Job Recalls and Worker Flows over the Life Cycle*

Justin Franco Lam†
University of Pennsylvania

Xincheng Qiu‡
University of Pennsylvania

February 21, 2022

Preliminary and Incomplete

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 in age. The fact is robust to an extensive set of controls and various alternative sample selections, and is confirmed in administrative data. Recalls lead to different wage outcomes than exit to new jobs or job to job transitions. Throughout the life cycle, wages are barely changed after recalls, and the distribution of wage changes is very concentrated. We find that a job-ladder search model with recall options can successfully account for all documented facts. The introduction of recall options provides a novel mechanism that reconciles the puzzle of a positive comovement between separation and job finding rate over the life cycle. The model highlights that the deterioration of matching efficiency in bad times hurts young workers more than old workers, because the young rely more on the matching function of the labor market to find a new job, whereas the old 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 Hanming Fang, Dirk Krueger, Iourii Manovskii, José-Víctor Ríos-Rull, and Andrew Shephard for their insightful advice and continuous support. We thank Francesco Agostinelli, Joachim Hubmer, Holger Sieg, and seminar participants at Penn Macro Lunch and Empirical Micro Lunch for helpful comments. We are responsible for all remaining errors.

†Department of Economics, University of Pennsylvania. Email: jflam@sas.upenn.edu.
‡Department of Economics, University of Pennsylvania. Email: qiux@sas.upenn.edu.

1 Introduction

An unemployed worker can leave the unemployment pool by either finding a new job (EUE' transitions) or returning to work for their previous employers (EUE transitions). In the U.S. labor market, over 40% of unemployment spells end with recalls (Fujita and Moscarini, 2017).[1] The labor market implication of layoffs are very different when recalls are taken into account. For instance, not all layoffs are inherently associated with job destruction, if the match capital can essentially be preserved for a large amount of separations. The pandemic labor market has clearly further corroborated that the incidence of recalls is crucial to understanding labor market dynamics (e.g., Forsythe et al., 2020; Ganong et al., 2021; Hall and Kudlyak, 2020).

Given such significant empirical prevalence and theoretical relevance, it is perhaps surprising that recalls are rarely incorporated into labor market research. The relatively scant evidence about recalls documented so far is mostly based on aggregate analyses, which hide dramatic heterogeneity among different workers. For example, given the massive literature on age-earnings profiles, it is natural to ask how does the recall behavior evolve over the life cycle. The main objective of this paper is therefore to study the life-cycle behavior of recalls, as a step towards bridging the gap between the quantitative importance of recalls and the inadequacy of labor market research on recalls.

Using the Survey of Income and Program Participation (SIPP), we document three novel facts on recalls over the life cycle. First, like many other well-known life-cycle patterns such as earnings, the recall share, defined as the share of unemployment-employment transitions that correspond to a recall rather than a new job, exhibits a steep age-gradient.[2] The recall share of an old worker is more than twice as high as that of an young worker. For instance, a 55-year-old worker has a recall share of 60%, while a 25-year-old worker has a recall share of 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. Although our main analysis is based on survey data thanks to the richness of SIPP, we corrobo-

[1] Recalls are also a prevalent feature in the European labor markets, although to a slightly lesser degree than in the U.S. labor market. 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] Fujita and Moscarini (2017) call this object the "recall rate." We instead reserve the terminology "recall rate" for the ratio of unemployment-employment transitions that are recalls divided by the unemployment stock, so that it is part of the "job finding rate."

rate our finding using the high quality of administrative data QWI to ensure that the life-cycle behavior of recalls we document is by no means any artifact of sampling issues.

Second, we further dissect the observed life-cycle profiles of recalls into two components, the *ex ante* expectations of likely to be recalled and the *ex post* outcomes of actually being recalled. Layoffs where workers are noticed with a recall date or expectation are often called "temporary layoffs" (TL). Temporary layoffs differ from recalls to the extent that laid-off workers with a recall expectation may not necessarily get rehired, and laid-off workers without a recall expectation may turn out to get rehired. We find that both the *ex ante* expectations—the share of employment-unemployment transitions that are temporary layoffs, and the *ex post* outcomes—the share of separated workers conditional on temporary layoffs or permanent layoffs that are eventually recalled, are increasing in age. Thus, both contribute to the life-cycle pattern realization of recalls, and we caution that it may lead to errors if one is ignored over the other, for example, by only looking at temporary layoffs.

Third, we examine how different paths of labor market reallocation transitions are associated with ultimate labor market outcomes such as wages. We find that recall (EUE), new job finding (EUE'), and job-to-job switching (EE') differ significantly in wage changes, both in terms of the level of the change and the life-cycle pattern of the wage. Using an event study design, we find that there are little wage changes after recalls, and such persistence in wages before and after recalls holds regardless of the age. However, the distribution of the wage change between the pre-unemployment and post-unemployment jobs for workers who move to a new job is very dispersed and the average wage change decreasing in age. In particular, the wage change for young workers bettween 25 and 30 making EUE' transitions is almost zero on average, while the wage loss for workers older than 50 making EUE' transitions is more than 10%. Interestingly, the wage change for job-to-job switchers (EE' transitions) is also declining in age, although the wage change is positive almost through out the whole life cycle.

To investigate the role of job recalls to labor market dynamics over the life cycle, We extend the Diamond-Mortensen-Pissarides paradigm 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 job recalls. Jobs are occasionally hit by idiosyncratic match productivity shocks, and workers and firms 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 quality is already good. For the same reason, they are less likely to change jobs. The presence of a recall option makes unemployed worker attached to a job, and hence the job-finding rate behaves similarly to the job-to-job rate, thus rationalizing a puzzle in the literature on the positive comovement of separation rate and job finding rate over the life cycle.

Finally, we show that deterioration of matching efficiency in bad times hurts young workers more than old workers. This is because the young rely more on the matching function of the labor market to find a new job, whereas the old rely less and are more likely to get recalled.

Related Literature. Despite the prevalence of recalls in the labor market, there is surprisingly little research on recalls, although there is an extensive literature on temporary layoffs. It is presumably because that the data requirements to measure TL are lower, as the survey only needs to ask the worker at a given point in time whether he or she expects to be recall, whereas to measure recalls one needs to keep track of the worker's labor market history. This paper first contributes to a small literature that documents empirical facts about 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 papers are among the first to notice the importance of accounting for recalls in the analysis of unemployment. More recent contributions include Fujita and Moscarini (2017), who revive the academic interest in recalls by documenting the large magnitude and strong cyclicality of recalls using SIPP, a nationally representative sample covering twenty years. They present a rich set of facts about recalls at the aggregate levels, for example, that recalled workers have longer pre-separation tenure, shorter unemployment duration, more stable post-separation employment relationship, and higher occupational mobility. We complement their paper by unveiling the aggregate patterns over the life cycle.

Although recalls and temporary layoffs are two closely related concepts, we elaborate their distinction from a life cycle point of view. Nekoei and Weber (2015) find 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. Similar findings are also confirmed by Fujita and Moscarini (2017) for the US, where around 85% of temporary layoffs and 17% of permanent separations are recalled. Although recalls align much more closely with TLs in the US than in Austria, the cross-sectional correlation between TL and recall is still only 0.67. Nekoei and Weber (2020) is an important step to build up the facts on temporary layoffs and recalls. We complement their study by providing a life cycle perspective of TL and recalls.

The policy relevance of recalls is most often related to the design of the unemployment insurance system, starting from the pioneering work by Feldstein (1976) and Topel (1983). It is well understood that the way how UI is financed can affect workers and firms separation and job search behavior. Albertini, Fairise and Terriau (2014) find that UI recipients are more likely to be recalled. They argue that the higher incidence of recalls among UI recipients is largely accounted for by experience rating in the UI financing system. Under the ER system, the firm-specific tax rate would be higher if its laid-off workers keep collecting UI benefits. Therefore, firms essentially internalize part of the impact of layoffs on workers. We find that although UI affects the level of recalls, it hardly affects the age profile of recalls.

Second, this paper adds to the 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. One key distinction in our model, on top of the obvious one that we have a life cycle model, is that we assume mothballing positions is costly, while mothballing is free in Fujita and Moscarini (2017). Fernández-Blanco (2013) studies a steady-state version of the model and 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. The "rest unemployment" by Alvarez and Shimer (2011) can also be interpreted as unemployment without active job search by workers who have a strong expectation of recall.

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. However, 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), but 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), and Cajner, Güner and Mukoyama (2021). We contribute to this literature by both empirically documenting the important heterogeneity of recalls over the life cycle and theoretically providing a life cycle search model that is consistent with the facts.

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 matching efficiency and examines its differential impact on young and old workers. Section 6 concludes and discusses future directions.

2 Empirical Facts

2.1 Data and Definition

We used the Survey of Income and Program Participation (SIPP), a collection of panel data that begins in different years, to document the life cycle behavior of job recalls. In particular, the panels used for the analysis are: 1990, 1991, 1992, 1993, 1996, 2001, 2004 and 2008.

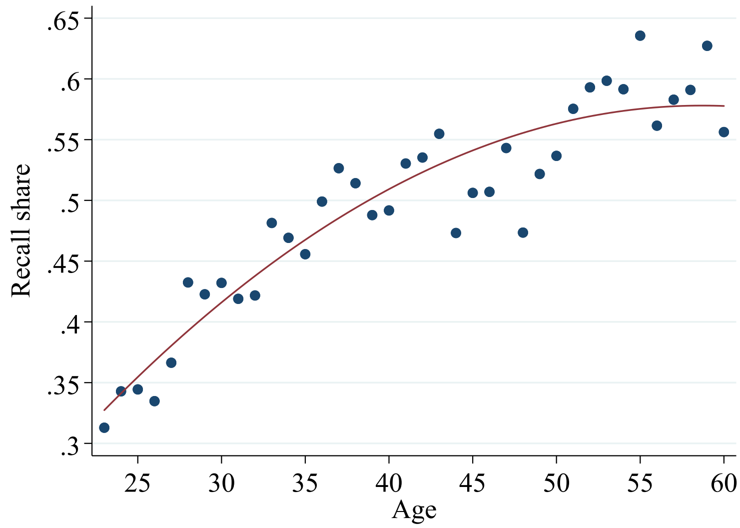
For each interview (also called a wave) in SIPP, questions will be asked about the preceding four-month period, hence our analysis can be conducted on a monthly frequency. The most important variable is the unique job ID assigned to each job of a respondent, where SIPP defines a job as a respondent-employer match. This allows us to identify if a worker has returned to their previous employer. In particular, we define an event to be a job recall if the worker has gone through a "employed-non employed-employed" transition (ENE) and returned to the same employer just before separation. Following Fujita and Moscarini (2017), we only consider job recalls to the most recent employer before separation and do not study recalls to other employers. Denoting ENE_t as the number of workers who get separated to non-employment at age t and get recalled back to their most recent employer and ENE'_t as the number of workers who separated from their job at age t and get out of non-employment to new employers, we can then define the recall share at age t as: $\frac{ENE_t}{ENE_t+ENE'_t}$. Note that in ENE'_t we exclude the cases where workers haven't had a job before, because by definition they cannot be recalled.

The assignment of job ID, however, has an issue. When a worker goes jobless for the entire four month wave, SIPP will assign a different job ID when they get employed next time, even though in reality this employer may be the same as just before the non-employment. The only exception is when a worker is temporarily laid off, then the last job ID will be carried forward. Fortunately, Stinson (2003) resolved this problem in panels 1990-1993 by retrospectively using information of the entire panel of each individual record, which is not available to interviewers when the survey is ongoing. Therefore, we regard the job IDs as reliable in the pre-1996 panels. Although the post-1996 panels still have the aforementioned issues with the job ID, thanks to the SIPP redesign in 1996, one advantage they have is that the definitions of labor market status are consistent with the monthly CPS. All in all, our main results on recall share will be based on the pre-1996 panels because job IDs are the most reliable there, while analyses that condition on labor market status will be based on the post-1996 panels with the same job recall imputation procedure as Fujita and Moscarini (2017). Robustness check using different panels are included in the appendix.

2.2 Life-Cycle Behavior of Recall

The main empirical fact is the increase in recall share over age. We plot a bin scatter graph of recall share over age in figure 1 and found that it almost doubled from 30% at age 23 to 58% at age 55.

Figure 1: Recalls over the Life Cycle



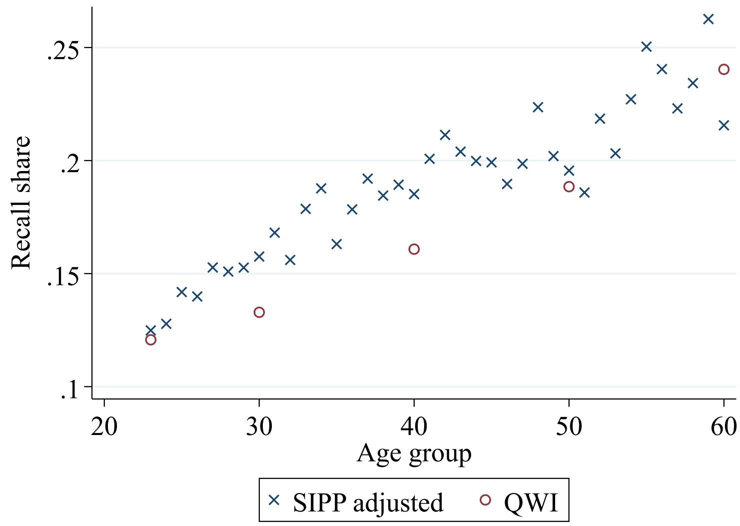
Notes: The figure plots the life cycle profile of the recall share.

2.3 Robustness of the Fact

Administrative Dataset. To cross check the increase in recall share over age is not due to SIPP mismeasurement, we used the high quality administrative data Quarterly Workforce Indicator (QWI) to document recall share over age as well. The definition of recalls in QWI is not completely consistent with our construction in SIPP. First, there is a time aggregation issue because QWI is of quarterly frequency while we construct recall share in SIPP based on monthly observations. Thus, QWI might miss the 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, allowing for recalls to any employers that the worker has worked for within a year and possibly without non-employment spell. To take care of the discrepancy, we reconstruct the recall share in SIPP to be consistent with the QWI. We collapse our monthly data to a quarterly frequency and allow for recalls to any employers that the worker has worked for within a year, possibly without non-employment spell. The results are plotted in figure 2. Reassuringly, the two profiles are similar to each other.

Extensive Controls. Robustness check with various controls are also conducted by running the

Figure 2: Recalls over the Life Cycle in QWI (Alternative Measure)



Notes: The figure reconciles the life cycle profile of recall share in Quarterly Workforce Indicator (QWI) and SIPP.

following regression:

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

where Recall is a dummy variable indicating whether the worker has been recalled. We then transform it into percentage terms by scaling it up by 100 so that we can interpret the coefficient in terms of recall shares. $\boldsymbol{X}$ is a vector of control variables. We run four sets of regression and report the coefficient in front of age in Table 1. In all of the specification, the coefficient in front of age is statistically significant and economically meaningful. In the second column, we include demographics: gender, education level, race and year dummies. In the third column, we add job characteristics to the second column controls: union, employer provided health insurance, occupation and industry. In the fourth column we include job tenure quadratic to the third column. In the fifth column, we add unemployment duration. In the sixth column, we add unemployment insurance recipiency and unemployment insurance amount. In the final column, we exclude seasonal workers.

Unemployment insurance. Although it has been documented that UI is an important factor that affects recalls (Feldstein, 1976; Katz and Meyer, 1990*b*,*a*; Albertini, Fairise and Terriau, 2014), we show that it does not drive the life cycle pattern we find. In particular, even after we control for a dummy variable indicating the UI recipiency status and the amount of UI benefits the worker received, the slope of age-recalls profile is barely changed.

Seasonal work. One natural concern is that most of the recalls are seasonal jobs. For example, Nekoei and Weber (2015) document that temporary layoffs are disproportionately common in the construction and tourism sector, although they are present in all other sectors as well. We define seasonal work following Coglianese and Price (2020). Even after we exclude seasonal jobs, the age-gradient in the recall share still exists and is almost as steep as in the full sample.

Table 1: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.759***	0.720***	0.526***	0.428***	0.448***	0.418***	0.401***
	(0.038)	(0.038)	(0.038)	(0.062)	(0.061)	(0.062)	(0.069)
Control	/	Demographics	Job Char.	Job Tenure	U Duration	UI	Seasonal
Observations	17602	17602	17537	5832	5832	5832	4694
R-squared	0.02	0.03	0.11	0.11	0.12	0.12	0.12

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

Notes: This table reports the regression results of various specifications. See main text for details.

2.4 Ex Ante vs Ex Post

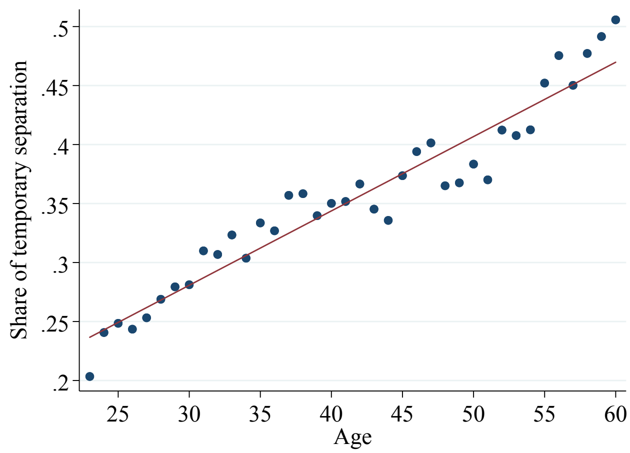
Is the increase in recall share over age driven by ex-ante arrangements or expectations (i.e. older workers separate more often with the bilateral expectation of getting recalled) or ex-post realisation (i.e. older workers get recalled more often regardless of bilateral expectation)?

We examine this by exploiting the difference between temporarily separated workers and permanently separated workers. Temporarily separated workers are separated workers with arrangements or expectations to return to the employer; whereas permanently separated workers are separated workers with no such expectations. A crude within-between decomposition is performed where we looked at the life cycle recall share for temporarily separated and permanently separated workers (within margin, ex-post) and the portion of temporarily separated workers over the life cycle (between margin, ex-ante). We follow Nekoei and Weber (2015) and Katz and Meyer (1990*b*) to measure recall expectation (and hence define temporary layoffs) at the beginning of the unemployment spell. The ex post rates we report are much more extreme than Nekoei and Weber (2015).

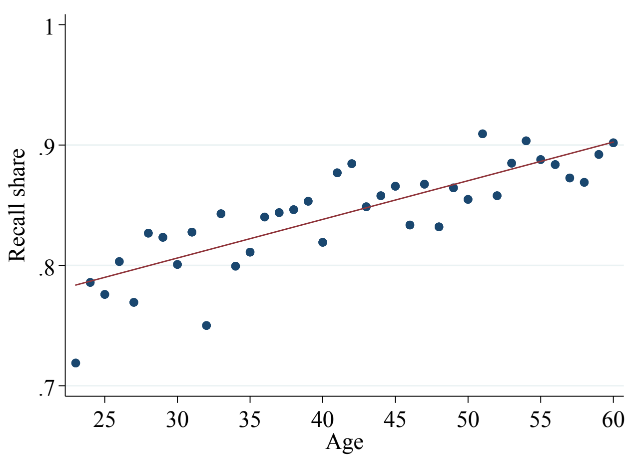
It turns out that both margins contribute to the increase in recall share over age. There are more older workers than young workers that think they are temporarily laid off. That is, hence a larger portion of old separated workers have ex-ante expectations of getting recalled. The life cycle profiles of *ex post* recall share for both temporarily separated workers and permanently separated workers are also increasing with age. As a result, we cannot ignore one or the other.

Figure 3: *Ex Ante* and *Ex Post*

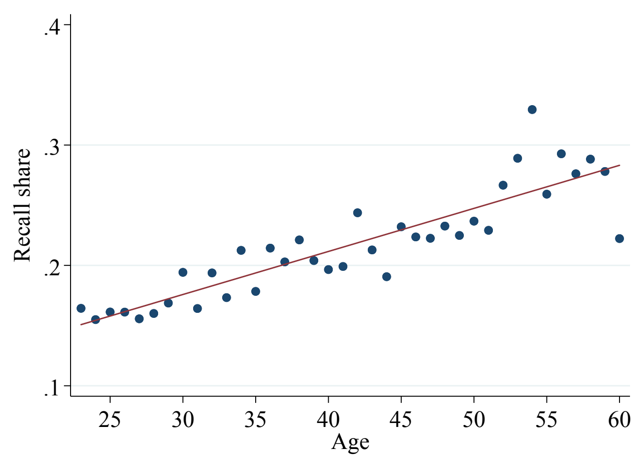
(a) *Ex Ante*



(b) *Ex Post*: TL



(c) *Ex Post*: PL



Notes: The figure plots that portion of separations that are temporary layoffs in the top panel and the ex post realized recall share conditional on temporary or permanent layoff in the bottom panel.

2.5 Wage Changes

Now we turn to the wage outcome of various labor market transitions: recall (EUE), new job finding (EUE'), and job-to-job switching (EE'). Using an event study design, we examine the real wage change before and after an "event" (one of EUE, EUE', or EE'), 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.

The regression specification is the following:

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

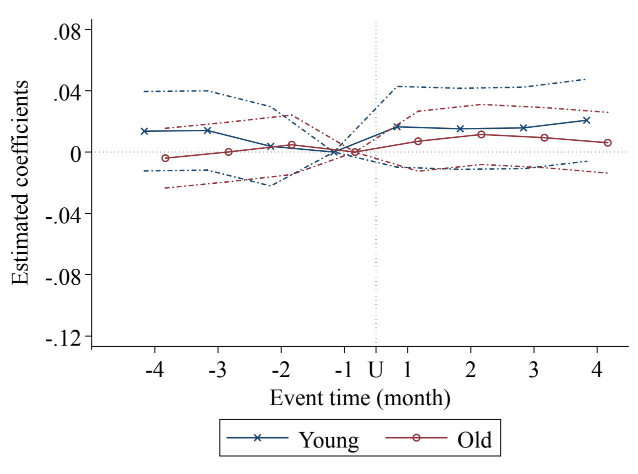
where $\ln w_{is\tau}$ denotes the log real wage of worker i at τ months before or after the event s. The event period is defined as relative to the month the worker gets separated and becomes non-employed. We take away the last month on the job before separation and the first month on the job after separation to reduce noise on wage information. Therefore, event time negative one here denotes the second last month on the job. The base period is set to be the second last month on the job before separation. $\boldsymbol{X}$ are a set of controls including education, race, gender, occupation before separation, industry before separation, and year dummies. I_{ist} is a set of indicators and takes 1 for worker i at τ periods before or after the event s. β_τ's are the main coefficients of interest and are plotted in Figure 4.

Recalled workers did not experience real wage changes regardless of age, whereas for workers finding new employers, old workers on average experienced a much higher wage loss than young workers. Workers making job-to-job transitions have a positive wage change on average, and expected wage increase is larger for young workers than old workers.

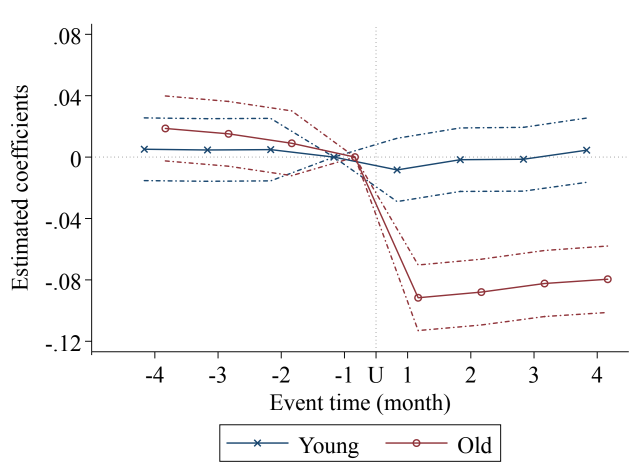
Instead of focusing on the mean, the whole distribution of wage changes is also informative. In Figure 5, we contrast the distribution of log real wage for recalled workers and those who find a new employers for both young and old. We find that for both young and old, the distribution for those who go to a new employer has a larger dispersion than those who are recalled. See Appendix Figure A-2 for the distribution of wage changes including job-to-job transitions.

Figure 4: Event Study

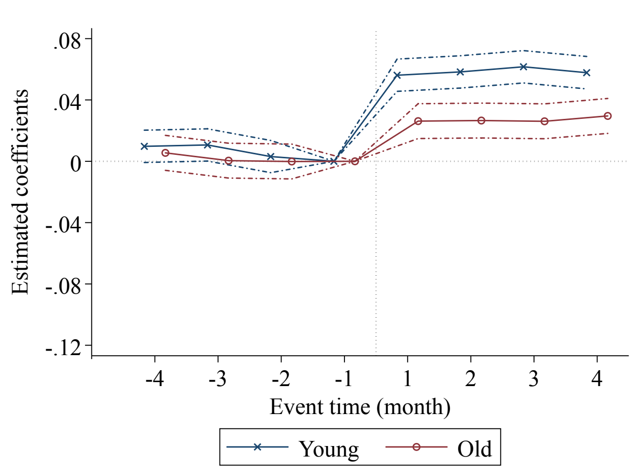
(a) Recalled workers



(b) New employer



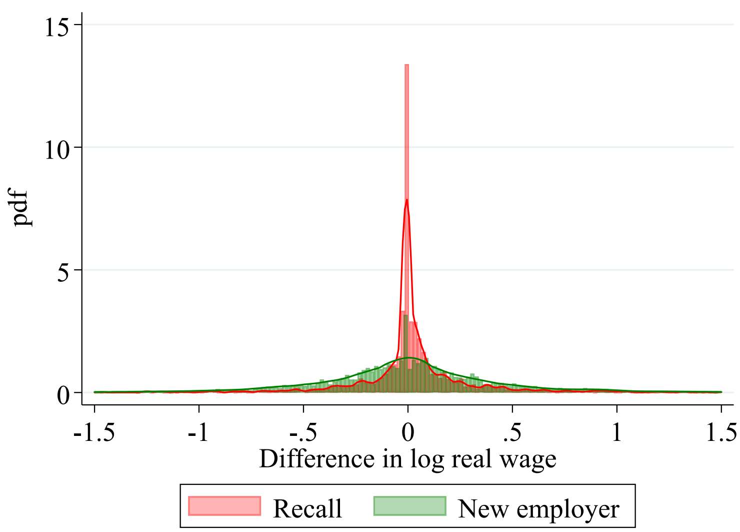
(c) Job to Job



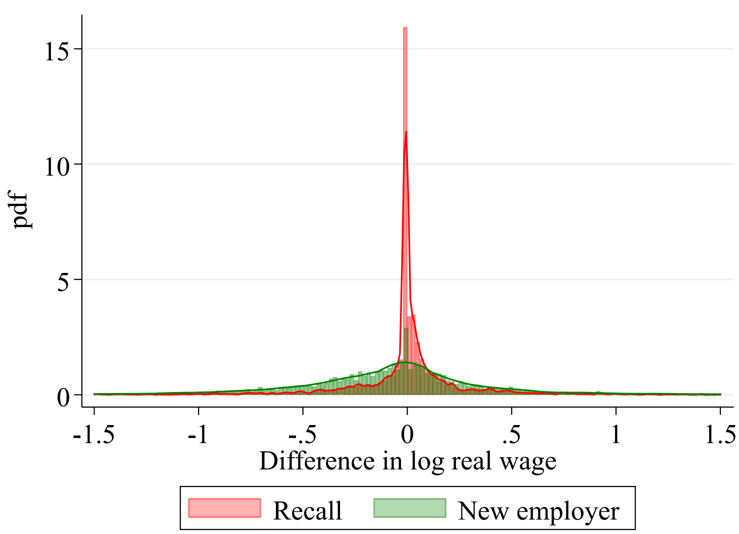
Notes: The figure plots the coefficients of the event study specifications for recalled workers (the top panel), for workers moving to a new employer after the jobless spell (the middle panel), and for workings making job-to-job transitions (the bottom panel). The blue lines are for young workers and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

Figure 5: The Distribution of Wage Changes

(a) Young workers



(b) Old workers



Notes: The figure plots the distribution of the wage changes specifications for recalled workers (ENE) and for workers moving to new employers after the jobless spell (ENE'). The top panel is for young workers and the bottom panel is for 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 and agents are infinitely lived. Agents are risk-neutral and discount the future at rate ρ. A worker-job match produces flow output $m\varepsilon$, where m is the match-specific productivity constant for each worker-job pair and ε is a productivity shock that evolves stochastically. The match-specific productivity is drawn from the $G(m)$ distribution upon meeting. The stochastic productivity process is described in detail below. Unemployed workers produce z at home.

The labor market is frictional. The matching process is governed by a matching function that exhibits constant returns to scale, $M(S, V)$, where S denotes the number of job seekers and V the number of vacancies. For notational 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. As is conventional, we 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 $p(\theta) = \theta q(\theta)$.

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. 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 two simplifying assumptions to facilitate analysis. 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. As a result, firms always have the incentive to mothball the position, rather than destroy the position, when a bad but temporary shock hits. 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.

Table 2: Summary of Possible Events

	Employed	Unemployed w/ recall option	Unemployed w/o recall option
Productivity shock	λ_e	λ_u	/
Destruction shock	δ	δ	/
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.

These assumptions are also made by Fujita and Moscarini (2017). Table 2 summarizes the possible events for employed workers, unemployed workers with a recall option, and unemployed workers without a recall option, 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.

Four events could happen during employment for a matched worker-job pair that is producing. (1) First, at Poisson rate λ_e, a new stochastic productivity component is independently drawn from the distribution $\varepsilon' \sim F_e$.[3] The match will endogenously separate with a recall option if it is hit by a sufficiently negative temporary productivity shock. (2) Second, at Poisson rate δ, the match is exogenously destroyed, and the match can never be resumed. It captures match dissolution for reasons orthogonal to match-specific productivity, such as firm closure and worker migration. (3) Third, at Poisson rate $\phi p(\theta)$, the employed worker receives an outside job offer, with match-specific productivity drawn from the distribution $m' \sim G$. For simplicity, we assume that the stochastic component always starts at $\bar{\varepsilon}$, the highest value, for new matches. The worker can decide whether to move to the new job or stay in the current match. If the worker leaves, the position becomes vacant and unattached. (4) Finally, at Poisson rate γ, the worker exits the labor force (e.g., retirement or death).

Similarly, four events could hit a separated match that is not producing but holds a recall option. (1) First, at Poisson rate λ_u, a new stochastic productivity component is drawn from $\varepsilon' \sim F_u$. If it exceeds a certain threshold, the worker will be recalled and the match will resume production. (2) Second, at Poisson rate δ, the mothballed position is exogenously destroyed. (3) Third, at Poisson rate $p(\theta)$, the unemployed worker receives an offer with $m' \sim G$ and $\varepsilon' = \bar{\varepsilon}$, and decides whether or not to accept it. The worker will compare the value of accepting the

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

new job offer with the value of waiting for the stochastic productivity component to improve at the previous match. If the worker leaves, the previous position becomes a brand new vacancy. (4) Finally, the worker retires 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 the last two events, 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 motive. 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 be reposted and receive zero value. 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, not the previous employer.

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. The Hamilton-Jacobi-Bellman equation for an employed worker at a job of match-specific productivity m and stochastic productivity ε is

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

where $w(m,\varepsilon)$ is the flow wage paid to the worker. Similarly, the Bellman equation for a producing job of match-specific productivity m and stochastic productivity ε is

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

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 $m\varepsilon - w(m,\varepsilon)$. These value functions reflect four possibilities. First, at rate λ_e, the job is hit by a new stochastic productivity component $\varepsilon' \sim F_e$, leading to an endogenous separation with attachment if $W(m,\varepsilon') < U(m)$ (because of the joint surplus sharing rule due to Nash bargaining, it is equivalent to $J(m,\varepsilon') < V(m)$); otherwise, the match keeps producing at the new productivity shock. Second, 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 $V_0 = 0$. Third, at rate $\phi p(\theta)$, the worker receives an outside offer drawn from $m' \sim G$ and moves to the new job if $W(m',\bar{\varepsilon}) > W(m,\varepsilon)$; otherwise, the worker sticks to the current job. If the worker is poached by the new position, the old position becomes an unattached vacancy. Finally, the worker exits the labor market at rate γ.

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

$$\begin{aligned}(\rho+\lambda_u+\delta+p(\theta)+\gamma)U(m) = z + \Bigg[\lambda_u \int \max\Big\{W(m,\varepsilon'), U(m)\Big\}\,\mathrm{d}F_u(\varepsilon') + \delta U_0 \\ + p(\theta)\int \max\Big\{W(m',\bar{\varepsilon}), U(m)\Big\}\,\mathrm{d}G(m') + \gamma\cdot 0\Bigg],\end{aligned} \tag{3}$$

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

$$\begin{aligned}(\rho+\lambda_u+\delta+p(\theta)+\gamma)V(m) = 0 + \Bigg[\lambda_u \int \max\Big\{J(m,\varepsilon'), V(m)\Big\}\,\mathrm{d}F_u(\varepsilon') + \delta\cdot 0 \\ + p(\theta)\int \mathbb{1}\Big\{W(m',\bar{\varepsilon}) \leq U(m)\Big\} V(m)\,\mathrm{d}G(m') + \gamma\cdot 0\Bigg],\end{aligned} \tag{4}$$

where the flow value is zero because no recruiting efforts are spent on the mothballed position. These two value functions admit four possibilities. First, at rate λ_u, a new stochastic productivity component is drawn from $\varepsilon' \sim F_u$ and the pair resumes production if $W(m,\varepsilon') > U(m)$; otherwise, the worker-job pair stays inactivated. Second, 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. Third, the worker receives an outside offer drawn from $m' \sim G$ and accepts the offer if $W(m', \bar{\varepsilon}) > U(m)$. When that happens, the job loses contact with its previous employee and becomes a brand new vacancy. 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 Bellman equation for an unemployed worker without a recall option is:

$$(\rho + p(\theta) + \gamma)U_0 = z + p(\theta) \int \max \left\{ W(m', \bar{\varepsilon}), U_0 \right\} \mathrm{d}G(m') + \gamma \cdot 0. \tag{5}$$

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 Bellman equation for a vacancy untied to any worker is

$$\begin{aligned}(\rho + q(\theta))V_0 = -\kappa + \frac{q(\theta)}{u + \phi(1-u)} \Bigg[\mu_0 \iint & \mathbb{1}\{W(m', \bar{\varepsilon})) > U_0\} J(m', \bar{\varepsilon}) \,\mathrm{d}G(m') \\ + \iint & \mathbb{1}\{W(m', \bar{\varepsilon})) > U(\tilde{m})\} J(m', \bar{\varepsilon}) \,\mathrm{d}\mu(\tilde{m}) \,\mathrm{d}G(m') \\ + \phi \iint & \mathbb{1}\{W(m', \bar{\varepsilon})) > W(\tilde{m}, \tilde{\varepsilon})\} J(m', \bar{\varepsilon}) \,\mathrm{d}\ell(\tilde{m}, \tilde{\varepsilon}) \,\mathrm{d}G(m') \Bigg],\end{aligned} \tag{6}$$

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 $\ell(m, \varepsilon)$ is the measure of employed workers at a job of match-specific productivity m and stochastic component ε. The flow recruiting cost of posting a vacancy is κ. The vacancy meets a worker at rate $q(\theta)$. The worker could be employed, unemployed with a recall option, or unemployed without a recall option, drawn randomly according to the equilibrium distribution of workers. If the worker accepts the job, a new match will be formed and start production. 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:

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

It is convenient to work with the surplus defined as $S(m, \varepsilon) \coloneqq W(m, \varepsilon) - U(m) + J(m, \varepsilon) - V(m)$. The bargaining breaks down if and only the surplus is negative. For convenience, we redefine the value of W and J to be 0 if the bargaining breaks down. Define an indicator function $\Phi(m, \varepsilon) \coloneqq \mathbb{1}\{S(m, \varepsilon) \geq 0\}$ for cases where the bargaining reaches agreements. Successful bargaining admits a surplus sharing rule with $(1-\beta)\left[W(m, \varepsilon) - U(m)\right] = \beta\left[J(m, \varepsilon) - V(m)\right]$.

Plugging in the above Bellman equations, we obtain the following wage equation:

$$
\begin{aligned}
w(m,\varepsilon) = (1-\beta)z &+ (1-\beta)p(\theta)\int \max\left\{W(m',\bar{\varepsilon}) - U(m)),0\right\} \mathrm{d}G(m') \\
&- (1-\beta)\phi p(\theta)\int \max\left\{W(m',\bar{\varepsilon})) - W(m,\varepsilon),0\right\} \mathrm{d}G(m') \\
&+ \beta m\varepsilon + \beta p(\theta)\int \mathbb{1}\left\{W(m',\bar{\varepsilon})) > U(m)\right\} V(m)\,\mathrm{d}G(m') \\
&- \beta\phi p(\theta)\int \mathbb{1}\left\{W(m',\bar{\varepsilon})) > W(m,\varepsilon)\right\} J(m,\varepsilon)\,\mathrm{d}G(m').
\end{aligned} \tag{7}
$$

The wage equation has an intuitive economic interpretation. The worker is paid a weighted average of the flow value of being unemployed (weighted by $1-\beta$) and the flow value of forming a match (weighted by β). The flow value of being unemployed includes home production z and the option value of finding a new match while staying unemployed (the first line), which is compensated by the option value of searching on the job (the second line). The flow value of forming a match includes production $m\varepsilon$ and the saved vacancy value with a recall option, which would otherwise be lost should the worker finds another job during the attached unemployment period (the third line). This value, however, is offset by the potential loss to the firm caused by the worker's on-the-job search (the fourth line).

3.3 Equilibrium

We consider a stationary equilibrium. The steady-state inflow-outflow balanced equation for unemployed workers without recall options is:

$$
\mu_0 p(\theta)\int \mathbb{1}\Big\{W(m',\bar{\varepsilon}) > U_0\Big\}\,\mathrm{d}G(m') = (1-\mu_0)(\delta+\gamma). \tag{8}
$$

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

$$
\begin{aligned}
&\mu(m)\left[\lambda_u \int \Phi(m,\varepsilon')\,\mathrm{d}F(\varepsilon') + p(\theta)\int \mathbb{1}\Big\{W(m',\bar{\varepsilon}) > U(m)\Big\}\,\mathrm{d}G(m') + \delta + \gamma\right] \\
&= \left[\int_{\varepsilon} \mathrm{d}\ell(m,\varepsilon)\right]\lambda_e \int (1-\Phi(m,\varepsilon'))\,\mathrm{d}F(\varepsilon').
\end{aligned} \tag{9}
$$

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

$$
\begin{aligned}
&\ell(m,\varepsilon)\left[\lambda_e + \phi p(\theta)\int \mathbb{1}\Big\{W(m',\bar{\varepsilon}) > W(m,\varepsilon)\Big\}\,\mathrm{d}G(m') + \delta + \gamma\right] \\
&= \left[\int_{\tilde{\varepsilon}} \mathrm{d}\ell(m,\tilde{\varepsilon})\right]\lambda_e f(\varepsilon)\Phi(m,\varepsilon) + \mu(m)\lambda_u f(\varepsilon)\Phi(m,\varepsilon) \\
&+ \mathbb{1}\{\varepsilon = \bar{\varepsilon}\}p(\theta)g(m)\left[\int_{\tilde{m}} \mathbb{1}\Big\{W(m,\bar{\varepsilon}) > U(\tilde{m})\Big\}\,\mathrm{d}\mu(\tilde{m}) + \mathbb{1}\Big\{W(m,\bar{\varepsilon}) > U_0\Big\}\mu_0\right] \\
&+ \mathbb{1}\{\varepsilon = \bar{\varepsilon}\}\phi p(\theta)g(m)\iint_{\tilde{m},\tilde{\varepsilon}} \mathbb{1}\Big\{W(m,\bar{\varepsilon}) > W(\tilde{m},\tilde{\varepsilon})\Big\}\,\mathrm{d}\ell(\tilde{m},\tilde{\varepsilon}).
\end{aligned}
\tag{10}
$$

A stationary equilibrium is defined as value functions $\{W, U, U_0, J, V, V_0\}$, wage policy $w(m,\varepsilon)$, labor market tightness θ, and measures $\mu_0, \mu(m), \ell(m,\varepsilon)$, such that:

1. The value functions $\{W, U, U_0, J, V, V_0\}$ satisfy Bellman equations (1)-(6);
2. The wage policy $w(m,\varepsilon)$ satisfies the wage equation (7) derived from Nash Bargaining;
3. The labor market tightness θ satisfies the free entry condition $V_0 = 0$;
4. The measures satisfy the steady-state inflow-outflow balanced equations (8)-(10).

The algorithm to solve the equilibrium is laid out in Appendix.

4 Calibration

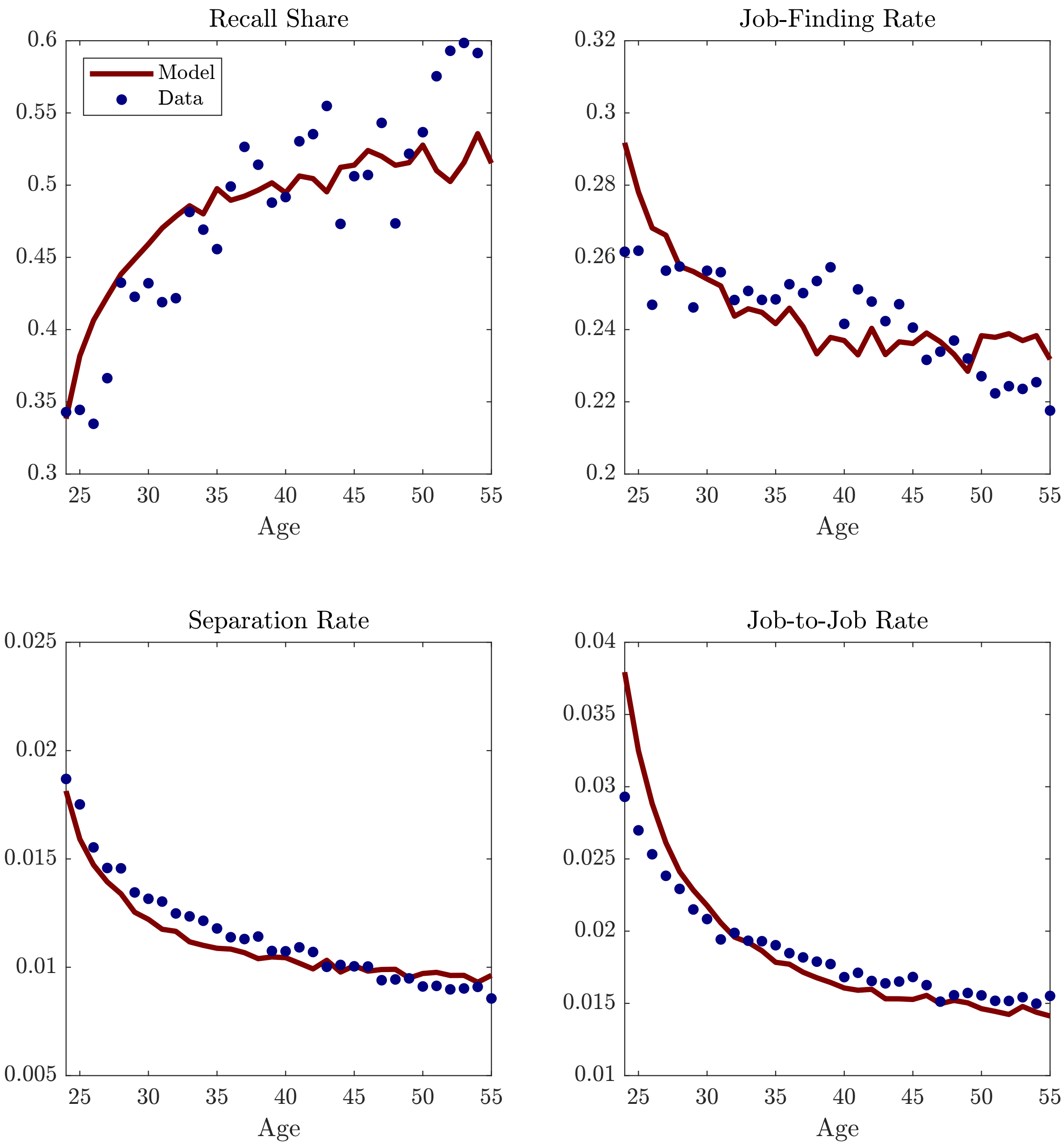
To calibrate the model we specify a functional form for the match distribution G, idiosyncratic productivity distribution F_u and F_e. We specify G to be a truncated normal distribution with mean μ_m, standard deviation σ_m and truncation point $\underline{m}$. For F_e, we choose a uniform distribution with support $[\underline{\varepsilon}, \bar{\varepsilon}]$. For For F_u, we choose the uniform distribution with the same support as F_e but with a mass point π at the highest epsilon $\bar{\varepsilon}$. Finally we parameterize a Cobb-Douglas matching function: $M(S,V) = AS^{\alpha}V^{1-\alpha}$. We calibrated the model to match the flow rates over the life cycle. The calibrated parameters are reported in Table 3.

Figure 6 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.

Table 3: Calibrated values

	Description	Value
μ_m	Mean of normal distribution	0.3016
σ_m	S.d. of normal distribution	0.1050
$\underline{m}$	Truncation point	0.2976
$\underline{\varepsilon}$	Lower bound of ε	0.4789
$\bar{\varepsilon}$	Upper bound of ε	0.7903
π	Probability mass of F_u	0.1850
A	Matching efficiency	0.3100
λ_u	Poisson rate of idiosyncratic shock (U)	0.1820
λ_e	Poisson rate of idiosyncratic shock (E)	0.0756
ϕ	On-the-job search intensity	0.4883
δ	Exogenous destruction rate	0.0017
z	Home production	0.1664

Figure 6: Labor Market Dynamics 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.

5 Application

We consider the differential impact of the drop in matching efficiency on young and old workers. To do so, we calculate the impulse response of the model economy to a one-time, unanticipated shock in matching efficiency. We focus on perfect foresight transition dynamics.

Algorithm. 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 $\{\tilde{\theta}_t^{i+1}\}_{t=1}^{T-1}$ 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

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

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

6 Conclusion

Recalls are a prevalent feature of the U.S. labor market. It is important to incorporate recalls into labor market research. In this paper, we provide a set of novel facts regarding recalls over the life cycle. We find that the share of unemployment spells that end with recalls is strongly increasing in 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 all the facts we document. The upshot is that once the empirical prevalence of recalls are seriously taken account into an otherwise standard job-ladder search model, one immediately realizes that the job finding rate is decreasing over the life cycle, due to the option value of the possibility of being recalled, thus reconciling the puzzle of the positive comovement between separation and job finding rate over the life cycle that a standard model has a hard time reproducing. We apply this insight to understand the differential impact of recessions on young and old workers. In particular, we consider a drop of the matching efficiency in bad times. Because young workers rely more on the outside labor market while old workers are more likely to get recalls, the young are hurt more by the deterioration of the matching efficiency.

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. 2014. "Unemployment insurance, Recalls and Experience Rating." *GATE WP*.

Alvarez, Fernando, and Robert Shimer. 2011. "Search and rest unemployment." *Econometrica*, 79(1): 75–122.

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

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.

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*.

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.

Forsythe, Eliza, Lisa B Kahn, Fabian Lange, and David G Wiczer. 2020. "Searching, recalls, and tightness: An interim report on the covid labor market." National Bureau of Economic Research.

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 search impacts of expanded unemployment benefits: Evidence from administrative micro data." *University of Chicago, Becker Friedman Institute for Economics Working Paper.*

Hall, Robert E, and Marianna Kudlyak. 2020. "Unemployed with jobs and without jobs." National Bureau of Economic Research.

Jansson, Fredrik. 2002. "Rehires and unemployment duration in the Swedish labour marketNew evidence of temporary layoffs." *Labour*, 16(2): 311–345.

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.

Nekoei, Arash, and Andrea Weber. 2020. "Seven Facts about Temporary Layoffs." *Working Paper.*

Røed, Knut, and Morten Nordberg. 2003. "Temporary layoffs and the duration of unemployment." *Labour Economics*, 10(3): 381–398.

Stinson, Martha H. 2003. "Technical Description of SIPP Job Identification Number Editing in the 1990-1993 SIPP Panels." *https://www.census.gov/content/dam/Census/programs-surveys/sipp/tech-documentation/user-notes/DescriptionSIPPJOBIDEDITING.pdf.*

Topel, Robert H. 1983. "On layoffs and unemployment insurance." *The American Economic Review*, 73(4): 541–559.

I Appendix

I.1 Additional Results

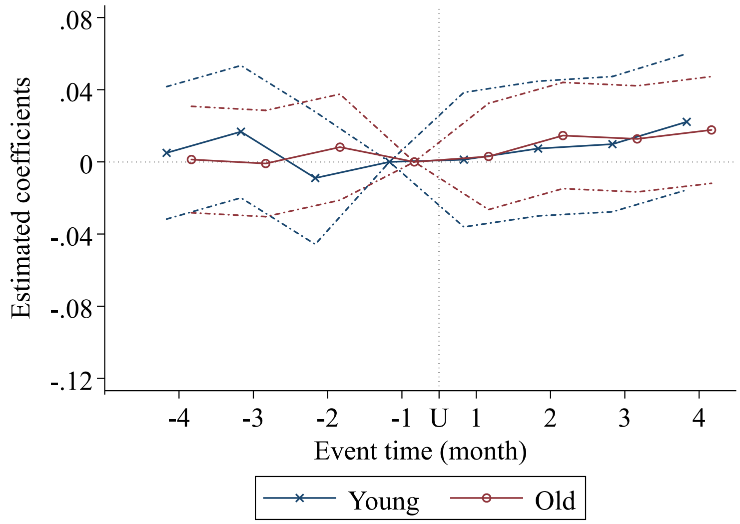
Table A-1: Age specification

	(1)	(2)	(3)
Age	0.526***	1.671***	6.542***
	(0.038)	(0.289)	(1.770)
Age^2		-0.015***	-0.141***
		(0.004)	(0.046)
Age^3			0.001***
			(0.000)
Specification	Linear	Quadratic	Cubic
Observations	17537	17537	17537
R-squared	0.11	0.11	0.11

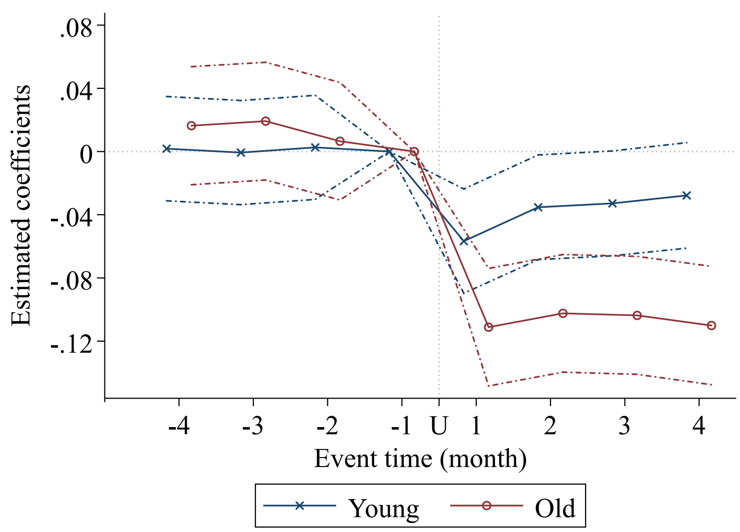
Standard errors, * p<0.10, ** p<0.05, *** p<0.01

Figure A-1: Event Study

(a) Recalled workers



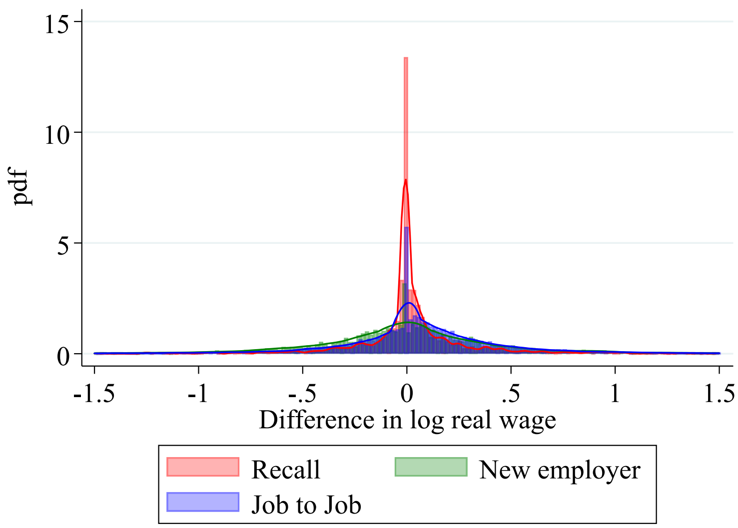
(b) New employer



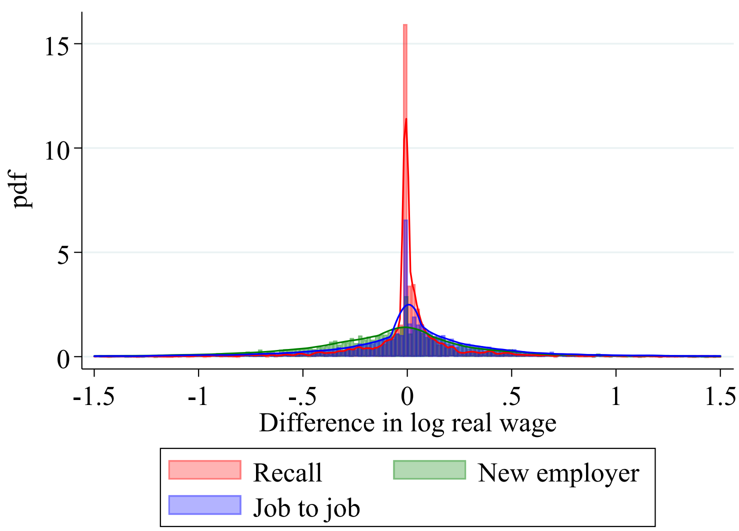
Notes: The figure plots the coefficients of the event study specifications for recalled workers (the top panel) and for workers moving to a new employer after the jobless spell (the bottom panel). The blue lines are for young workers and the red lines are for old workers. Data is from all panels, imputed recalls

Figure A-2: The Distribution of Wage Changes

(a) Young workers



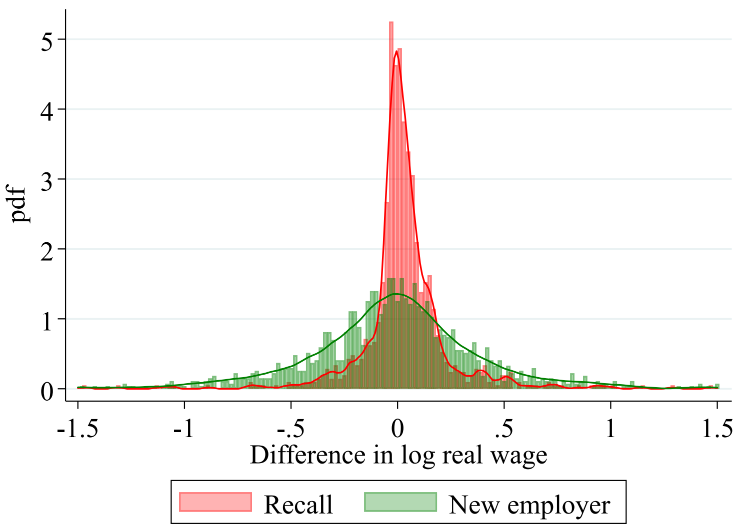
(b) Old workers



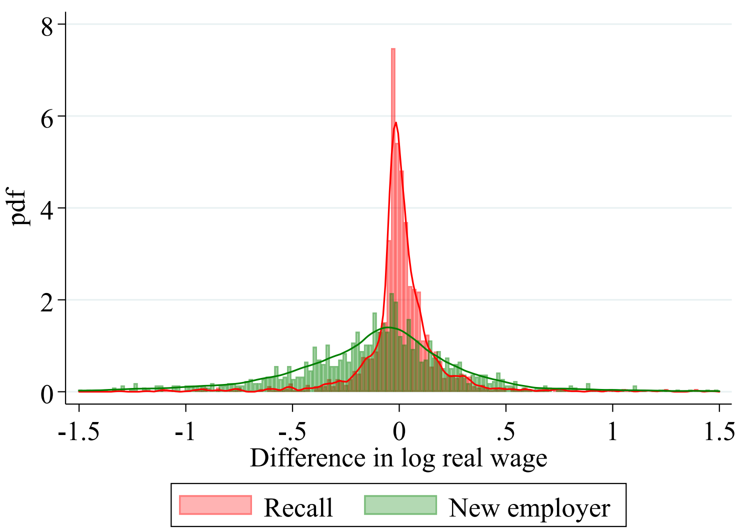
Notes: The figure plots the distribution of the wage changes specifications for recalled workers (ENE) and for workers moving to new employers after the jobless spell (ENE'). The top panel is for young workers and the bottom panel is for old workers.

Figure A-3: The Distribution of Wage Changes Pre 96

(a) Young workers



(b) Old workers



Notes: The figure plots the distribution of the wage changes specifications for recalled workers (ENE) and for workers moving to new employers after the jobless spell (ENE'). The top panel is for young workers and the bottom panel is for old workers.