed decline in the separation probability to non-employment over this period implies that EE mobility

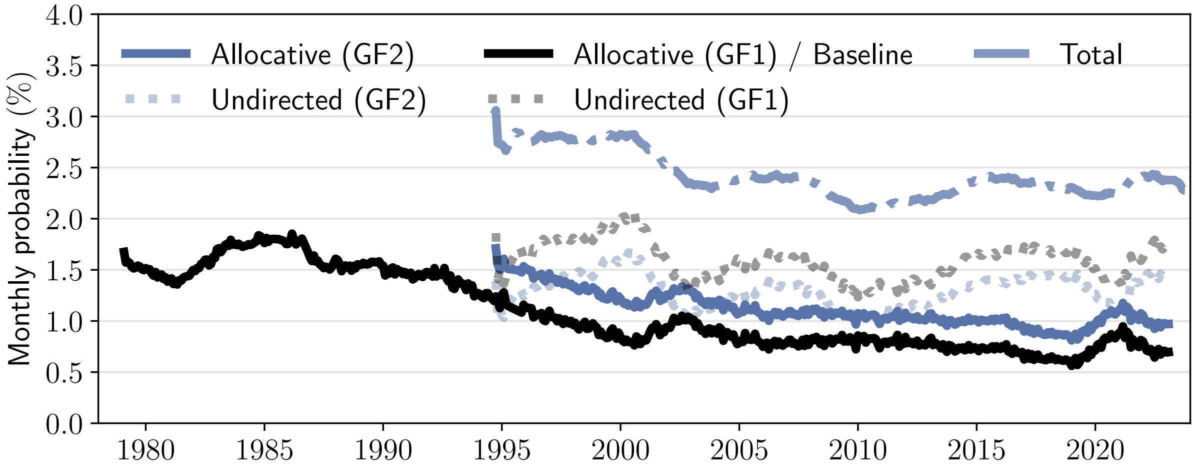

Figure 8: Allocative and undirected EE mobility according to the two godfather models, which by construction sum to total EE mobility according to Fujita, Moscarini and Postel-Vinay (Forthcoming).

must have declined. Conversely, holding fixed the separation probability to non-employment, a shrinking gap between the offer and wage distributions must be the result of lower EE mobility.

In a statistical sense, this decomposition shows that a shrinking gap between the wage offer and wage distributions is the main reason we infer a decline in allocative EE mobility. That being said, the separation channel remains important in terms of accounting for some episodes, such as the increase in the EE transition probability in the Pandemic recession.

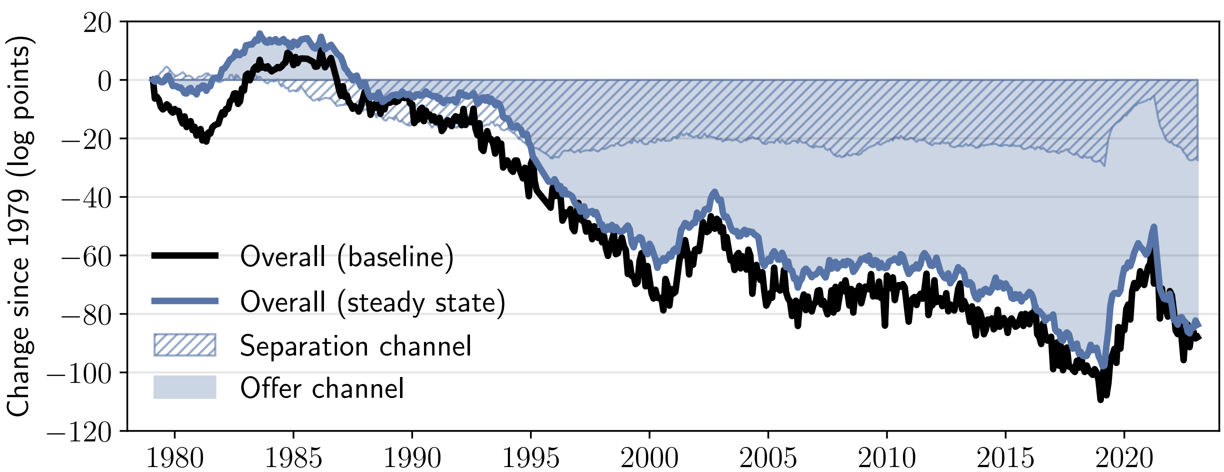

Figure 9: Decomposition of allocative EE mobility into the separation probability channel and the offer channel based on (7).

Figure 10 illustrates further the offer channel by plotting the wage and offer distributions using pooled data in 1980–1999 and 2000–2019. We normalize wages to the mean of the offer distribution in each decade. The wage distribution is visibly shifted less to the right of the offer distribution in the later period. We infer based on this that allocative EE mobility declined.

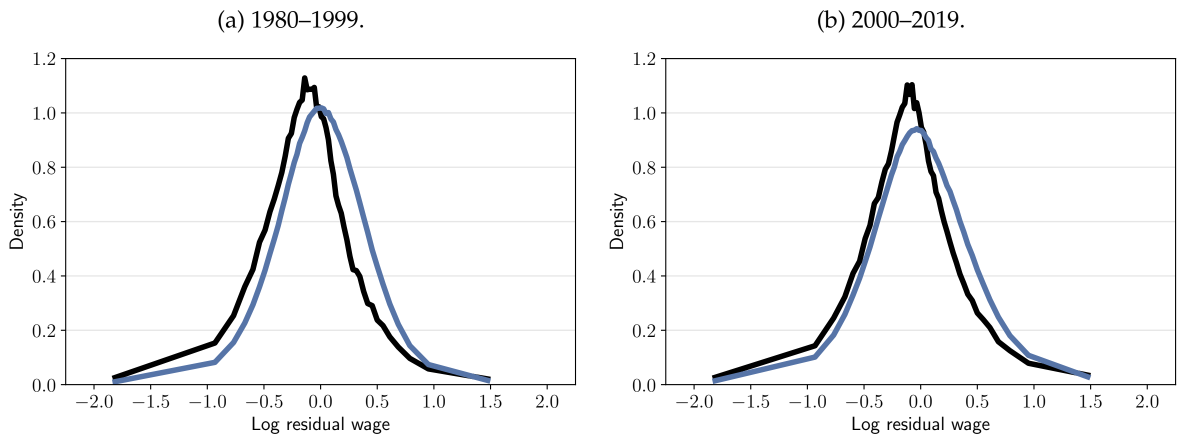

Figure 10: Residual wage offer (black) and wage (blue) distributions in 1980-1999 and 2000-2019.

Figure 11 provides an alternative illustration of why we estimate a decline in allocative EE mobility. Panel a plots the difference in average log wages and average log offered wages over time. We include both the gap prior to any residualization, the gap after residualizing wages off demographics, that after also taking out three digit occupation-year fixed effects, and that after also controlling for a worker's wage 12 months prior. While the raw gap is substantially larger than the residual gap—indicating that hires from non-employment tend to come from subpopulations that systematically earn less—all measures indicate a decline in the gap over time. One possibility is that the smaller gap between the overall wage distribution and the wage offer distribution reflects weaker wage growth on the job. Panel b suggests that this is not the case, finding little evidence of a decline in residual wage growth on-the-job (which is uniformly tiny).

Another possibility is that recent hires from non-employment are less negatively selected over time. While in our baseline we control for rich observable characteristics, such selection might also take place in unobservable dimensions. Panel c plots the average residual wage of hires from non-employment 10–12 months earlier. Consistent with negative selection on unobservables, recent hires from non-employment earned lower wages 10–12 months earlier.[20] Yet, we observe no pronounced trend in such selection. Consequently, controlling for the prior wage does little to the estimated relative decline in allocative EE mobility over time in panel a (but it makes the series noisier by shrinking the sample by roughly 60 percent). More directly, panel d plots within-individual residual wage growth over the first 12 months since an individual was hired from non-employment.[21] Although the series is noisy due to its small sample size, it shows a clear downward trend, consistent with workers climbing the job-ladder less.

[20] The pattern would also arise in a model with "slippery" lower rungs, as in Jarosch (2023).

[21] To maximize sample size, we include individuals who were hired from non-employment 12-14 months earlier. Wage growth refers to year-on-year wage growth between two ORG surveys.

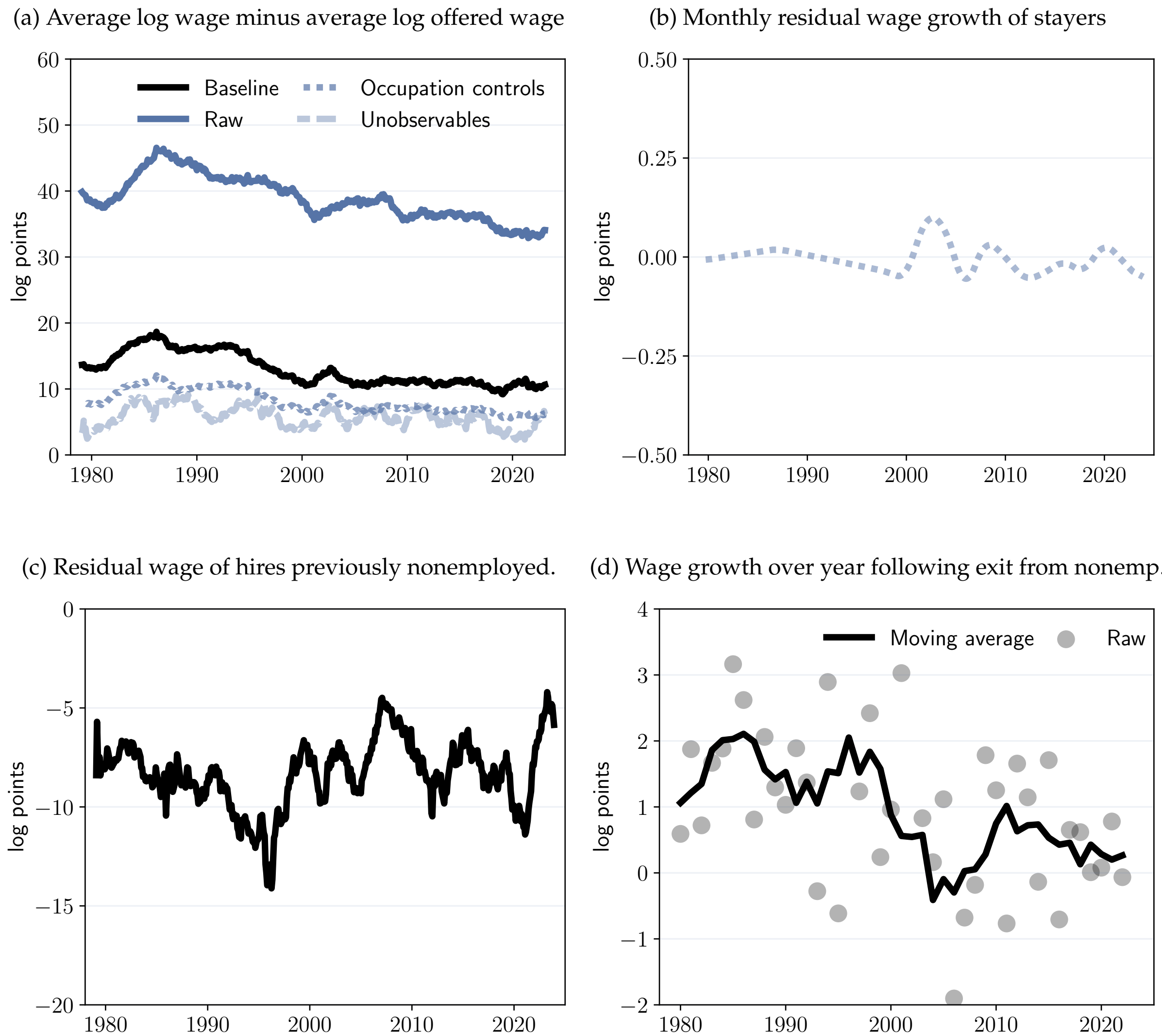

Figure 11: Key identifying moments.

4.2 Fact II: Over one percentage point decline in associated wage growth

A recent literature stresses the central role of EE mobility for wage growth (Karahan et al., 2017; Moscarini and Postel-Vinay, 2017; Ozkan, Song and Karahan, 2023; Tanaka, Warren and Wiczer, 2023). We would hence expect the decline in EE mobility to contribute to weaker wage growth.

Figure 12 confirms this intuition based on equation (5), finding a decline in monthly residual wage growth due to EE mobility of about 0.15 percentage points from the 1980s until now. Allowing for on-the-job growth in residual wages has only a small effect on both the level and the trend, due to the fact that such wage growth is uniformly small. Including also three digit occupation-year fixed effects when residualizing wages lowers estimated wage growth due to EE mobility, but does not change the relative decline over time. Finally, while further residualizing a worker's current wage off her prior wage has little additional impact on EE mobility, it lowers the estimated wage growth associated with EE mobility. Furthermore, it reduces the estimated decline in wage growth due to EE mobility to show a decline from about 0.25 percentage points monthly to 0.15 percentage points today, or about a one percentage point decline in annual wage growth.

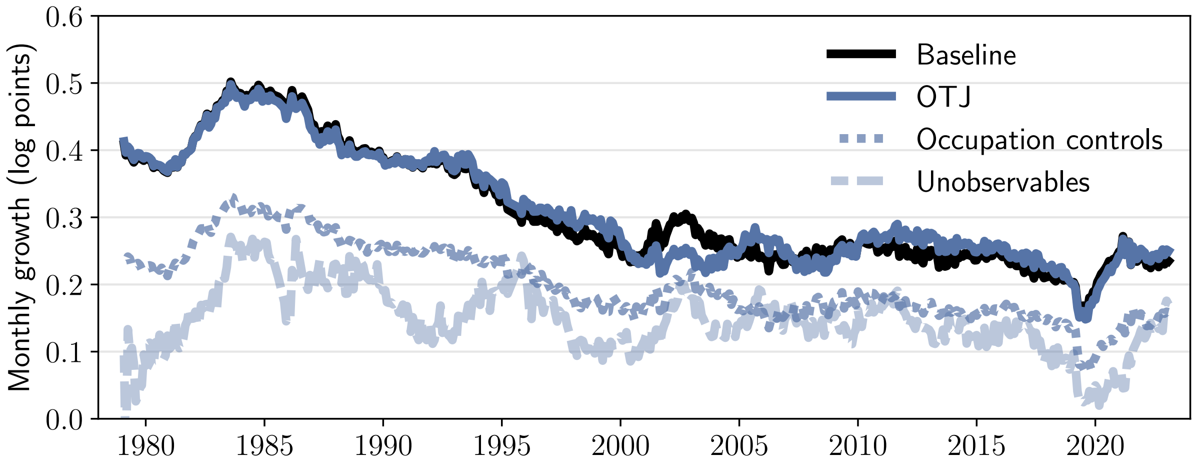

Figure 12: Monthly growth in residual wages associated with EE mobility in the baseline model (black), the OTJ model with on-the-job wage growth (dark blue dotted), and the unobservables model with controls also for the wage 10–12 months earlier (light blue dashed).

Figure 13 uses the OTJ model to provide an estimate of overall residual wage growth of continuously employed workers, as well as residual wage growth on-the-job. The latter is uniformly small, consistent with earlier findings (Molloy et al., 2016). Consequently, the decline in overall wage growth once we include on-the-job wage growth, shown in gray, tracks closely wage growth due to EE mobility. For reference, we also include the corresponding moment in the SIPP, constructed as the product of the median percent change in wages between month $t-1$ and $t+1$ for workers who made an EE transition toward a higher paying job in month t times the average EE transition probability toward higher paying jobs in month t.[22]

4.3 Fact III: Particularly large declines among women, less educated and new cohorts

Because different groups of workers display different labor market outcomes (Elsby, Hobijn and Şahin, 2010), the decline in EE mobility could be the result of shifts in the composition of the workforce. Alternatively, it could have taken place within demographic subpopulations. If so, it is worthwhile to assess whether some subpopulations experienced particularly stark declines. Appendix 7.3 uses a shift-share analysis to document a relatively modest role for shifts in the demographic composition of the workforce in accounting for the aggregate decline in EE mobility. Motivated by this finding, we focus in this section on dissecting the decline by subpopulations.

[22]We use medians instead of averages in the SIPP to limit the impact of a few outliers (using averages instead results in the same changes over time, but generally a higher level of wage growth).

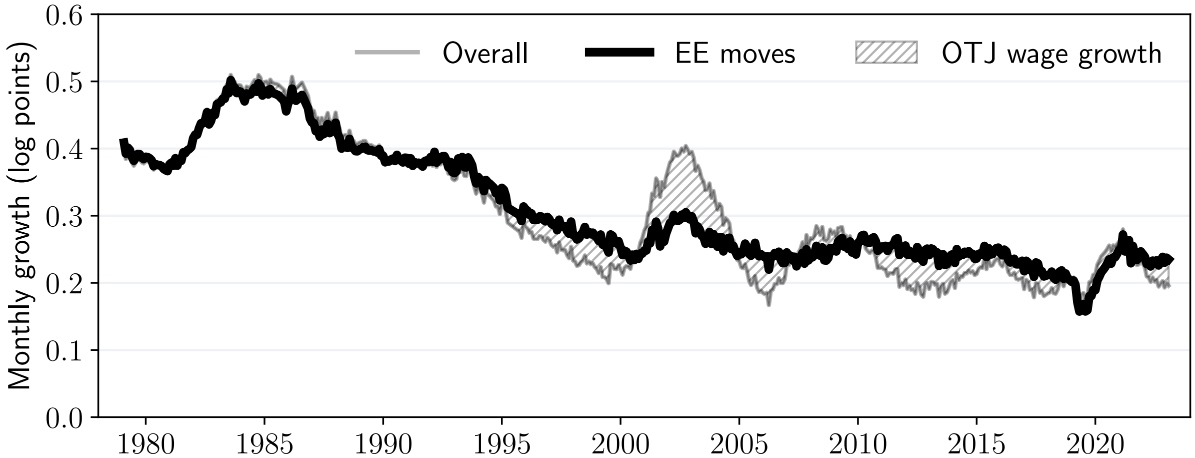

Figure 13: Monthly growth in residual wages associated with EE mobility in the OTJ model and in the SIPP. The SIPP series shows the product of the median percent wage gain upon an EE transition times the monthly probability of making an EE move (both are conditional on moving to a higher paying job).

Given our focus on secular trends and the restricted number of observations available when focusing in on particular subgroups, to reduce noise we increase the smoothing to $T = 30$ months so that we obtain five-year averages and we reduce the number of wage bins to $N = 10$.[23]

Gender. Figure 14 shows that allocative EE mobility and the associated wage growth were larger for women throughout the period, which coincided with women making rapid advancements in the labor market (Goldin, 2014). However, in levels both measures fell by more for women over time, *ceteris paribus* contributing to slower convergence in the gender pay gap (Blau and Kahn, 2006; Blair and Posmanick, 2023). Also in relative terms, the decline in allocative EE mobility was more pronounced for women, but the difference relative to men is smaller.

Race. According to Figure 15, white and black workers had similar rates of allocative EE mobility in the 1980s (panel a), as well as similar wage growth associated with EE mobility (panel b). Over time, EE mobility and its associated wage growth declined for both groups.

Education. 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 first half of our sample (Figure 16). This supports the findings by Haltiwanger, Hyatt and McEntarfer (2018). Since then, the job ladder for those with at most a high-school degree experienced a dramatic collapse, so that today they just as

[23]It makes little difference if we set $N = 10$, $N = 20$, $N = 50$ or $N = 100$ for both the aggregate results above as well as those within sub-population that we present here. With a high number of bins, however, we end up estimating a negative poaching separation rate in some bins at some points in time, presumably due to sampling error. While the EE transition probability remains positive since it is the average across all bins, it is nevertheless not economically sensible to have a negative poaching separation rate. For this reason, we prefer to set a lower number of grid points.

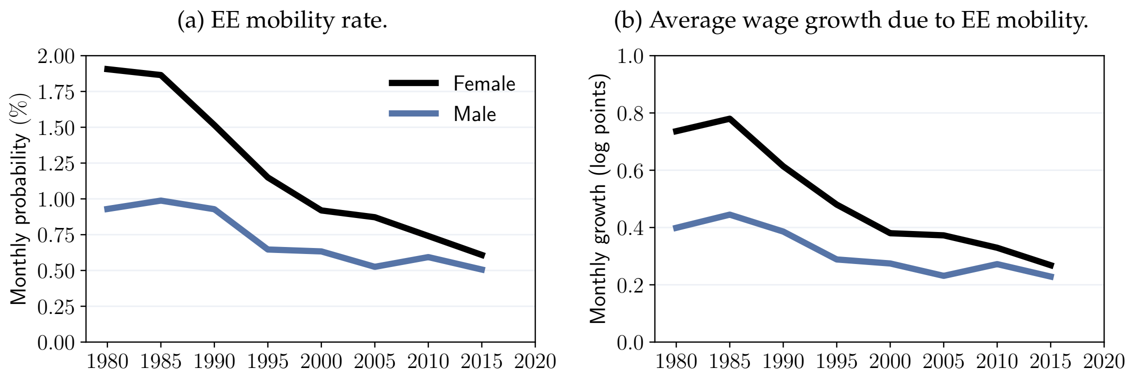

Figure 14: EE transition probability and associated wage growth by gender. All mobility is to higher-paying jobs.

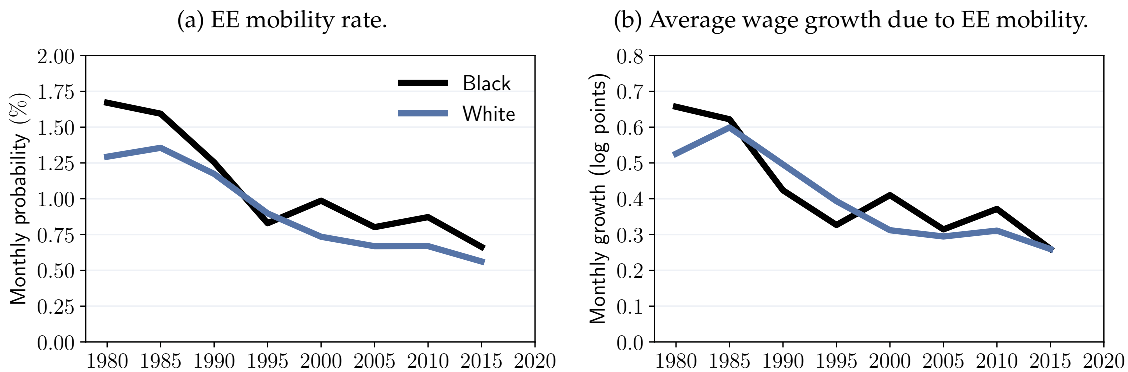

Figure 15: EE transition probability and associated wage growth by race. All mobility is to higher-paying jobs.

likely to make an EE transition toward a higher paying job than their more educated peers. These trends in EE mobility are reflected in changes in the wage growth associated with EE mobility.

Occupation. Figure 17 shows that the decline in allocative EE mobility is visible across occupation groups,[24] but there is significant heterogeneity. We find that workers in relatively well-paid managerial, professional and technical services have experienced a relatively small decline in EE mobility toward higher paying jobs. However, workers in low-skill services, a category including restaurant workers, security guards, janitors, cleaners, child care workers and beauticians, have seen a particularly pronounced slowdown in their upward mobility.

[24]We define these groups following Autor and Dorn (2013) using the consistent `occ2010` classification provided by IPUMS.

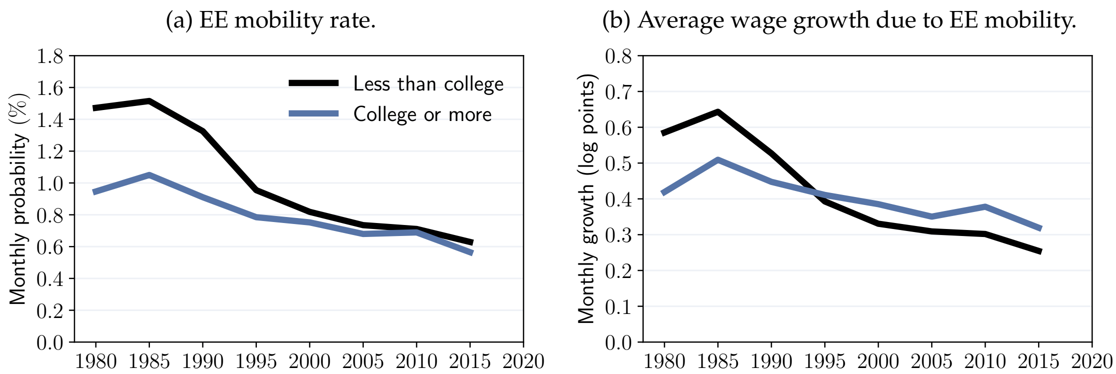

Figure 16: EE transition probability and associated wage growth by education. All mobility is to higher-paying jobs.

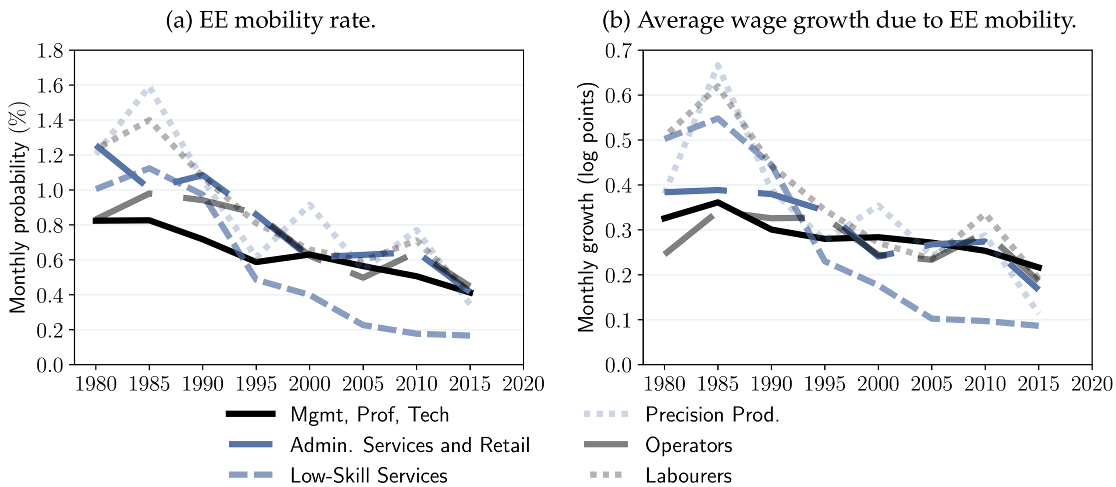

Figure 17: EE transition probability and associated wage growth by broad occupation groups. All mobility is to higher-paying jobs.

Age and cohort. Figure 18 shows that young workers consistently have a higher EE transition probability toward higher paying jobs than their older peers, consistent with the findings in Haltiwanger, Hyatt and McEntarfer (2018). Over time, however, young workers experienced a more pronounced decline in such mobility (Bosler and Petrosky-Nadeau, 2016 draw a similar conclusion based on the SIPP 1996–2013). These trends are particularly concerning given the importance of EE mobility for young workers' career advancement (Topel and Ward, 1992). Indeed, panel b shows a sharp deceleration in wage growth associated with EE mobility for young workers.

The patterns in Figure 18 are suggestive of a cohort component to the decline, whereby new cohorts are systematically less likely to make an EE transition toward a higher paying job than their older peers. To investigate this hypothesis, Figure 19 plots the age profile of allocative EE mobility for the the 1955-59, 1965-69, 1975-79 and 1980-84 cohorts. Recent cohorts display an

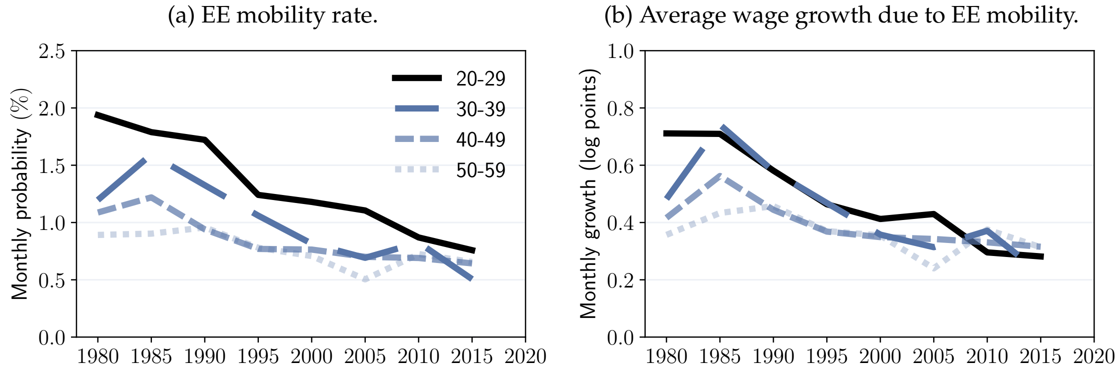

Figure 18: EE transition probability and associated wage growth by age. All mobility is to higher-paying jobs.

overall lower EE transition probability toward higher paying jobs at all ages.

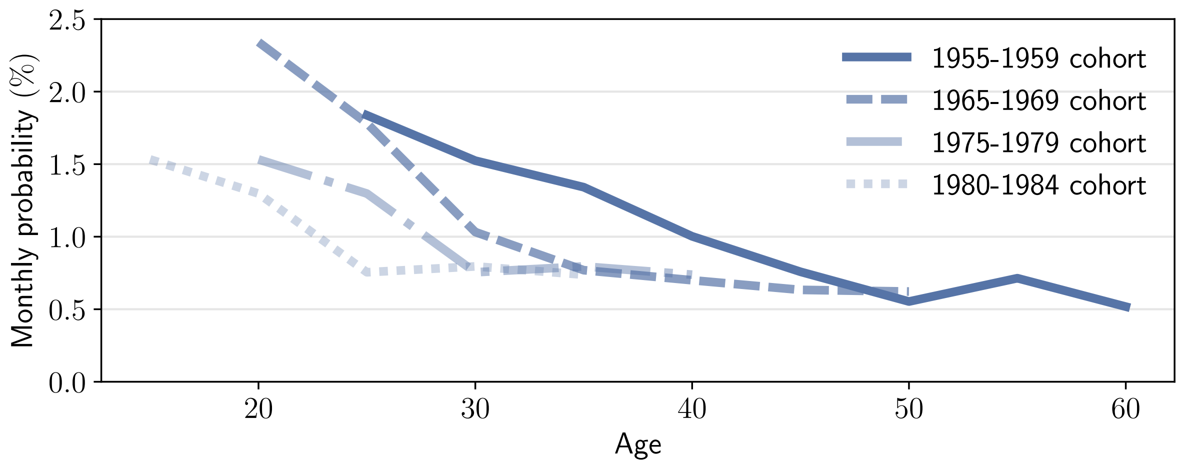

Figure 19: Age profile of EE transition probability estimated in the model for the 1955–1959 cohort (solid), the 1965–1969 cohort (dashed), 1975–1979 cohort (dash-dotted), and 1980–1984 cohort (dotted). All mobility is to higher-paying jobs.

To quantify the contributions of time, age and cohort effects toward the overall decline, we build on a literature doing the same for wages (Heckman, Lochner and Taber, 1998; Lagakos et al., 2018). Specifically, we project the allocative EE transition probability at time t for age group a of cohort c on time fixed effects (ϕ_t), age fixed effects (ψ_a) and cohort fixed effects (ξ_c)[25]

$$EE_{t,a,c} \quad = \quad \phi_t \; + \; \psi_a \; + \; \xi_c \; + \; \varepsilon_{t,a,c} \tag{18}$$

As is well-known, without a restriction, equation (18) cannot be identified due to perfect collinearity between time, age and cohort effects. Motivated by the theoretical prediction that mobility

[25]While we estimate (18) in levels, substantively similar results hold if we alternatively estimate it in logs.

should settle at some age, we impose the restriction that mobility does not change between ages 50 and 59. This assumption is sufficient to separate changes in the effect of time, age and cohort.

Figure 20 decomposes the overall decline in allocative EE mobility into the role of time, age and cohort effects. Because older workers are less mobile and the U.S. workforce aged substantially over this period, the age effects account for some of the aggregate decline. Time effects are behind most of the initial increase as well as some of the decline in the late 1990s and early 2000s. Since 2005, however, they contributed to an *increase* in allocative EE mobility, *ceteris paribus*. Hence, most of the secular decline in the aggregate EE transition probability is accounted for by the fact that new cohorts are less dynamic than their older peers.

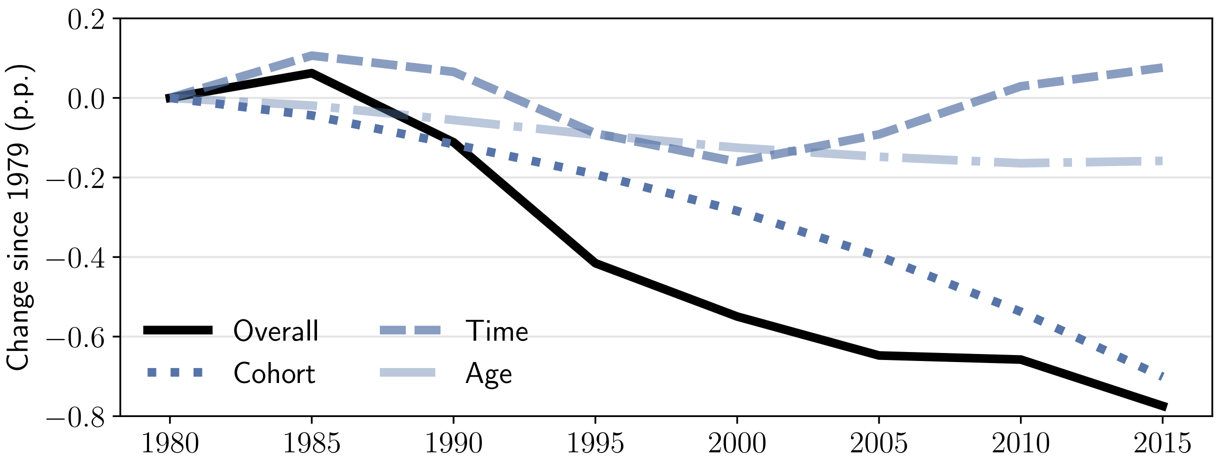

Figure 20: Change in EE transition probability overall (solid) and broken down in its time (dashed), age (dash-dotted), and cohort (dotted) components.

5 Understanding the decline in allocative EE mobility

In this section, we explore potential forces behind the decline in allocative EE mobility. We first provide evidence that the decline is unlikely to be driven by an improvement in workers' existing matches. Second, we argue that it is likely not the result of a worsening matching efficiency. Finally, we highlight a link with increases in labor market concentration.

5.1 Are workers better matched today?

One possibility is that allocative EE mobility is lower because workers are better matched today, so that they make fewer transitions in search of better matches (Mercan, 2017; Pries and Rogerson, 2022). To investigate this hypothesis, recall from (4) that if we assume that the employed and non-employed sample from the same wage offer distribution, we can decompose the EE transition probability into the job finding probability and the acceptance probability

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

Figure 21 implements this decomposition, finding that workers are slightly *more* likely to accept offers today than they were in the 1980s. Molloy et al. (2016) similarly argue based on the lack of a long-run trend in starting wages that workers are not better able to immediately locate a good match today. Further supporting this view, Appendix 7.4 shows that the average wage gain upon an EE transition toward a higher paying job rose over this period, both according to our structural estimate and in the SIPP. In contrast, if workers were better matched today, we may have expected a *lower* conditional gain associated with an EE move. We conclude based on this evidence that EE mobility is lower today due to a lower job finding probability of the employed.

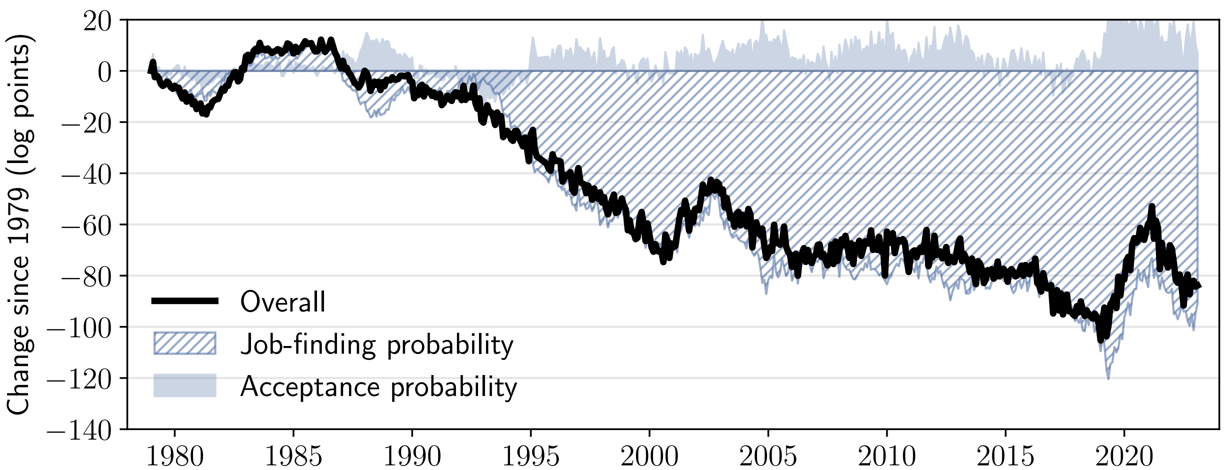

Figure 21: Decomposition of allocative EE mobility into the job-finding probability and the acceptance probability. In solid black is the benchmark EE transition probability. Under the assumption that employed and unemployed draw offers from the same distribution is the decomposition in job-finding and acceptance probabilities.

5.2 Did the labor market become worse at matching workers and firms?

To understand the potential forces behind the decline in the job finding probability of the employed, it is useful to extend the partial equilibrium model of Section 2 to a general equilibrium one via the following standard assumptions. First, suppose that the employed search with search efficiency $s_t \geq 0$ relative to the non-employed. Second, let firms advertise jobs subject to some vacancy posting cost. Third, postulate a homogeneous of degree one aggregate matching function $\mathcal{M}_t(V, S)$ that gives the meeting probabilities as a function of the total number of vacancies V and effective number of searching workers S. Then the job finding probabilities of the non-employed and employed are

$$\lambda_t^n \;=\; \mathcal{M}_t\left(\frac{V_t}{S_t},1\right), \qquad \text{and} \qquad \lambda_t^e \;=\; s_t\mathcal{M}_t\left(\frac{V_t}{S_t},1\right)$$

Consequently, changes in, for instance, the matching function, aggregate vacancies, or aggregate search intensity have a proportional impact on the job finding probabilities of the employed and non-employed. To gain insights into the sources of the changes in allocative EE mobility, it is hence useful to also study changes in the non-employment-to-employment transition probability.

Figure 22 shows that the job finding probability of the employed fell by much more than that of the non-employed (both series are expressed in log deviations relative to their values in 1979). From the perspective of benchmark equilibrium theories of the labor market, it is hard to reconcile these divergent patterns as the result of, for instance, a worsening matching efficiency or less job creation by firms. Instead, our results point to forces that disproportionately reduced the job finding probability of the employed. For instance, the increasing prevalence of non-competes could have discouraged job shopping by the employed (Gottfries and Jarosch, 2023). Alternatively, increasing labor market concentration could have reduced outside job options for the employed, with less of an effect on the job finding prospects of the non-employed (Bagga, 2023; Jarosch, Nimczik and Sorkin, 2024). We offer some further evidence consistent with this hypothesis below.

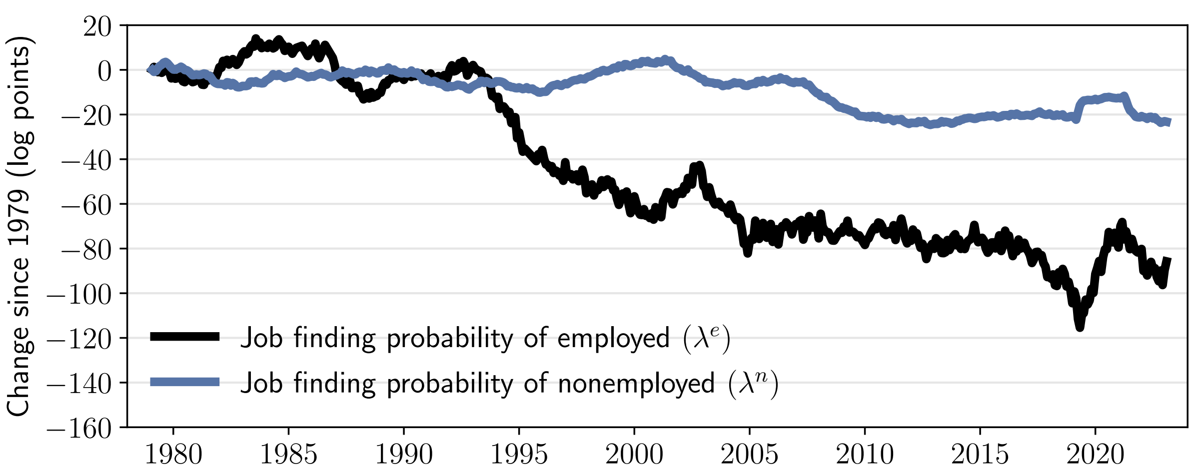

Figure 22: Log point change in the the job finding probability out of employment (black) and non-employment (blue). All changes are since 1979.

5.3 Labor market concentration

One possible explanation behind the larger decline in the job finding probability of the employed relative to the non-employed is increasing labor market concentration that reduced the opportunities for job shopping (Bagga, 2023; Berger et al., 2023; Jarosch, Nimczik and Sorkin, 2024). For

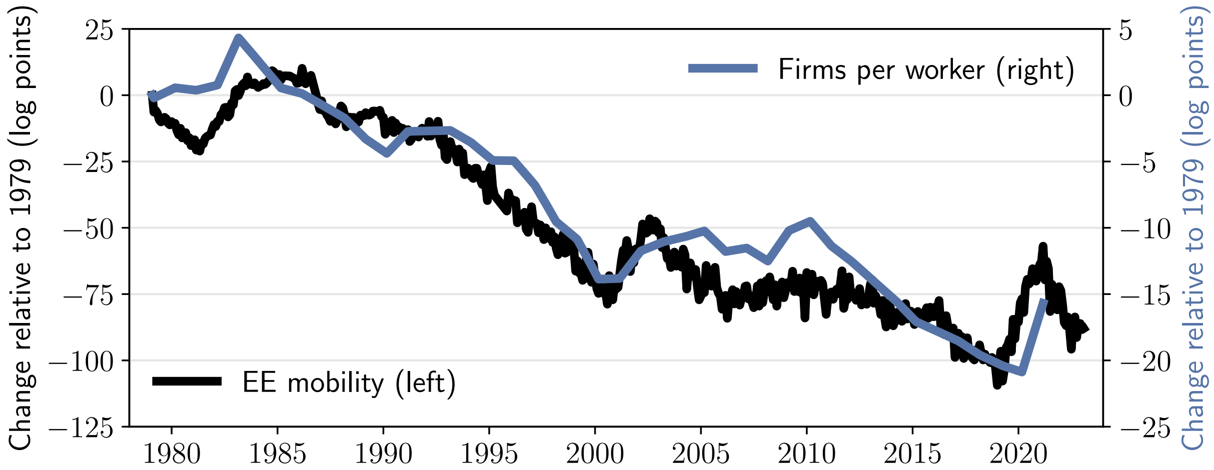

Figure 23: Log point change in allocative EE mobility against log point change in firms per worker for the US.

instance, Jarosch, Nimczik and Sorkin (2024) argue that employers can commit to not rehire workers who separate from them, thus reducing outside options for employed workers relative to the non-employed. Indeed, the strong time series correlation between the number of employers per worker and allocative EE mobility as plotted in Figure 23 suggests that the two may be related.

To investigate this hypothesis further, we re-estimate EE mobility across U.S. states plus Washington D.C. within five year bins. We merge the resulting EE transition probability with data on the ratio of firms to workers from the BDS, which covers essentially all private sector employment between 1978 and 2021. Given that we bin the data into five year bins, we restrict attention to 1980–2019, which offers the additional benefit that it avoids the Pandemic recession and recovery.

Figure 24 visualizes the data by plotting the log change in allocative EE mobility between 1980–1989 and 2010–2019 across U.S. states. While all states experienced declines in allocative EE mobility, it was more pronounced in some areas. Moreover, although there is some evidence of spatial correlation with smaller declines in the middle of the country, it is fairly weak. Figure 25 plots allocative EE mobility and the ratio of firms to workers aggregated to the nine Census divisions. Both series are in logs and expressed relative to the average across all Census divisions at a point in time (equivalent to residualizing off time fixed effects) and the Census division mean over the entire sample period (equivalent to taking out division fixed effects). In general, when a division experienced a greater relative increase in market concentration, it saw a disproportionate decline in allocative EE mobility. Moreover, only one region experienced a monotone change in the relative firms/worker ratio over this 45 year period.

Figure 26 plots within-state log differences of the ratio of firms to workers and various labor market outcomes between 1980–1989 and 2010–2019. States that experienced larger increases in labor market concentration saw greater declines in allocative EE mobility (panel a). This is not accounted for by a lower acceptance probability (panel b), but by a lower job finding probability

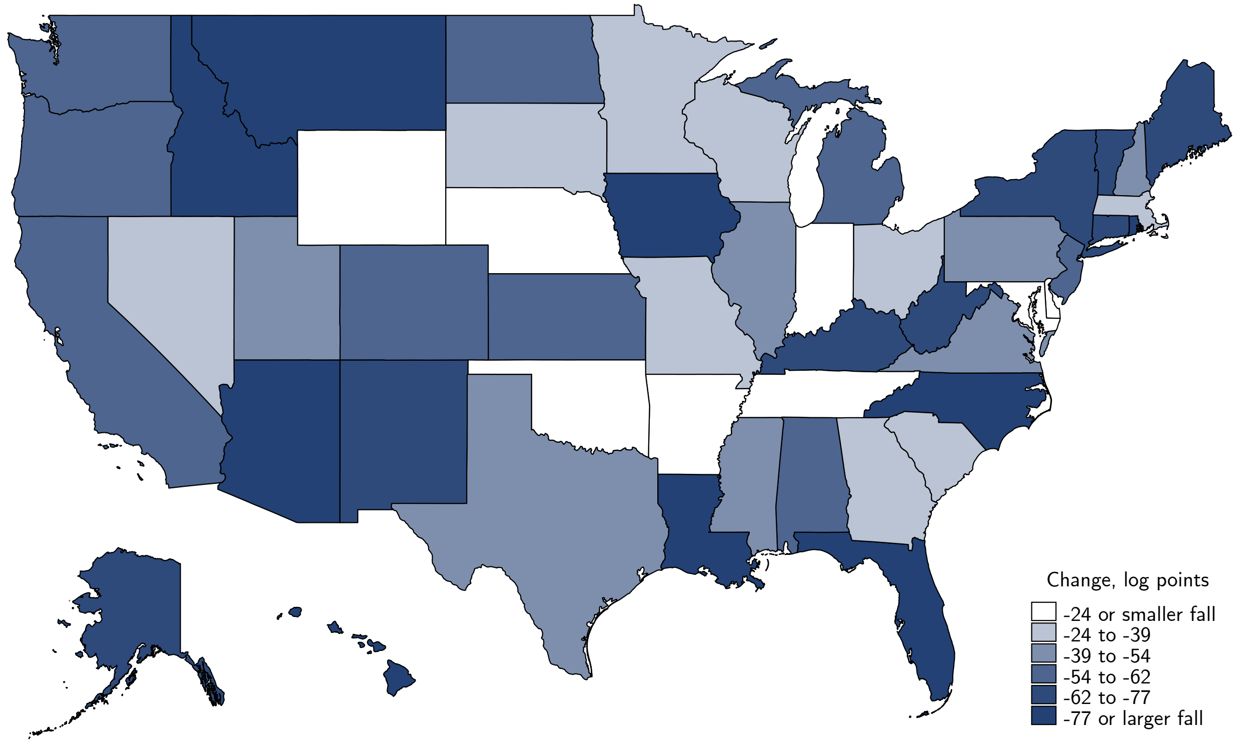

Figure 24: Log point change in allocative EE mobility between 1980–1989 and 2010–2019.

of the employed (panel c). In contrast, the correlation with changes in the job finding probability of the non-employed is much weaker (panel d).

We investigate these conditional correlations more formally by projecting various labor market outcomes at the state-five year period level ($y_{s,t}$) on measures of labor market concentration ($c_{s,t}$). We focus on two measures of concentration: the ratio of firms to workers and the share of employment in firms with 1000 or more employees. We run regressions of the form

$$y_{s,t} \quad = \quad \beta c_{s,t} \; + \; \xi_s \; + \; \phi_t \; + \; \varepsilon_{s,t} \tag{19}$$

Throughout, we control for state fixed effects (ξ_s) and time fixed effects (ϕ_t). Both the dependent and independent variables are in logs, allowing us to interpret β as an elasticity.[26] Although we find these conditional correlations interesting, we stress that they should not be interpreted to reflect a causal effect.

Table 1 displays our results. Panel A uses raw market concentration measures, while panel B first residualizes these off a sector fixed effect. That is, panel B accounts for the possibility that changes in market concentration may arise mechanically as a result of shifts in sectoral composition, if sectors differ in market concentration. The first row shows that a one percent increase in the number of firms per worker is associated with a 1.4 percent increase in allocative EE mobility.

[26]We present results treating all variables in levels in Appendix 7.4.

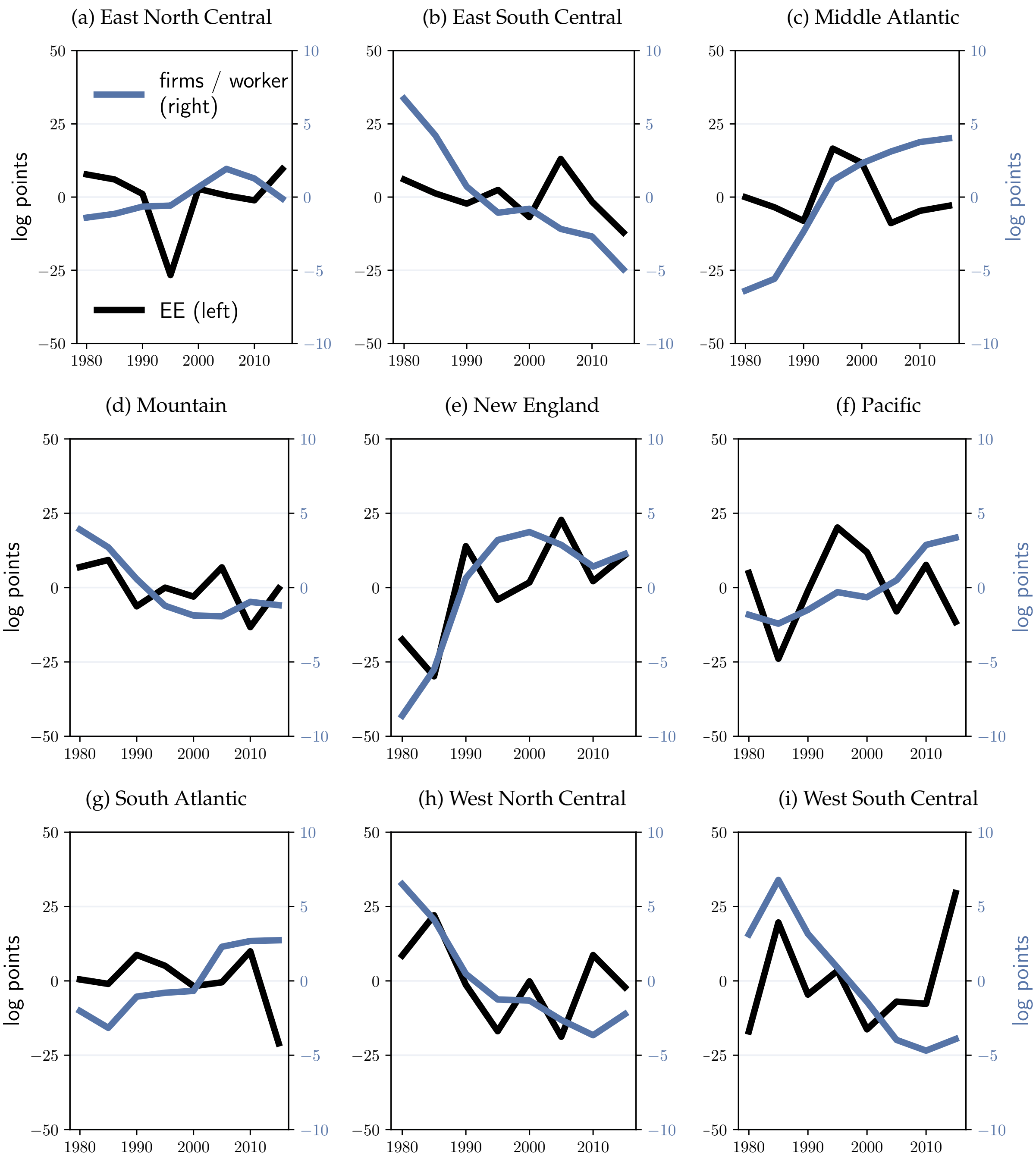

Figure 25: Allocative EE mobility and market concentration as measured by the ratio of firms to workers over time by U.S. Census division. All mobility is to higher-paying jobs.

It is associated with a 1.5 percent increase in annual wage growth due to EE mobility. The decrease in EE mobility is not the result of a lower acceptance probability, but a lower arrival probability of outside job offers for employed workers. The job finding probability of the non-employed is only weakly correlated with changes in firms per worker. Qualitatively, these results are consistent with the aggregate time trends in the U.S. The second and third rows show similar results using

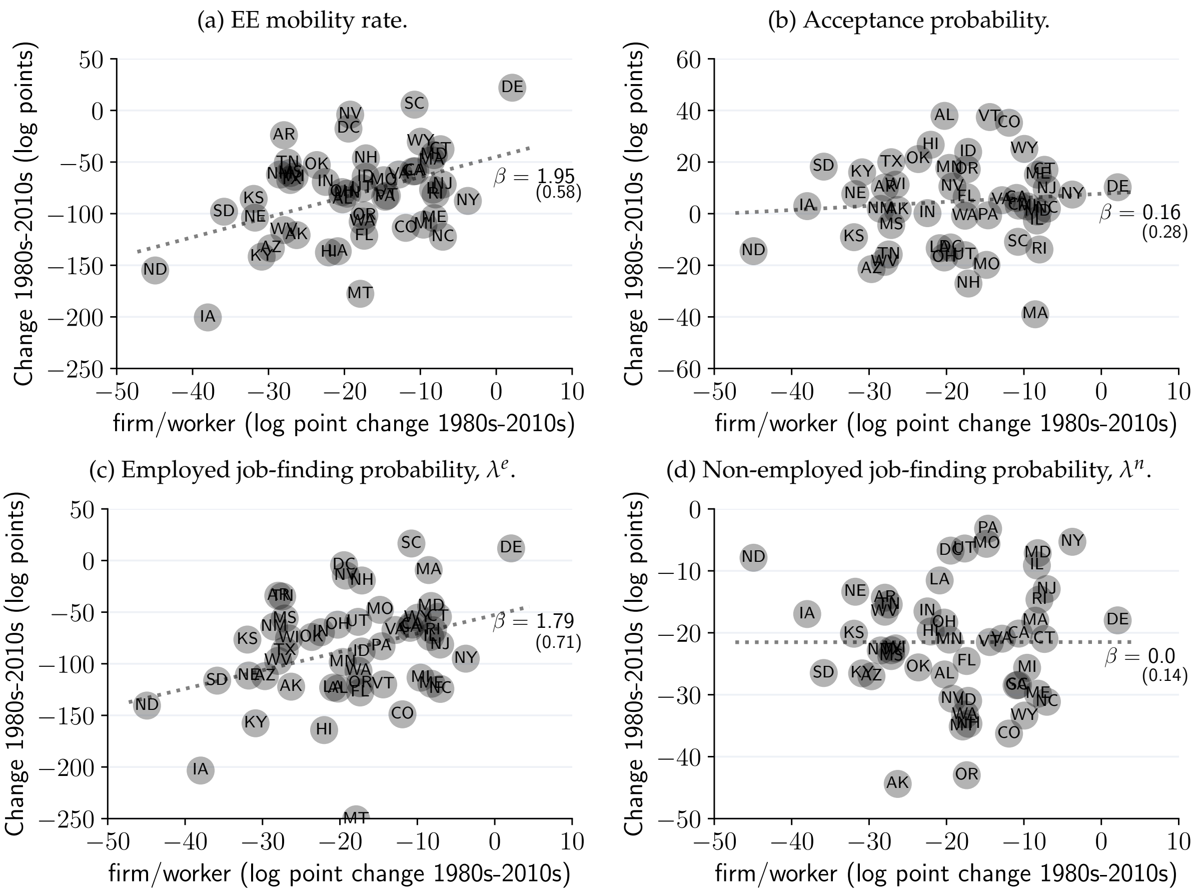

Figure 26: Changes in allocative EE mobility (a), the acceptance probability (b), the job-finding probability of the employed (c), and the job-finding probability of the non-employed (d) by market concentration as measured by number of firms per worker. All outcomes are in logs and graphs show long-differences within a U.S. state plus Washington D.C. between 1980-1989 and 2010–2019. All mobility is to higher-paying jobs.

alternative concentration measures. Across the board, results change little if we first take out a sector fixed effect from the measures of market concentration.

To provide a sense of the magnitude of these patterns, Figure 27 uses the cross-sectional estimates to predict the impact of a more than 20 log point decline in the number of firms per worker in the U.S. since the early 1980s (panel a) on national level labor market outcomes. There are several important caveats associated with this, including the facts that we treat the estimates as causal and that we disregard any aggregate equilibrium effects that are absorbed in the time fixed effects. With these caveats in mind, panel b suggests that increases in labor market concentration could have been an important factor behind the decline in allocative EE mobility that we observed over the past 40 years. In particular, a falling number of employers per worker predicts a 37 log point decline in EE mobility, relative to the 90 log point fall in the data. When we residualize the falling number of employers per worker on sector fixed effects, we observe a larger decline in employ-

	(1)	(2)	(3)	(4)	(5)
	EE	Δw	Acceptance Probability	λ^e	λ^n
			A. Raw labor market concentration		
Firms per worker	1.793*** (0.556)	1.799*** (0.534)	0.094 (0.239)	1.699*** (0.554)	-0.063 (0.102)
Emp. Share of Large Firms ($\geq$ 1000 emp.)	-1.535*** (0.414)	-2.005*** (0.469)	-0.160 (0.205)	-1.375*** (0.443)	-0.231 (0.136)
Emp. Share of Small Firms ($<$ 100 emp.)	2.009*** (0.675)	2.366*** (0.778)	0.109 (0.230)	1.900*** (0.675)	0.161 (0.151)
			B. Residual labor market concentration		
Firms per worker	1.656*** (0.641)	1.619*** (0.637)	0.295 (0.297)	1.361*** (0.692)	-0.228 (0.109)
Emp. Share of Large Firms ($\geq$ 1000 emp.)	-1.642*** (0.509)	-2.217*** (0.562)	-0.254 (0.245)	-1.389*** (0.554)	-0.197 (0.158)
Emp. Share of Small Firms ($<$ 100 emp.)	2.015*** (0.845)	2.434*** (0.940)	0.322 (0.280)	1.693*** (0.891)	0.006 (0.169)
N	405	405	405	405	405

Table 1: OLS estimates of equation (19) using data from 51 U.S. States and Washington DC and eight five-year time periods between 1980–2019. All variables are in logs and all specifications include state and period fixed effects. Robust standard errors in parentheses, clustered at the state level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

ers per worker, indicating that more concentrated sectors have become a smaller share of the US economy. Changes in residual employers per worker predict a nearly 53 log point fall, over 60% of the overall fall in allocative EE mobility. The change in residual employers per worker accounts for nearly three-quarters of the decline in wage growth due to EE mobility (panel c). Furthermore, increasing labor market concentration predicts virtually no change in the acceptance probability (panel d), so that the decline in EE mobility is driven by a lower job finding probability of the employed (panel e). Finally, increases in labor market concentration are only associated with a small change in the job finding probability of the non-employed (panel f). These predictions are both qualitatively and quantitatively in line with U.S. national trends over this period.

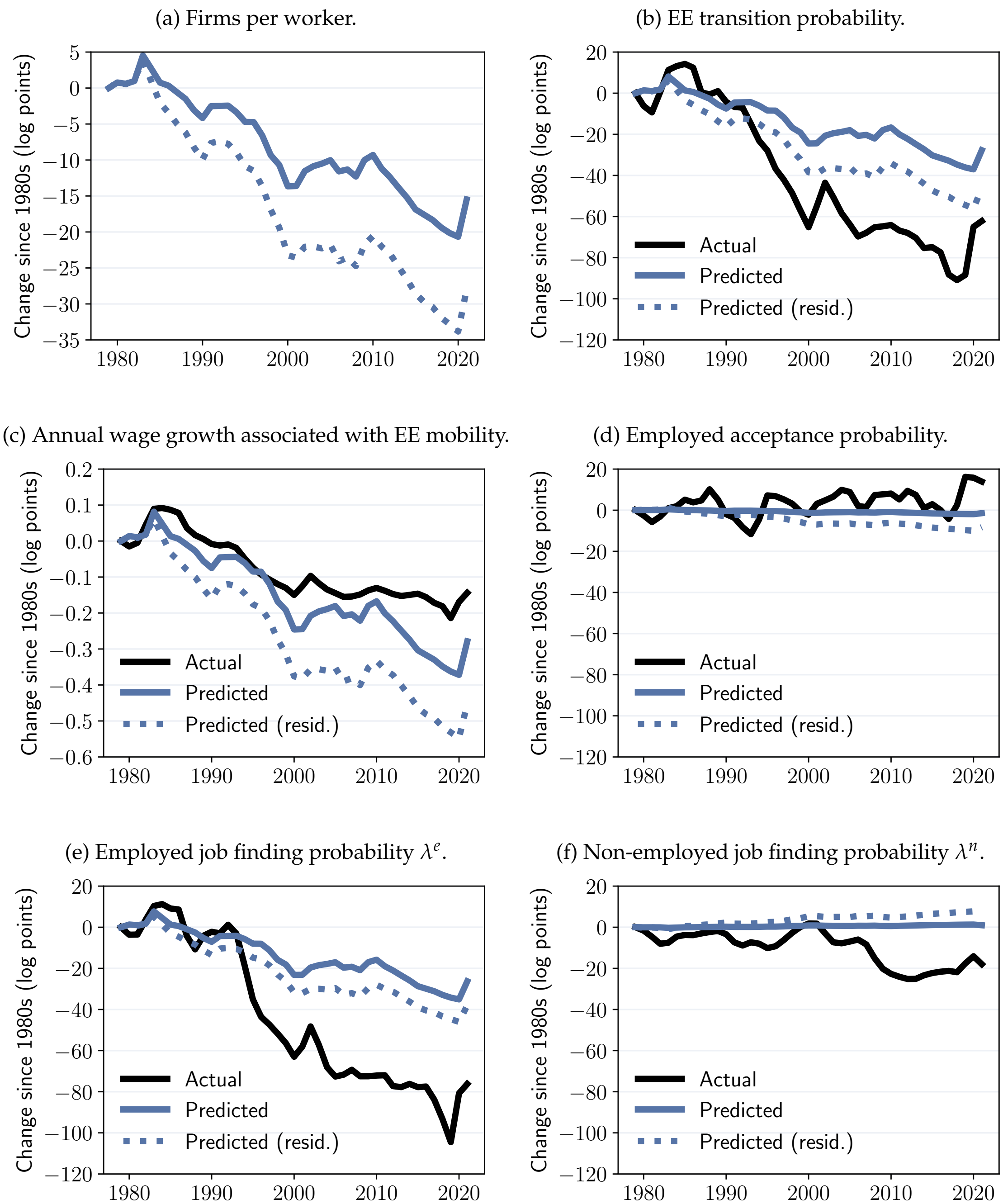

Figure 27: Panel (a) shows the change in market concentration as measured by firms per worker. The remaining panels show the actual (black) and predicted (blue) labor market variables where the prediction is the cross-sectional point estimate from regression (19) multiplied by the national change in concentration. Displayed in order are EE transition probability (b), the associated average wage change (c), the acceptance probability (d), the employed job-finding probability (e), and the non-employed job-finding probability (f). All variables are in logs.

6 Conclusion

We develop a methodology to consistently estimate EE mobility toward higher paying jobs based on publicly available micro data from the U.S. over the past half century, overcoming two challenges faced by the literature. First, we are able to estimate a consistent series for EE mobility between 1979 and 2023. Second, we isolate the component of EE mobility that systematically reallocates workers up the job ladder. We establish three long-run trends in such allocative EE mobility in the U.S. First, such mobility fell by half between 1979 and 2023. Second, this decline translated to over a one percentage point fall in annual wage growth associated with EE mobility. Third, women, those without a college degree, and recent cohorts saw particularly large declines.

We proceed to analyze three prominent potential explanations for the decline. We find little support for the hypothesis that allocative EE mobility is lower today because workers are better matched with their existing jobs. Furthermore, the decline does not appear to be the result of the labor market being less efficient at matching workers and firms. Instead, we provide evidence based on long-run variation across U.S. states that is consistent with the view that greater labor market concentration reduced workers' ability to transition toward higher paying employers.

Future work should further investigate the causes of the decline of the U.S. job ladder and in particular its relationship with competition in the labor market, as well as whether policy can play a role in fostering a more dynamic, inclusive labor market.

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7 Appendix

7.1 Further validation

Figure 28 provides an alternative validation of our methodology by instead using cross-sectional data. Specifically, it plots EE mobility over the life-cycle according to our structural estimate and the various raw measures, pooling all years of data. As we noted above, the level of mobility is substantially higher in the raw CPS than what our measure suggests (or the SIPP for that matter). The relative decline in EE mobility with age, however, is similar across the four measures, with our structural estimate indicating a somewhat smaller decline in EE mobility with age.

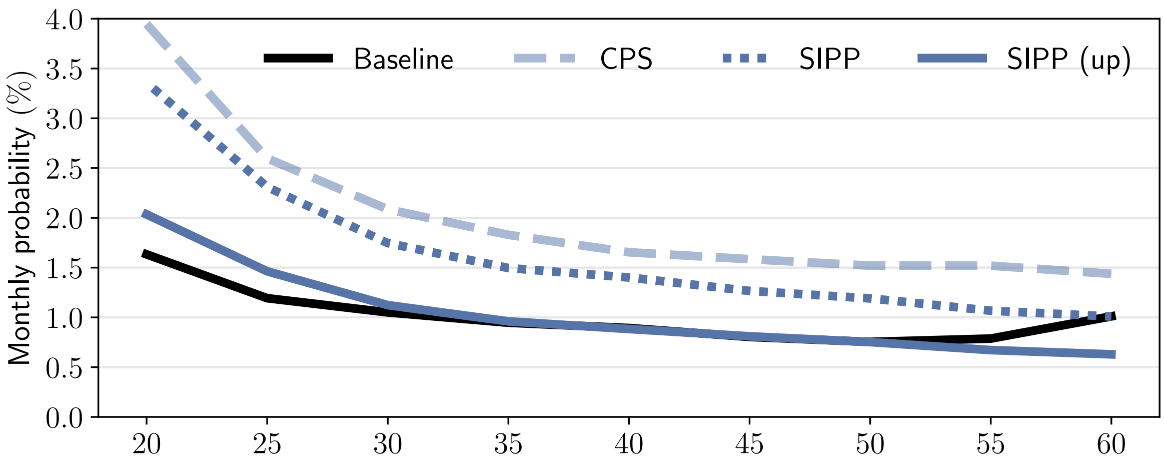
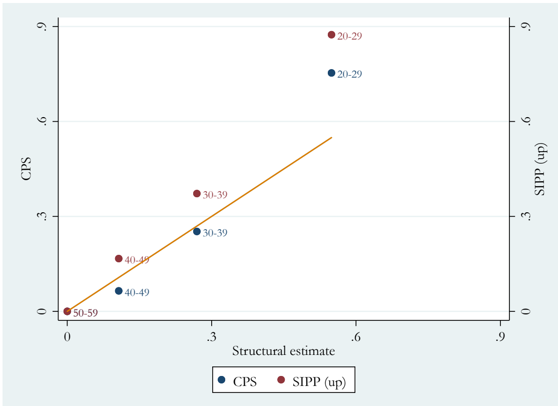


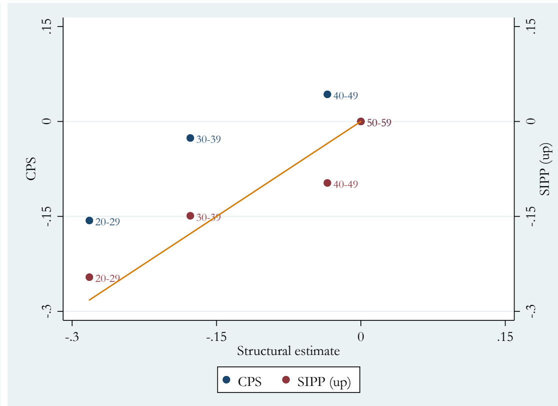
Figure 28: Comparison between the EE transition probability implied by the baseline model (black), the raw overall EE transition probability in the CPS (dark blue) and the SIPP (lighter blue), and the raw EE transition probability towards higher-paying jobs in SIPP (lightest blue) over the life-cycle, pooling all years of available data.

Figure 29 further validates our measure by contrasting differences in EE mobility by age and education across the various measures, both in levels and changes over time. In panel a, we plot the transition probability for each age group in log deviations from that of the oldest age group according to each measure. As we noted above, the structural estimate indicates a somewhat smaller relative decline in EE mobility with age than the raw measures (as indicated by the fact that the raw measures are generally above the 45 degree line). Panel b shows the change in EE mobility by age group between 1995–1999 and 2010–2014, expressed relative to the change of the oldest age group. As we discuss further below, younger workers experienced disproportionate declines in EE mobility. The structural estimate matches well these patterns in the raw data.

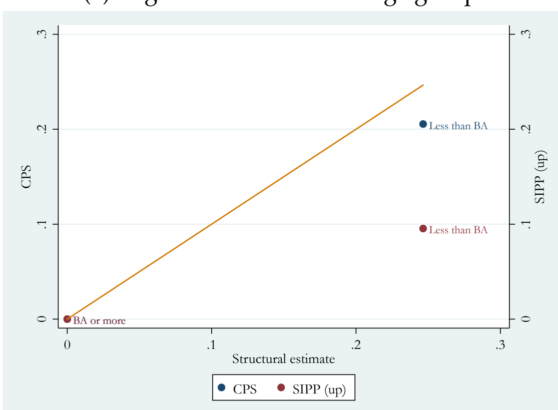
Panel c expresses the EE mobility rate of those with less than a college degree relative to those with a bachelor's degree or higher. Less educated workers have a higher EE transition probability according to both our structural estimate and the raw data, with the structural estimate indicating somewhat larger differences. Over time, less educated workers experienced disproportionate declines in EE mobility, as we discuss further below. The structural estimate matches well the raw data patterns (panel d). We view these validation exercises as indicating that our structural estimate captures well key aspects of EE mobility in the data.



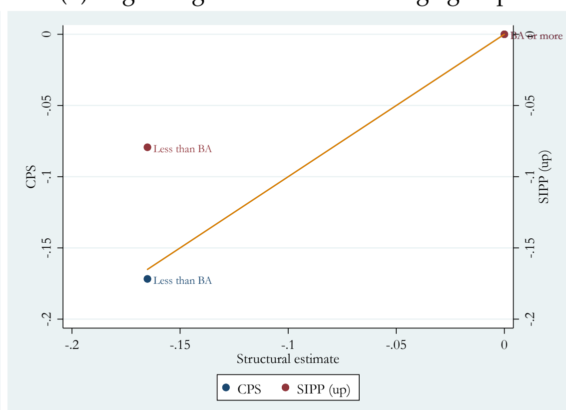
(a) Log difference to oldest age group.



(b) Log change relative to oldest age group.



(c) Log difference to college group.



(d) Log change relative to college group.

Figure 29: EE transition probability according to the raw CPS and the SIPP against that implied by the structural model across age/education groups in levels (panels a and c) and changes between 1995–1999 and 2010–2014 (panels b and d). The SIPP measure conditions on mobility to a higher paying job. All mobility is to higher-paying jobs.

7.2 Worker flows, job flows and churn

While our finding of a decline in EE mobility mirrors the well-known decline in job reallocation over this period (Davis and Haltiwanger, 2014; Decker et al., 2016), we stress that it does not follow mechanically from the latter. To see why, note that the overall worker reallocation rate—the sum of hires and separations divided by employment—can be written as the sum of *job reallocation* and *worker churn*—worker flows over and above what is necessary to reallocate jobs

$$\underbrace{WR_t}_{\text{worker reallocation}} = \underbrace{2 \times EE_t}_{\text{poaching flows}} + \underbrace{\delta_t}_{\text{separations to non-employment}} + \underbrace{\lambda_t^n \frac{1-e_t}{e_t}}_{\text{hires from non-employment}} \tag{20}$$

$$= \underbrace{JR_t}_{\text{job creation + job destruction}} + \underbrace{Churn_t}_{\text{replacement hiring}} \tag{21}$$

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 would remain with the firm whenever it hires a new worker to replace someone who left.

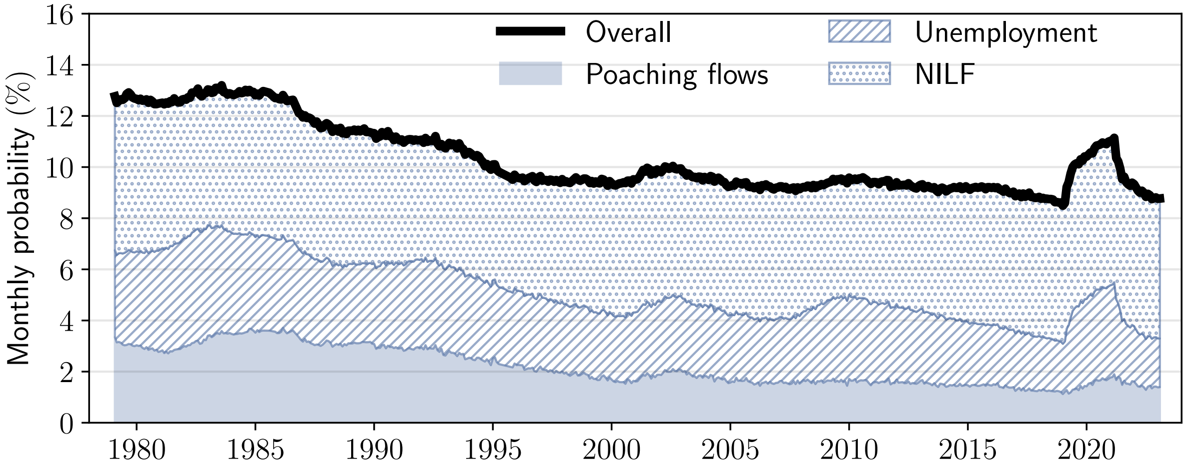
Figure 30 decomposes overall worker reallocation following (20)–(21) (using the baseline model). During the 1980s, EE mobility toward higher paying jobs constituted roughly a quarter of overall worker flows. Flows in and out of unemployment accounted for about 30 percent of overall flows, with the remainder 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 non-employment (Fujita and Moscarini, 2017; Hall and Kudlyak, 2022), this likely understates the role of EE mobility for overall worker reallocation. Moreover, a nontrivial share of workers make EE transitions toward lower paying jobs (Tjaden and Wellschmied, 2014; Sorkin, 2018). Accounting for these would boost the importance of EE transitions, but lower the share of EE transitions toward higher paying jobs. Finally, the CPS is known to suffer from labor force status classification error, which inflates gross flows between employment and non-employment (Abowd and Zellner, 1985). Accounting for this would increase the relative importance of EE transitions. Disregarding these measurement issues, we find that worker reallocation is four times as large as job reallocation.[27]

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 (panel a). 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. 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 (panel b).

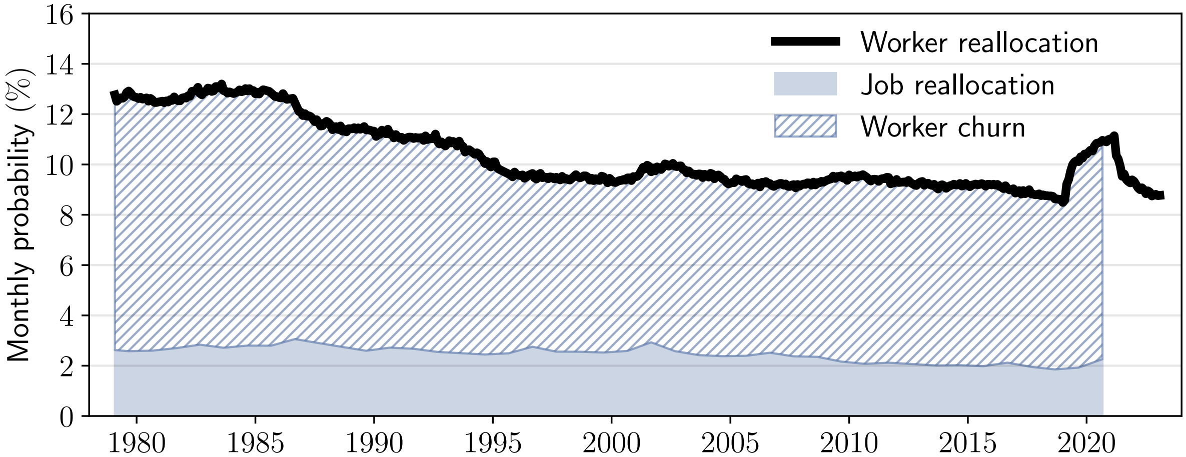
7.3 Shift-share

In this section we run counterfactual exercises to determine what the EE mobility probability would have been if the distribution across age and education had not changed between 1979 and

[27] 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.



(a) Worker relocation decomposition in poaching and non-employment flows as stated in equation (20).



(b) Worker reallocation decomposed in job reallocation and churn following equation (21).

Figure 30: Overall worker reallocation decomposed following (20)–(21). Monthly job reallocation here is the annual rate divided by 12 (available from the Census Bureau's *Business Dynamics Statistics* until 2021).

2023.

Suppose we have N individuals, indexed by i, for whom we know the age, $a \in \mathrm{N}_+$, employment status, $e \in 0, 1$ (where 0 is nonemployment, and 1 is employment), the education level $c \in 0, 1$ (where 0 is no college, and 1 is college or more), and whether they switched jobs from the previous period, $j \in 0, 1$. The overall EE mobility rate can be written as

$$EE_t = \frac{\sum_i j(i) \cdot e(i)}{\sum_i e(i)}$$

The EE mobility probability for those in age group a, education group c is is

$$EE_t^{a,c} = \frac{\sum_i j(i) \cdot e(i) \cdot \mathbb{1}\left[a(i) = a\right] \cdot \mathbb{1}\left[c(i) = c\right]}{\sum_i e(i) \cdot \mathbb{1}\left[a(i) = a\right] \cdot \mathbb{1}\left[c(i) = c\right]}$$

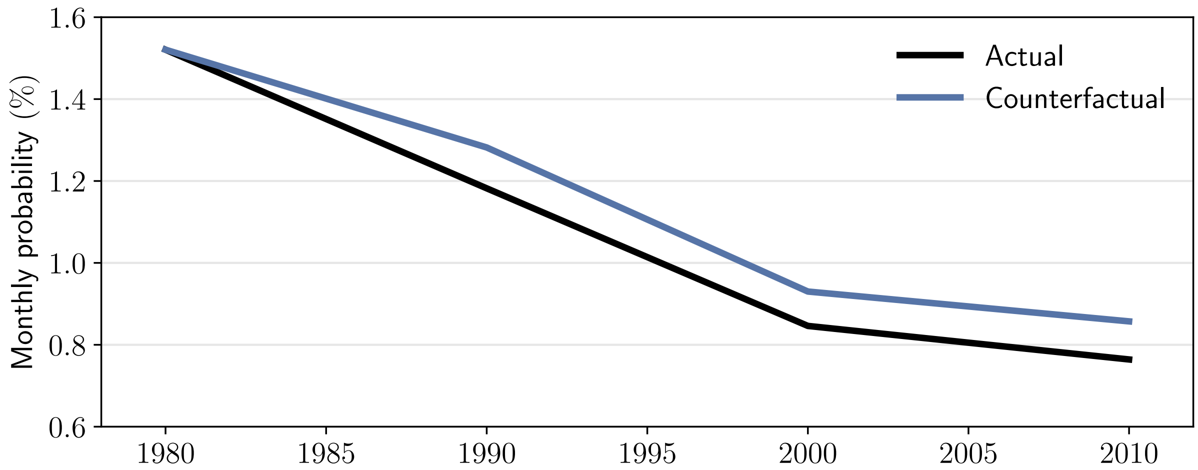


Figure 31: Results from shift-share counterfactual exercise. The blue series captures the counterfactual shift in EE mobility that can be explained purely by changes in the age and educational status composition of the population.

How do we decompose the overall EE mobility probability in the age by education EE probabilities? We can re-write the overall EE probability as

$$
\begin{aligned}
EE_t &= \frac{\sum_i j(i) \cdot e(i)}{\sum_i e(i)} = \frac{\sum_{(a,c)} \sum_i j(i) \cdot e(i) \cdot \mathbb{1}\left[a(i)=a\right] \cdot \mathbb{1}\left[c(i)=c\right]}{\sum_i e(i)} \\
&= \sum_{(a,c)} \left\{ \frac{1}{\sum_i e(i)} \cdot \left(\sum_i j(i) \cdot e(i) \cdot \mathbb{1}\left[a(i)=a\right] \cdot \mathbb{1}\left[c(i)=c\right] \right) \right\} \\
&= \sum_{(a,c)} \left\{ \frac{\sum_i e(i) \cdot \mathbb{1}\left[a(i)=a\right] \cdot \mathbb{1}\left[c(i)=c\right]}{\sum_i e(i)} \cdot \frac{\sum_i j(i) \cdot e(i) \cdot \mathbb{1}\left[a(i)=a\right] \cdot \mathbb{1}\left[c(i)=c\right]}{\sum_i e(i) \cdot \mathbb{1}\left[a(i)=a\right] \cdot \mathbb{1}\left[c(i)=c\right]} \right\} \\
&= \sum_{(a,c)} \left\{ \frac{\sum_i e(i) \cdot \mathbb{1}\left[a(i)=a\right] \cdot \mathbb{1}\left[c(i)=c\right]}{\sum_i e(i)} \cdot EE_t^{a,c} \right\}
\end{aligned}
$$

Denote the term $\frac{\sum_i e(i) \cdot \mathbb{1}[a(i)=a] \cdot \mathbb{1}[c(i)=c]}{\sum_i e(i)}$ as $w_{a,c}$, the share of of the employed workers of age a and education e relative to all employed workers. Then

$$
EE_t = \sum_{(a,c)} w_{a,c} \cdot EE_t^{a,c}
$$

We construct the *counterfactual* EE probability in which workers shares by age $\times$ education are fixed to 1980. This captures the effect that the change in the (joint) age/education distribution over the past 40 years had on mobility. We do so keeping fixed to 1980 the weights $w_{a,c}$

$$
\widehat{EE}_t = \sum_{(a,c)} w_{a,c}^{1980} \cdot EE_t^{a,c}
$$

7.4 Average wage gain upon an EE move

Figure 32 shows the wage gain *conditional* on making an EE transition according to both the model and the SIPP data.[28] The latter is for workers moving to higher paying jobs. 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 to suggest that the decline in mobility is not the result of workers being better matched in their current jobs.[29]

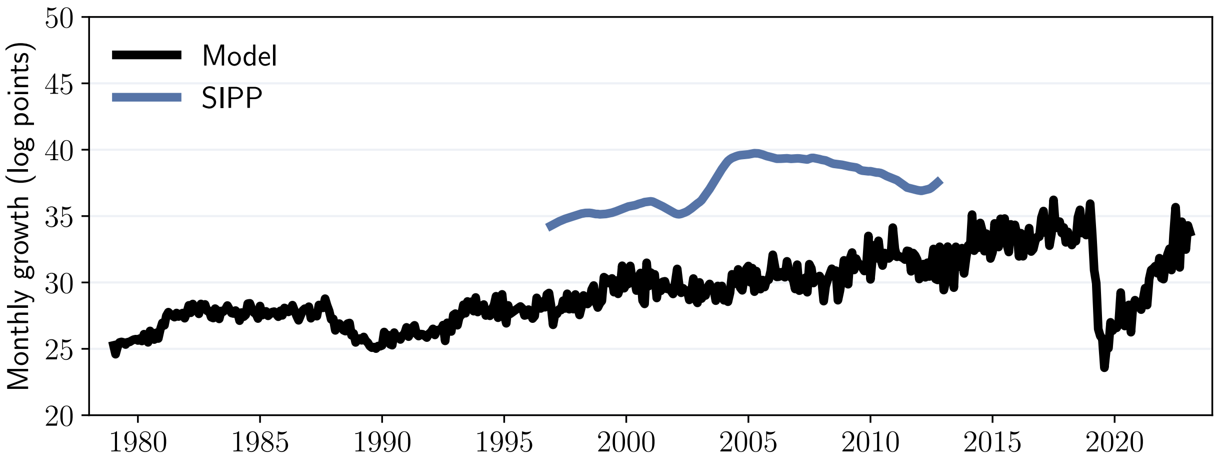


Figure 32: Wage growth conditional on switching to a higher-paying employer in model (black) and in the SIPP (blue).

[28] As we noted above, we use median instead of means in the SIPP in order to limit the impact of a few outliers. Using the average instead results in a similar increase over time, but a higher level of wage growth.

[29] This interpretation depends on the underlying offer distribution. If the offer distribution is Pareto, the conditional wage gain upon an EE transition is independent of the wage distribution, and hence completely uninformative about the extent of mismatch.

7.5 Additional Results for Labour Market Concentration

We present below alternative cross-state estimates based on identical specifications as above, but with both the dependent and independent variables in levels instead of logs.

	(1) EE	(2) Δw	(3) Acceptance Probability	(4) λ^e	(5) λ^n
A. Raw labor market concentration					
Firms per worker	0.250*** (0.060)	0.130*** (0.028)	0.418 (2.598)	0.501*** (0.154)	0.026 (0.128)
Emp. Share of Large Firms ($\geq$ 1000 emp.)	-0.028*** (0.012)	-0.017*** (0.007)	-0.408 (0.349)	-0.047*** (0.027)	-0.055 (0.034)
Emp. Share of Small Firms ($<$ 100 emp.)	0.040*** (0.010)	0.023*** (0.005)	-0.906 (1.027)	0.074*** (0.025)	0.047 (0.030)
B. Residual labor market concentration					
Firms per worker	0.272*** (0.074)	0.135*** (0.036)	4.287 (6.527)	0.586*** (0.182)	-0.139 (0.124)
Emp. Share of Large Firms ($\geq$ 1000 emp.)	-0.028*** (0.015)	-0.018*** (0.008)	-1.074 (0.779)	-0.044*** (0.034)	-0.049 (0.041)
Emp. Share of Small Firms ($<$ 100 emp.)	0.046*** (0.013)	0.027*** (0.006)	-0.836 (0.969)	0.082*** (0.031)	0.038 (0.036)
N	405	405	405	405	405

Table 2: OLS estimates of equation (19) using data from 51 U.S. States and Washington DC and eight five-year time periods between 1980–2019. All variables are in levels and all specifications include state and period fixed effects. Large firms are defined as firms with 1000 employees or more, and small firms are defined as those with fewer than 100 employees. Robust standard errors in parentheses, clustered at the state level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

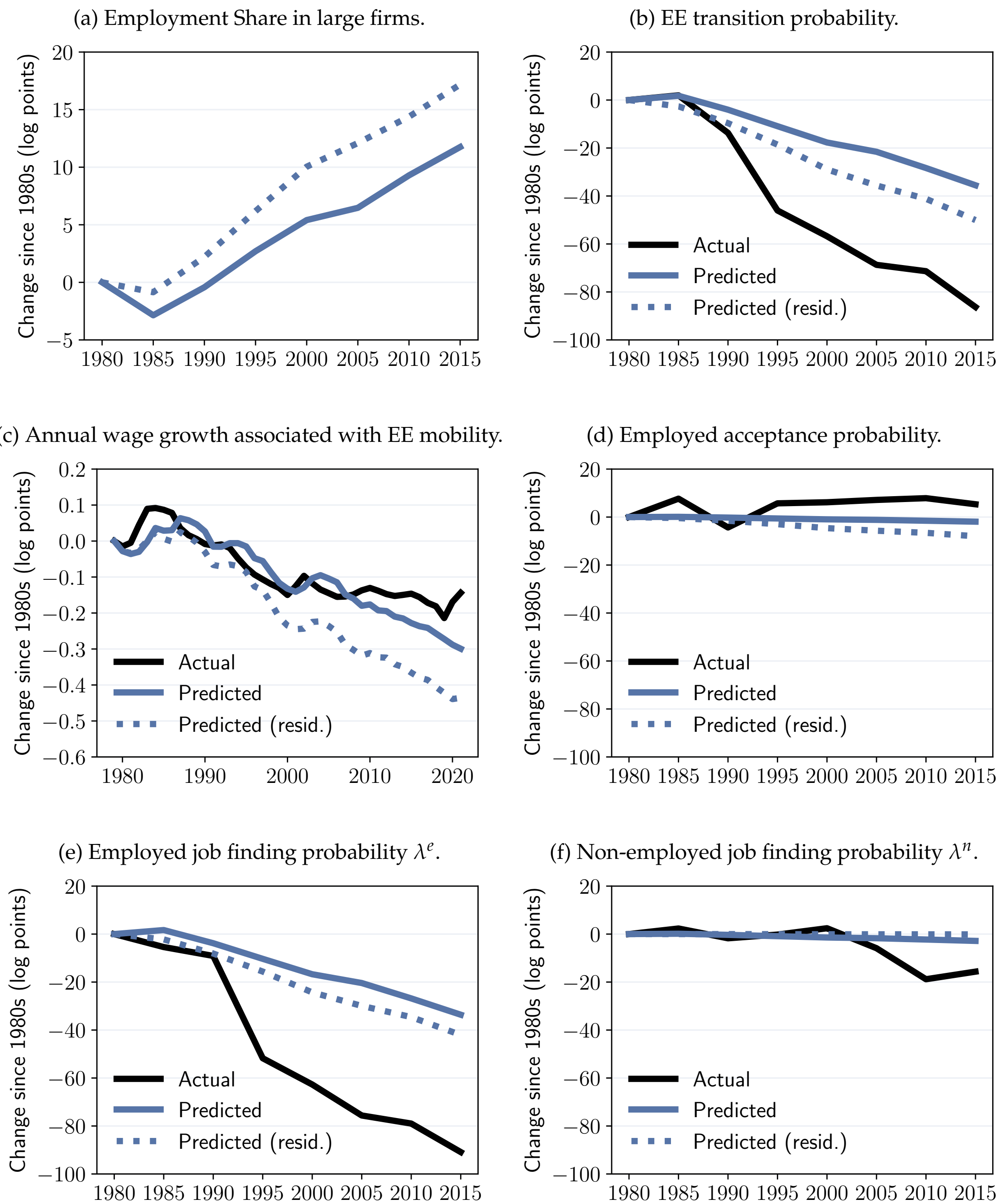


Figure 33: Panel (a) shows the change in market concentration as measured by the share of large firms (those with at least 1000 employees). The remaining panels show the actual (black) and predicted (blue) labor market variables where the prediction is the cross-sectional point estimate from regression (19) multiplied by the national change in concentration. Displayed in order are EE transition probability (b), the associated average wage change (c), the acceptance probability (d), the employed job-finding probability (e), and the non-employed job-finding probability (f). All variables are in logs.

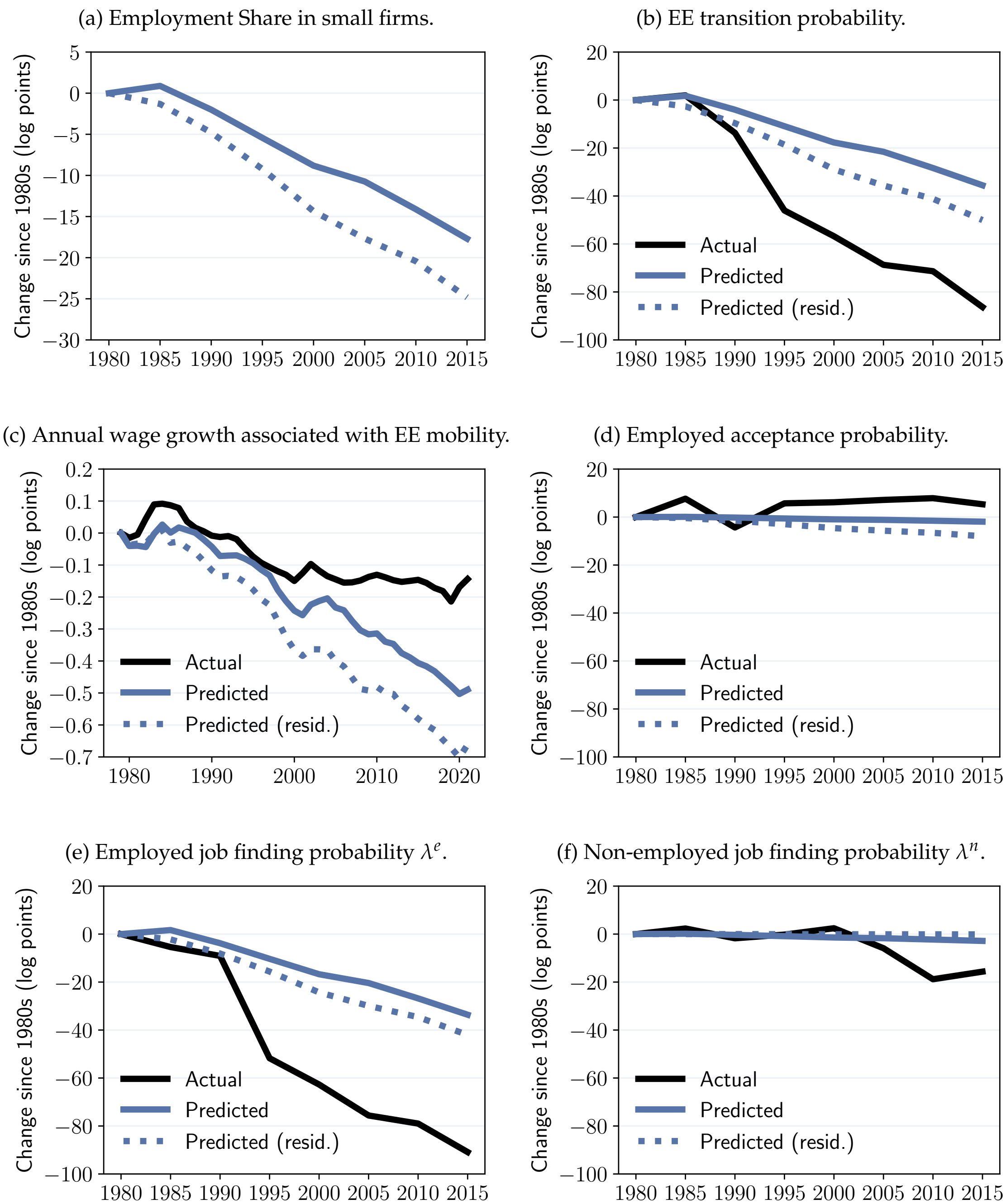


Figure 34: Panel (a) shows the change in market concentration as measured by the employment share of small firms (with fewer than 99 employees). The remaining panels show the actual (black) and predicted (blue) labor market variables where the prediction is the cross-sectional point estimate from regression (19) multiplied by the national change in concentration. Displayed in order are EE transition probability (b), the associated average wage change (c), the acceptance probability (d), the employed job-finding probability (e), and the non-employed job-finding probability (f). All variables are in logs.