Job Recalls and Worker Flows Over the Life Cycle*

Justin Franco Lam[†]
University of Pennsylvania

Xincheng Qiu[‡]
Arizona State University

April 17, 2024

Abstract

The share of jobless spells that end with recalls, i.e., returning to the previous job, as opposed to finding a new job, is strongly increasing over the life cycle. Throughout the life cycle, wage changes associated with recalls are concentrated at zero, different from the wage change behavior of new-job findings or job-to-job transitions. We find that the introduction of recall options into a job-ladder search model provides a novel mechanism that reproduces a declining job finding rate over the life cycle. The model quantitatively accounts for empirical patterns of life-cycle labor market dynamics. Deterioration of aggregate matching efficiency in bad times hurts labor market entrants more than experienced workers, because job-finding prospects of entrants rely more on the matching function of the labor market, whereas experienced workers rely less and get more recalls.

Keywords: Recalls, Unemployment, Search and Matching, Life Cycle, Worker Flows
JEL Codes: E24, J24, J64

*We are grateful to José-Víctor Ríos-Rull, Iourii Manovskii, Hanming Fang, Dirk Krueger, and Joachim Hubmer for their advice. We thank seminar participants at Midwest Macro, RIDGE Labor Workshop, and EEA-ESEM, for helpful comments.

[†]Department of Economics, University of Pennsylvania. Email: jflam@sas.upenn.edu.
[‡]Department of Economics, Arizona State University. Email: xincheng.qiu@asu.edu.

1 Introduction

An unemployed worker leaves the unemployment pool by either finding a new job or returning to work for their previous employers. In the US labor market, over 40% of unemployment spells end with recalls (Fujita and Moscarini, 2017).[1] The pandemic labor market has further demonstrated that the incidence of recalls is crucial to understanding labor market dynamics.[2] The labor market implication of layoffs are very different when recalls are taken into account. For instance, layoffs are not necessarily associated with job destruction, if the match capital can be preserved by recalls.

This paper investigates the life-cycle behavior of recalls, revealing vast heterogeneity in workers' job finding behavior over the life cycle. Using the Survey of Income and Program Participation (SIPP), we document novel facts on recalls over the life cycle. First, the recall share, defined as the share of unemployment-to-employment transitions that go back to the previous jobs rather than new jobs, exhibits a steep age-gradient. The recall share of an old worker is more than twice as high as that of an young worker. For instance, among 55-year-old workers who leave unemployment, 60% of them return to their previous employers, while a 25-year-old worker has a recall share of only lower than 30%. Such a steep age-gradient in recalls is robust to an extensive set of controls, including gender, education, race, occupation, industry, tenure, unemployment duration, unemployment insurance (UI) status, employer-provided health insurance status, and union status. The pattern is hardly changed if we exclude seasonal jobs. Furthermore, we also confirm the life-cycle profile of recalls in the Quarterly Workforce Indicators (QWI), which is in turn tabulated from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee microdata.

Second, we examine how different paths of labor market reallocation transitions are associated with labor market outcomes such as wages. We find that recalls (ENE), new-job findings (ENE$'$), and job-to-job switches (EE$'$) differ significantly in wage outcomes, both in terms of the level of the wage change and the life-cycle pattern of the wage change. Using an event study design, we find that wages remain largely unchanged following recalls, and such constancy in wages before and after recalls holds across different age groups. However, the distribution of wage changes between pre-separation and post-separation jobs for workers transitioning to new jobs is highly dispersed, with the average wage change decreasing with age. Specifically, young workers between 23 and 35 making ENE$'$ transitions experience only a mild wage loss of about

[1] Recalls are also prevalent in European labor markets. For example, see the evidence in Nekoei and Weber (2015) for Austria (35%), Alba-Ramírez, Arranz and Muñoz-Bullón (2007) for Spain (36%), Jansson (2002) for Sweden (45%), and Røed and Nordberg (2003) for Norway (32%). Numbers in the parentheses refer to the estimates of the overall recall share reported by each paper.

[2] Examples include Cajner et al. (2020); Forsythe et al. (2022); Ganong et al. (2021); Hall and Kudlyak (2022).

3% on average, whereas workers between 35 to 60 experience a big wage loss exceeding 10% in ENE′ transitions. Interestingly, for job-to-job switchers (EE′ transitions), the wage change also decreases in age, but it remains positive through out the life cycle.

To investigate the role of job recalls to labor market dynamics over the life cycle, We extend the Diamond-Mortensen-Pissarides model in two aspects. First, we allow for the potential of returning to a former job after a period of unemployment into the model. Second, we introduce a job ladder of match-specific productivity and allow for on-the-job search to address the life-cycle dynamics of unemployment, separation, job-finding, job-to-job transition, and recalls. Jobs are occasionally hit by idiosyncratic shocks, and workers and employers can decide whether to keep producing or separate. A larger fraction of older workers are employed in the top of the job ladder. As a result, they separate less, but are more likely to go back to the previous job conditional on separation, because the match is already of a high quality. For the same reason, they are less likely to switch jobs. The presence of a recall option makes an unemployed worker attached to a job, and hence the job-finding rate behaves similarly to the job-to-job transition rate, thus reconciling a puzzle in the literature on the positive comovement of separation rate and job finding rate over the life cycle (Chéron, Hairault and Langot, 2013).

The model is calibrated to the US labor market. It quantitatively matches all salient features of labor market dynamics over the life cycle. We apply the calibrated model to study an experiment of a negative shock to the aggregate matching efficiency (see, e.g., Gavazza, Mongey and Violante, 2018). We show that deterioration of matching efficiency in bad times hurts labor market entrants more than experienced workers. This is because labor market entrants rely more on the labor market matching to find a job, whereas experienced workers rely less and get more recalls. The quantitative analysis reveals that a decrease in aggregate matching efficiency during the Great Recession results in a nearly 50% decrease in the job finding rate for new entrants, in contrast to a less than 20% decrease for experienced workers. These findings are consistent with the empirical observation during the Great Recession.

To summarize, this paper makes three contributions. First, it empirically documents a novel fact on the life-cycle behavior of recalls. Second, it proposes a simple search theory of recalls, and demonstrates that incorporating recalls into an otherwise standard job-ladder model naturally rationalizes the life-cycle behavior of the job-finding rate and separation rate. Third, it provides a new mechanism to understand the disproportionately negative impacts of recessions on new entrants to the labor market.

Related Literature. Despite the prevalence of recalls in the labor market, there is little research on recalls. This paper first contributes to a small literature that documents empirical facts on recalls. Early important contributions include Katz (1986) using the Waves 14 and 15 of the Panel Study of Income Dynamics (PSID), and Katz and Meyer (1990*b*) using a supplemental survey of a sample of unemployment insurance (UI) benefits recipients from Missouri and Pennsylvania between October 1979 and March 1980, both of which first notice the importance of accounting for recalls in the analysis of unemployment. More recent contributions include Fujita and Moscarini (2017), who document the large magnitude and strong cyclicality of recalls, and Gertler, Huckfeldt and Trigari (2022), who document sizeable and countercyclical "loss-of-recall." We complement these aggregate analyses by unveiling the heterogeneity over the life cycle.

Second, this paper adds to theoretical models on recalls. Feldstein (1976) is the first to provide a theory for temporary layoffs and study how they are effected by unemployment insurance and tax policies. Fujita and Moscarini (2017) introduce a recall option in the workhorse search and matching model a là Mortensen and Pissarides (1994) and study its business cycle behavior. Fernández-Blanco (2013) studies a steady-state version of the model where firms can commit to contracts. The key trade-off is between providing workers with insurance and with incentives not to search while waiting for a recall. We study a job-ladder model with recalls, and analyze both the cross-sectional differences in the steady state and the heterogeneous responses to aggregate shocks.

Third, this paper provides a novel perspective to worker flows over the life cycle and contributes to life-cycle search models. The life cycle profiles of EU rate, UE rate, and EE rate, as well as transitions in and out of the labor force, have been documented by Menzio, Telyukova and Visschers (2016) using the 1996 panel of the SIPP and Choi, Janiak and Villena-Roldán (2015) using the monthly data files from the Current Population Survey (CPS) between January 1976 and April 2013. Our finding cautions that a summary statistics of job finding rate masks vast heterogeneity in the job finding behavior. For example, we find that although the job finding rate is relatively flat over the life cycle (it is slightly declining if anything), for old workers most of the job finding is returning to previous employers. Theoretical contributions of worker flows over the life cycle include Chéron, Hairault and Langot (2011), Chéron, Hairault and Langot (2013), Esteban-Pretel and Fujimoto (2014), Menzio, Telyukova and Visschers (2016), Gorry (2016), and Cajner, Güner and Mukoyama (2021). We show that incorporating recalls breaks the equivalence in the separation margin and acceptance margin as pointed out by Chéron, Hairault and Langot (2013), thereby providing a simple life cycle search model that is consistent with all worker flows.

Finally, this paper contributes to understanding the disproportionately negative impacts of recessionary periods on labor market entrants (Kahn, 2010; Oreopoulos, Von Wachter and Heisz, 2012; Arellano-Bover, 2022; Rothstein, 2023). Specifically, it introduces a novel mechanism that attributes the harsher consequences faced by new entrants during economic downturns to their lack of previous job affiliations and consequently, no recall options. To this end, we provide a quantitative theory how the cross-section moves over the business cycle.

Road Map. The rest of the paper is organized as follows. In Section 2, we describe the empirical facts of recalls over the life cycle. In Section 3, we describe the model and show that its theoretical implications are in line with the data. Section 4 presents the quantitative performance of the model. Section 5 performs an experiment of a drop in the aggregate matching efficiency and examines its differential impact on labor market entrants and experienced workers. Section 6 concludes.

2 Empirical Facts

We study the life cycle behavior of job recalls using the Survey of Income and Program Participation (SIPP). SIPP is a collection of panel data that begin in different years. For each interview (also known as a wave) in SIPP, questions are asked about the preceding four months, making it feasible to conduct the analysis at the monthly frequency. A unique feature of SIPP is that it allows for the measurement of recalls, as it assigns a unique job ID to each employer for each respondent. Combining this information with the panel design of the survey, we can therefore identify if a worker has returned to her previous employer after a jobless spell.

We define an event as a job recall if the worker has gone through an employment-to-nonemployment-to-employment transition and returned to the same employer she worked for before the separation.[3] Denote ENE_t the number of workers who get separated to nonemployment at age t and then get recalled back to their most recent employer, and ENE'_t the number of workers who get separated at age t and get out of nonemployment to new employers. We define the recall share as the share of nonemployment outflows that transitions back to the previous employers:[4]

$$\text{Recall Share}_t = \frac{\mathrm{ENE}_t}{\mathrm{ENE}_t + \mathrm{ENE}'_t}.$$

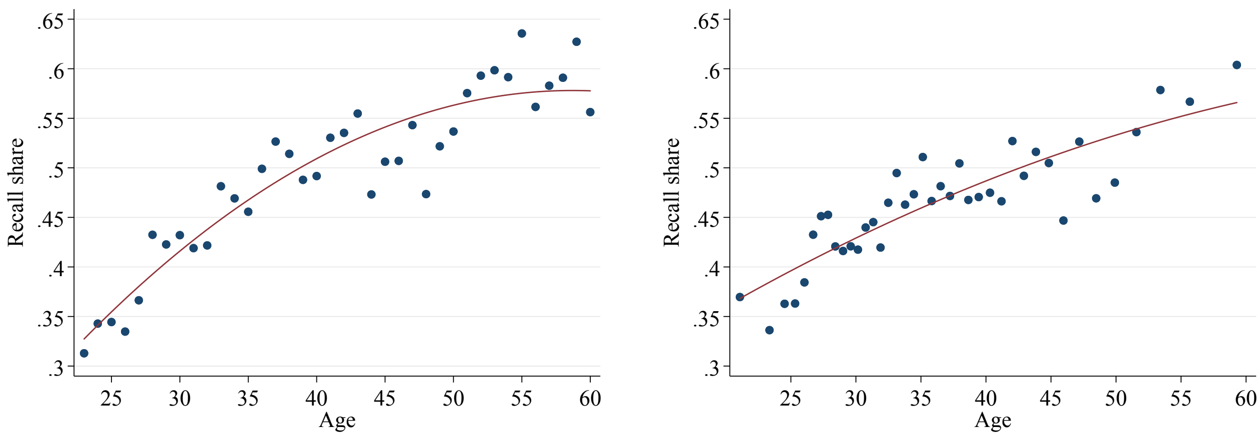
Note that in this definition, workers who have not had a job before are not considered, as they do not even have the possibility of being recalled.

[3]We only consider job recalls to the most recent employer before separation and do not study recalls to earlier employers. The same practice has been adopted in Fujita and Moscarini (2017). This is due to the data limitation that SIPP only provides a short panel that last for a few years, so that it is less useful to track earlier employers before the respondent entered the survey.

[4]Fujita and Moscarini (2017) call this object the "recall rate." We instead reserve the terminology "recall rate" for the job-finding rate due to recalls, i.e., unemployment-employment transitions that are recalls divided by the unemployment stock, so that it is part of the overall job finding rate.

Figure 1: Recalls Over the Life Cycle

(a) Without Controls (b) With Controls



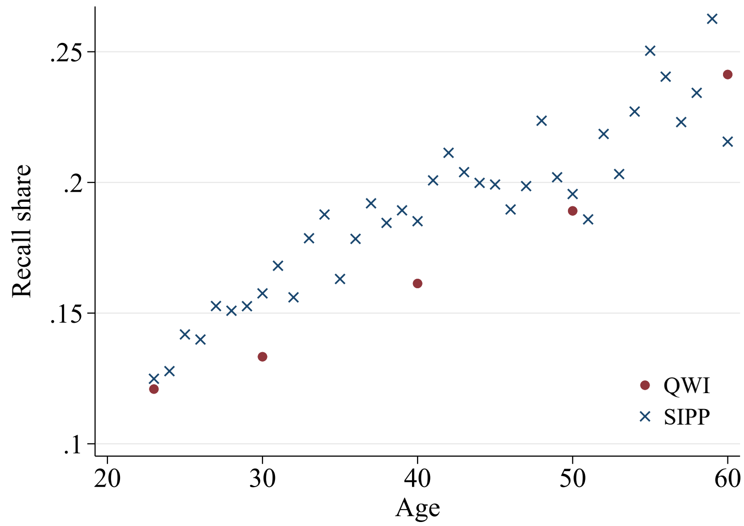
Notes: The figure plots the life cycle profile of the recall share without controls (left) and with controls (right). Controls include gender, education, race, occupation, industry, job tenure quadratic, unemployment duration, union membership, unemployment insurance recipiency status and amount, employer-provided health insurance, and year fixed effect.

2.1 Life-Cycle Behavior of Recalls

Figure 1 shows the binscatter plot of recall share against age. The left panel plots the raw relationship without any controls. For 25-year-old workers, only one third of separated workers go back to their previous jobs. However, for 55-year-old workers, 60% of workers who separate from their jobs end the jobless spell by returning to the same job prior to separation. Namely, the recall share of an experienced worker almost doubles that of a young worker. As discussed below, the fact is confirmed in administrative data, and is robust to an extensive set of controls and various alternative sample selections.

Administrative data. We confirm the empirical finding of an increasing recall share over the life cycle using the high-quality Quarterly Workforce Indicator (QWI) data. The QWI dataset is a data product published by the Census Bureau and is aggregated from the administrative microdata in the Longitudinal Employer-Household Dynamics (LEHD) program. The definition of recalls in QWI is not identical to our construction using SIPP. There are two main discrepancies. First, there is a time aggregation issue in QWI because it is at the quarterly frequency, while we construct recall shares in SIPP at the monthly frequency. The monthly frequency is in general more suitable for analysis on the US labor market as it has high mobility, and is in particular more suitable for the study of recalls because recalls typically involve short unemployment durations. The QWI definition would miss recalls that happened within a quarter. Second, when calculating the share of hires that are recalls, QWI does not restrict attention to hires from the most recent employer but allows for recalls to any employers that

Figure 2: Recalls Over the Life Cycle in QWI



Notes: The figure plots the life cycle profile of recall share in Quarterly Workforce Indicator (red dots) and SIPP adjusted to the QWI definition (blue crosses). See the main text for details of the adjustment.

the worker has worked for within a year and possibly without non-employment spell. To take care of these two differences, we reconstruct the recall share in SIPP in the same way as defined by QWI. Specifically, we collapse the monthly SIPP data to a quarterly frequency and allow for recalls to any employers that the worker has worked for within a year and possibly without non-employment spell. Figure 2 reports the result using this alternative definition both in SIPP (blue crosses) and QWI (red dots). Reassuringly, the two profiles are similar to each other. Both confirm that the recall share is strongly increasing over the life cycle. A 55-year-old worker is twice as likely as a 25-year-old worker to return to her previous employer after a jobless spell.

Extensive controls. The finding that the recall share is increasing over the life cycle is robust to an extensive set of controls. Consider the following spell-level regression

$$\text{Recall}_i = \alpha + \beta \text{Age}_i + \boldsymbol{\gamma} \boldsymbol{X}_i + \varepsilon_i,$$

where Recall_i is a dummy variable indicating whether the nonemployment spell ends up with a recall. We then transform it into percentage points by scaling it up by 100 so that the coefficient can be interpreted in terms of changes in recall shares. The vector $\boldsymbol{X}_i$ denotes a set of control variables as explained below. Table 1 report the estimated coefficient of interest, β, in various specifications. Column (1) reports the simple regression of recalls on age without additional controls. In Column (2), we include worker demographics—gender, education, race, together with year fixed effects. In Column (3), we add job characteristics on top of the controls in the second column, including the union status, employer-provided health insurance, and occupation and industry fixed effects. In Column (4), we further add a quadratic term in job tenure. In all specifications, the estimated coefficient is statistically significant and economically large. After controlling for both the worker's and the job's observable characteristics, we find that one more year of age is on average associated a 0.5 percentage point increase in the recall share. This translates to about an increase of 20 percentage points in the recall share for a 40-year working career.

Moreover, it has been documented that the design of the unemployment insurance can be an important factor that impacts recalls (Feldstein, 1976; Katz and Meyer, 1990*a*,*b*; Albertini, Fairise and Terriau, 2023). We verify that unemployment insurance does not drive the life cycle pattern of recalls that we find. In Column (5) of Table 1, we add unemployment duration as an additional control variable. In Column (6), we further control for a dummy variable indicating the UI recipiency status and the amount of UI benefits the worker received. The result is barely changed.

The right panel of Figure 1 visualizes the residual relationship between the recall share and age, after controlling for an extensive set of covariates, including worker demographics such as gender, education, and race, job characteristics such as occupation fixed effects, industry fixed effects, union membership, employer-provided health insurance, job tenure quadratic, as well as unemployment duration, unemployment insurance recipiency status and amount, and year fixed effect.

Seasonal and temporary work. One potential concern is that if workers doing seasonal or temporary jobs are more likely to be recalled and if older workers are more likely to take up seasonal or temporary work, then this might drive the observed increasing recall share over the life cycle.[5] We identify seasonal workers in SIPP following the methodology proposed by Coglianese and Price (2020). Specifically, for a spell where a worker goes from employment to non-employment and back to employment, we classify the worker to be a seasonal worker if the starting month of the two employment period is spaced between 10 to 14 months apart. The logic is that a worker that starts working around the same month in a year is more likely to be a seasonal worker (e.g., ski coaches). Column (7) in Table 1 reports the result by excluding seasonal workers. Even after we exclude seasonal workers, the age-gradient in the recall share still exists and is almost as steep as in the full sample.

We also look at temporary jobs in the Current Population Survey (Flood et al., 2021). The CPS classifies a job to be temporary if the worker is (i) working until project is completed, (ii) hired to temporarily replace another worker, (iii) hired for a fixed period of time, or (iv) the

[5]For example, Nekoei and Weber (2015) document that temporary layoffs are more common in the construction and tourism sector than other sectors. These two sectors exhibit strong seasonal patterns.

Table 1: Estimated Coefficients of Age on Recall Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.759***	0.720***	0.526***	0.521***	0.530***	0.528***	0.502***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.037)	(0.037)	(0.040)
Control	/	Demographics	Job Char.	Job Tenure	U Duration	UI	Seasonal
Observations	17602	17602	17537	17537	17537	17537	14754
R-squared	0.02	0.03	0.11	0.11	0.15	0.15	0.16

Standard errors, * p<0.10, ** p<0.05, *** p<0.01

Notes: This table reports the coefficients of age on recall share from various regression specifications. We gradually add more control variables from Column (1) to Column (6). Column (7) excludes seasonal workers. See main text for details.

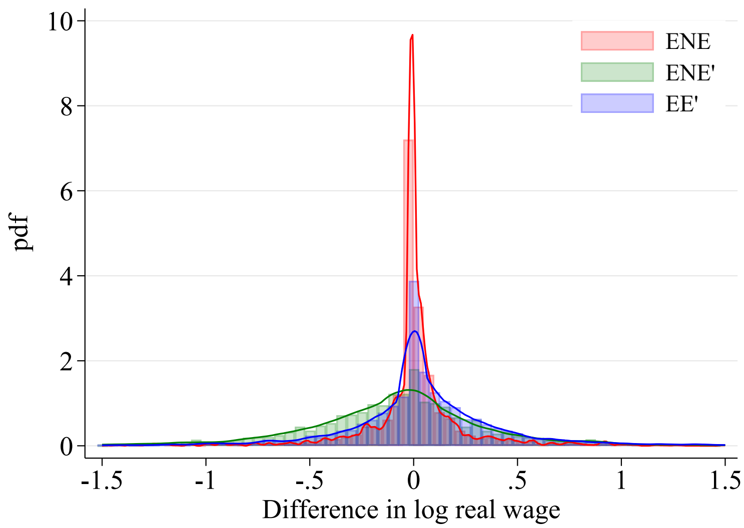
job is seasonal. Figure A-3 in the appendix plots the life-cycle profile of the share of workers with a temporary job. Contrary to the concern, young workers are in fact much more likely to have a temporary job than old workers, ruling out the possibility that temporary jobs drive the empirical regularity of a positive age gradient in the recall share.

Discussion on data quality. The quality of the recall measure crucially depends on the accuracy of the assignment of job IDs. Stinson (2003) document that job IDs are subject to miscoding—when a worker has been jobless for the entire four-month wave, SIPP will assign a different job ID anyway when they get employed next time, even though in reality the employer may be the same one prior to separation, except for when a worker is temporarily laid off, in which case the last job ID is indeed carried forward. Stinson (2003) has resolved this issue in panels 1990–1993 by retrospectively using confidential employer name information. Therefore, we regard the job IDs and hence recalls as reliable after the correction by Stinson (2003). Although our baseline results are based on the pre-1996 panels in which we have accurate job IDs, we have also repeated the same analysis in the post-1996 panels after we correct for the measurement error in recalls using the imputation procedure proposed by Fujita and Moscarini (2017) and reported robustness checks using different panels and imputed recalls in Appendix Figure A-1–A-2.

2.2 Wage Changes Associated with Different Transitions

In this section, we study the wage changes associated with various labor market transitions—Figure 3 compares the distributions of log real wage changes for recalls (ENE), finding a new job after nonemployment (ENE′), and job-to-job switches without nonemployment spells (EE′). The substantial differences in these three distributions confirm that these transitions are meaningfully distinct, as they have substantially different consequences on the wage outcomes.

Figure 3: The Distribution of Wage Changes of Labor Market Transitions



Notes: The figure plots the distribution of the wage changes for recalled workers (ENE), workers moving to new employers after the jobless spell (ENE′), and workers moving to new employers without going through nonemployment (EE′).

Three notable findings emerge. First, the distribution of wage changes for workers who are recalled by their former employers (ENE, the red distribution) is tightly concentrated around zero and the pdf spikes at zero, indicating barely any change in log real wages for the majority of recalled workers. This means that returning to a previous employer often does not result in wage penalties or premiums. The distribution of wage changes for recalled workers exhibits an extremely high kurtosis, suggesting that recalls might be an important contributor to the high kurtosis of the distribution of earnings changes documented by Guvenen et al. (2021).[6]

Second, the distribution for workers moving to new employers after a period of nonemployment (ENE′, the green distribution) does not have such a spike at zero. Quite the opposite, the distribution displays a pronounced dispersion over a wider range of wage changes, suggesting a considerable heterogeneity in wage outcomes for workers moving to new employers subsequent to nonemployment. Moreover, the distribution is asymmetric, and has a larger mass on the left side of the distribution. This means that these workers are more likely to experience a decrease in wages upon reentry into the new employment.

Third, the distribution for workers transitioning to new employers without an intervening period of nonemployment (EE′, the blue distribution) demonstrates intermediate dispersion; it exhibits a level of dispersion that exceeds that of the ENEs yet does not reach the dispersion observed among ENE′s. This implies that the wage at the new employer after an EE′ transition

[6] Hubmer (2018) shows that adjusting for recalls substantially increases the kurtosis measure in his quantitative model.

generally differs less from the previous wages compared to ENE′ transitions. The distribution is asymmetric, too, but it has a larger mass on the right side of the distribution, meaning that these workers are more likely to experience an increase in real wages at the new job.

Having established the distinctions in wage consequences associated with different labor market transitions, we now turn to examine how these wage changes differ by young and old workers. To do so, we formally analyze the real wage change after an event (defined as one of ENE, ENE′, or EE′) using an event study design, and contrast the behavior of the young (below or equal to age 35) and the old (above age 35 and below or equal to 60). We focus on workers who have worked on the job for at least 5 months both before separation and after separation, in order to have a long enough window for the event study specification.

Consider the following regression

$$\ln w_{is\tau} = \alpha + \sum_{\tau=-4}^{4} \beta_\tau I_{is\tau} + \boldsymbol{\gamma} \boldsymbol{X}_{is} + \varepsilon_{is\tau},$$

where $I_{is\tau}$ is a set of indicators that takes 1 for worker i at τ periods before or after the event s, and $\ln w_{is\tau}$ denotes the log real wage of worker i at τ months before or after the event s. The event period is defined as relative to the month the worker gets separated. We drop the last month on the old job before separation and the first month on the new job after separation because these two months often involve incomplete working spells. The vector $\boldsymbol{X}$ denotes a set of controls including education, race, gender, occupation before separation, industry before separation, and year dummies. The data samples are pre-1996 SIPP panels, see Appendix Figure A-5 that includes all panels.

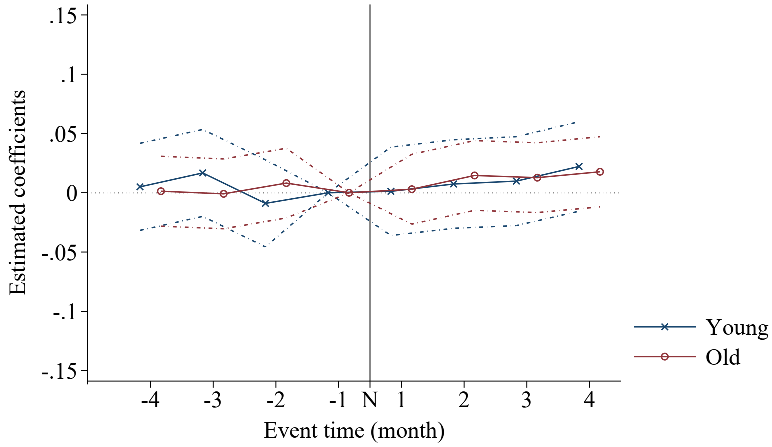
The coefficients of interest are β_τ's and are plotted in Figure 4. The blue lines show the estimated coefficients for young workers and the red lines for old workers. Dashed lines plot the corresponding 95% confidence intervals. Event time -1 here denotes the last month on the job before the month of separation, which is set to be the base period, so that its coefficient is normalized to 0 and has no standard errors.

Panel (a) of Figure 4 shows that for those who end up with returning to their previous employers after a jobless spell, the estimated coefficients fluctuate tightly around zero both before and after the event, suggesting that on average there is barely any wage change after recalls. This is true for both young and old workers, as the two lines are almost on top of each other and the 95% confidence intervals all cover zero.

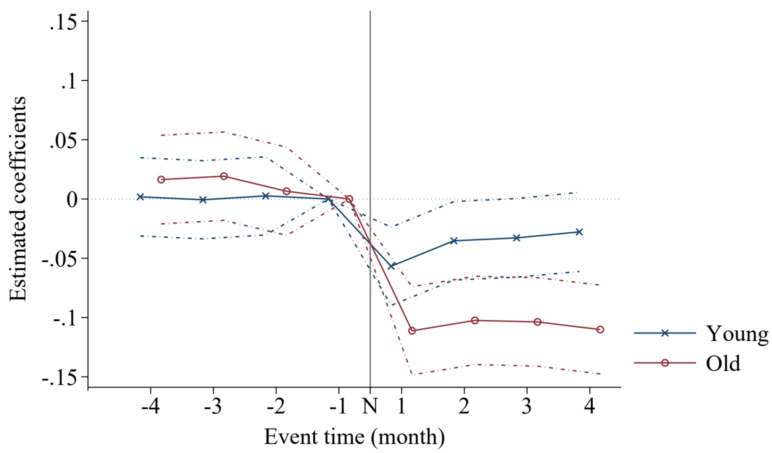
Panel (b) of Figure 4 reveals a noticeable drop in the wage for old workers starting a new job after non-employment. Specifically, the wage on average decreases sharply by more than 10%, and does not recover at least in the four months post new employment. However, the blue

Figure 4: Wage Changes Associated with Different Transitions

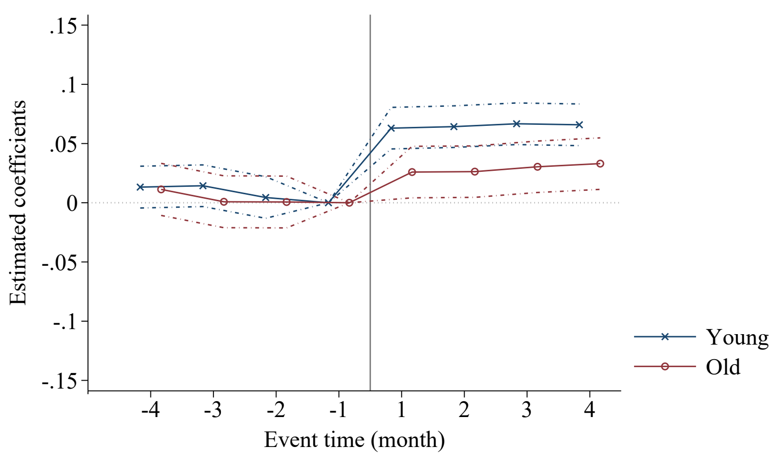
(a) Recalls (ENE)



(b) New Job Findings (ENE′)



(c) Job-to-Job Switches (EE′)



Notes: The figure plots the coefficients of the event study specifications for recalls (the top panel), for workers moving to a new employer after the jobless spell (the middle panel), and for job-to-job transitions (the bottom panel). The blue lines are for young workers (age 23-35) and the red lines are for old workers (age 35-60). Dashed lines plot the 95% confidence intervals.

line shows a much milder decline after the event of only about 3%. This suggests that young workers moving to a new employer after a jobless spell on average experience a small wage decline, but old workers moving to a new employer after a jobless spell on average experience a very large wage loss.

Panel (c) of Figure 4 plots the wage change for workers who transition directly from one job to another. The wage for a young worker is estimated to increase significantly after moving to a new job by more than 6%, while the old group experiences a much less pronounced increase of only less than 3%. Thus, workers making job-to-job transitions have a positive wage change on average, and the expected wage increase is larger for young workers than old workers.

3 Model

To understand the relevance of job recalls to labor market dynamics over the life cycle, we extend the Diamond-Mortensen-Pissarides paradigm in two aspects. First, given the empirical prevalence of recalls, we introduce in the model the possibility of getting back to the previous job after an unemployment spell. Second, we introduce a job ladder of match-specific productivity and allow for on-the-job search to speak to the life-cycle dynamics of unemployment, separation rate, job-finding rate, job-to-job transition rate, as well as job recalls.

3.1 Environment

Time is continuous, agents are infinitely lived, risk-neutral and discount the future at rate ρ. A worker-job match produces flow output m, where m is the match-specific productivity constant for each worker-job pair. Upon meeting, the match-specific productivity is drawn from the distribution $F(m)$. Both employment and attached unemployment (with a recall option) involve an idiosyncratic production shock that will be described in detail below. Unemployed workers produce z at home.

There are three employment statuses in this model. A worker can be employed at a job, unemployed but attached to a job with a recall option, and unemployed without a recall option (either a new entrant or an unemployed worker that loses contact with her previous employer). Analogously, a position can be matched with a worker producing, vacant but attached to a worker with a recall option, and vacant without a recall option (either a brand new vacancy or an old position that loses contact with its previous employee). We make several simplifying assumptions to facilitate analyses. First, it is costless to mothball a position waiting for possible recalls. This is a reasonable assumption as firms do not exert recruiting efforts for mothballed positions, as opposed to standard vacancies that are actively looking for workers to fill the job.

Table 2: Summary of Possible Events

	Employed	Unemployed w/ recall option	Unemployed w/o recall option
Cost shock	λ_e	λ_u	/
Destruction shock	δ	δ	/
Godfather quit shock	ζ	ζ	/
Job offer arrival	$\phi p(\theta)$	$p(\theta)$	$p(\theta)$
Labor force exit	γ	γ	γ

Notes: This table summarizes possible events in the model with their corresponding notations.

As a result, when a bad but temporary shock hits, employers always have the incentive to first mothball the position rather than immediately destroying it. Second, the recall option is lost when the worker starts a new job. We thereby focus on recalls from unemployment to the most recent employer. Third, no mothballing is allowed before production. That is, a recall option is only possible after the worker has worked and produced in the match. These assumptions are also made in Fujita and Moscarini (2017).

The labor market is frictional. The matching process is governed by a matching function $M(S, V)$ that exhibits constant returns to scale, where S denotes the number of job seekers and V the number of vacancies. For notation convenience, we use lower-case letters to denote the rates of corresponding variables normalized by the size of the labor force. We allow for on-the-job search so that the measure of effective searchers is $s := u + \phi(1 - u)$, where u is the unemployment rate and ϕ is the relative search intensity of the employed workers. Denote by $\theta = v/s$ the effective labor market tightness. The contact rate is thus $p(\theta) = M(1, \theta)$ for unemployed workers, $\phi p(\theta)$ for employed workers and $q(\theta) = M(\theta^{-1}, 1)$ for vacant jobs, with $p(\theta) = \theta q(\theta)$. Table 2 summarizes the possible events for workers with different employment statuses which we now turn to in the following paragraph. These events occur symmetrically to producing jobs, mothballed positions (i.e., vacant jobs with a recall option), and new vacancies (i.e., vacant jobs without a recall option), respectively, and hence are not repeated.

Five events could happen during employment for a matched worker-job pair that is producing. First, at Poisson rate λ_e, an idiosyncratic cost shock is independently drawn from the distribution $\varepsilon' \sim G_e$. The match will endogenously separate if it is hit by a sufficiently large cost shock.[7] Second, at Poisson rate $\phi p(\theta)$, the employed worker receives an outside job offer,

[7] This assumption admits a parsimonious formulation of potentially persistent shocks. The Poisson rate λ_e controls how persistent the idiosyncratic productivity is. When λ_e is low, changes occur infrequently and hence the shock is more persistent.

with match-specific productivity drawn from the distribution $m' \sim F$. The worker can decide whether to move to the new job or stay in the current match. We assume no counteroffer matching. If the worker leaves, the position becomes vacant and unattached.[8] Third, at Poisson rate δ, the match is exogenously destroyed with the worker becoming unemployed, and the match can never be resumed. It captures match dissolution for reasons orthogonal to the match quality, such as firm closure and worker migration. Fourth, at Poisson rate ζ the worker receives a godfather quit shock and moves to a new job. This can be alternatively interpreted as the match got destroyed and they immediately got a job offer drawn from the distribution F. It is a standard trick in the literature to allow for job-to-job transitions towards worse matches. Finally, at Poisson rate γ, the worker exits the labor force.

Similarly, five events could hit a separated match that is not producing but holds a recall option. First, at Poisson rate λ_u, a reactivation cost shock is drawn from $\varepsilon' \sim G_u$. If the reactivation cost is below a certain threshold, the worker will be recalled and the match will resume production. Second, at Poisson rate $p(\theta)$, the unemployed worker receives an offer with $m' \sim F$, and decides whether or not to accept it. The worker will compare the value of accepting the new job offer with the value of waiting for the reactivation opportunity at the previous match. If the worker leaves, the previous position becomes unattached to the worker. Third, at Poisson rate δ, the mothballed position is exogenously destroyed. Fourth, similar to employed workers, at Poisson rate ζ workers would receive a godfather quit shock and move to a new job. Finally, the worker leaves the labor market at Poisson rate γ.

The problem for unemployment and vacancies without a recall option is simple and behaves similarly to standard models. For an unemployed, unattached worker, only a new job offer arrival or an exit shock could happen. For a vacancy without a recall option, the firm pays a flow recruiting cost κ and meets a worker at rate $q(\theta)$.

The model is closed as in the standard DMP paradigm. First, the free entry condition for vacancy posting pins down the job creation incentives. As a result, a firm tied to its most recent employee will prefer waiting for the recall possibility, rather than posting a new vacancy that yields zero expected value. A position vacated by the employee leaving for another new job will deliver zero value if reposted, so it is no different from posting a brand new vacancy. Second, wages are determined by Nash bargaining, with a fraction β of the surplus accruing to the worker. As in Fujita and Moscarini (2017), we assume that the outside option of bargaining is separation with a recall option for both workers and firms. When the worker receives an outside offer on the job and bargains with a new potential employer, the outside option of bargaining is separation with a recall option of getting back to the new employer, rather than the previous employer, so we abstract away from counteroffer matching.

[8] Qiu (2022) provides a detailed analysis of vacated vacancies arising from workers quitting their positions.

3.2 Value Functions

This section presents the value functions. Let W, U, U_0, J, V, V_0 be the values of an employed worker, an attached unemployed worker, an unattached unemployed worker, a producing job, an attached vacancy, an unattached vacancy, respectively. Since the three value functions on the firm side mirror those for the workers, we present the value function for worker and firm together grouped by the employment status.

Producing workers and jobs. We first define the indicator for a match that continues production even when hit by a cost shock, $B(m,\varepsilon') = \mathbb{1}\Big\{J(m) - \varepsilon' > V(m)\Big\}$. The complement of the indicator is then: $\overline{B}(m,\varepsilon') = 1 - B(m,\varepsilon')$. The Hamilton-Jacobi-Bellman equation for an employed worker at a job of match-specific productivity m is

$$\begin{aligned}(\rho + \lambda_e + \phi p(\theta) + \delta + \zeta + \gamma)W(m) = w(m) + \Bigg[\lambda_e \int \Big\{B(m,\varepsilon')W(m) + \overline{B}(m,\varepsilon')U(m)\Big\}\,\mathrm{d}G_e(\varepsilon') \\ + \phi p(\theta) \int \max\Big\{W(m'), W(m)\Big\}\,\mathrm{d}F(m') + \delta U_0 + \zeta \int W(m')\,\mathrm{d}F(m') + \gamma \cdot 0\Bigg],\end{aligned} \tag{1}$$

where $w(m)$ is the flow wage paid to the worker. Similarly, the HJB equation for a producing job of match-specific productivity m is

$$\begin{aligned}(\rho + \lambda_e + \phi p(\theta) + \delta + \zeta + \gamma)J(m) = m - w(m) + \Bigg[\lambda_e \int \max\Big\{J(m) - \varepsilon', V(m)\Big\}\,\mathrm{d}G_e(\varepsilon') \\ + \phi p(\theta) \int \mathbb{1}\Big\{W(m') \leq W(m)\Big\} J(m)\,\mathrm{d}F(m') + \delta \cdot 0 + \zeta \cdot 0 + \gamma \cdot 0\Bigg],\end{aligned} \tag{2}$$

where $\mathbb{1}\{\bullet\}$ is an indicator function that takes 1 if $\bullet$ is true and 0 otherwise. The firm gets the residual flow profit from output net wage $m - w(m)$. These value functions reflect the five possible events described in the previous subsection. First, at rate λ_e, the job is hit by a stochastic cost shock $\varepsilon' \sim G_e$, leading to an endogenous separation with attachment if $J(m) - \varepsilon' \leq V(m)$; otherwise, the firm pays the cost ε' and continues producing. Second, at rate $\phi p(\theta)$, the worker receives an outside offer drawn from $m' \sim F$ and moves to the new job if $W(m') > W(m)$; otherwise, the worker sticks to the current job. If the worker is poached successfully by the new position, the old position becomes an unattached vacancy. Third, the match is exogenously destroyed at rate δ so that the worker becomes unemployed without a recall option and the job becomes vacant without attachment, in which case we have already invoked the free entry condition $V_0 = 0$. Fourth, the worker receives a godfather quit shock and will go to a new job with match quality drawn from F. Finally, the worker exits the labor market at rate γ.

Separated workers and jobs with recall options. The HJB equation for an unemployed worker with a recall option to her previous employer of match quality m solves

$$(\rho+\lambda_u+p(\theta)+\delta+\zeta+\gamma)U(m) = z + \Bigg[\lambda_u \int \Big\{B(m,\varepsilon')W(m)+\overline{B}(m,\varepsilon')U(m)\Big\}\,\mathrm{d}G_u(\varepsilon') \\ + p(\theta)\int \max\Big\{W(m'),U(m)\Big\}\,\mathrm{d}F(m') + \delta U_0 + \zeta\int W(m')\,\mathrm{d}F(m') + \gamma\cdot 0\Bigg]. \tag{3}$$

where z is the flow value from home production. The value of a vacant firm with a recall option is written as:

$$(\rho+\lambda_u+p(\theta)+\delta+\zeta+\gamma)V(m) = 0 + \Bigg[\lambda_u \int \max\Big\{J(m)-\varepsilon',V(m)\Big\}\,\mathrm{d}G_u(\varepsilon') \\ + p(\theta)\int \mathbb{1}\Big\{W(m')\leq U(m)\Big\}V(m)\,\mathrm{d}F(m') + \delta\cdot 0 + \zeta\cdot 0 + \gamma\cdot 0\Bigg], \tag{4}$$

where the flow value is zero because no recruiting efforts are spent on the mothballed position. These two value functions characterize five possible events. First, at rate λ_u, a stochastic reactivation cost is drawn from $\varepsilon' \sim G_u$ and the pair resumes production if $J(m)-\varepsilon' > V(m)$; otherwise, the worker-job pair stays inactivated. Second, at rate $p(\theta)$, the worker receives an offer drawn from $m' \sim F$ and accepts the offer if $W(m') > U(m)$, in which case the job loses contact with its previous employee and becomes a brand new vacancy. Third, the connection is destroyed at rate δ, in which case the worker becomes unemployed without being attached to any employer, and similarly, the job becomes an unattached vacancy. Fourth, the worker receives a godfather quit shock and will go to a new job with match quality drawn from F. Finally, the worker exits the labor market at rate γ.

Unemployment and vacancies without recall options. The value functions for unemployed workers and vacancies without recall options are standard. The HJB equation for an unemployed worker without a recall option is:

$$(\rho+p(\theta)+\gamma)U_0 = z + p(\theta)\int \max\Big\{W(m'),U_0\Big\}\,\mathrm{d}F(m') + \gamma\cdot 0. \tag{5}$$

The unemployed worker without a recall option produces a flow value of z, receives an offer at rate $p(\theta)$ and exits the labor market at rate γ. The HJB equation for an unattached vacancy is

$$\begin{aligned}\rho V_0 = -\kappa + \frac{q(\theta)}{u+\phi(1-u)} \Big[\mu_0 \int \mathbb{1}\Big\{W(m') > U_0\Big\} \big(J(m') - V_0\big) \, \mathrm{d}F(m') \\ + \iint \mathbb{1}\Big\{W(m') > U(\tilde{m})\Big\} \big(J(m') - V_0\big) \, \mathrm{d}\mu(\tilde{m}) \, \mathrm{d}F(m') \\ + \phi \iint \mathbb{1}\Big\{W(m') > W(\tilde{m})\Big\} \big(J(m') - V_0\big) \, \mathrm{d}\ell(\tilde{m}) \, \mathrm{d}F(m') \Big] \\ + \zeta \frac{1-\mu_0}{v} \int \big(J(m') - V_0\big) \, \mathrm{d}F(m'),\end{aligned} \tag{6}$$

where u is the measure of all unemployed workers, μ_0 is the measure of unemployed workers without recall options, $\mu(m)$ is the measure of unemployed workers with a recall option attached to a job of match quality m, and $\ell(m)$ is the measure of employed workers at a job of match-specific productivity m. The flow recruiting cost of posting a vacancy is κ. The vacancy meets a worker at rate $q(\theta)$. The worker could be unemployed without a recall option (the first line), unemployed with a recall option (the second line), or employed with a job (the third line), drawn randomly according to the equilibrium distribution of workers. If the worker accepts the job, a new match will be formed and start production. The vacancy could also be forced to be matched a worker due to the godfather shock (the last line). In equilibrium, the free entry condition pins down the level of labor market tightness that satisfies $V_0 = 0$.

Nash bargaining. The wage is determined by Nash bargaining:

$$w(m) = \arg\max_{w} \big[W(m) - U(m)\big]^{\beta} \big[J(m) - V(m)\big]^{1-\beta}.$$

The bargaining breaks down if and only if the surplus is negative. Successful bargaining adheres to a surplus sharing rule with $(1-\beta)\big[W(m) - U(m)\big] = \beta\big[J(m) - V(m)\big]$. In the interest of conciseness, we present the wage equation in Appendix II.1.

Equilibrium. We first consider a stationary equilibrium and will introduce aggregate shocks later in Section 5. To conserve space, we present the inflow-outflow balance equation in the Appendix II.2. A stationary equilibrium is defined as value functions $\{W, U, U_0, J, V, V_0\}$, wage policy $w(m)$, labor market tightness θ, and measures $\mu_0, \mu(m), \ell(m)$, such that:

(1) The value functions $\{W, U, U_0, J, V, V_0\}$ satisfy Bellman equations (1)–(6);

(2) The wage policy $w(m)$ satisfies the wage equation derived from Nash Bargaining (II.1);

(3) The labor market tightness θ satisfies the free entry condition $V_0 = 0$;

(4) The measures satisfy the steady-state flow-balance equations (A2)–(A4).

4 Quantitative Analysis

4.1 Calibration

In this section, we calibrate the model in steady state to the life cycle properties of worker flows. We begin with externally calibrated parameters. The monthly discount rate is set to $\rho = 0.0041$ that corresponds to 5% annual interest rate. We set the worker bargaining power to $\beta = 0.5$, a standard value in the literature. We parameterize the matching function to be Cobb-Douglas, i.e., $M(S, V) = AS^{\alpha}V^{1-\alpha}$, and impose $\alpha = \beta = 0.5$, a convention in the literature motivated by the Hosios condition although it does not imply constrained efficiency in our setting with recalls and on-the-job search. We set the labor force exit rate to $\gamma = 0.000521$ at the weekly frequency, which roughly corresponds to a 40-year working career. These externally calibrated parameters are summarized in Table 3.

Now we turn to parameters calibrated internally. We parameterize the match quality distribution F to be Weibull with shape parameter μ_m and scale parameter σ_m, following Bagger et al. (2014) who study life cycle wage dynamics. The lower bound of the match quality distribution is normalized to 1. For simplicity and transparency, we parameterize the idiosyncratic cost shock distributions G_u and G_e to be uniform, with mean and standard deviation of $(\mu_{G_u}, \sigma_{G_u})$ and $(\mu_{G_e}, \sigma_{G_e})$, respectively. In addition to these 6 parameters associated with the distributions, we are left with another 8 parameters: Poisson arrival rates λ_u, λ_e, matching efficiency A, on-the-job search intensity ϕ, exogenous job destruction rate δ, the arrival rate of the godfather quit shock ζ, vacancy posting cost κ, and home production z. In total there are 14 parameters to be internally calibrated.

We target the empirical moments of worker flows, including the recall share, job finding rate, separation rate, and job-to-job rate. Specifically, we target three points on the life cycle profiles these worker flows, using the age bin of 23–24 (the initial point), 35–36 (the middle point), and 49–50 (the end point). We target the vacancy to unemployment ratio to be 1 and the ratio of home production to average productivity to be 0.47 as measured by Chodorow-Reich and Karabarbounis (2016). Note that we have an endogenous component of labor productivity in the model due to the acceptance margin, so we still have to calibrate z internally. We calibrate the model by minimizing the log distance between model predicted moments and their empirical counterparts. Table 4 reports the parameters that are internally calibrated. Figure 5 shows that the life cycle worker flow profiles are matched tightly. We now discuss how these moments are informative in pinning down the parameters.

The distribution of match quality, F, plays a crucial role in determining how match quality is evolving over the life cycle, hence influencing the life-cycle properties of worker flow rates.

Table 3: Externally calibrated parameters

Symbol	Description	Value	Interpretation
ρ	Discount rate	0.001	5% annual interest rate
α	Matching function elasticity	0.5	Symmetric matching elasticity
β	Worker bargaining power	0.5	Symmetric bargaining power
γ	Retiring rate	0.000521	Expected 40 years of working

Notes: This table reports externally calibrated parameters. Flow rates are displayed at the weekly frequency.

For instance, the convex and decreasing job-to-job transition rate observed over the life cycle is informative of the skewness of the match quality distribution F. A positively skewed match quality distribution, characterized by a larger mass at the lower end, makes it much easier for a young worker with a low match quality to find a better match when searching on the job, than an old worker who tends to be already at the top of the job ladder. Additionally, the level of the job-to-job transition rates among old workers sheds light on how long the job ladder is. Thus, the worker flow rates inform the shape and scale parameter of the match quality distribution.

The life cycle profile of the separation rate is informative of the idiosyncratic maintenance cost shock during employment, G_e. The life cycle profile of the recall share is immediately informative of the idiosyncratic reactivation cost shock during attached unemployment, G_u. The levels of the rates are informative about the arrival rate, λ_e and λ_u, respectively.

The level of the job finding rate informs the matching efficiency A. The relative ratio of job-to-job rate to unemployed workers' job finding rate informs on-the-job search intensity ϕ. In the data, older workers still make a lot of job-to-job transitions. Given that in the model, older workers are likely on the top of the job ladder and would thus unlikely to accept a new job for pecuniary reasons, the godfather shock ζ is therefore needed to match the job-to-job rate for older workers.

The exogenous job destruction rate δ describes how frequently jobs are destroyed without a possibility for the separated workers to return. If matches get hit by a destruction shock more often, more matches will get separated and a smaller share of matches will be recalled. Thus, the recall share and separation rate are informative moments. Our estimate of monthly 0.001 is of similar magnitude to Fujita and Moscarini (2017)'s estimate of 0.002. Note that we have different environments so the two estimates are not directly comparable. For instance, the parameter is designed to capture the rate of losing recall option in Fujita and Moscarini (2017). In our model, both on-the-job search and godfather shock contribute to the loss of recall, too.

Table 4: Internally calibrated parameters

	Description	Value
μ_F	Weibull Shape	1.8783
σ_F	Weibull Scale	0.07463
μ_{G_u}	Mean of G_u	6.0179
σ_{G_u}	Standard deviation of G_u	1.8106
μ_{G_e}	Mean of G_e	6.0507
σ_{G_e}	Standard deviation of G_e	1.5702
λ_u	Arrival rate of idiosyncratic shock (U)	0.0612
λ_e	Arrival rate of idiosyncratic shock (E)	0.012
A	Matching efficiency	0.0615
ϕ	On-the-job search intensity	0.6083
δ	Exogenous destruction rate	0.00025
ζ	Godfather shock	0.00083
κ	Vacancy posting cost	0.1054
z	Home production	0.535

Notes: This table reports internally calibrated parameters. Flow rates are displayed at the weekly frequency.

The model is numerically solved at the weekly frequency and a transition matrix across employment status and match quality m can be obtained from policy functions. The transition matrix is then used to calculate monthly flow rates, for which we observe the counterpart in the data. Workers enter the model at age 21 and are assumed to start with unattached unemployment. The algorithm to solve the equilibrium is laid out in Appendix II.3.

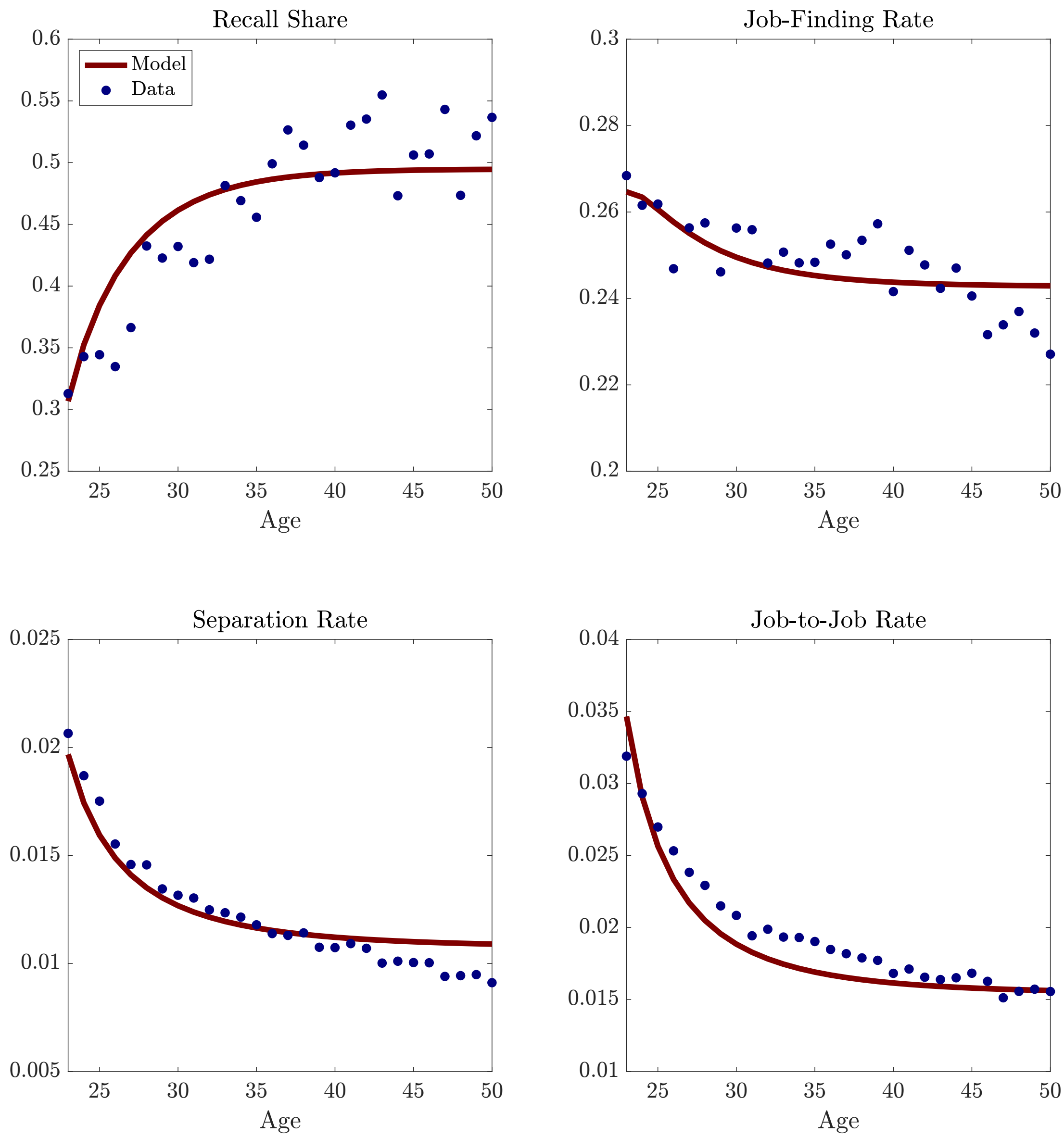
4.2 Model Fit

Figure 5 plots the model predictions (red line) and the data (blue dots) of labor market dynamics over the life cycle, including the recall share, job finding rate, separation rate, and job-to-job rate. The job finding rate, separation rate and job-to-job rate are constructed from the CPS, which is the gold standard of measuring worker flows in the US labor market, averaged from 2000 to 2019. As can be seen from Figure 5, the model not only qualitatively but also quantitatively reproduces the life cycle profiles of all flow rates. The model is able to generate an increase in the recall share from 30% at age 23 to 50% at age 50, a decrease in the job finding rate from 26% at age 23 to 24% at age 50, a decrease in the separation rate from 2% to 1%, and a decrease in the job-to-job rate from 3.5% to 1.5%. It is worth pointing out that the model is parsimonious without free age-dependent parameters. Matching both the level and the shape of life-cycle profiles of worker flow rates is a nontrivial success.

Model Mechanism. The driving force of the model to reproduce life-cycle worker flow rates is that match quality increases over the life cycle on average. As workers age, they climb up the job ladder gradually to jobs with higher match quality. For matches with better match quality, the separation rate is lower, and conditional on separation, the probability of getting recalled is higher. Similarly, employed workers with a higher match quality job or unemployed workers attached to a higher match quality job are more selective and less likely to accept new offers given that they already have a good option in hand.

External Validation. We use the model predictions on wage changes associated with different transitions as a test to the model, as they are not targeted in the calibration procedure. To do so, we conduct the same analysis using the event study specification on the simulated data, as is done in the empirical analysis. We define younger workers as those below or equal to 35 years old and older workers as those above 35 years old. Figure 6 plots the estimated coefficients and shows a very similar pattern for wage changes associated with different transitions to the data, for both young and old workers. For workers getting recalled, the wage does not change regardless of their age. For workers finding a job at a new employer after unemployment, older workers on average suffer from a larger wage loss because they tend to higher match quality than younger workers, resulting in a larger drop from the job ladder. For workers making job to job switches, younger workers on average experience a higher wage gain than older workers because younger workers tend to be at the bottom of the job ladder, and hence are more likely to get a better outside offer.

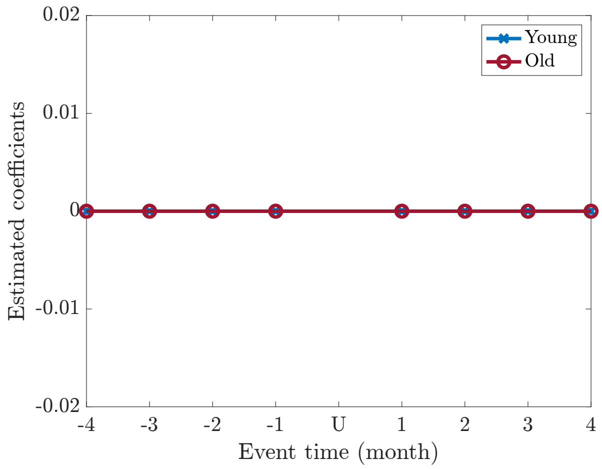
Figure 5: Worker Flows over the Life Cycle



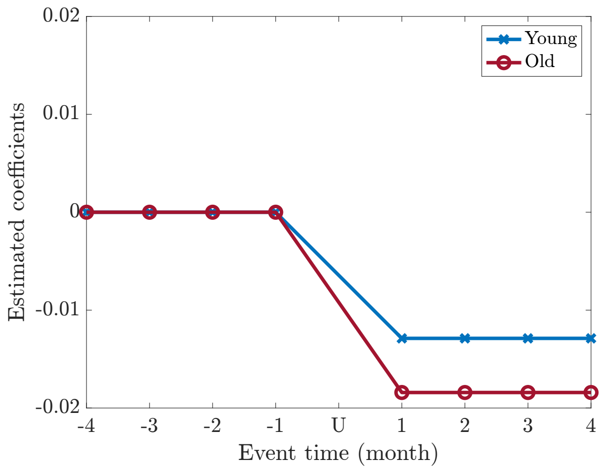
Notes: This figure plots the model predictions (red line) and the data (blue dots) of labor market dynamics over the life cycle, including the recall share, job finding rate, separation rate, and job-to-job rate.

Figure 6: External Validation: Wage Changes

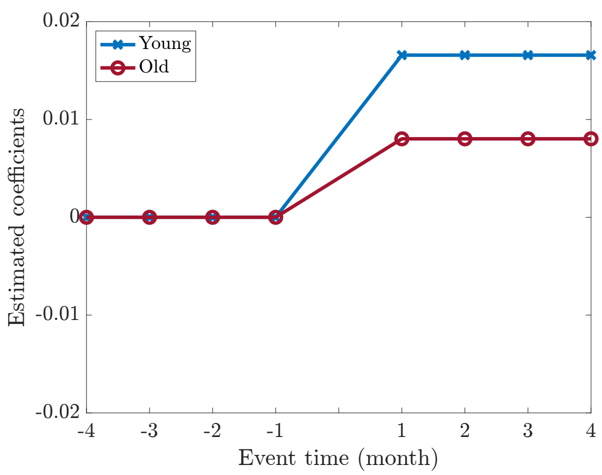
(a) Recalls (ENE)



(b) New Job Findings (ENE′)

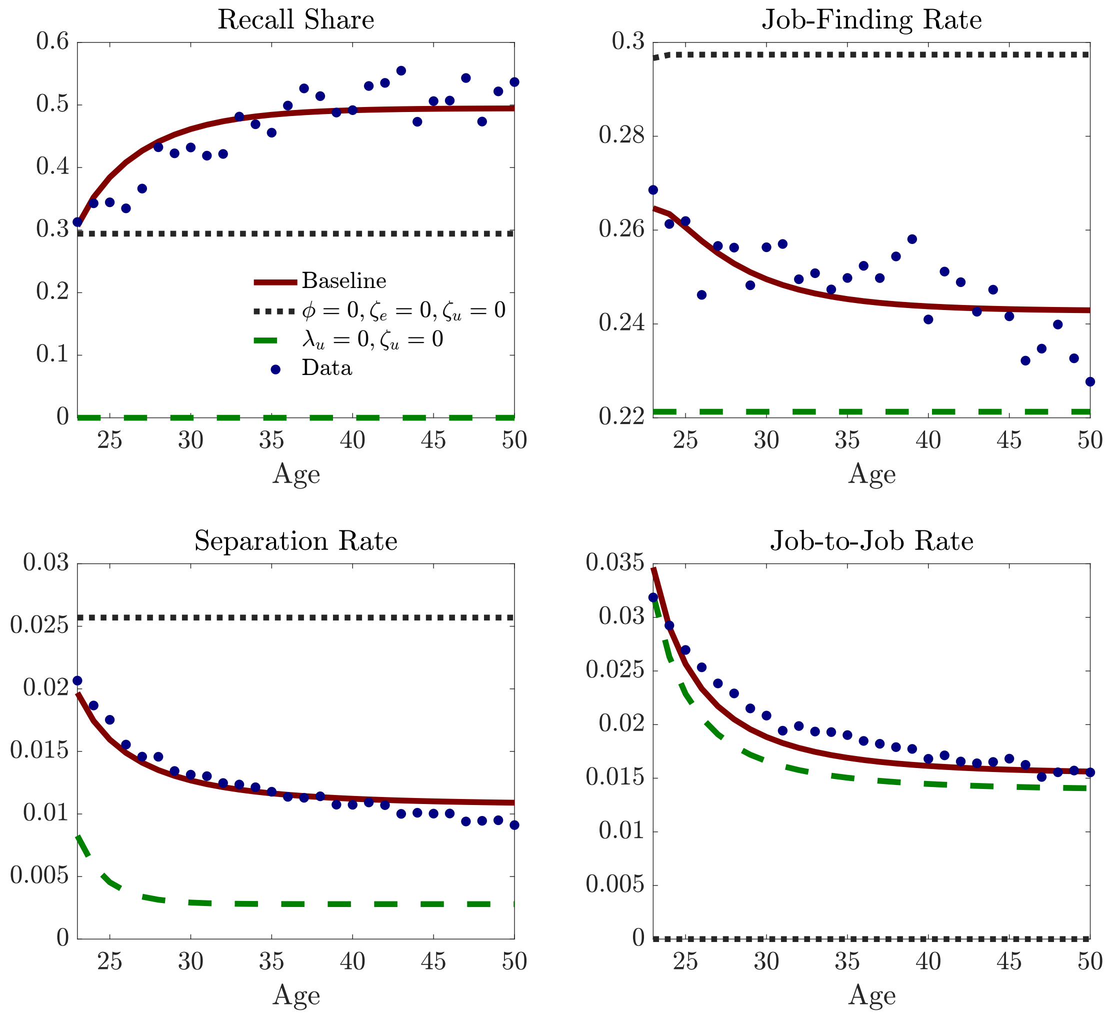


(c) Job-to-Job Switches (EE′)



Notes: The figure plots the coefficients of the event study specifications for recalled workers (top panel), for workers moving to a new employer after the jobless spell (middle panel) and for workers making job-to-job transitions (bottom panel)in the simulated data set. The blue lines are for young workers and the red lines are for old workers.

Figure 7: Worker Flows over the Life Cycle in Limiting Economies



Notes: The figure plots the two limiting economies. The black dotted lines refer to the limiting economy without on-the-job search, where the match quality distribution F is degenerate, on-the-job search intensity is $\phi = 0$, and the god-father shock arrival rate is $\zeta = 0$. The green dashed lines refer to the limiting economy without recalls, where the reactivation shock arrival rate is $\lambda_u = 0$ (and $\zeta_u = 0$ for consistency).

4.3 Discussion

Limiting Economy I: Model without on-the-job search. Consider a limiting economy of the model where the match quality distribution, F, collapses to a degenerate distribution, and the on-the-job search intensity, ϕ, goes to zero (as well as the godfather shock arrivale rate $\zeta \to 0$). This limiting economy is plotted in the black dotted lines in Figure 7. In this case, the model converges to the model of recalls as in Fujita and Moscarini (2017), and features no life-cycle patterns—all flow rates are constant.[9] Our model extends Fujita and Moscarini (2017) by introducing a job ladder and allowing for on-the-job search (in addition to some other minor modifications for quantitative purposes). The extended model not only matches the rising recall share over the life cycle, but also matches the life-cycle patterns of other worker flow rates, including the job-finding rate, separation rate, and job-to-job transition rate.

Limiting Economy II: Model without recalls. Consider another limiting economy of the model where we eliminate recalls by setting $\lambda_U = 0$ and $\zeta_e = 0$. This limiting economy is plotted in the green dashed lines in Figure 7. In the model without recalls, the job finding rate is flat over the life cycle. This is because in the standard model without recalls, unemployed workers are identical and they will accept any job that delivers a higher value than unemployment. In the model with recalls, however, unemployed workers are different—some are unattached and others are attached to different jobs. Such heterogeneity among unemployed workers leads to different reservation cutoffs and hence job-finding rate. In particular, older unemployed workers are more likely to be attached to a job with a higher match quality, so they are pickier in their job search, resulting in a lower job-finding rate. Among the employed, workers still climb up the job ladder, so that the separation rate and the job-to-job rate are decreasing over the life cycle.

Models on worker flows over the life cycle. As Chéron, Hairault and Langot (2011) and Chéron, Hairault and Langot (2013) point out, a difficulty the standard search model applied to life cycle settings is to match the decreasing job separation rate and decreasing job finding rate over age at the same time. This is because in that environment, job finding and job separation utilizes the same reservation threshold. A decreasing job separation rate requires the reservation threshold for idiosyncratic productivity to decrease with age, while a decreasing job finding rate requires the reservation threshold to increase with age. Such a contradiction makes it hard to match the two profiles simultaneously. This is resolved in our setting, because in the presence of recall options, the reservation threshold for unemployed workers' acceptance decision is different from the reservation threshold for employed workers' separation decision. On one hand, the reservation threshold for separation is decreasing because match surplus is higher as workers climb up the job ladder. On the other hand, the reservation threshold for accepting a new job is increasing because unemployed workers attached to a higher match quality job are pickier.

[9] If anything, there is a slight increase in the job-finding rate for the very young workers, because they start to have the option of being recalled.

5 Application

It is well-documented that labor market entrants during recessions have suffered disproportionately more than others—recession entrants have lower wages and employment and these negative effects can persist for a long time (Kahn, 2010; Oreopoulos, Von Wachter and Heisz, 2012; Arellano-Bover, 2022; Rothstein, 2023). Also, the youth unemployment rate is much more sensitive to aggregate conditions than older workers (see, for example, Scarpetta, Sonnet and Manfredi, 2010, for systematic evidence across OECD countries). This paper proposes a new explanation to the differential resilience to a negative aggregate shock based on recalls.

A defining feature of labor market entrants is that they do not have a previous job and hence no recall option. In bad times, the labor market is slack. Labor market entrants rely more on the labor market condition than experienced workers because they need to find their first job by receiving a new offer, whereas (part of) unemployed experienced workers have the chance of getting recalled back to their previous employer. Therefore, in periods when the labor market condition deteriorates, the job finding rate of new entrants tends to drop more than experienced workers.

To formalize the idea, we take the calibrated structural model as a laboratory to investigate the differential impact of a drop in matching efficiency on job finding rate among labor market entrants and experienced workers. The aggregate matching efficiency, the rate at which the labor market matches job searchers and vacant positions, declines in recessions. For example, see Barnichon and Figura (2015), Cheremukhin and Restrepo-Echavarria (2014), Davis, Faberman and Haltiwanger (2013), Gavazza, Mongey and Violante (2018) for references for the drop of the aggregate matching efficiency during recessions. We compute the impulse response of the model economy to a one-time, unanticipated shock in aggregate matching efficiency and track the change in job finding rate relative to the steady state value for labor market entrants and workers with 20 years of experience. We illustrate how the model responds to the aggregate matching efficiency shock by considering the transitional dynamics to a path of aggregate matching efficiency given by

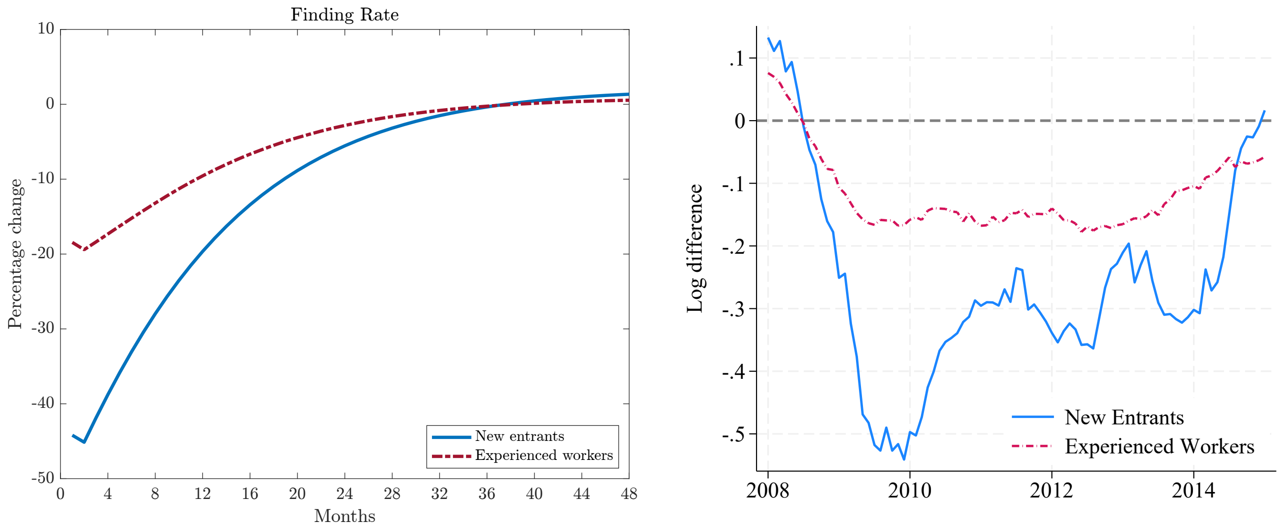
$$\ln A_1 = \ln A_{ss} - \varepsilon_0, \quad \text{and} \quad \ln A_t = (1-\rho)\ln A_{ss} + \rho \ln A_{t-1}, \forall t > 1,$$

where the size of the initial drop in log matching efficiency is set to be $\varepsilon_0 = 0.45$ and the persistence of the process is set to $\rho = 0.98$ (Gavazza, Mongey and Violante, 2018). The algorithm on how to solve for the transitional dynamics is laid out in Appendix II.3.2.

Panel (a) of Figure 8 shows the transitional dynamics in response to such an aggregate matching efficiency shock. The job finding rate of new entrants decreases by almost 50% initially while that of experienced workers only decreases by less than 20%. The gap between

Figure 8: Impulse Response of Job Finding Rate to Matching Efficiency Shock

(a) Model (b) Data



Notes: The left panel plots the percentage change in the job finding rate (relative to the steady state) for new labor market entrants and experienced workers in response to a matching efficiency shock in the model. The right panel plots the log change in the job finding rate for new labor market entrants and experienced workers during the Great Recession.

the two profiles capture the differential impact on job finding rate between the two groups of workers. As the matching efficiency improves, both profiles recover and it takes three years for the gap to disappear. If we switch off the possibility of getting recalled, new entrants and experienced workers' job finding rate will be the same, since there is no longer heterogeneity for workers in unemployment.

Panel (b) of Figure 8 shows how the job-finding rate of entrants and experienced workers evolve during the Great Recession. We see a clear pattern that the job-finding rate of entrants drops much more, consistent with the larger response in the model prediction. In fact, the magnitude of the drop in the model prediction is also quantitatively very similar to the data counterpart. Figure A-7 further shows how the job-finding rates of entrants and experienced workers evolve over the business cycle in general. We find again that the job-finding rate of entrants is much more volatile over the business cycle.

6 Conclusion

Recalls are prevalent in the labor market. In this paper, we provide a set of novel facts regarding recalls over the life cycle. We find that the share of unemployment spells ending in recalls increases markedly with age. The recall share of a 55-year-old worker is twice as high as that of a 25-year-old worker. We present a search-and-matching model with recall options and a job ladder that successfully accounts for the worker flow rates over the life cycle. Once the empirical prevalence of recalls is accounted for, an otherwise standard job-ladder search model would be able to reproduce a decreasing job finding rate over the life cycle due to the option value of the possibility of being recalled, thus reconciling the positive comovement between separation and job finding rate over the life cycle.

We apply this insight to understand the differential impact of recessions on labor market entrants versus more experienced workers. In particular, a drop of the aggregate matching efficiency in bad times disproportionately affects new entrants, because they rely more heavily on the broader labor market, while older workers are more likely to get recalls. This provides a new perspective in understanding why recessions hit new entrants harder than their experienced counterparts.

References

Alba-Ramírez, Alfonso, José M Arranz, and Fernando Muñoz-Bullón. 2007. "Exits From Unemployment: Recall or New Job." *Labour Economics*, 14(5): 788–810.

Albertini, Julien, Xavier Fairise, and Anthony Terriau. 2023. "Unemployment Insurance, Recalls, and Experience Rating." *Journal of Macroeconomics*, 75: 103482.

Arellano-Bover, Jaime. 2022. "The Effect of Labor Market Conditions at Entry on Workers' Long-Term Skills." *Review of Economics and Statistics*, 104(5): 1028–1045.

Bagger, Jesper, François Fontaine, Fabien Postel-Vinay, and Jean-Marc Robin. 2014. "Tenure, Experience, Human Capital, and Wages: A Tractable Equilibrium Search Model of Wage Dynamics." *American Economic Review*, 104(6): 1551–96.

Barnichon, Regis, and Andrew Figura. 2015. "Labor Market Heterogeneity and the Aggregate Matching Function." *American Economic Journal: Macroeconomics*, 7(4): 222–49.

Cajner, Tomaz, Ilhan Güner, and Toshihiko Mukoyama. 2021. "Gross Worker Flows over the Life Cycle." *Working Paper*.

Cajner, Tomaz, Leland D Crane, Ryan A Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz. 2020. "The US Labor Market during the Beginning of the Pandemic Recession." *Brookings Papers on Economic Activity*.

Cheremukhin, Anton A, and Paulina Restrepo-Echavarria. 2014. "The Labor Wedge as a Matching Friction." *European Economic Review*, 68: 71–92.

Chéron, Arnaud, Jean-Olivier Hairault, and François Langot. 2011. "Age-Dependent Employment Protection." *The Economic Journal*, 121(557): 1477–1504.

Chéron, Arnaud, Jean-Olivier Hairault, and François Langot. 2013. "Life-Cycle Equilibrium Unemployment." *Journal of Labor Economics*, 31(4): 843–882.

Chodorow-Reich, Gabriel, and Loukas Karabarbounis. 2016. "The Cyclicality of the Opportunity Cost of Employment." *Journal of Political Economy*, 124(6): 1563–1618.

Choi, Sekyu, Alexandre Janiak, and Benjamín Villena-Roldán. 2015. "Unemployment, Participation and Worker Flows Over the Life-Cycle." *The Economic Journal*, 125(589): 1705–1733.

Coglianese, John M, and Brendan M Price. 2020. "Income in the Off-Season: Household Adaptation to Yearly Work Interruptions." *Upjohn Institute Working Paper 20-337*.

Davis, Steven J, R Jason Faberman, and John C Haltiwanger. 2013. "The Establishment-Level Behavior of Vacancies and Hiring." *The Quarterly Journal of Economics*, 128(2): 581–622.

Esteban-Pretel, Julen, and Junichi Fujimoto. 2014. "Life-Cycle Labor Search with Stochastic Match Quality." *International Economic Review*, 55(2): 575–599.

Feldstein, Martin. 1976. "Temporary Layoffs in the Theory of Unemployment." *Journal of Political Economy*, 84(5): 937–957.

Fernández-Blanco, Javier. 2013. "Labor Market Equilibrium with Rehiring." *International Economic Review*, 54(3): 885–914.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2021. "Integrated Public Use Microdata Series, Current Population Survey: Version 9.0 [dataset]." *Minneapolis, MN: IPUMS*.

Forsythe, Eliza, Lisa B Kahn, Fabian Lange, and David Wiczer. 2022. "Where Have All the Workers Gone? Recalls, Retirements, and Reallocation in the COVID Recovery." *Labour Economics*, 78: 102251.

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

Ganong, Peter, Fiona Greig, Max Liebeskind, Pascal Noel, Daniel Sullivan, and Joseph Vavra. 2021. "Spending and Job-Finding Impacts of Expanded Unemployment Benefits: Evidence from Administrative Micro Data." *University of Chicago, Becker Friedman Institute for Economics Working Paper*.

Gavazza, Alessandro, Simon Mongey, and Giovanni L Violante. 2018. "Aggregate Recruiting Intensity." *American Economic Review*, 108(8): 2088–2127.

Gertler, Mark, Christopher Huckfeldt, and Antonella Trigari. 2022. "Temporary Layoffs, Loss-of-Recall, and Cyclical Unemployment Dynamics." *NBER Working Paper*.

Gorry, Aspen. 2016. "Experience and Worker Flows." *Quantitative Economics*, 7(1): 225–255.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song. 2021. "What Do Data on Millions of U.S. Workers Reveal About Lifecycle Earnings Dynamics?" *Econometrica*, 89(5): 2303–2339.

Hall, Robert E, and Marianna Kudlyak. 2022. "The Unemployed With Jobs and Without Jobs." *Labour Economics*, 79: 102244.

Hubmer, Joachim. 2018. "The Job Ladder and Its Implications for Earnings Risk." *Review of Economic Dynamics*, 29: 172–194.

Jansson, Fredrik. 2002. "Rehires and Unemployment Duration in the Swedish Labour Market — New Evidence of Temporary Layoffs." *Labour*, 16(2): 311–345.

Kahn, Lisa B. 2010. "The Long-Term Labor Market Consequences of Graduating from College in a Bad Economy." *Labour economics*, 17(2): 303–316.

Katz, Lawrence F. 1986. "Layoffs, Recall and the Duration of Unemployment."

Katz, Lawrence F, and Bruce D Meyer. 1990*a*. "The Impact of the Potential Duration of Unemployment Benefits on the Duration of Unemployment." *Journal of Public Economics*, 41(1): 45–72.

Katz, Lawrence F, and Bruce D Meyer. 1990*b*. "Unemployment Insurance, Recall Expectations, and Unemployment Outcomes." *The Quarterly Journal of Economics*, 105(4): 973–1002.

Menzio, Guido, Irina A Telyukova, and Ludo Visschers. 2016. "Directed Search over the Life Cycle." *Review of Economic Dynamics*, 19: 38–62.

Mortensen, Dale T, and Christopher A Pissarides. 1994. "Job Creation and Job Destruction in the Theory of Unemployment." *The Review of Economic Studies*, 61(3): 397–415.

Nekoei, Arash, and Andrea Weber. 2015. "Recall Expectations and Duration Dependence." *American Economic Review*, 105(5): 142–46.

Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz. 2012. "The Short- and Long-Term Career Effects of Graduating in a Recession." *American Economic Journal: Applied Economics*, 4(1): 1–29.

Qiu, Xincheng. 2022. "Vacant Jobs." University of Pennsylvania.

Røed, Knut, and Morten Nordberg. 2003. "Temporary Layoffs and the Duration of Unemployment." *Labour Economics*, 10(3): 381–398.

Rothstein, Jesse. 2023. "The Lost Generation?: Labor Market Outcomes for Post-Great Recession Entrants." *Journal of Human Resources*, 58(5): 1452–1479.

Scarpetta, Stefano, Anne Sonnet, and Thomas Manfredi. 2010. "Rising Youth Unemployment During The Crisis: How to Prevent Negative Long-term Consequences on a Generation?" *OECD*.

Stinson, Martha H. 2003. "Technical Description of SIPP Job Identification Number Editing in the 1990-1993 SIPP Panels." *US Census*.

APPENDICES FOR ONLINE PUBLICATION

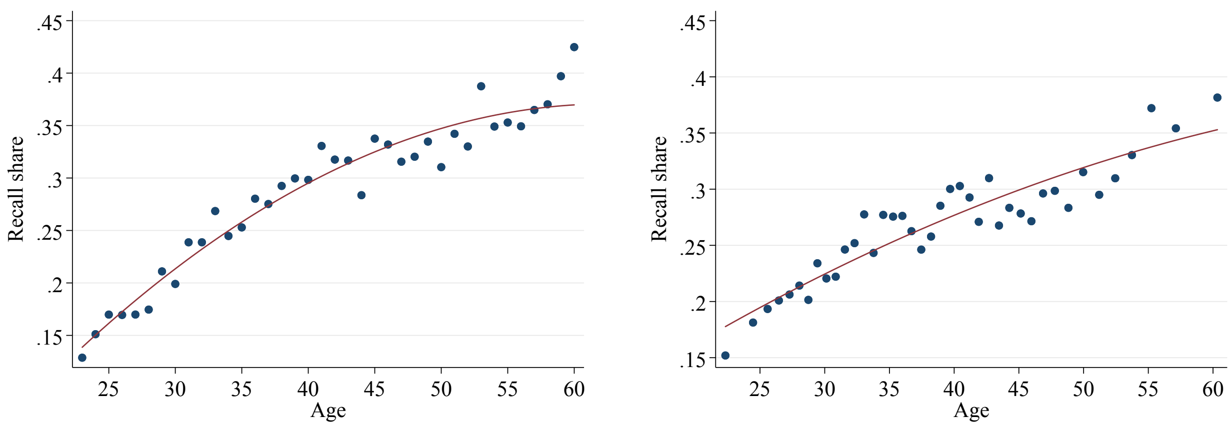
I Empirical Appendix

I.1 Post-1996 SIPP Panels

Figure 1 plots the recall share over the life cycle using pre-1996 SIPP panels, as the data quality on job IDs is the highest thanks to Stinson (2003). Here we reproduce the results using the post-1996 SIPP panels, and confirm the same findings. Figure A-1 shows the binscatter plot of the recall share against age with and without controls, and Figure A-2 plots the same figure with imputed recalls following Fujita and Moscarini (2017)'s methodology described below. Both figures display a robust age gradient in recalls.

Figure A-1: Recalls Over the Life Cycle: Post-1996 Panels

(a) Without controls (b) With controls

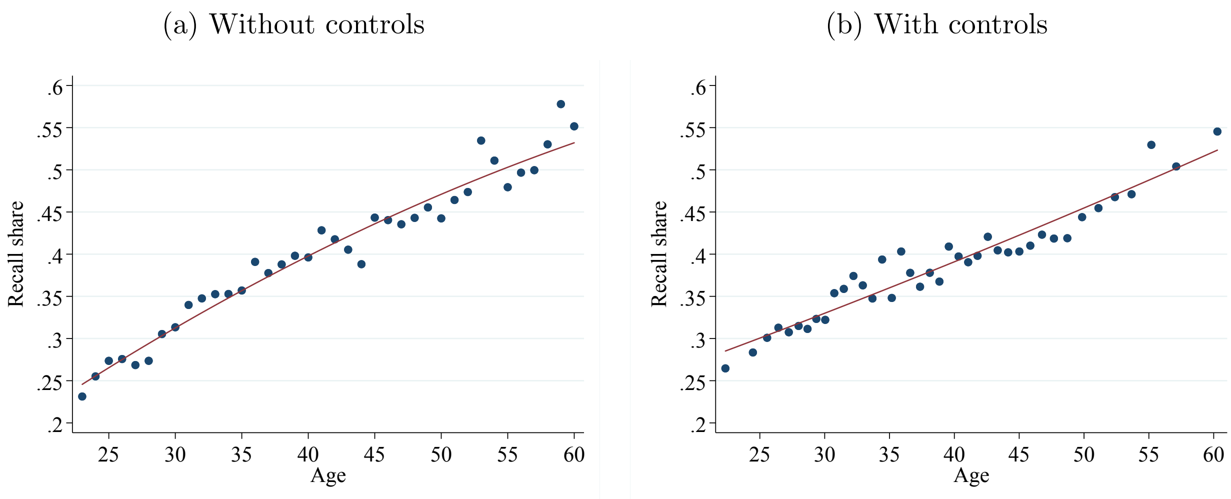


Notes: The figure plots the life cycle profile of the recall share without controls (left) and with controls (right) for post-1996 panels.

I.2 Imputed Recalls

To deal with missing recalls in the post-1996 SIPP panels, we follow the imputation procedure as in Fujita and Moscarini (2017). As an overview, the sample is first divided into two categories: "short" spells of non-employment that last up to two months, and "long" spells of non-employment that last three months or more. For both categories, a "reference sample" is utilized to estimate a logit regression model that predicts recalls based on observable worker and spell characteristics such as the duration of non-employment, occupation changes, etc. The

Figure A-2: Recalls Over the Life Cycle: Imputed



Notes: The figure plots the life cycle profile of the imputed recall share without controls (left) and with controls (right) for post-1996 panels.

coefficients obtained from the regression model are then used to generate multiple randomized imputations for each relevant spell.

To impute recalls for the long spells (ENE spells with non-employment duration of three months or longer) in the post-1996 panels, we use the corresponding data in the 1990-1993 panels as the reference sample. The following variables are included in the logit regression: quadratic polynomials in age, education categories (less than high school, high school graduate, some college, and college degree or higher), gender, union membership at initial employment, employer-provided health care (EPHC) at initial employment, address change, union status change, EPHC change, non-employment duration (3-6 months, 7-9 months, 10- 12 months, 13 months or longer), occupation switch and industry switch dummies at the three-digit level classification, as well as interactions of the two switching dummies, initial occupation and industry dummies (79 occupational categories and 44 industry categories), log wage change between initial and last employment, captured as a categorical variable based on the following intervals: $(\infty, -0.5], (-0.5, -0.05], (-0.05, 0.03], (0.03, 0.5], (0.5, \infty]$, national unemployment rate to control for aggregate labor market conditions, and month-of-separation dummies to control for seasonality.

For short spells (ENE spells with non-employment duration of one or two months) in the post 1996 panels, we impute recall if the spell satisfies three requirements: (i) it does not begin as temporary layoffs (TL); (ii) it crosses an interview wave; (iii) it does not lead to an occupational switch. Note that, to be conservative, when we observe a worker who reports two different occupations in the two consecutive interviews in the short spell, we directly mark it as not a recall.[10] This choice follows from the observation that, among these short cross-seam spells, less than 10 percent of the occupational switchers in the pre-1996 panels are recalled (see online Appendix Table A.14 in Fujita and Moscarini, 2017). The reference sample for imputation is the analogous sample of within-wave short spells in the 1996–2008 panels. The regression uses basically the same variables as above with a few differences. First, we do not use occupation and industry switch dummies (the sample is only for occupation stayers). Second, initial occupation and industry dummies (a total of 123 dummies) are dropped to maintain the efficiency of the estimation, given that this sample has much fewer observations. Third, we also use a labor market status variable, TL vs. PS, which was not feasible for long spells as measurement of labor market status in the SIPP is not comparable before and after 1996. Lastly, we also add panel dummies, because the short spells are imputed within the 1996-2008 panels.

Once the logit regressions have been estimated, we proceed to simulate discrete recall outcomes (0 or 1) for all spells that are considered unreliable, using the predicted probabilities. We conduct 50 replications of the simulation and the imputed recall outcome is an average of these simulations.

I.3 Age Polynomials

Table A-1 conducted a robustness check on the recall share age gradient by running regression of recall on polynomials of age. In particular, we add square of age and cubic of age to a regression of recall on age. All coefficient are statistically significant at the 1% level.

I.4 Temporary Job

Figure A-3 plots the life-cycle profile of the share of workers with a temporary job. Young workers are in fact much more likely to have a temporary job than old workers, ruling out the possibility that temporary jobs drive the empirical regularity of a positive age gradient in the recall share.

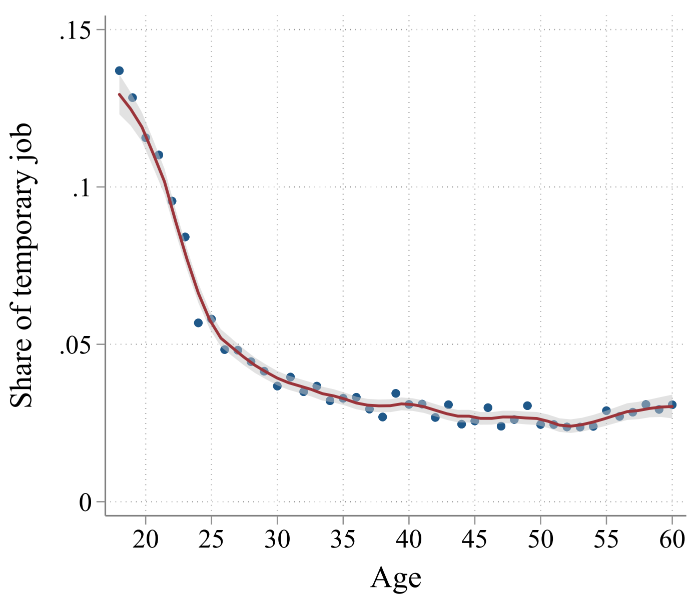
[10] This choice is conservative because crossing a seam introduces error also in occupational codes, marking an occupation-stayer, who was likely to be recalled, as an occupation-switcher.

Table A-1: Age Polynomials

	(1)	(2)	(3)
age	0.528***	1.397***	6.286***
	(0.037)	(0.282)	(1.728)
age^2		-0.011***	-0.138***
		(0.004)	(0.044)
age^3			0.001***
			(0.000)
Specification	Linear	Quadratic	Cubic
Observations	17537	17537	17537
R-squared	0.15	0.15	0.15

Standard errors, * p<0.10, ** p<0.05, *** p<0.01

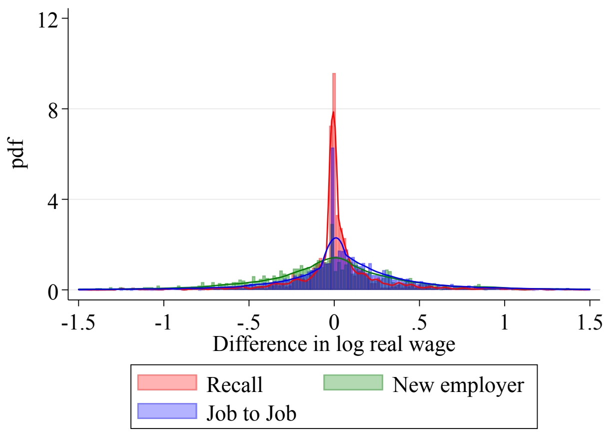
Figure A-3: Temporary Jobs Over the Life Cycle



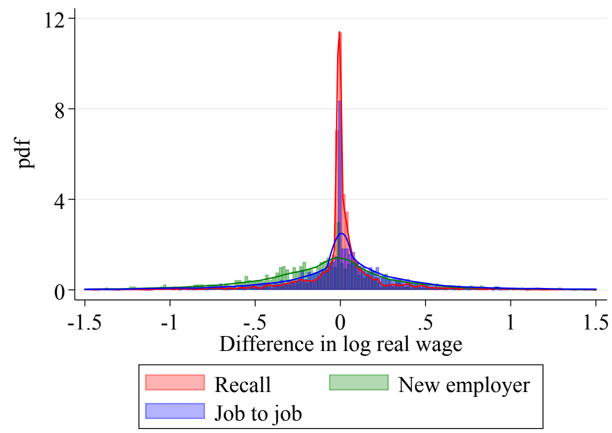
I.5 Wage Changes Associated with Different Transitions

Figure A-4: The Distribution of Wage Changes: pre-1996 panels

(a) Young Workers



(b) Old Workers



Notes: The figure plots the distribution of the wage changes for recalled workers (ENE), for workers moving to new employers after the jobless spell (ENE') and for job-to-job switches without jobless spell (EE'). The left panel is for young workers and the right panel is for old workers. Data sample: pre-1996 SIPP panels.

Figure A-4 separates the distributions of wage changes as plotted in Figure 3 by young and old workers. For both young and old workers, the wage change for recalled workers is the highly concentrated at zero, while the wage change for job-to-job switchers and workers who found a new employer after going through non-employment are much more dispersed.

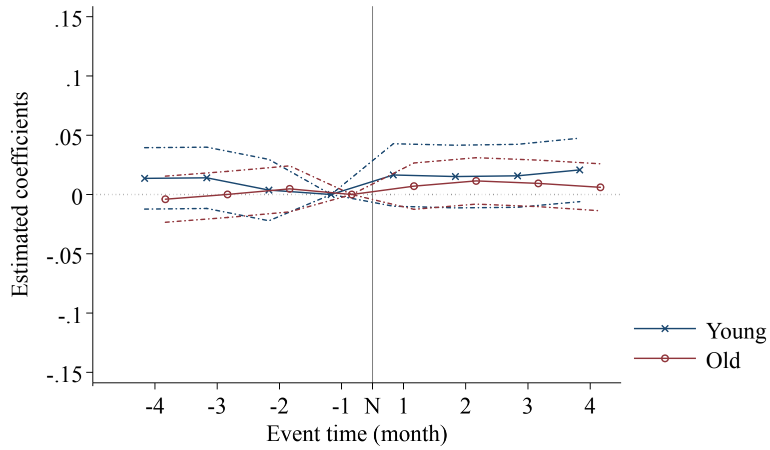
Figure A-5 repeated the regression event study in the empirical section using imputed recalls and all SIPP panels. The same pattern emerged: (1) the wage change for recalled workers is concentrated at zero for both young and old workers; (2) the wage decline for old workers finding a new employer after going through non-employment is larger than young workers; (3) the wage increase for young workers making job-to-job switches is larger than old workers.

I.6 Ex Ante vs. Ex Post

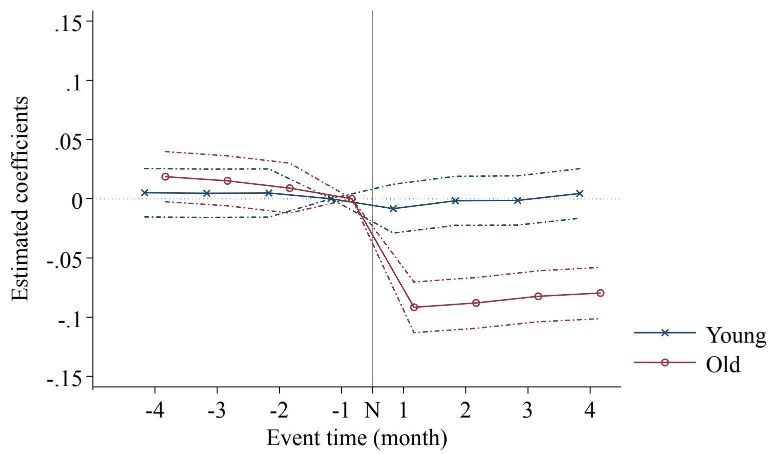
We dissect the observed life-cycle profiles of recalls into two components, the *ex ante* expectations of getting recalled and the *ex post* outcomes of getting recalled. Oftentimes recalls are expected—upon an arrangement of temporary layoff, workers are noticed with a recall date or an expectation to be recalled in a near future. But such arrangements do not necessarily result in actual recalls, for example, when the worker finds a new job during temporary layoff or when the firm decides not to reinstate the former position.

Figure A-5: Wage Changes Associated with Different Transitions

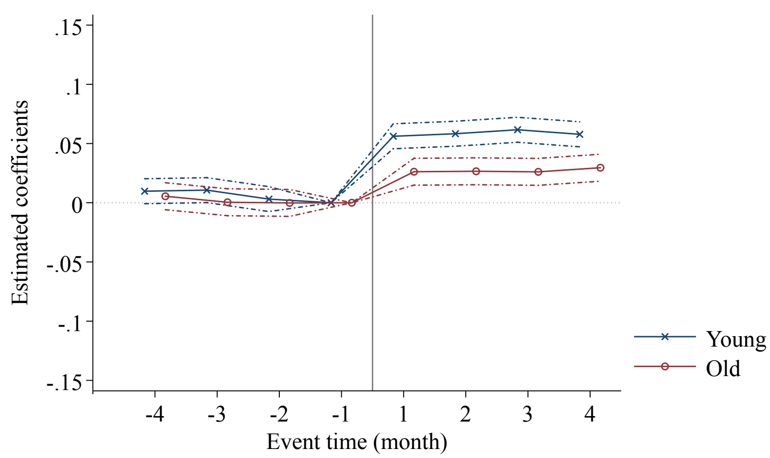
(a) Recalls (ENE)



(b) New Job Findings (ENE′)



(c) Job-to-Job Switches (EE′)



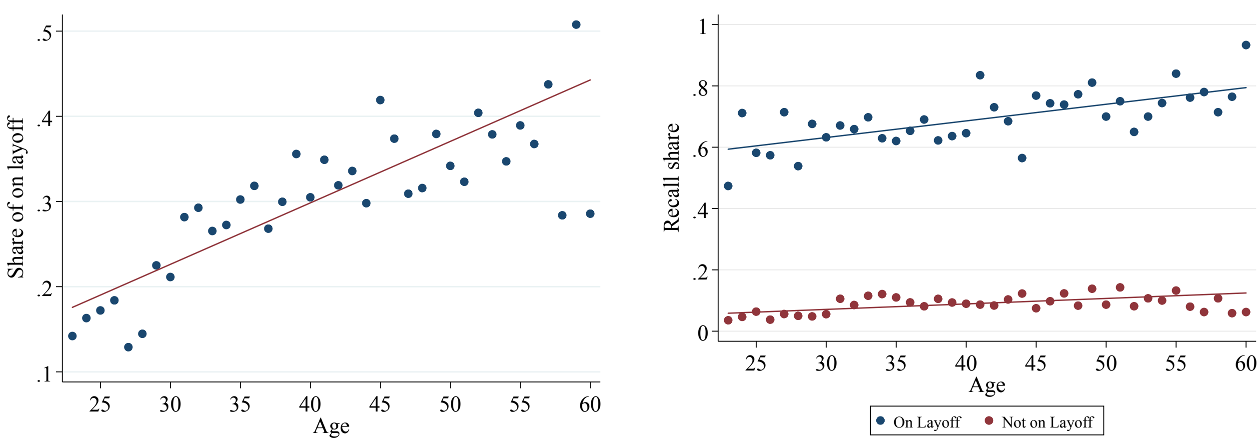
Notes: The figure plots the coefficients of the event study specifications for recalls (the top panel), for workers moving to a new employer after the jobless spell (the middle panel), and for job-to-job transitions (the bottom panel). The blue lines are for young workers (age 23-35) and the red lines are for old workers (age 35-60). Dashed lines plot the 95% confidence intervals.

We examined this aspect by leveraging the "on layoff" status as reported in SIPP. As mentioned in Gertler, Huckfeldt and Trigari (2022), using the "on layoff" status gives a more accurate description of whether the worker has been permanently separated from her previous employer. In the SIPP interviews, respondents are asked if they were on layoff at anytime during the previous four months, and if they answered yes, they would be further asked whether they were given a date to return to work or received any other indication that they would be recalled to work within six months as confirmation. A worker is classified to be on layoff if the worker has been given an exact date to return to work or has a recall expectation within six months.[11] To tease out the role of ex ante expectations, we calculate the portion of workers, among those who had an ENE or ENE′ spell, who report to be on-layoff during non-employment. As of the ex post realizations of recalls, we calculate the recall share of workers conditional on their on-layoff status during non-employment.

Is the increase in recall share over the life cycle mainly driven by ex-ante arrangements or ex-post realizations? Figure A-6 shows that both the *ex ante* expectations—the share of employment-to-nonemployment transitions that are on layoff, and the *ex post* outcomes—the share of separated workers that are eventually recalled conditional on their layoff status, are increasing in age.

Figure A-6: The *Ex Ante* and *Ex Post* Decomposition of the Life-Cycle Profile of Recalls

(a) *Ex Ante* (b) *Ex Post*



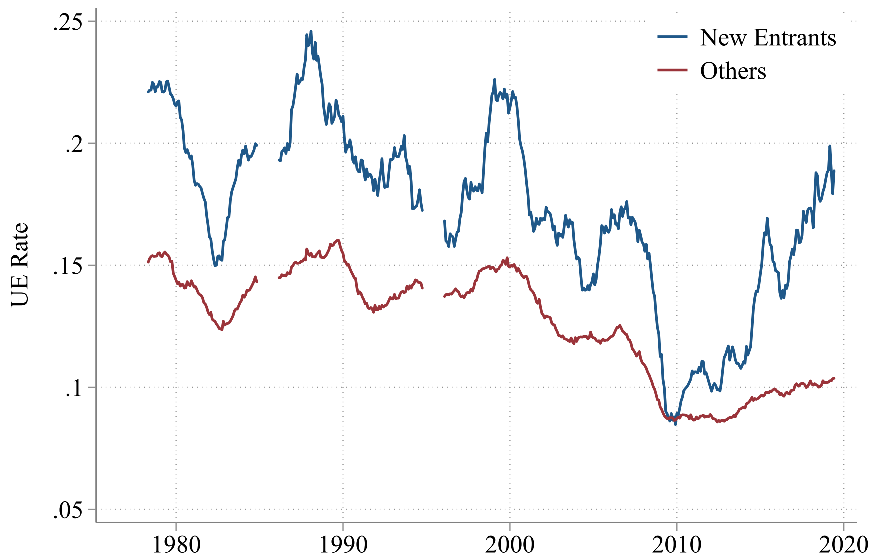
Notes: The figure plots the portion of separations to non-employment that are on layoff over the life cycle (left panel) and the ex post realized recall share conditional on layoff status (right panel). The on layoff status only exist for post-1996 panels.

[11]Note that *recalls* and *on layoff* are two related but distinct concepts. Nekoei and Weber (2015) found in Austrian administrative data that 19% of permanent separations are in fact unexpectedly recalled *ex post*, while only 58% of temporary layoffs end up with actual recalls.

I.7 Job-Finding Rate of Labor Market Entrants over the Business Cycle

Figure A-7 illustrates the job-finding rates for labor market entrants compared to non-entrants over the business cycles, using the Current Population Survey (CPS). The blue line, representing new entrants, fluctuates significantly over the whole sample period, indicating a higher volatility in their job-finding rates relative to the red line, which denotes the rates for others already in the labor market. Notably, during downturns, new entrants face a much more pronounced decline in the job-finding rate. This underscores the heightened sensitivity of new labor market entrants to the aggregate labor market conditions compared to those already in the labor market.

Figure A-7: Job Finding Rate of Entrants and Non-Entrants over the Business Cycle



Notes: The figure plots the job-finding rate of labor market entrants and non-entrants over the business cycle, using the CPS data.

II Theoretical Appendix

II.1 Wage Equation

Plugging in the HJB equations (1,2,3,4) into the surplus sharing rule, we can derive the following wage equation:

$$
\begin{aligned}
w(m) = \beta m + \beta\lambda_e\left[\int \max\left\{J(m)-\varepsilon', V(m)\right\}dG_e(\varepsilon') - J(m)\right] \quad &\text{(A1.1)}\\
+ \beta p(\theta)\int \mathbb{1}\left\{W(m') > U(m)\right\}V(m)dF(m') \quad &\text{(A1.2)}\\
- \beta\lambda_u\left[\int \max\left\{J(m)-\varepsilon', V(m)\right\}dG_u(\varepsilon') - V(m)\right] \quad &\text{(A1.3)}\\
- \beta\phi p(\theta)\int \mathbb{1}\left\{W(m') > W(m)\right\}J(m)dF(m') \quad &\text{(A1.4)}\\
+ (1-\beta)z + (1-\beta)\lambda_u\left[\int \left\{B(m,\varepsilon')W(m) + \overline{B}(m,\varepsilon')U(m)\right\} \mathrm{d}G_u(\varepsilon') - U(m)\right] \quad &\text{(A1.5)}\\
+ (1-\beta)p(\theta)\int \max\left\{W(m') - U(m), 0\right\}dF(m') \quad &\text{(A1.6)}\\
- (1-\beta)\lambda_e\left[\int \left\{B(m,\varepsilon')W(m) + \overline{B}(m,\varepsilon')U(m)\right\} \mathrm{d}G_e(\varepsilon') - W(m)\right] \quad &\text{(A1.7)}\\
- (1-\beta)\phi p(\theta)\int \max\left\{W(m') - W(m), 0\right\}dF(m') \quad &\text{(A1.8)}
\end{aligned}
$$

The wage equation has an intuitive economic interpretation. The worker is paid a weighted average of the flow value of forming a match (weighted by β) and the flow value of being unemployed (weighted by $1-\beta$). The flow value of forming a match includes flow production m and the potential loss due to idiosyncratic cost shock (A1.1). In addition, it also includes a saved vacancy value with a recall option, which would otherwise be lost should the worker finds another job during the attached unemployment period (A1.2). However, it has to be offset by the option value arising from a reactivation cost (A1.3). Lastly, it is compensated by the potential loss to the firm caused by the worker's on-the-job search (A1.4). Similarly, the flow value of being unemployed includes home production z and the potential gain due to the arrival of a reactivation opportunity (A1.5). In addition, it also includes an option value of the worker finding a better offer (A1.6). However, it has to be offset by the value change arising from an endogenous separation (A1.7). Lastly, it is compensated by the option value of searching on the job (A1.8).

II.2 Inflow-Outflow Balance Equations

The steady-state inflow-outflow balanced equation for unemployed workers without recall options is:

$$\mu_0 p(\theta) \int \mathbb{1}\Big\{W(m') > U_0\Big\} \, \mathrm{d}F(m') = (1-\mu_0)\,(\delta+\gamma). \tag{A2}$$

The steady-state inflow-outflow balanced equation for unemployed workers with recall options is: for all m,

$$\begin{aligned} &\mu(m)\Big[\lambda_u \int B(m,\varepsilon')\,\mathrm{d}G_u(\varepsilon') + p(\theta)\int \mathbb{1}\Big\{W(m') > U(m)\Big\}\,\mathrm{d}F(m') + \delta + \zeta + \gamma\Big] \\ &= \ell(m)\lambda_e \int \overline{B}(m,\varepsilon')\,\mathrm{d}G_e(\varepsilon'). \end{aligned} \tag{A3}$$

The steady-state inflow-outflow balanced equation for employed workers is: for all m,

$$\begin{aligned} &\ell(m)\Big[\lambda_e \int \overline{B}(m,\varepsilon')\,\mathrm{d}G_e(\varepsilon') + \phi p(\theta)\int \mathbb{1}\Big\{W(m') > W(m)\Big\}\,\mathrm{d}F(m') + \delta + \zeta + \gamma\Big] \\ &= \mu(m)\int B(m,\varepsilon')\,\mathrm{d}G_u(\varepsilon') \\ &+ p(\theta)f(m)\Big[\int \mathbb{1}\Big\{W(m) > U(\tilde{m})\Big\}\,\mathrm{d}\mu(\tilde{m}) + \mathbb{1}\Big\{W(m) > U_0\Big\}\mu_0\Big] + \zeta f(m)\int d\mu(\tilde{m}) \\ &+ \phi p(\theta)f(m)\int \mathbb{1}\Big\{W(m) > W(\tilde{m})\Big\}\,\mathrm{d}\ell(\tilde{m}) + \zeta f(m)\int d\ell(\tilde{m}). \end{aligned} \tag{A4}$$

II.3 Algorithm

II.3.1 Steady State

A stationary equilibrium consists of value functions $\{W, U, U_0, J, V, V_0\}$, wage policy $w(m)$, labor market tightness θ, and measures $\mu_0, \mu(m), \ell(m)$. We obtain them by using a standard nested loop procedure with value function iteration for general equilibrium. Give an initial guess of θ^0 and value functions $\{W^{i,0}, U^{i,0}, U_0^{i,0}, J^{i,0}, V^{i,0}, V_0^{i,0}\}$:

1. Suppose we are now at iteration i in the outer loop for θ. Given the guess of θ^i , obtain the job offer arrival rate for unemployed workers without recall option $p(\theta^i)$

2. Suppose we are now at iteration k in the inner loop for the value functions. Given the guess of value functions $\{W^{i,k}, U^{i,k}, U_0^{i,k}, J^{i,k}, V^{i,k}, V_0^{i,k}\}$ and $p(\theta^i)$, obtain the wage policy $w^{i,k}(m)$ using

3. Plug in $\{W^{i,k}, U^{i,k}, U_0^{i,k}, J^{i,k}, V^{i,k}, V_0^{i,k}\}$ and $w^{i,k}(m)$ to the right hand side of (1)-(5) to update the value functions

4. If the tolerance for value functions is satisfied, move to step 5. Otherwise, use the updated value function and go back to step 2

5. Given the value functions, solve for the inflow-outflow equations (A2)-(A4) to obtain $\mu_0, \mu(m), \ell(m), \ \forall m$

6. Plug the steady state equilibrium distribution to (6) and invoke the free-entry condition (i.e. impose $V_0 = 0$) in the equation) to solve for an implied $\tilde{\theta}$

7. If the tolerance is satisfied, done. Otherwise, update the labor market tightness

$$\theta^{i+1} = \omega\theta^i + (1-\omega)\tilde{\theta}^i$$

   with some dampening factor ω. Go back to step 1.

II.3.2 Transitional Dynamics

Consider a transition path of T periods, where T is large. Period T will feature the old steady state equilibrium. Guess a path of labor market tightness, $\{\theta_t^0\}_{t=1}^{T-1}$.

1. Suppose we are now at iteration i. Given the path of tightness $\{\theta_t^i\}_{t=1}^{T-1}$ and the terminal value functions, we solve for the path of value functions backwards.

2. Given the path of value functions and associated policy functions, we solve for the path of measures using the law of motion forwards.

3. Solve for the path of labor market tightness $\{\tilde{\theta}_t^i\}_{t=1}^{T-1}$ that is consistent with the period-by-period free entry condition.

4. If the tolerance is satisfied, done. Otherwise, update the guess for the path of tightness to

$$\theta^{i+1} = \omega\theta^i + (1-\omega)\tilde{\theta}^i$$

   with some dampening factor ω (store the path of tightness as a vector). Go back to step 1.