Earnings Dynamics, Transitions, and Stepping-stone Employers

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Abstract

This article studies the prevalent earnings cuts upon transitions (ECUTs) in the U.S. labor market. Using data from the Longitudinal Employer-Household Dynamics and the National Survey of College Graduates, I identify workers' transition motivations and quantify the incidence of ECUTs by motivation type. I find that pecuniary motivation is the major driver for transitions. Yet many movers reporting it as the sole motivation still experience ECUTs. Further analyses show that workers who transition for pecuniary reasons have higher future earnings growth and higher probability of subsequent transitions. I argue that certain employers serve as "stepping-stones" by offering better prospects for moving to better employers. Pursuing stepping-stone employers thus represents a pecuniary motivation for job transitions and partially explains ECUTs. To formalize this mechanism, I develop a random search model in which employers differ in both quantity and quality of job offer arrival rates. Estimated results show that stepping-stone employers, particularly those with higher rates of quality offers, function as a critical pecuniary motivation for transitions and ECUTs.

Keywords: Earnings cuts; Earnings dynamics; Transitions; Motivations for transitions; Stepping-stone employers.

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1 Introduction

In standard search theory, workers typically climb up the job ladder by transitioning to higher-paying jobs (e.g. McCall, 1970; Burdett and Mortensen, 1998). However, an expanding body of micro-datasets reveals that a substantial portion of job-to-job or employer-to-employer transitions involve earnings or wage cuts, with these cases generally exceeding a third of such transitions.[1] [2] The prevalence of earnings cuts upon transitions (hereafter, ECUTs) may indicate inefficiencies within the labor market or declines in worker well-being. Understanding the motivations behind ECUTs provides insights into underlying labor market dynamics and identifying potential targets for policy intervention.

Recent research has proposed several potential explanations for ECUTs across four main dimensions. First, limitations in data structure may introduce measurement errors that overestimate the incidence of "real" cuts upon transitions (e.g. Bertheau and Vejlin, 2022). Second, certain employer characteristics, such as better productivity or learning environment, lead workers to accept lower initial wages in anticipation of future wage growth within the same employer (e.g. Postel-Vinay and Robin, 2002; Cahuc et al., 2006; Gregory, 2020). Third, non-wage compensation, or job amenities, may play a role in ECUTs (e.g. Hall and Mueller, 2018; Sorkin, 2018). Finally, ECUTs may result from reallocation shocks, or so-called "Godfather shock", which relate to the individual reasons including family-related or school-related issues (e.g. Moscarini and Postel-Vinay, 2018).[3] While these explanations offer valuable insights, empirical evidence quantifying their relative contributions to transitions and earnings cuts remains scarce, constraining our understanding of the primary drivers of ECUTs. Furthermore, there is limited exploration of how specific employer characteristics might shape future earnings trajectories following these transitions.

This paper addresses the aforementioned challenges from two main parts. First, I utilize the Longitudinal Employer-Household Dynamics (LEHD) and the National Survey of College Graduates (NSCG) data to empirically examine transitions and

[1] For instance, Postel-Vinay and Robin (2002) report that 32-55% of job-to-job transitions in France involve real wage reductions, while Fujita (2010) find a similar share of 30-54% in the UK. In the U.S., Sorkin (2018) estimate that earnings cuts occur in approximately 37% of employer-to-employer (EE) transitions and around 40% of all transitions across 27 states.

[2] As explained in Fujita et al. (2024) 'job-to-job' (J2J) may be internal restructuring and reorganizations within the employer. Although I acknowledge the effect of J2J transition on earnings, this paper focus on the EE transitions. The distinction will be identified in the data section.

[3] The "Godfather shock" refers to a shock on workers analogous to "an offer they can't refuse," a phrase famously delivered by Marlon Brando in Francis Ford Coppola's film *The Godfather*.

earnings dynamics. These datasets provide a unique lens through which we can analyze the motivations behind transitions and their impact on earnings dynamics. The empirical findings introduce an often-overlooked pecuniary motivation for job transitions: the prospect of future transitions to other employers, which I refer to as "stepping-stone motivation". Employers that prompt this motivation are termed "stepping-stone employers". Accordingly, the second part of this paper is to formalize the concept of stepping-stone employers and study its role in transitions and ECUTs, while also taking into account the wage-tenure profile and non-pecuniary motivations.

I begin by investigating the share of transitions with earnings cuts in U.S. labor markets using the LEHD dataset. Consistent with previous findings, I document that earnings cuts occur in roughly one-third to two-fifths of EE transitions. This pattern holds consistently across years and largely stable across worker characteristics, including gender, education level, and age.

Given the frequent occurrence of ECUTs, the empirical analysis unfolds in three stages. First, I investigate the driving factors behind these transitions and their associated earnings cuts. Using the administrative data, I verify that the prevalent ECUTs are not primarily attributable to location difference or measurement errors in transition timing. By linking the LEHD data with NSCG data, I further identify the underlying motivations for these transitions and quantify the ECUT share associated with each motivation. The results indicate that while non-pecuniary factors play a significant role, pecuniary motivations predominate, accounting for approximately 60% of all transitions. Importantly, non-pecuniary explanations alone do not fully account for the occurrence of ECUTs. Notably, 29% of workers who report only moving for pecuniary reasons still experience earnings cuts, suggesting that these workers may anticipate future earnings gains following the initial transitions.

Second, I extend the analysis of pecuniary motivations for transitions by investigating the relationship between transition motivations and the post-transition earnings trajectories. My analysis reveals that workers who move for pecuniary reasons exhibit an post-transition earnings growth rate 6 percentage points higher than those who transition for non-pecuniary reasons. This differential in earnings growth persists consistently over a 1-6 year horizon following the initial transition. The effect is particularly pronounced for workers who experienced ECUTs. These findings highlight the strategic role of pecuniary-driven transitions in navigating labor market dynamics.

Third, I explore whether certain employers act as "stepping-stones" for workers

and how this concept influences transitions and ECUTs. I define stepping-stone employers as those that offer better opportunities for transitioning to more desirable employers. Workers may therefore accept lower earnings in exchange for improved future prospects. Using LEHD data, I document that firm-level transition rates exhibit both significant dispersion and persistence. Regression results indicate a negative relationship between transition rate of one firm to other higher-paying firms and workers' earnings changes upon moving into the firm. Additionally, movers driven by pecuniary motives have a 5% higher probability of making subsequent transitions three years after initial transitions, compared to those motivated by non-pecuniary factors. These findings suggest that the pursuit of stepping-stone employers represents another form of pecuniary motivation in job transitions.

Building on these empirical results, I develop a search model to formalize and further examine the role of stepping-stone employers in labor market dynamics. In this model, each employer is characterized by three key attributes: employer group, productivity, and offer arrival rate. The employer group determines the distribution of productivity and offer arrival rate. Departing from the conventional search models, offer arrival rates are constructed as vectors, indicating the employer groups from which the offers are sent. The heterogeneity of vectorized offer arrival rates is the key to make employers function as "stepping-stones" for workers.

The vectorized arrival rate captures both the quantity and quality of future job offers. This arrival rate consist of two components: a scalar and a vector. The scalar component measures the quantity aspect of potential offers. Conversely, the vector component represents the conditional probability of transitioning from the current employer group to other employer groups upon receiving an offer, thus capturing the quality dimension of prospective opportunities. Together, these quantity and quality components of future job opportunities critically influence workers' decision-making within the labor market.

The model further integrates job-specific amenities and individual shocks, allowing for a detailed decomposition of transition motivations into pecuniary and non-pecuniary drivers. Among pecuniary motivations, I distinguish between "productivity motivation" and a "stepping-stone motivation." The stepping-stone motivation captures a worker's incentive to transition toward employers offering a more favorable arrival rate. This rate can be enhanced by either a higher scalar component (a greater volume of job offers), or a vector component (signifying an increased likelihood that offers come from more productive employers), or both.

The model, calibrated using LEHD data, successfully replicates key labor market moments. It also aligns well with the untargeted ECUT share, and its breakdown by reported motivations from the linked NSCG-LEHD data. Additionally, the model yields insights into the role of stepping-stone employers, which is not directly observable from the data. Notably, 48% of all transitions and 52% of transitions with earnings cuts involves stepping-stone motivations. Furthermore, approximately 40% of transitions for stepping-stone employers are associated with earnings cuts. These findings underscore stepping-stone motivation as a major pecuniary motivation, not only for transitions but also for earnings dynamics in the labor market.

Finally, I highlight the role of stepping-stone employers through three counterfactual experiments, each isolating a distinct dimension of employer heterogeneity in offer arrival rates while holding other parameters constant. Specifically, I control for variations in the quantity, quality, and combined attributes of offer arrival rates. These counterfactuals suggest that the influence of stepping-stone employers primarily manifests through the heterogeneity in offer quality encountered by workers engaged in on-the-job search. Moreover, without stepping-stone employers, ECUT share is about 22% (or 8 percentage points) lower than the baseline scenario. These exercises further illustrate that stepping-stone motivation plays a significant role in driving pecuniary-motivated transitions and the incidence of ECUTs in the labor market.

Literature Review

This article speaks to an extensive literature that uses micro-level data to study earnings dynamics and transitions (e.g. Abowd et al., 1999; Kopczuk et al., 2010; Card et al., 2013; Jinkins and Morin, 2018; Song et al., 2019). Much of the existing research has focused on the declining earnings associated with transitions, using either matched employer-employee data (e.g. Postel-Vinay and Robin, 2002; Sorkin, 2018; Briggs et al., 2019), or survey data (e.g. Fujita, 2010; Visschers and Wiczer, 2022; Faberman et al., 2022). Recent studies have begun to integrate these two data sources to provide a more comprehensive view of the labor market. For example, Flaaen et al. (2019) linked LEHD to the Survey of Income and Program Participation (SIPP), while Haltiwanger et al. (2023) merged the Current Population Survey (CPS) with LEHD data. This paper extends this line of inquiry by linking LEHD data with the National Survey of College Graduates (NSCG) to analyze ECUTs in the U.S. labor market and investigate its underlying causes. To the best of our knowledge, this is the first study to examine ECUTs in U.S. with detailed worker characteristics, quantifying the motivations of these transitions and the associated earnings reductions.

This paper examines the drivers of ECUTs by analyzing self-reported reasons from linked survey-administrative data. This methodology bridges multiple strands of literature on the determinants of job transitions and the associated earnings reductions, particularly drawing from two key areas. The first area recognizes that earnings cuts may reflect non-pecuniary job characteristics, as acknowledged in several studies (e.g. Sullivan and To, 2014; Hall and Mueller, 2018; Taber and Vejlin, 2020). Some structurally estimate the non-pecuniary value of jobs (e.g. Lamadon et al., 2022, 2024). For example, Sorkin (2018) estimates the non-pay value of jobs by analyzing worker mobility through a revealed preference framework, which presumes universally held firm rankings among workers and overlooks other potential causes for ECUTs, such as pecuniary motivations and individual shocks. Additionally, Lentz et al. (2023) allows for wage and non-wage attributes through both worker and firm heterogeneity. Nevertheless, due to data limitations, studies in this domain lack direct evidence on the relative importance of non-pecuniary versus pecuniary motivations in transitions and ECUTs. This paper shed light on this literature by directly exploiting pecuniary and non-pecuniary reported motivations for transitions and empirically distinguishing their impact on earnings dynamics.

The second strand of literature emphasizes pecuniary motivations as the primary explanation for the occurrence of ECUTs. This research often quantifies the long-term pecuniary returns associated with workers' forward-looking decisions to change employers. It is well-established that workers' choices are driven by expectations of future benefits. For example, Topel and Ward (1992) provide compelling evidence that workers frequently change employers, and these job transitions are positively correlated with long-term earnings growth. Similarly, Borovičková and Macaluso (2024) examine heterogeneous job ladders through a life-cycle perspective, showing that early-career employer transitions generally lead to wage increases, especially for high-income workers. By leveraging linked survey-administrative data, I contribute by examining how these motivations align with subsequent earnings outcomes and to further investigate the influence of specific employer characteristics on this relationship.

In the context of forward-looking decision-making, the literature often emphasizes the role of employer characteristics (productivity) in offering wage-tenure profile within the job. For instance, Postel-Vinay and Robin (2002) and Cahuc et al. (2006) develop a novel sequential auction model in which workers may accept wage cuts to transition to employers with higher productivity, who promise greater future wage growth within the job. Since then, a growing body of research has further refined this

wage-setting mechanism, incorporating heterogeneity among both workers and employers. For example, Gregory (2020) explores the impact of heterogeneous learning environments regarding employer characteristics on workers' human capital accumulation.[4] Jarosch (2023) examines how differing separation rates across jobs introduce a trade-off between wages and job security for workers.

This paper further contributes by introducing "stepping-stone employers" as another pecuniary explanation of transitions and ECUTs. While the concept of "stepping-stone" is not new in the literature, there has been limited investigation into how employer-level heterogeneity in offer arrival rates affects earnings dynamics until very recently.[5] For instance, Nimczik (2023) employs a data-driven approach to endogenously identify labor markets where firms vary in their ability to attract and release workers. Similarly, Berger et al. (2024) examine the concentration of granular markets, demonstrating how this concentration leads to heterogeneous arrival rates for workers. Additionally, Del Prato (2023) introduces the concept of "connectivity" as a employer attribute that captures heterogeneity in meeting rates, empirically approximating this attribute using a firm's degree centrality within the job-to-job network to study labor dynamics in Italy. However, he classifies connectivity as a non-pecuniary factor in transitions, disregarding job preferences. This paper distinguishes from existing literatures by defining stepping-stone employers with heterogeneous vectorized offer arrival rates that captures both quantity and quality of future offers. I relate this notion to pecuniary motivation for transitions and quantify its role in labor market.

Roadmap

The remainder of the paper is organized as follows. Section 2 describes datasets of this paper. Section 3 examines the patterns of ECUTs and the reported motivations for transitions, and their relationship with future earnings dynamics. Section 4 provide suggestive evidence that some employers function as stepping-stones for workers. Section 5 develops a search model to formalize stepping-stone employers and quantitatively analyze their role in transitions and ECUTs. Finally, Section 6 concludes.

[4] Arellano-Bover and Saltiel (2024) empirically demonstrates significant heterogeneity in learning opportunities across firms.

[5] Previous literatures view "stepping-stone" differently. For example, Nyarko and Jovanovic (1997) models "stepping-stone" jobs as positions where workers acquire transferable skills through specific tasks, prompting movement to other occupations. Booth et al. (2002) conceptualize "stepping-stone" jobs as transitory positions that can lead to improved job matches, particularly when a transition moves workers from temporary to permanent roles. This paper builds on these insights by focusing directly on the dynamics of employer-to-employer transitions, incorporating both learning and skill accumulation mechanisms within the broader framework of job mobility.

2 Data

In this study, I employ three datasets to examine worker transitions in the U.S. labor market: the Longitudinal Employer-Household Dynamics (LEHD), the National Survey of College Graduates (NSCG), and a unique dataset created by linking the two. I use LEHD dataset to examine the patterns of ECUTs in the U.S. and to explore transition rates at the firm level. The NSCG offers insights into workers' motivations for transitioning between employers. After linking the NSCG with the LEHD, I relate the transition motivations to earnings dynamics and future mobility patterns. The analysis covers employment records from 2010 to 2019 across 28 U.S. states.[6]

2.1 The Longitudinal Employer-Household Dynamics

The LEHD data set is matched employer-employee data of quarterly earnings.[7] Because it is constructed from unemployment insurance (UI) records, an employer is a state-level UI account.[8] For a firm with a single establishment, this concept aligns directly with the firm itself. However, for firms operating across multiple states, this concept applies to a unit smaller than the entire firm.[9] Sorkin (2018) suggests that working conditions tend to be more homogeneous within establishments than across an employer's various locations. Consequently, adopting a narrower definition of the employer, focused on establishments, may be more appropriate for accurately capturing compensating differentials.

I clean the LEHD data by closely following Sorkin (2018).[10] First, I restructure the data into an annual panel, assigning each worker a primary employer for each year based on the employer providing the highest total earnings within that calendar year. Moreover, I require the following restrictions: (1) workers are aged 20-60 (in-

[6] AZ, CA, CO, CT, DE, IN, KS, MA, MD, ME, MT, ND, NE, NJ, NM, NV, OH, OK, PA, SC, SD, TN, TX, UT, VA, WA, WI, WY. See a map in Appendix A.1.

[7] "Earnings" are defined by UI records. They includes "gross wages and salaries, bonuses, stock options, tips and other gratuities, and the value of meals and lodging". They do not reflect "employer contributions to Old-age, Survivors, and Disability Insurance (OASDI), health insurance; unemployment insurance, workers' compensation, or private pension and welfare funds" (BLS 1997, 44). See Abowd et al. (2009) for details about the LEHD.

[8] Employers and firms are considered interchangeable throughout this paper.

[9] Firms could have multiple UI accounts in many states or in one state if the they have business in multiple industries. In the Successor-Predecessor Files (SPF), cross-state firm relocations are not identified here, and such events would be interpreted as separations in the original state and accessions in the destination state.

[10] The dataset employed by Sorkin (2018) covers the period from 2000 to 2008 and includes 27 states that overlap with those analyzed in this paper.

clusive); (2) firms must employ a minimum of 20 workers; (3) annualized earnings are converted to 2011 dollars using CPI-U, with a minimum threshold of $3,200.[11] The resulting annualized LEHD panel contains approximately six hundred million worker-year observations, encompassing one million distinct workers and five hundred and forty thousand firms.

Second, I classify all transition into two types: employer-to-employer (EE) and employer-to-nonemployment-to-employer (ENE).[12] Specifically, I define an EE transition as occurring when the dominant employer in year t differs from that in year $t-1$, and there is at least one overlapping quarter of employment with both employers. This overlapping quarter can fall in either year $t-1$ or year t, depending on the timing of the transition. An ENE transition is defined as the scenario where the dominant employer changes, but the transition does not qualify as an EE transition. It is important to note that workers who exit the dataset and do not return cannot be observed. These missing observations might represent unemployment, self-employment, or gig work. In such cases, the type of transition is unobservable.

Third, to address potential data inaccuracies when large groups of workers move from one employer to another in consecutive periods, I adjust the employer identifiers using the Successor-Predecessor File. Specifically, I apply a threshold-based rule: if 70% or more of employer A's workforce shifts to employer B, I interpret this as a relabeling or acquisition and exclude these cases from EE transition counts.

2.2 The National Survey of College Graduates

The NSCG is a longitudinal survey that collects information on employment, educational backgrounds, and demographic characteristics of the college-educated science and engineering workforce in the United States.[13] I utilize four survey cycles that together document respondents' answers from the week of October 1, 2010, to the week

[11] In the Appendix A.2, I analyze the dispersion of earnings using the Abowd et al. (1999) (AKM) estimation, and summarize the disclosed statistics in Table A1.

[12] Sorkin (2018) follows Hyatt et al. (2014) and Bjelland et al. (2011) in this classification of transitions. Their classification is similar to the "within/adjacent quarter approach" in Haltiwanger et al. (2018).

[13] According to NSCG estimation technique: The final analysis of NSCG estimation weights account for several factors, including the following: (1) Adjustments to account for undercoverage of recent immigrants and undercoverage of recent degree-earners; (2) Adjustment for incorrect names or incomplete address information on the sampling frame; (3) Differential sampling rates; (4) Adjustments to account for non-locatability and unit nonresponse; (5) Adjustments to align the dataset distribution with population controls; (6) Trimming of extreme weights; (7) Overlap procedures to convert weights that reflect the population of each individual frame (2013 ACS, 2015 ACS, 2017 ACS, and 2019 ACS) into a final dataset weight that reflects the 2021 NSCG target population. The final dataset weights enable data users to derive survey-based estimates of the NSCG target population.

of February 1, 2019.[14]

The questionnaire of the NSCG provides detailed information about labor participation. Specifically, in the Part B of the Questionnaire, respondents are asked a series of questions about their past employment.

Question B1:

Were you working for pay or profit during both of these time periods: the week of February 1, t_1, and the week of February 1, t_2.

In Question B1, t_1 and t_2 are the starting and ending year of the survey, respectively. For instance, in cycle year 2013, $t_1 = 2013, t_2 = 2010$; in cycle year 2019, $t_1 = 2019, t_2 = 2017$. As shown in the Table Table 1, 79% of the respondents and 93.5% of employed workers marked "Yes" indicating they were working for pay/profit.[15] Workers who answer "Yes" to Question B1 are guided to Question B2.[16]

Question B2:

(If Yes) During these two time periods - (survey reference periods) - were you working for... [Mark one answer.]

1. *Same employer <u>and</u> in same type of job*
2. *Same employer <u>but</u> in different type of job*
3. *Different employer <u>but</u> in same type of job*
4. *Different employer <u>and</u> in different type of job*

As shown in the Table 1, 72% of the workers are stayers, marking the first response. Selections 2, 3, or 4 indicate movers who changed jobs during the survey reference periods. We can tell whether the transition is J2J transition (option 2) or EE transition (options 3 or 4) from the question. This paper focus on the latter one, which account for about three quarters of transitions from the Table 1.

Table 1 shows the basic characteristics of the respondents and answers about their employment. Consistent with Bick et al. (2022), weekly working hours is heavily concentrated around 40 hours. The reported annual salary is nominal and increasing.

[14]Specifically, the reference periods survey cycle 2013, 2015, 2017, and 2019, are Oct. 1, 2010-Feb. 1, 2013, Feb. 1, 2013 - Feb. 1, 2015, Feb. 1, 2015 - Feb. 1, 2017, and Feb. 1, 2017 - Feb. 1, 2019, respectively.

[15]The respondents include all labor force status. But workers unemployed or not in labor force are not working for pay/profit.

[16]The answer "No" for B1 and the choice 1 of B2 will lead to question part C about other work-related experience, which will be not discussed in this paper.

The demographics and labor force status are stable across cycle years, with 53% male, average age around 44, more than 60% of married workers, and about 2.6% unemployment rate. The unweighted count includes respondents who may be surveyed in multiple cycles. The last column take account of observations from all four survey cycles.

Table 1. Summary of NSCG

Characteristics	**Cycle Year**				**All**
	2013	**2015**	**2017**	**2019**	
Male	0.530	0.532	0.543	0.546	0.537
Age	43.93	44.26	45.53	44.64	44.55
Married	0.656	0.673	0.690	0.677	0.673
Weekly hours worked	41.92	42.02	41.60	41.32	41.72
Annual salary (nominal)	77,889.16	83,727.09	88,842.13	90,468.57	84,924.70
Labor Force Status					
Employed	0.834	0.844	0.832	0.844	0.839
Unemployed	0.034	0.024	0.024	0.021	0.026
Not in labor force	0.122	0.132	0.144	0.135	0.136
If employed, work for pay/profit	91.71	94.03	94.24	94.26	93.48
If “Yes”, (during survey periods)					
1 Same employer and job	0.700	0.727	0.733	0.730	0.722
2 Same employer different job	0.084	0.077	0.072	0.076	0.077
3 Different employers same job	0.122	0.119	0.119	0.118	0.119
4 Different employers and job	0.094	0.078	0.076	0.076	0.082
Observations	104,599	91,000	83,672	92,537	371,808

For workers who report to have two different employers during the survey periods (options 3 or 4), they are guided to Question B3 about the motivation for transitions.

Question B3:

Why did you change your employer or your job? [Mark Yes or No for each item.]

1. *Pay, promotion opportunities*
2. *Working conditions (e.g., hours, equipment, working environment)*
3. *Job location*
4. *Change in career or professional interests*
5. *Family-related reasons (e.g., children, spouse's job moved)*
6. *School-related reasons (e.g., returned to school, completed a degree)*
7. *Laid off or job terminated (includes company closings, mergers, buyouts, grant or contract ended)*
8. *Retired*
9. *Some other reasons*

This question offers valuable insights into the motivations behind job transitions. First, workers are allowed to report multiple reasons, which is quantitatively important to understand worker decisions in practice. Second, Questions B1-B3 are stable and consistent across these four surveys. The respondents are also drawn from the same dataset frame (the ACS). Third, the provided options encompass the likely drivers of transitions, including pecuniary reasons, amenities (e.g. working conditions, locations), individual reasons (e.g. family-related, school-related, changed interest or career), and others (e.g. retire, laid off, some other reason).[17] [18] In Ma (2024), I study the motivation behind transition with various datasets, and argue that the NSCG is the best data among them at addressing transition motivations.

[17]The pecuniary reasons for workers when changing employers typically revolves around financial incentives and benefits that the employer can provide with direct or indirect monetary gains. In this paper, I consider the reason/motivation as "pecuniary" if it affects worker utility only through wages protocol that is related to employer characteristics. In this sense, "Pay/promotion opportunities" definitely is pecuniary motivation. "Job location" and "Change in career or professional interests" may be argued by some literature (e.g. Baum-Snow and Pavan, 2012; Visschers and Wiczer, 2022; Bilal, 2023) as pecuniary-related, but they are also mostly related to personal fulfillment, job satisfaction, and overall well-being (e.g. Farzin, 2009, mentions the non-pecuniary aspect of the geographical location of work), or more related to individual shock. Thus, I categorize them into non-pecuniary.

[18]Survey data by Faberman et al. (2022) report that 11 percent of employed searchers cite either relocation or advance notice of a layoff as their primary motivation for on-the-job search. But it is unclear how much this "job security" factor can account for the observed transitions. By tracking workers across two consecutive surveys, I can compare their reported job security satisfaction ratings for their two main jobs, adjusting for the importance assigned to these jobs by the workers themselves. The model of this paper, however, attributes the separation rates solely to worker characteristics. For the purpose of this paper, this factor should be categorized under "Other."

2.3 The Linked LEHD-NSCG

To study the relationship between employment and reported reasons of transitions, I construct a quarterly panel from 2010Q1 to 2019Q1 by appending and merging four NSCG surveys to the LEHD data based on the unique protected identification key.[19]

I focus on the sample with consistent workers and movers with one transition during the survey period. Specifically, "consistent movers" are those whose employment histories in the LEHD align with the data reported in the NSCG. In contrast, "inconsistent movers" either report to have changed employers/jobs not observed in the LEHD, or they report remaining with the same employer during the survey reference period but are observed to have transitioned according to LEHD records.[20]

Furthermore, some workers report multiple employer changes within a single survey reference period, which could obscure the relationship between their reported transition motivations and their actual labor market behavior. To address this, I restrict the sample to workers who are observed to change employers only once during each survey reference period. Table 2 indicates that about 20% of consistent movers are dropped from this restriction.

To increase the sample size and enhance the analysis of how initial transition motivations relate to future earnings and subsequent transitions, I supplement the dataset by appending employment records from the LEHD for consistent workers. This is particularly important because, after linking the NSCG to the LEHD, many workers who responded to only one survey no longer have observable employment data after the survey cycle year.

[19] Details on the data linking and restrictions are provided in Appendix A.3.

[20] There are many possible explanations for this inconsistency. (1) Respondents in the NSCG may report job transitions that have occurred more recently or might anticipate future transitions that haven't yet been captured in the LEHD's administrative records. (2) In the NSCG, job transitions are self-reported, which may include non-traditional changes, such as internal job transfers within the same company, changes in job roles, or changes in contract status. These may not always be captured as job transitions in the LEHD data, which focuses on firm-level separations and hires. (3) Large firms with multiple locations or subsidiaries may report workers under different UI accounts, leading LEHD to track a job transition when the worker has just moved within the same firm or its subsidiaries. (4) Respondents to the NSCG might misremember or incorrectly report their employment transitions, particularly if the transition occurred some time ago or involved multiple employers in a short period. (5) Workers may hold multiple jobs at the same time, with the LEHD capturing only the job with the highest earnings or the most consistent employment record. A transition in the secondary job might be reported in NSCG but missed in LEHD.

Table 2 presents summary statistics for all consistent workers and for movers who experienced a single transition during the survey reference period.[21] The statistics in the first five rows, drawn from the NSCG data, are broadly similar to those reported in Table 1, despite the fact that workers in the linked data tend to be younger. This suggests that inconsistent workers mainly come from older people who may work fewer weekly hours. In addition, statistics of age, gender, and marital status for one-transition movers are not significantly different from all movers including the ones with multiple transitions. The fifth row shows the quarterly real earnings from the LEHD, which count into the supplemented employment records.[22]

Table 2. Summary of the Linked NSCG-LEHD

Consistent dataset	**All Movers**	**One-Transition Movers**
Male worker share	0.53	0.54
Married worker share	0.60	0.61
Average age	35.6	35.7
Average weekly hours worked	42.2	42.6
Mean quarterly real earnings	23,620	25,160
# Firms	39,500	28,000
# Workers	24,500	19,500
# Obs.	229,000	173,000

The numbers are rounded.

[21] Dillon (2021a,b) linked the NSCG 2010 to the LEHD to evaluate conceptual alignment, coverage, and agreement of employment history and employer information. She find that the LEHD data provides very coverage of the NSCG dataset (93.95%). Her analysis found that 74.87 percent of the linked dataset agreed on employment status, and nearly a third (31.96%) of the linked LEHD salary data is within five percent of the NSCG value.

[22] Although I include weighted datasets in analyzing cross-sectional patterns like the distribution of transitions motivations and the earnings cuts upon transitions, I focus on the unweighted datasets to track and study the earnings dynamics after transitions. Because, according to NSCG estimation technique, weights are not designed to account for all possible external factors or shocks that may influence the outcomes after the endogenous choice. Weights computed at one point in time may not accurately reflect the worker's representativeness in subsequent periods, especially if the worker's situation changes significantly due to endogenous choices or external shocks. The dataset weights may obscure the causal pathways of these endogenous choices because weights are typically designed to adjust for sampling probabilities, not for endogenous decision-making processes. In addition, to tack longer employment history, I keep the employment records from the LEHD if the workers are surveyed in some years of NSCG but not seen after. So, for these workers, the survey weight would be missing after the survey periods. Therefore, weighted analysis might not adequately capture the dynamic changes resulting from endogenous choices and external shocks.

The linked data offer two key insights into EE transitions and earnings dynamics. First, the linked data make use of the question in the NSCG that prompt workers to report the starting month and year of their principal job, as illustrated below.

Question A20: *During what month and year did you start this job (that is, the principal job you held during the week of February 1, [cycle year])?*

This information is crucial to identify EE transitions as discussed in Section 3.1. Given that the data are structured as a quarterly panel, the month and year when a job begins allow us to accurately pinpoint the first full quarter of earnings under the new employer. While the survey also records the month and year of the last paid work for unemployed respondents, this information pertains only to those who are currently unemployed and thus does not provide a reliable indicator for determining the end date of the last job held by currently employed workers.

Second, the linked LEHD-NSCG data with identified motivations for transitions enable a detailed examination of ECUTs and their relationships with subsequent transitions and earnings dynamics. Without distinguishing transition motivations, observed post-transition earnings may obscure the rational basis of the initial transition decision. For instance, individuals transitioning for non-pecuniary reasons may follow distinct post-transition earnings trajectories compared to those motivated by pecuniary factors. Likewise, workers transitioning due to workplace conditions may have a lower likelihood of subsequent transitions than those driven by pecuniary incentives. Analyzing ECUTs solely through post-transition earnings could yield misleading conclusions, as aggregate earnings dynamics may mask significant heterogeneity in transition motives. Therefore, identifying the motivations for initial transitions is essential for accurately linking ECUTs to future earnings outcomes and the probability of subsequent transitions.

3 Earnings Dynamics and Transitions

In this section, I first examine earnings cuts upon transitions (ECUTs) in U.S. labor market. Based on this feature, I identify and analyze the patterns of transition motivations and their relationship with ECUTs.

3.1 ECUTs in U.S.

Using the annualized panel from the LEHD, I measure the frequency of ECUTs. Figure 1 presents the ECUT shares by year, categorized by transition types as defined in Section 2. The ECUT rate remains persistent at approximately 38% among all transitions, with a lower rate of 36% for employer-to-employer (EE) transitions. These results indicate that ECUTs are both persistent and frequent in the U.S. labor market.

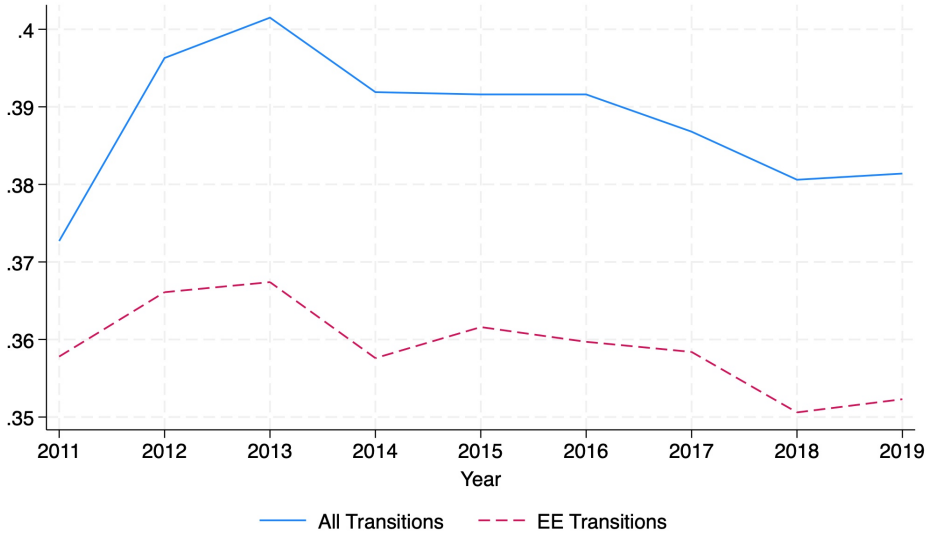


Figure 1. ECUT share

Furthermore, I examine the share of ECUTs across different worker characteristics. As shown in Panel A of Table 3, the ECUT rate, measured across all types of transitions, is lower for college graduates compared to non-college workers; however, the difference is not substantial. Similarly, the disparity in the ECUT rate between male and female movers is minimal. While movers under the age of 40 have a lower ECUT rate than those aged 40 and over, more than a third of transitions among younger movers still involve earnings cuts.

Moreover, earnings cuts remain prevalent even when applying a more restrictive criterion for defining ECUT incidence. Specifically, when ECUT is defined as a drop in earnings of more than 5% upon transition, Table 3 shows that over a third of transitions still result in earnings cuts. This suggests that a significant proportion of ECUTs are not merely due to minor reductions in earnings. Overall, Figure 1 and Panel A of Table 3 demonstrate that earnings cuts upon transitions are common in the U.S. labor market, irrespective of education level, gender, or age.

Nevertheless, two primary types of measurement error could bias the reported ECUT share. The first arises from the well-documented variation in earnings across locations.[23]. Glaeser (2012) shows that U.S. workers in metropolitan areas with populations exceeding 1 million earn, on average, 30 percent more than their counterparts in rural areas. Similarly, Roca and Puga (2017) find that workers obtain earnings premium when they relocate to larger cities. On the other hand, the cost of living also varies significantly across regions. For example, a worker moving from Manhattan, New York City, to Rochester, New York State, might see a 10 percent decrease in earnings, but this reduction may not constitute a real cut, since the cost of living in Rochester is much lower than in Manhattan.[24] If many transitions are of this nature, accounting for location changes would explain a substantial share of observed ECUTs.

To address location concerns, I focus on the workers whose employers before and after the transitions are both located in the same county.[25] Panel B of Table 3 presents this county-specific ECUT share. Compared to the unconditional ECUT share in Panel A, we observe that the ECUT share for movers within the same county is higher for EE transitions, but lower for ENE and thus all transitions. However, these differences are not substantial, and the ECUT shares are generally similar. This suggests that regional factors are not the primary drivers of frequent ECUTs.

The second source of measurement error arises from the timing of employment, which conflates EE transitions with ENE transitions, particularly when data frequency is quarterly or annual. As highlighted by Bertheau and Vejlin (2022), the absence of precise start and end dates for employment spells in most datasets hinders our understanding of EE transitions. When an employer at time t differs from that at $t-1$, naively calculating the difference in earnings between t and $t-1$ may result in an overestimation of the ECUT ratio if the new job begins at t, and an underestimation if it starts at $t-1$. Consequently, the ECUT share presented in Table 3, based on annualized earnings, may be biased towards 50%.

[23]Numerous studies have examined the possible mechanisms behind this phenomenon, such as Baum-Snow and Pavan (2012) and Roca and Puga (2017). However, this is not the focus of this paper.

[24]For information on cost of living in county/metro area/state, see data from MIT Living Wage Calculator.

[25]Appendix A.4 details how I identify and control the counties of employers in the LEHD.

Table 3. ECUT Share in U.S.

Transition Type	Cutoff	All Workers	Education Level		Gender		Age	
			College or Higher	Non-College	Male	Female	< 40	≥ 40
Panel A: Unconditional								
All Transitions	0%	0.3883	0.3845	0.3895	0.3896	0.3869	0.3655	0.4329
	5%	0.3553	0.3492	0.3572	0.3565	0.3540	0.3357	0.3933
EE Transitions	0%	0.3587	0.3582	0.3588	0.3615	0.3558	0.3352	0.3999
	5%	0.3189	0.3160	0.3199	0.3217	0.3161	0.2991	0.3538
Number of all transitions		88,420,000	21,240,000	67,180,000	45,760,000	42,660,000	5,843,000	30,000,000
Panel B: Within Counties								
All Transitions	0%	0.3847	0.3823	0.3855	0.3867	0.3827	0.3626	0.4241
	5%	0.3478	0.3427	0.3494	0.3493	0.3462	0.3301	0.3793
EE Transitions	0%	0.3630	0.3650	0.3624	0.3679	0.3585	0.3374	0.4062
	5%	0.3206	0.3201	0.3207	0.3251	0.3163	0.2992	0.3565
Number of all transitions		32,880,000	8,079,000	24,800,000	16,390,000	16,490,000	21,090,000	11,790,000

The number of all transitions are rounded with four significant digits.

To mitigate measurement issues, I use the reported job start dates from the linked NSCG-LEHD dataset. If a worker's employer at time t differs from the employer at time $t-1$, I compare the first full quarterly earnings with the new employer to the last full quarterly earnings with the previous employer, and define the ECUT accordingly. Specifically, since the end date of the last job is unknown, I use the earnings at $t-2$ as the last full quarterly earnings, ensuring the worker was employed by the same employer from time $t-3$ to $t-1$. If the transition occurs at $t^* = t-1$, the first full quarterly earnings are taken from t. If the transition occurs at $t^* = t$, I define the first full quarterly earnings as those at $t+1$. I ensure that the worker is continuously employed by the same employer across adjacent quarters for the accuracy of full quarterly earnings. Ultimately, the data identifies approximately 13,000 transitions, encompassing around 12,000 distinct movers.

Table 4. ECUT share of Linked NSCG-LEHD data and LEHD data

	NSCG-LEHD		LEHD
	Robust Measure	Naive Measure	Annualized
ECUT share	0.380	0.435	0.382
Total Transitions	13000	13000	8079000

Number of transitions are rounded to thousands.

The ECUT share based on this robust measure is shown in the first column of Table 4, labeled "Robust Measure." For comparison, the second column of Table 4, labeled "Naive Measure," reports the ECUT share derived by simply comparing quarterly earnings across periods where a different employer is observed. Since the linked data only cover college graduates, the third column provides the ECUT share and total number of transitions for movers with a bachelor's degree or higher within the same county, using annualized LEHD data as presented in Panel B of Table 3.

Table 4 conveys two main points from . First, it is important to use adjacent full earnings periods to accurately capture the share of ECUTs, as ECUT share is approximately five percentage points higher when measured without considering transition timing. Second, the ECUT share of all transitions for college graduates from the annualized LEHD data closely aligns with the ECUT share measured with the linked NSCG-LEHD data.

In sum, ECUTs are persist with notable frequency across the U.S. labor market over the years, irrespective of worker characteristics, and this ECUT share is hardly attributed to measurement errors.

3.2 Transition Motivations and ECUTs

ECUTs are a prominent feature of the U.S. labor market, but what underlying mechanisms drive this phenomenon? Addressing this question requires us to identify the primary motivations behind transitions and ECUTs. If non-pecuniary factors dominate, then non-wage job attributes or individual-specific shocks may provide key explanations for ECUTs. Alternatively, if pecuniary motives are the primary drivers, understanding the specific pecuniary factors contributing to observed ECUTs becomes crucial.

Using the NSCG dataset, I find that pecuniary reason emerge as the predominant reason for changing employers. Figure 2 displays the distribution of reported motivations for all EE movers from February 2010 to February 2019. The top panel reports all selected motivations, including multiple-choice responses, and reveals that pecuniary reasons overwhelmingly drive transitions. Specifically, 56% of movers cite "pay or promotion opportunities" as a key factor. Nevertheless, amenities - such as working conditions and locations - also contribute meaningfully to these transitions. While individual reasons, such as a change in interests or family-related concerns, play a comparatively smaller role, they are not trivial in explaining transitions.

The the bottom panel of Figure 2 focuses on cases where a single reason was indicated, excluding "layoff or job termination" as a motivation.[26] This analysis further highlights the dominance of pecuniary motivation, with 6% of movers indicating it as their exclusive reason for changing employers. These patterns are consistent across survey cycles and are robust to the use of weighted data.

Using the linked NSCG-LEHD data, Table 5 displays ECUT share and number of transitions by motivations. The categories are defined as follows: "payonly" captures transitions driven solely by pecuniary reasons, specifically "pay or promotion opportunities"; "payplus" represents transitions motivated by both pecuniary and non-pecuniary reasons; and "nopay" refers to transitions motivated exclusively by non-pecuniary factors. We find that pecuniary motivations account for approximately 65% of all transitions, with 8% of transitions driven purely by pecuniary considerations.

[26] 12% of all EE movers choose "layoff or job terminated" as their sole reason for transitions, with the majority entering a period of unemployment before their next employment.

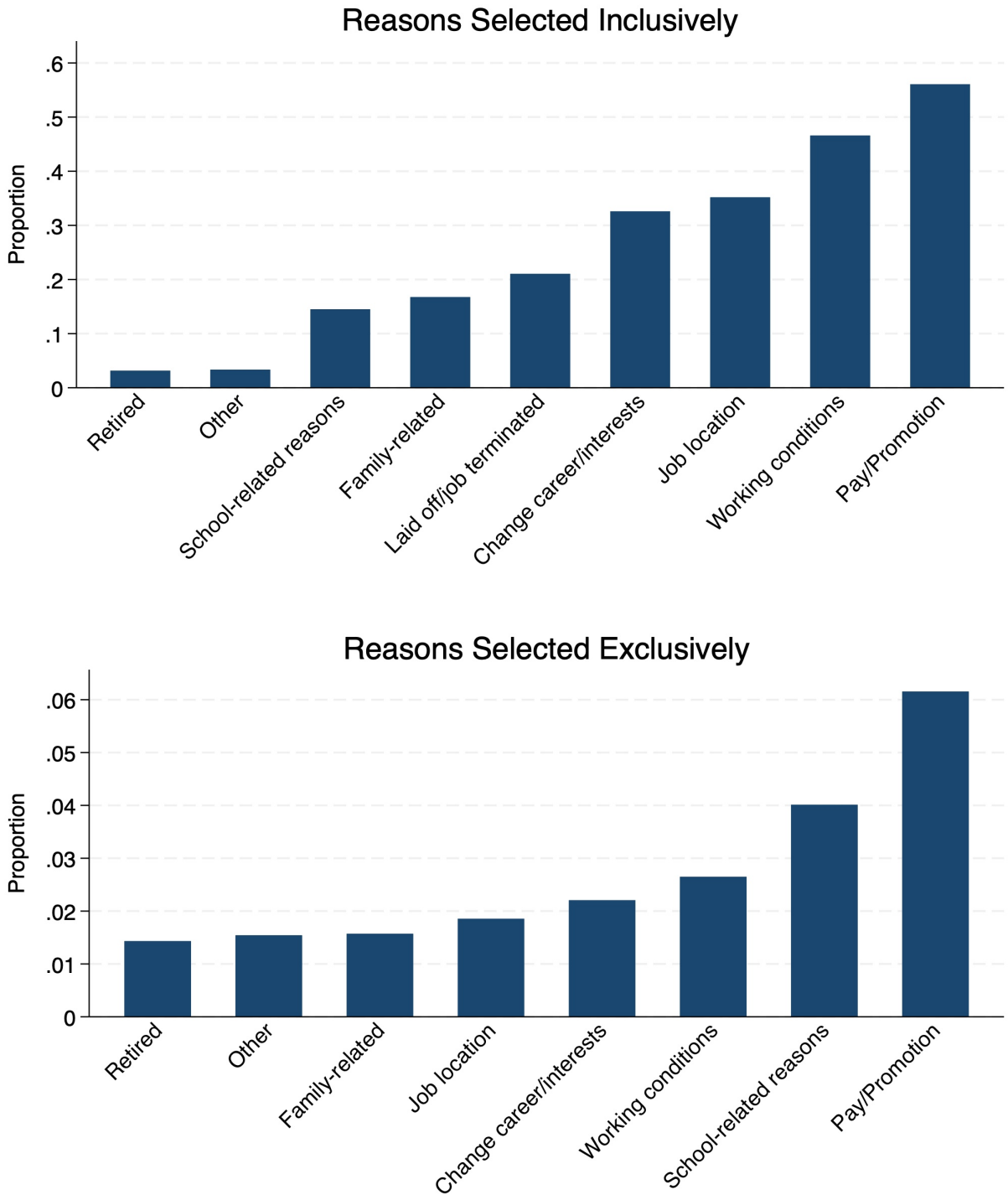


Figure 2. Reported Reasons for Transitions

Furthermore, transitions motivated by pecuniary reasons are associated with lower rates of ECUT compared to those driven by non-pecuniary factors. In Table 5 , workers who transitioned for pecuniary reasons alone exhibit a 28.8% share of ECUT under the robust measure, while those driven by both pecuniary and non-pecuniary motivations display a 29.7% share. In contrast, transitions motivated solely by non-pecuniary reasons show a significantly higher ECUT share of 53.9%. Additionally, the naive measure indicates that ECUT shares are notably higher for pecuniary-driven transitions and somewhat lower for non-pecuniary transitions.

Table 5. ECUT Share by Motivations

Motivations	Robust Measure	Naive Measure	Total Transitions
payonly	0.288	0.400	1100
payplus	0.297	0.396	7400
nopay	0.539	0.508	4500

Dataset: Linked NSCG-LEHD

I reexamines the statistics from Table 5 and illustrates in Figure 3 the proportion of pecuniary versus non-pecuniary motivations for employer transitions, conditioned on whether the transition involved an earnings cut (ECUT=1) or not (ECUT=0). Among transitions with earnings cuts (ECUT=1), approximately half are driven solely by non-pecuniary factors, with 6.2% of these transitions occurring for exclusively non-pecuniary reasons. In contrast, for transitions without earnings cuts (ECUT=0), about one-quarter are motivated purely by non-pecuniary factors, while the share of transitions driven exclusively by pecuniary reasons rises to 9.4%.

The relationship between pecuniary motives and the incidence of ECUTs raises a key hypothesis: workers driven by pecuniary reasons may face a trade-off between immediate earnings and future earnings upon transition. In the following, I will examine whether post-ECUT earnings outcomes are consistent with these underlying transition incentives.

3.3 Transition Motivations and Earnings after ECUTs

In this subsection, I apply OLS regression to show that pecuniary motivation relates to higher post-transtion earning growths. Consider a worker i, who is employed by

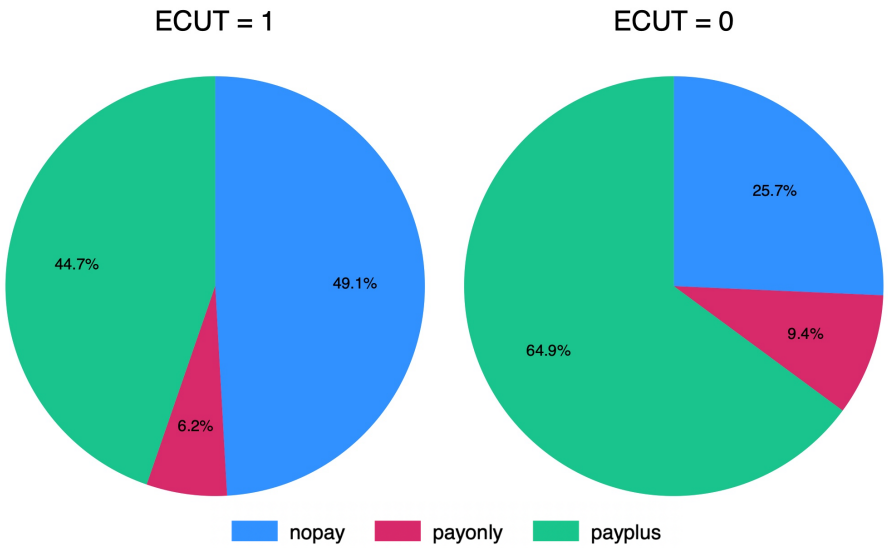


Figure 3. Motivations by Transitions with/without Earnings Cuts

employer j' in quarter $t-1$ and transitions to employer j in quarter t. Let $w_{it+\tau}$ denote worker i's future earnings τ quarters after the transition, where k referes to the employer at that time.[27] For simplicity, I define the worker's base earnings of transition in t, $\tilde{w}_{it}$, as the last full quarterly earnings from employer j'.[28] I define the indicator variable, $D_{it}^{paytotal} = 1$, if worker i reports pecuniary motivation for the transition (denoted "paytotal", including "payonly" and "payplus").

I estimate the following regression, where the dependent variable is the log wage ratio $log(\frac{w_{it+\tau}}{\tilde{w}_{it}})$:

$$log(\frac{w_{it+\tau}}{\tilde{w}_{it}}) = \beta_1^\tau D_{it}^{paytotal} + \beta_2^\tau X_{it} + \beta_3^\tau Z_{j(i)t} + \alpha_i^\tau + \lambda_{j(i)}^\tau + \eta_t^\tau + \epsilon_{ijt}^\tau, \tag{1}$$

where X_{it} represents time-varying worker characteristics (including wage growth at transitions, wage growth at the prior employer, weekly working hours at the current employer, a polynomial in age, and marital status), and α_i captures time-invariant worker characteristics (e.g., gender, race). Similarly, $Z_{j(i)t}$ denotes time-varying characteristics of the employer j where worker i is employed (such as employment size, payroll growth), while $\lambda_{j(i)}$ controls for time-invariant employer characteristics (e.g.,

[27] The employer k could either be j (the current employer) or a new employer, depending on whether the worker undergoes a subsequent transition. The probability of such transitions will be addressed in the next section.

[28] Formally, $\tilde{w}_{it} = w_{it-2}$. Since transitions may occur during quarter $t-1$, I restrict the sample to workers employed at firm j' from quarter $t-3$ to $t-1$ to ensure the availability of full quarterly earnings in $t-2$.

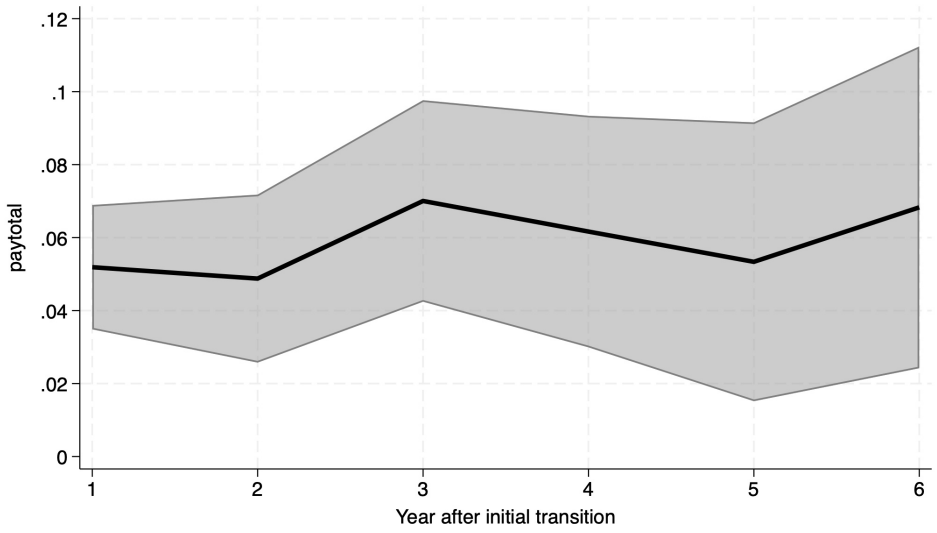


Figure 4. $\hat{\beta}_1^\tau$ and 90% Confidence Interval

sector and state). Finally, η_t is year fixed effect of quarter t.

We are interested in the coefficients β_1^τ with future horizon $\tau \in \{4, 8, 12, 16, 20, 24\}$. Figure 4 shows workers who transitioned for pecuniary reasons consistently experienced higher wage growth compared to those who transitioned for non-pecuniary reasons. The wage growth premium fluctuates slightly across different time horizons, peaking at 3 years after the initial transition (6.0%) and being lower in earlier and later periods. Overall, the results indicate that the motivations behind transitions are consistent with post-transition earnings trajectories.

4 Stepping-stone Employers

The growth in post-transition earnings encompasses both the earnings growth within the initial employer following the transition and the gains associated with the employers after subsequent transitions.[29] This decomposition informs the introduction of "stepping-stone employers" as a distinct pecuniary motivation.

Definition: *Stepping-stone employers are those that provide workers with enhanced prospects for future transitions to more desirable employers.*

[29]Pending U.S. Census approval, I will provide detailed disclosure of post-transition earnings trajectories, breaking down growth into contributions from within-employer advancements and earnings increases due to further transitions.

Stepping-stone employers shape both worker mobility and earnings dynamics through firm-level heterogeneity in transition rates. To begin with, I document the dispersion and persistence of firm-level transition rates. I analyze whether the transition rate from one firm to higher-paying employers is systematically associated with workers' earnings growths following their transitions into the firm. I then establish a link between the pecuniary motivation driving initial transitions and the probability of subsequent transitions.

4.1 Transition Rates on Firm Level

The existence of stepping-stone employers hinges on heterogeneous transition rates on employer level. I construct a firm-level panel by aggregating the LEHD data by firm ID and year. I calculate firm-level Employer-to-employer (EE) transition rates, denoted by Π_t^j, as the ratio of a firm's workers making EE transitions to its total employment in year t. The average firm-level EE transition rate, weighted by firm size, is 0.062. When firms are categorized into three groups based on their fixed effects in wage payments (described in greater detail in the following subsection), the results in Table 10 reveal significant dispersion in firm-level transition rates. Specifically, the weighted average EE rates for the three groups are 0.076, 0.059, and 0.051, respectively, with corresponding standard deviations within each group of 0.045, 0.046, and 0.043.

I next establish the persistence of firm-level transition rates by estimating the following specification:

$$\Pi_t^j = \beta \Pi_{avg(t)}^j + \epsilon_t$$

where $\Pi_{avg(t)}^j$ is the three-year average transition rate before year t.[30] Table 6 presents the results of various specifications. Columns (1) shows the results of simple OLS regressions. Regression in column (2) drops extreme values of the regressors that are larger than 0.7 or lower than 0.01. Column (3) replicates the regression from column (1), but applies employment size as weights. Similarly, column (4) extends the specification in column (2) by also weighting by employment size and including year fixed effects. The findings consistently demonstrate that transition rates exhibit significant persistence.

[30] In Appendix C, I use the firm-level transition rate in the previous year, Π_{t-1}^j, as an alternative proxy to predict Π_t^j. The results are robust.

Table 6. Persistence of firm-level transition rates

Π_t^j	(1)	(2)	(3)	(4)
$\Pi_{avg(t)}^j$	0.91	0.95	0.91	0.96
	(0.0005)	(0.0004)	(0.005)	(0.0004)
Year FE	N	Y	N	Y
R^2	0.72	0.72	0.79	0.80
Observations	2,342,000			

The number of observation is rounded with fours significant digits.
Std.errs are included in the brackets.

4.2 Transition Rates and Earnings Dynamics Upon Transitions

The intuition behind the role of stepping-stone employers in ECUTs is that workers may accept lower wages from current employers at the beginning if they anticipate higher probabilities of transitioning to more desirable firms, based on the employer's past transition patterns. This reflects not only the scale of firm-level transition rates but also the direction of these transitions in determining labor market outcomes. I test this intuition in two steps.

First, I use higher-paying firms as proxy for "more desirable" employers. To rank firms by their pay levels, I estimate the firm fixed effects using the method introduced by Abowd et al. (1999) (hereafter, AKM), as described below:

$$\log w_{it} = \alpha_i + \psi_{j(it)} + X_{it}\beta + \varepsilon_{it} \tag{2}$$

where w_{it} is the annualized earnings of worker i in year t, α_i is worker fixed effect, $\psi_{j(it)}$ is the fixed effect of firm j where worker i is employed, and X_{it} is a set of covariates including higher-order polynomial terms in age.[31]

I partition the estimated firm fixed effects, $\hat{\psi}_j$, into three distinct groups.[32] Firms in Group 3 offer the highest wages, followed by those in Group 2, with firms in Group 1 offering the lowest wages. Figure 5 illustrates the average flow ratio of workers who make EE transitions across these groups. A majority of workers transitioning within

[31]The control variables follow the specification in Song et al. (2019). Table A1 in the Appendix presents the decomposition of earnings dispersion and compares it with other studies that utilize LEHD data.

[32]The choice of three groups is not critical to the analysis. This choice was made for two reasons: (1) an odd number of groups facilitates analyzing labor flows from the middle group to the others, maintaining a symmetric distribution of higher and lower $\hat{\psi}_j$; and (2) increasing the number of groups would complicate the data disclosure process without providing additional analytical insights.

their own employer groups. Transitions from Group 1 to Group 3 are infrequent, occurring with a probability of only 15.5%, while moves from Group 3 to Group 1 are even rarer, with a probability of 7.3%.

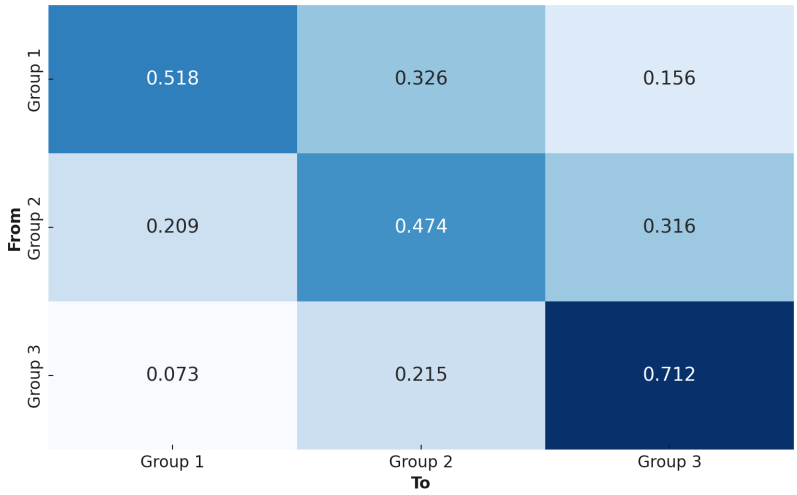


Figure 5. Labor Flow Ratio Between Firm Groups

In the second step, I examine the relationship between the transition rate of one firm to higher-paying firm groups and the earnings changes of worker who just move into this firm. Specifically, I denote π_{jt}^{up} as the expected transition rate, in year t, from employer j to higher-paying employers. Then, I estimate the following regression for workers who have recently made EE transitions in the LEHD panel:

$$\Delta \log(w_{it}) = \beta_1^{up} \pi_{j(i)t}^{up} + \beta_2 x_{it} + \beta_3 z_{j(i)t} + \alpha_i + \eta_t + \epsilon_{ijt}, \tag{3}$$

where the dependent variable $(\log(w_{it}) - \log(w_{it-1}))$ captures the change in log earnings for worker i in year t following the EE transition, with w_{it} representing annualized earnings in year t. The explanatory variables on the right-hand side includes α_i, a worker fixed effect; x_{it}, a set of time-varying worker characteristics (e.g., a polynomial function of age); z_{jt} time-varying employer characteristics; and η_t, a year fixed effect.[33]

I employ two estimation strategies. The first is an OLS regression, which directly uses the three-year average transition rates prior to year t from firm j to higher-payingfirms, serving as proxies for π_{jt}^{up}.[34] The second approach leverages these three-year average transition rates as instruments in a Two-Stage Least Squares (2SLS)

[33] In addition to firm size and growth, z_{jt} also includes π_{jt}^{down} which represents the expected transition rate from employer j to lower-paying employers in year t.

[34] The term $\pi_{j(i)t}^{up}$ captures instances where worker i transitions from group 3 to either group 2 or 3,

framework to predict π_{jt}^{up}. Intuitively, we expect the coefficients of the upward transition rates, β_1^{up}, to be negative if there is a "stepping-stone" premium in wages.

The negative estimators in Table 7 are consistent with our hypothesis. The first two columns report OLS estimates, while columns (3) and (4) present results from the 2SLS specification. Given that π_{jt}^{up} is constructed between 0 and 1, the findings suggest that a one percentage point increase in the transition rate to higher-paying employer groups is associated with a 1.6 to 1.8 percentage point decrease in the earnings growth rate upon transitioning to employer j.

Table 7. Earnings dynamics upon transitions and transition rates

	OLS		**2SLS**	
$\Delta \log(w_{it})$	(1)	(2)	(3)	(4)
π_j^{up}	-1.65	-1.64	-1.81	-1.81
	(0.009)	(0.009)	(0.011)	(0.011)
Year FE	Y	Y	Y	Y
Worker FE	Y	Y	Y	Y
State FE	N	Y	N	Y
Observations		9,652,000		

The number of sample observation is rounded with four significant digits.
Std.errs are included in the brackets.

4.3 Transition Motivations and Subsequent Transitions

Workers often undergo additional transitions within a relatively short period following an initial move. In this part, I examine the link between pecuniary motivations and the probability of subsequent transitions. Table 8 presents the unconditional probability of subsequent transitions with the number of years since the initial transition increases.

In the following regression, the regressor is a dummy variable, $\mathbb{I}\{j_{t+\tau} \neq j_t\}$, which takes the value of one if worker i transitions to a different employer j within τ quarters ($\tau = 4, 8, 12, \ldots, 24$) after their initial move.

$$\mathbb{I}\{j_{t+\tau} \neq j_t\} = \beta_1^\tau D_{it}^{pay} + \beta_2^\tau X_{it} + \beta_3^\tau Z_{jt} + \alpha_i^\tau + \lambda_j^\tau + \eta_t^\tau + \epsilon_{ijt}^\tau, \tag{4}$$

as well as transitions from group 2 to group 3. Conversely, $\pi_{j(i)t}^{down}$ represents the probability that worker i moves from group 3 to either group 2 or 1, or transitions from group 2 to group 1.

Table 8. Unconditional probability of subsequent transitions

Years after initial transition	1	2	3	4	5	6
Unconditional prob.	0.057	0.200	0.350	0.445	0.517	0.558
Observations	10500	8400	7000	5300	4200	2600

Dataset: Linked NSCG-LEHD

where D_{it}^{pay} is the dummy variable indicating the pecuniary reason selected, and other variables are the same as those in the equation (1). Specifically, X_{it} is time-varying worker characteristics (including wage growth at transitions, wage growth at the prior employer, weekly working hours at the current employer, a polynomial in age, and marital status), and α_i represents time-invariant worker characteristics (e.g., gender, race). Similarly, $Z_{j(i)t}$ includes time-varying characteristics of the employer j where worker i is employed, such as employment size, payroll growth, while $\lambda_{j(i)}$ controls for time-invariant employer characteristics (e.g., sector and state). η_t is year fixed effect of quarter t.

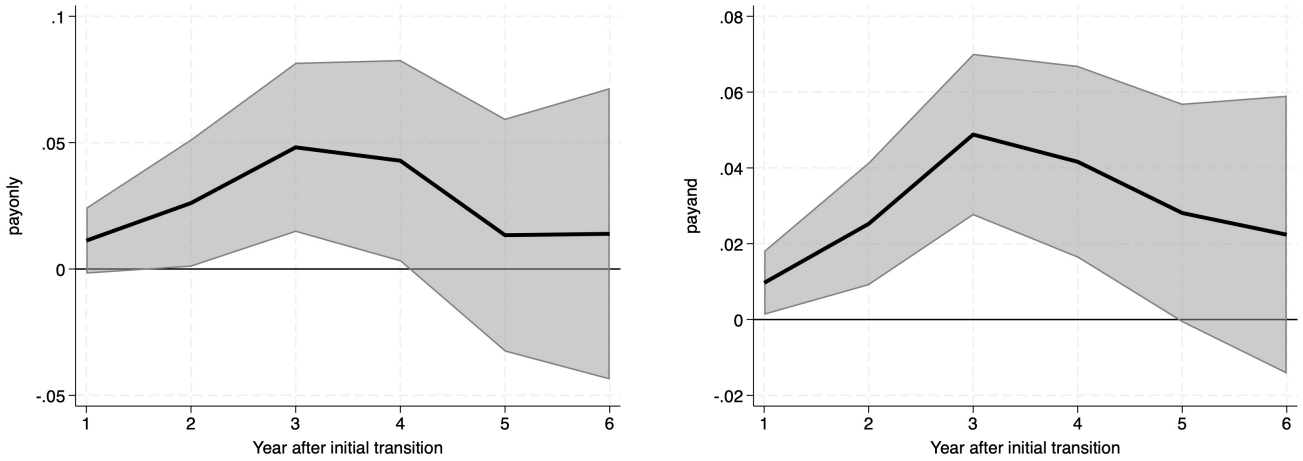
I construct two indicators for D_{it}^{pay}. The first, labeled "payonly," takes a value of one if the worker reports moving solely for pecuniary reasons. The second, labeled "payand," expands the definition of "payonly" to include movers motivated by pecuniary reasons as well as other non-pecuniary factors, with the exception of "working conditions."[35]

The estimation results reveal a positive correlation between pecuniary motivations for the initial job transition and the likelihood of subsequent transitions. Specifically, Figure 6a demonstrates that workers who transition primarily for pecuniary reasons tend to experience an elevated probability of making additional transitions over the next four years. This relationship is statistically more significant in Figure 6b, where the sample size is larger. However, we observe that, in either panel, the effect peaks at 5% in year three and then diminishes.

4.4 Discussion

One possible concerns regarding estimating the role of stepping-stone employers lies in the fact that observed transition rates may primarily reflect the characteristics of workers hired by these firms, rather than firm-specific attributes. For instance, some

[35]The exclusion of 'working conditions' is crucial, as shown in Appendix D, their strong negative impact on subsequent transitions obscures the positive effects of pecuniary motivations.



(a) Indicator: payonly

(b) Indicator: payand

Figure 6. $\hat{\beta}_1^{\tau}$ and 90% Confidence Interval

firms may disproportionately employ workers with a higher propensity for job transitions. However, if this is the case, firm-level transition rates should have a negligible effect on workers' earnings changes following a transition into these firms, after controlling for worker characteristics and fixed effects. The results in regression (3) suggest that this concern is unlikely to be significant.

In summary, this section provides empirical evidence that firms exhibit heterogeneity in their transition rates to better firms. These transition dynamics should influence workers' initial earnings when they strategically switch employers. Moreover, workers who transition for pecuniary reasons tend to experience higher probabilities of subsequent transitions. The findings introduces an additional pecuniary motivation that drives workers to make transitions - "stepping-stone employers," , attracting workers who seek to improve their prospects for future transitions to more desirable positions. The presence of stepping-stone employers, alongside other factors, shapes earnings dynamics during labor market transitions.

5 Model

To quantify the aggregate impact of stepping-stone employers, I develop a discrete-time partial equilibrium model of wage and employment dynamics within a frictional labor market, where jobs (matches) vary across three dimensions: employer's productivity, employer's offer arrival rates, and match-specific preferences. This model

enables a quantitative decomposition of transition motivations, including the role of stepping-stone employers, and assesses their effects on both earnings and transition dynamics.

5.1 Environment

Search and Matching

Workers randomly search and match with employers. The sequence of events within each period follows this order:

(i) At the beginning of the period, employed workers produce output and receive their wages w, while unemployed workers receive a flow value b_x.

(ii) An exogenous separation shock δ_x then occurs, which transitions a fraction of employed workers into unemployment the next period.[36]

(iii) The remaining employed workers, along with the unemployed, engage in random search activities, with the offer arrival rates depending on their current employment states and the characteristics of the employer. Employers send take-it-or-leave-it offers.

(iv) Upon receiving an offer, a worker draws her match-specific preference ϕ and decides whether to move, renegotiate, or maintain the status quo.[37]

(v) If no offer arrives during the period, the worker may experience a reallocation (Godfather) shock that forces either a transition to a new employer or to unemployment.[38]

Workers

Workers live infinitely and are heterogeneous in their time-invariant ability type $x \in X$. Workers are either employed or unemployed. The utility per period for an employed worker is $u(w, \phi)$ and $u(b_x, 0)$ for an unemployed worker.

Employer

Each employer of type y is defined by three characteristics: (1) the employer group g to which it belongs; (2) its productivity, p_y; and (3) its vector of offer arrival rate, $\overrightarrow{\lambda_y}$.

[36] This paper assumes that separation rates primarily depend on worker characteristics, as suggested by survey data indicating that they play a secondary role in employer transitions. However, the extent to which job security is more closely tied to worker versus employer characteristics remains debated in the literature. For example, Bonhomme and Jolivet (2009) view job security as a worker-valued job amenity, while Jarosch (2023) attributes it to employer characteristics. Sorkin (2018) models job security as a hybrid of both worker and employer characteristics.

[37] The offer contains perfect information ex ante about the employer characteristics and job preference.

[38] This shock reflects non-pecuniary factors driving job transitions beyond the consideration of job-specific amenities.

Formally, we represent an employer of type y as $y = (g, p_y, \overrightarrow{\lambda_y})$.

Introducing the employer group allows to model the quality of each offer. Specifically, each employer group $g \in \{1, 2, \ldots, G\}$ is associated with distinct distributions of employer's productivity and the distribution of the arrival rates, such that $p_y \sim F_g$ and $\overrightarrow{\lambda_y} \sim \Lambda_g \times \Gamma_g$.

I introduce a vectorized offer arrival rate, $\overrightarrow{\lambda_y} = [\lambda_{g1}, ...\lambda_{gg'}, ...\lambda_{gG}]'$, where $\lambda_{gg'}$ represents the offer arrival rate from group g' to group g. The probability of receiving no offers is assumed to lie within the interval $(0, 1)$, or equivalently, $\sum \lambda_{g\cdot} \in (0, 1)$. I divide the vectorized arrival rate into two distinct components, such that

$$\overrightarrow{\lambda_y} = \sum \lambda_{g\cdot} \underbrace{\left[\frac{\lambda_{g1}}{\sum \lambda_{g\cdot}}, ..., \frac{\lambda_{gg'}}{\sum \lambda_{g\cdot}}, ..., \frac{\lambda_{gG}}{\sum \lambda_{g\cdot}}\right]'}_{G \text{ elements}} = \tilde{\lambda}_y \cdot \overrightarrow{R_y}.$$

The first component, $\tilde{\lambda}_y$, represents the total arrival rate of offers to employer y, and is assumed to follow group-specific distribution Λ_g. This scalar component captures the quantity of potential offers that may reach the employer. The second component is a normalized vector, $\overrightarrow{R_y} = [r_{gg'}]_{1\times G}$, which follows group-specific distribution, Γ_g, and characterizes the quality of those offers. Each element, $\frac{\lambda_{gg'}}{\sum \lambda_{g\cdot}} = r_{gg'}$, denotes the conditional probability that an offer comes from employer g', given that an offer has arrived at employer g. In contrast, the arrival rates for unemployed workers are assumed to be predetermined but in a similar construction, such that

$$\overrightarrow{\lambda_u} = \tilde{\lambda}_u \overrightarrow{R_u} = \tilde{\lambda}_u \underbrace{[r_{u1}, ...r_{ug'}, ...r_{uG}]'}_{G \text{ elements}}$$

The benefits of decomposing the arrival rate into two distinct components are:
(a) It distinguishes the quality of arrived offers from the quantity of these offers, which helps model the stepping-stone employers. The structure of these vectors implies that both the probability of receiving job offers and the characteristics of the employers making those offers play a role in the workers' decisions. As such, "better" opportunities may encompass a higher probability of receiving competing offers (quantity), a greater likelihood of offers from more desirable employers (quality), or a combination of both factors.
(b) This decomposition simplifies both the estimation and simulation processes by reducing the problem from requiring assumptions about G distinct distributions to just two distributions for constructing $\tilde{\lambda}_y$ and $\overrightarrow{R_y}$. Specifically, I assume $\tilde{\lambda}_y \sim \Lambda_g$, and

$\overrightarrow{R_y} \sim \Gamma_g$. Moreover, the separated components allow for a direct comparison with prior studies where the scalar component is constant, and the offer quality is irrelevant, such that $r_{gg'} = 1/G$.

Decisions and Wage Dynamics

Agents make decisions within a sequential auction framework, following Cahuc et al. (2006) and Postel-Vinay and Robin (2002). In this model, wages are determined through a bargaining process between employer and worker with a threat offer. I denote a (matched) offer of a job by a worker and employer in type y as θ. θ is characterized by the employer's attributes p_y and $\overrightarrow{\lambda}_y$, and the worker's job-specific preference ϕ. Formally, the matched offer is $\theta = (p_y, \overrightarrow{\lambda}_y, \phi)$, while a threat offer sent from employer y' is similarly expressed as $\theta' = (p_{y'}, \overrightarrow{\lambda_{y'}}, \phi')$. When a worker's outside option is unemployment, the threat offer is denoted by θ_u.

Let $U(x)$ represent the value of unemployment for a worker of type x. For an employed worker x with current offer θ and a threat offer θ', her value is $W(x, \theta, \theta')$. Correspondingly, $J(x, \theta, \theta')$ denotes the value that the employer y obtains from the match with worker x.

The joint surplus generated by a match is defined as:

$$S(x, \theta, \theta') = max\{W(x, \theta, \theta') - U(x) + J(x, \theta, \theta'), 0\},$$

Only matches with strictly positive surplus are formed and sustained. If the match is formed by an employer and an unemployed worker, the joint surplus is:

$$S(x, \theta, \theta_u) = \frac{W(x, \theta, \theta_u) - U(x)}{\alpha},$$

where parameter α is worker share of the joint surplus, implying worker's bargaining power.

When a worker of type x, with current offer θ and a threat offer θ', receives a new offer $\theta_z = (p_z, \overrightarrow{\lambda}_z, \phi_z)$ from employer z, her decision will be one of the following three cases.

Case 1: The worker accepts θ_z. Let $\Omega_1(x, \theta, \theta')$ denote the set of offers in this case. Formally, $\theta_z \in \Omega_1(x, \theta, \theta') \equiv \{\theta_z | S(x, \theta_z, \theta) > S(x, \theta, \theta')\}$. The wage is determined by the following surplus-sharing rule:

$$W(x, \theta_z, \theta) - U(x) = S(x, \theta, \theta') + \alpha[S(x, \theta_z, \theta) - S(x, \theta, \theta')].$$

Case 2: The worker rejects the offer but updates the threat offer to θ_z. The set of offers for this case is denoted by $\Omega_2(x,\theta,\theta')$. Formally, $\theta_z \in \Omega_2(x,\theta,\theta') \equiv \{\theta_z | S(x,\theta_z,\theta) \leq S(x,\theta,\theta'), W(x,\theta,\theta_z) > W(x,\theta,\theta')\}$. The worker remains with her current employer but renegotiates her wage based on the new threat, with the wage satisfying:

$$W(x,\theta,\theta_z) - U(x) = S(x,\theta_z,\theta) + \alpha[S(x,\theta,\theta') - S(x,\theta_z,\theta)].$$

Case 3: The worker discards θ_z. That is, $\theta_z \in \Omega_3(x,\theta,\theta') \equiv (\Omega_1 \cup \Omega_2)^{\complement}$. This case happens when θ_z would not improve the joint surplus.

The sequential auction protocol captures the wage dynamics and transitions. In *Case 1*, a transition takes place, which may result in an ECUT, where wages can increase, decrease, or remain constant depending on the characteristics of the new contract, θ_z, and the threat offer, θ. In contrast, *Case 2* describes scenarios where no transition occurs, and wage adjustments are strictly upward, reflecting a increasing wage-tenure profile within the current employer. Finally, in *Case 3*, the contract remains unchanged, and wages stay constant.

5.2 Value Functions

An unemployed worker in type x has value

$$\begin{aligned} U(x) \quad &= \quad u(b_x, 0) \quad + \\ \beta\Bigg[&(1-\tilde{\lambda}_u)U(x) + \tilde{\lambda}_u \sum_{g_z} r_{ug_z} \int \Bigg(\iiint max\{W(x,\theta_z,\theta_u), U(x)\} dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \Bigg) dH(\phi_z) \Bigg]. \end{aligned} \tag{5}$$

In the bracket, the first term is the expected value if no offer received. The second term is the expected value of receiving a new offer θ_z sent by the employer in type $z = (g_z, p_z, \overrightarrow{\lambda_z})$ and with a match preference ϕ_z.[39]

An employed worker in type x under the contract $\theta = (p_y, \lambda_y, \phi)$ and with threat

[39]Note that the employer group g only indirectly affects the value of an offer by determining the distribution of the productivity and the vectorized offer rates of the employer. Given the productivity, arrival rates, and the match preference, employer group is irrelevant to workers' decisions.

offer $\theta' = (p_{y'}, \overrightarrow{\lambda_{y'}}, \phi')$ has value

$$
\begin{aligned}
W(x,\theta,\theta') = u(w(x,\theta,\theta'),\phi_y) \quad + \quad \beta\Big\{ \delta_x U(x) \quad + \quad (1-\delta_x)\Big[\tilde{\lambda}_y \sum_{g_z} r_{gg_z} \times \\
\int_\phi \Big(\iiint_{\Omega_1} W(x,\theta_z,\theta) dF_{g_z}(p_z) d\Lambda_{g_z}(\tilde{\lambda}_z) d\Gamma_{g_z}(r_{g_z g'}) + \iiint_{\Omega_2} W(x,\theta,\theta_z) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} + \\
\iiint_{\Omega_3} W(x,\theta,\theta') dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \Big) dH(\phi_z) \quad + \quad (1-\tilde{\lambda}_y)\Big((1-\rho) W(x,\theta,\theta') + \\
\rho \sum r_{ug_{z'}} \int \Big(\iiint \max\{W(x,\theta_{z'},\theta_u), U(x)\} dF_{g_{z'}} d\Lambda_{g_{z'}} d\Gamma_{g_{z'}} \Big) dH(\phi_{z'}) \Big) \Big] \Big\}.
\end{aligned}
\tag{6}
$$

The first term is current flow value at employer y, and the second is discounted future value. Specifically, after the wage, $w(x,\theta,\theta')$, is paid, an exogenous match destruction shock realizes. Subsequently, the workers that stayed on their jobs may receive outside job offers. Given an offer at hand, she may move to a new employer of certain group, or use the offer to renegotiate. In either case, her negotiation threat offer gets updated. If the new outside offer is not good enough to use, she continues on her current job. Nevertheless, if there is no offer arrived, a reallocation shock may force the worker to move to another employer.

The value of employer y having employed a worker in type x is

$$
\begin{aligned}
J(x,\theta,\theta') = & f(x,p_y) - w(x,\theta,\theta') + \beta(1-\delta_x)\Big[(1-\tilde{\lambda}_y)(1-\rho) J(x,\theta,\theta') + \tilde{\lambda}_y \sum r_{gg_z} \times \\
& \int_\phi \Big(\iiint_{\Omega_2} J(x,\theta,\theta_z) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} + \iiint_{\Omega_3} J(x,\theta,\theta') dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \Big) dH(\phi_z) \Big]
\end{aligned}
\tag{7}
$$

It includes the current profit, $f(x,p_y) - w(x,\theta,\theta')$, and discounted future values. An unmatched job has no continuation value. A matched job value will continue only if the arrived outside offer falls into *Case 2* or *Case 3* above. Using the definition of joint

surplus along with the bargaining protocol, Appendix E derives the joint surplus,

$$
\begin{aligned}
S(x,\theta) = \max \Bigg\{ 0, \quad & c(\phi_y) \quad + \quad f(x,p_y) \quad - \quad b_x \\
& - \beta\alpha\tilde{\lambda}_u \sum r_{ug_z} \iiiint S(x,\theta_z) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) \\
& + \beta(1-\delta_x) \Big[\alpha\tilde{\lambda}_y \sum r_{gg_z} \iiiint_{\Omega_1} [S(x,\theta_z) - S(x,\theta)] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) \\
& \qquad + (1-\tilde{\lambda}_y)\rho\alpha \sum r_{ug_z} \iiiint S(x,\theta_z) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) \\
& \qquad + [1-\rho(1-\tilde{\lambda}_y)] S(x,\theta) \Big] \quad \Bigg\}
\end{aligned}
\tag{8}
$$

The joint surplus first reflects current total flow surplus $c(\phi_y) + f(x,p_y) - b_x$. From Appendix E, when utility is quasilinear in wage, i.e. $u(w,\phi) = w + c(\phi)$, the joint surplus function does not depend on the outside threat, i.e. $S(x,\theta,\theta') = S(x,\theta)$. As a consequence of the transferable utility, wages do not enter the expression and neither does any future renegotiation that reallocate worker's share within the match. The second line reflects the opportunity cost of searching in unemployment. The continuation value first consists of the possibility that the worker receive a new offer and move to a new employer. It also includes the expected value of being reallocated to another job, as in the fourth line. The last line captures the continuation value when none of shocks realized.

5.3 Equilibrium

Given the environment of the model, the equilibrium is defined as follows:

1. The value functions (5)-(7) solve the worker's and employer's optimization problems;
2. Workers and employers split the total surplus that satisfy the equation (8);
3. Transitions and wages are the results of the negotiations between workers and employers following one of three specified Nash bargaining cases;
4. The stationary distributions satisfy the condition that the inflows equal the outflows of workers across employment states and employer types.

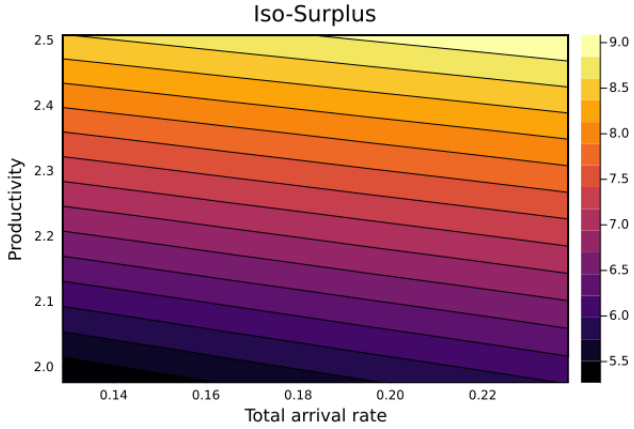
5.4 Theoretical Results

5.4.1 Effect of Vectorized Arrival Rates

Joint surplus, $S(x, \theta)$, is key to worker's decisions. From equation (8), surplus is increasing with match specific preference (ϕ), employer productivity (p), and total arrival rate ($\tilde{\lambda}$):

$$\frac{\partial S}{\partial \phi} > 0, \quad \frac{\partial S}{\partial p} > 0, \text{ and } \frac{\partial S}{\partial \tilde{\lambda}} > 0.$$

There is a tradeoff between productivity and total offer arrival rates when holding the joint surplus constant. This is illustrated as a negative relationship in an iso-surplus contour plot in Figure 7.[40]



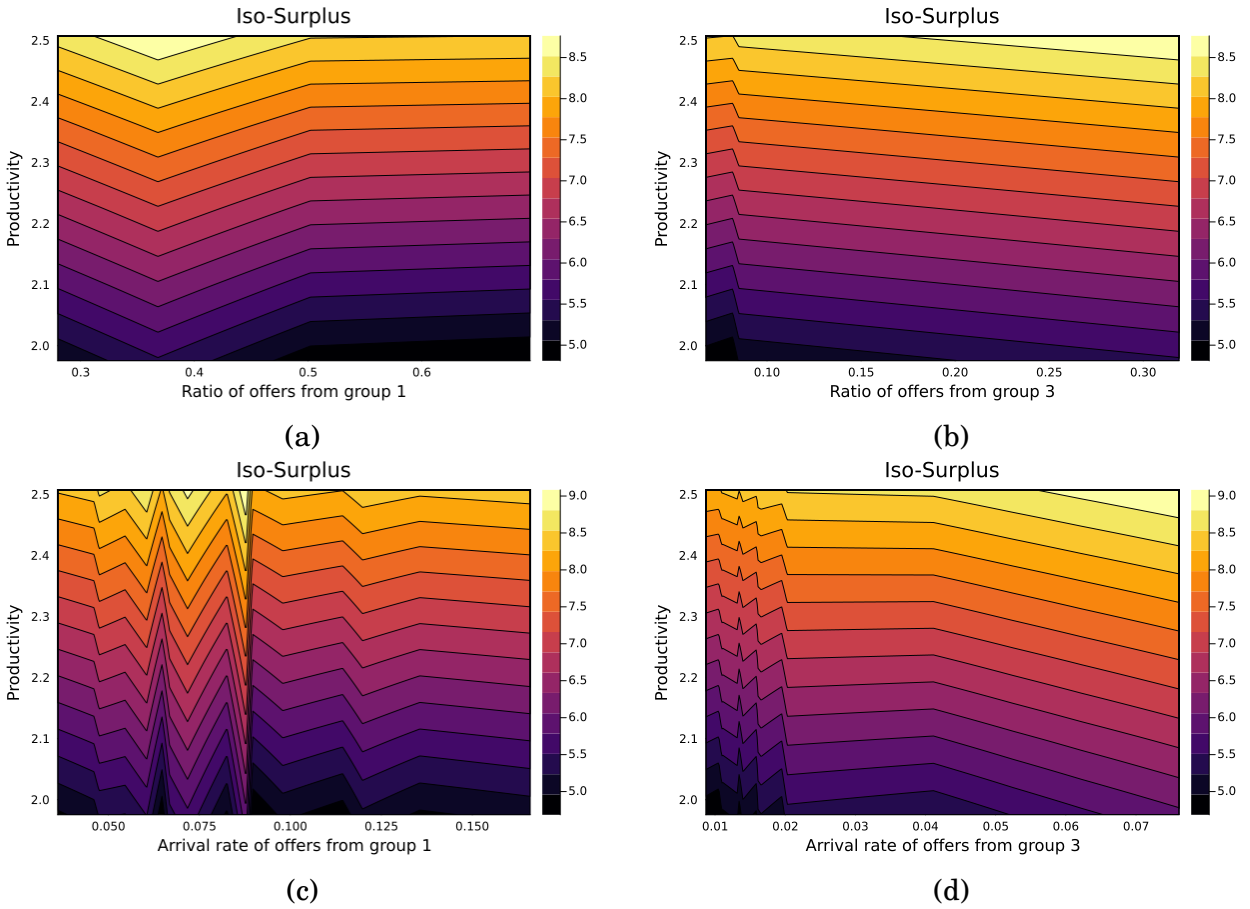
*Joint surplus of a match in employer group 2.

Figure 7. Relationship between productivity and total arrival rate

However, this tradeoff needs not hold for the arrival rate of offers sent from a particular employer group. That is, if we increase the arrival rate of offers from a specific employer group ($\lambda_{gg'}$), we may not see productivity decreasing given the surplus value. Because increasing the probability of receiving offer from a specific employer group may lead to lower probability of receiving offers from other employer groups, which could result in lower joint surplus. This is a key result with the introduction of vector component in the arrival rate $\overrightarrow{R_y}$. In Figure 8, I predefine 3 employer groups where group 1 represents lower-productivity group and group 3 corresponds to higher-productivity employer group.[41] All figures show the joint surplus value in group 2.

[40] This is consistent with the plot by Del Prato (2023).

[41] Using the calibrated parameters in Section 5.5, average productivity of employer group 1 is 30% lower than that in group 2, and average productivity of group 3 is 47% higher than group 2.



Joint surplus of a match in employer group 2.
The x axes in left and right panel represent the conditional probability of the offer from group 1 (r_{21}) and group 3 (r_{23}), respectively, given an arrived offer to a firm in group 2.

Figure 8. Relationship between productivity and vectorized arrival rates

Figures 8a and 8b show a non-monotonic relationship between productivity and the proportion of offers from other employer groups, the offer "quality"[42]. The non-monotonicity arises because an increase in the conditional probability of offers from one employer group reduces that from other groups, which may lower the joint surplus of the match. Figures 8c and 8d illustrate the combined effects of offer quantity ($\tilde{\lambda}$) and offer quality ($\overrightarrow{R_y}$) on the tradeoff with productivity.[43] While higher offer arrival rates may be beneficial, this is not universally true; offers from lower-productivity firms (group 1) may be less desirable despite their higher frequency.

Two main takeaways from Figure 8: (a) The relationship between productivity and

[42]The horizontal axes in panel (a) and (b) are represented by r_{21} and r_{23}, respectively.
[43]The horizontal axes in panel (c) and (d) are represented by λ_{21} and λ_{23}, respectively.

arrival rates from specific employer groups is not strictly monotonic, as it varies with the heterogeneity in offer quality; (b) The value of a job match depends not only on the quantity of the offers arrived at an employer but also on the quality of the offers, as indicated by their origins and composition. Empirically, this implies that workers may transition to new employers with lower productivity and receive fewer offers during on-the-job search compared to their previous employer. However, these offers may come with a higher likelihood of being from high-productivity employers.

5.4.2 Motivations for Transitions

The decision to transit from employer y to employer y' is directed by the *Case 1* in wage contract: workers make transitions if and only if the new surplus high enough so that, given a constant bargaining power, the worker will enjoy more surplus. Based on the factors that would affect the total surplus of a match, I categorize motivation into four types:

(1) Amenity: A motivation that induce transition by improved preference for the match, characterized by $\phi_y < \phi_{y'}$.

(2) Productivity: A motivation that induce transition by higher productivity, such that $p_y < p_{y'}$.

(3) Stepping-stone: A motivation that induce transition by "better" offer arrival rate. A "better" offer arrival rate should increase the joint surplus controlling other factors. Formally, $\lambda_{y'}$ of employer y' is better than the arrival rate in employer y if $S(x,\theta) < S(x,\tilde{\theta})$, where $\tilde{\theta} = (p_y, \lambda_{y'}, \phi_y)$.

(4) Others: A motivation that induce transition by other reasons not categorized above (e.g. family or school), due to the reallocation shock.

I further categorize the four motivations into pecuniary and non-pecuniary ones. Pecuniary motivation refers to any transition driven by higher productivity or the prospect of working for stepping-stone employers. In contrast, non-pecuniary motivations include factors such as job amenities and personal considerations unrelated to direct financial gains. As illustrated in Figure 9, motivations (1) to (3) are not mutually exclusive; workers may transition for multiple of these reasons once an offer is received. The reallocation shocks captures transitions driven by individual-specific or other non-pecuniary factors.

The concept of stepping-stone motivation stems from the heterogeneity in vectorized arrival rates of offers. The scalar component, $\tilde{\lambda}$, represents the quantity of future offers, and $\overrightarrow{R_y}$ captures the quality of those offers. Importantly, offer quality becomes

relevant only when the productivity distribution varies across employer groups; otherwise, stepping-stone dynamics merely reflect differences in offer quantity. Both the quantity and quality of offers, along with employer productivity, influence the wage dynamics as well as the job transitions.

5.5 Parameterization and Calibration

I calibrate the model using the LEHD dataset at an annual frequency. Five parameters are calibrated externally, including the discount factor, β, which is set at 0.96 to match an annual interest rate of 4%. In addition, fifteen parameters are calibrated internally using the Simulated Method of Moments (SMM). Table 9 summarizes the parameters and the empirical moments used as calibration targets. Although the internally calibrated parameters are listed alongside their respective targets, they are estimated jointly.

Worker-Related Parameters

Worker abilities are assumed to follow a Pareto distribution, $Pareto(x; \iota, x_m) = 1-(\frac{x_m}{x})^{\iota}$, where the scale parameter $x_m = 1.0$. The shape parameter ι is internally calibrated to match the observed earnings growth among stayers. Worker bargaining power, α, is internally set to match $\bar{w}_0/\bar{w}$, where $\bar{w}_0$ represents the average earnings of newly employed workers, and $\bar{w}$ denotes the average earnings of all workers. We further assume four distinct worker types, corresponding to the four educational levels in the LEHD dataset.[44] The separation rate for each worker type, δ_x, is predetermined using the observed ENE rates across these education levels in the LEHD data.

Match-specific preferences are parameterized by ϕ, which is discretized into three grid points uniformly distributed over the interval $(0, \bar{\phi})$. Consistent with earlier assumptions, utility is quasilinear in wages, with match-specific preference function $c(\phi) = \phi$.

The arrival rate for unemployed workers, $\lambda_u = \tilde{\lambda}_u \overrightarrow{R_u}$, consists of a scalar component, $\tilde{\lambda}_u = 0.87$, corresponding to a quarterly job-finding rate of 0.4 (Birinci et al., 2023), and a vector component, $\overrightarrow{R_u}$, which is calibrated to match the outflow rates from unemployment based on ENE transition rates of $(0.3930, 0.2870, 0.3200)$ from the LEHD data. The flow value for unemployed workers is normalized to $b = 1.0$. Additionally, the reallocation shock parameter is calibrated to match the overall average employer-to-employer (EE) transition rate.

[44] The four levels of educational attainment are: "less than high school," "high school," "some college," and "bachelor's degree or higher."

Employer-Related Parameters

I model three employer groups ($G = 3$), corresponding to the three employer groups established by the AKM firm fixed effects, as outlined in Section 4. For the purposes of the simulation, I partition the productivity distribution evenly across these three groups.

The production function is specified as $f(x, p) = x + p$, where productivity p follows a log-normal distribution, $log(p) \sim N(\mu_p, \nu_p^2)$. I externally set the variance $\nu_p = 0.35$ to match the observed standard deviation of estimated firm fixed effects. Subsequently, I calibrate μ_p internally to ensure that the replacement rate $b/\mathbf{E}(w) = 0.4$, reflecting the ratio of claimants' weekly benefit amount (WBA) to their average weekly wage.[45]

The arrival rate is a product of a scalar component and a vector component, each following different group-specific distributions. I internally calibrate the distributions of these components to match the moments of the transition rate distribution. The scalar component of the arrival rates is assumed to follow a Beta distribution with group-specific parameters, i.e., $\Lambda_g \sim \text{Beta}(\kappa_g, \sigma_g)$. For each employer group g, I choose values of κ_g and σ_g to compare the simulated moments and two empirical moments of the firm-level EE rate weighted by employment sizes.[46] Within each group, p_y and $\tilde{\lambda}_y$ are assumed to be independently drawn. However, when considering all three groups together, p_y and $\tilde{\lambda}_y$ exhibit a negative correlation.

The vector component $\overrightarrow{R_y}$ is assumed to follow a Dirichlet distribution, $Dir(\overrightarrow{\gamma_g})$, with group-specific parameters $\overrightarrow{\gamma_g} = (\gamma_{g1}, \gamma_{g2}, \gamma_{g3})$.[47] To calibrate $\overrightarrow{\gamma_g}$ for each employer group g, I utilize the estimated labor flow ratios across the three employer groups, as illustrated in Figure 5. The approximation of R_y proceeds in two steps:

(Step 1) Initiation: For each employer group g, I choose an initial value of vector $\overrightarrow{\gamma_g}$ close to the referenced vector $\widehat{\overrightarrow{\gamma_g}}$. The referenced vector is derived by the property of the Dirichlet distribution based on the empirical moments from the LEHD. Appendix F presents the detailed derivation.

(Step 2) Discretization: I discretize the distribution of vectors using a method analogous to vector quantization (VQ), following four stages. First, I generate a simulated dataset via Monte Carlo sampling from a Dirichlet distribution, $Dir(\overrightarrow{\gamma_g})$, with an initial vector value $\overrightarrow{\gamma_g}$. Second, I apply k-means clustering to the Monte Carlo sample,

[45] For more information, refer to the UI Replacement Rates Report from the U.S. Department of Labor.

[46] Appendix F shows the derivation of the referenced value used for the initial selection.

[47] Dirichlet distribution is a multivariate generalization of the beta distribution. For more information, refer to Chapter 26 of Johnson et al. (1995) or Chapter 40 of the first edition of Continuous Multivariate Distributions.

with the number of clusters corresponding to a pre-specified number of grid points. Third, I extract the centroids of each cluster, where k-means clustering minimizes within-cluster variance to ensure that these centroids serve as representative approximations of different segments of the distribution. These centroids are then used as grid points for the vector component $\overrightarrow{R_y}$. Finally, I assign workers to these centroids with probabilities proportional to the relative frequency of observations in each cluster, ensuring a probabilistic match between workers and the discretized representation of the distribution.

5.6 Quantitative Results

5.6.1 Model Validations

As shown in Table 10, the model performs well across several dimensions. It replicates the dispersion in earnings dynamics by aligning with key targets such as the earnings gap and the earnings growth of stayers and EE movers. Moreover, the model captures the wage level through the replacement rate, $b/\mathrm{E}(w)$. In addition, the model generates significant labor market dynamics, accurately reflecting the directed transition rates from unemployment to each employer group and the transitions between employer groups.

I further evaluate the model's fit using the untargeted share of EE transitions involving earnings cuts (ECUT share), which is the primary focus of this paper. In Table 11, the first column shows the ECUT shares from the linked NSCG-LEHD data (row 1-3) and the LEHD (row 4-5). Columns 2 and 3 show simulated ECUT shares from the model. Since the linked data only include workers with bachelors or higher, I compare the ECUT shares by motivations to those for the highest ability workers in the model. The first row reports the ECUT shares, from both data and model, for transitions driven exclusively by pecuniary motivations ("payonly"). The second row shows shares for transitions motivated by a combination of pecuniary and amenity considerations ("payplus"), while the third row displays shares for transitions driven purely by amenity-based or other non-pecuniary factors ("nopay"). While the model slightly under-predicts ECUT share relative to the data for the "payonly" category, the simulated shares demonstrate close alignment with the linked NSCG-LEHD data.

Furthermore, the model aligns closely with the observed ECUT shares reported in Table 3. Specifically, it estimates that 37.5% of EE transitions involve ECUTs, which corresponds closely to the observed 36.3% ECUT share for EE transitions within the

Table 9. Calibration

Param.	Description	Value	Targets
External Calibration			
β	Discounting rate	0.96	Risk-free interest rate 4%
b	Unemployment flow value	1.0	Normalization
ν_p	Std. of productivity distribution	0.35	S.d. of firm fixed effect
$\tilde{\lambda}_u$	Scalar component of λ_u	0.87	Quarterly job-finding rate 0.4
δ_x	Separation rates by worker type	$(.108, .092, .086, .070)$	ENE rates by education levels
Internal Calibration			
α	Worker bargaining power	0.36	Earnings gap $1 - \bar{w}_0/\bar{w}$
ι	Shape param. of Worker ability	2.8	Earnings growth of stayers
ρ	Reallocation shock	0.015	Overall mean EE rate
R_u	Vector component of λ_u	$(0.425, 0.275, 0.300)$	Outflow from unemployment
μ_p	Mean of productivity	0.8	Replacement rate $b/\mathbf{E}(w)$
$\bar{\phi}$	Upper bound of match preference	1.2	Earnings growth of movers
(κ_1, σ_1)	Shape parameters of Λ_1	$(12.3, 58.0)$	EE rate distribution of group 1
(κ_2, σ_2)	Shape parameters of Λ_2	$(11.8, 52.8)$	EE rate distribution of group 2
(κ_3, σ_3)	Shape parameters of Λ_3	$(27.1, 63.7)$	EE rate distribution of group 3
γ_1	Parameter of $\Gamma_1 = Dir(\gamma_1)$	$(4.9, 1.25, 0.35)$	Outflow ratio from group 1
γ_2	Parameter of $\Gamma_2 = Dir(\gamma_2)$	$(3.4, 2.9, 0.8)$	Outflow ratio from group 2
γ_3	Parameter of $\Gamma_3 = Dir(\gamma_3)$	$(3.7, 11.8, 6.8)$	Outflow ratio from group 3

Table 10. Targeted Moments

Moment	**Model**	**Data**
General Targets		
Earning gap $1 - \bar{w}_0/\bar{w}$	0.267	0.165
Earning growth of stayers	0.030	0.048
Earning growth of EE movers	0.168	0.178
Replacement rate $b/\mathbf{E}(w)$	0.32	0.40
Overall mean EE rate	0.058	0.062
Outflow ratio from unemployment	(0.360,0.305,0.335)	(0.393,0.287,0.320)
Group-specific Targets		
Average EE rate in group 1	0.074	0.076
S.d. of EE rate in group 1	0.045	0.045
Outflow from group 1	(0.518, 0.326, 0.156)	(0.543, 0.296, 0.161)
Average EE rate in group 2	0.056	0.059
S.d. of EE rate in group 2	0.048	0.046
Outflow from group 2	(0.209, 0.474, 0.316)	(0.257, 0.450, 0.293)
Average EE rate in group 3	0.046	0.051
S.d. of EE rate in group 3	0.043	0.043
Outflow from group 3	(0.073, 0.215, 0.712)	(0.092, 0.226, 0.682)

same county. Similarly, the model generates 31.2% of transitions that are associated with earnings declining more than 5%, closely mirroring the observed figure of 32.1%. Additionally, the modelâĂŹs ability to replicate similar ECUT shares across high-ability workers and all worker types is supported by the observations in Table 3. For subsequent analyses, motivations and transitions will be assessed across all worker types.

Table 11. ECUT Share: Data vs. Model

Motivations	Data	Model	
		Highest Ability Worker	All Worker Types
payonly	0.29	0.18	0.15
payplus	0.30	0.34	0.32
nopay	0.54	0.59	0.59
All (cutoff=0%)	0.363	0.383	0.375
All (cutoff=5%)	0.321	0.314	0.312

*Row 1-3 are ECUT shares from the linked NSCG-LEHD data which include workers with bachelor degrees or higher. Row 4-5 are ECUT shares from the LEHD data.

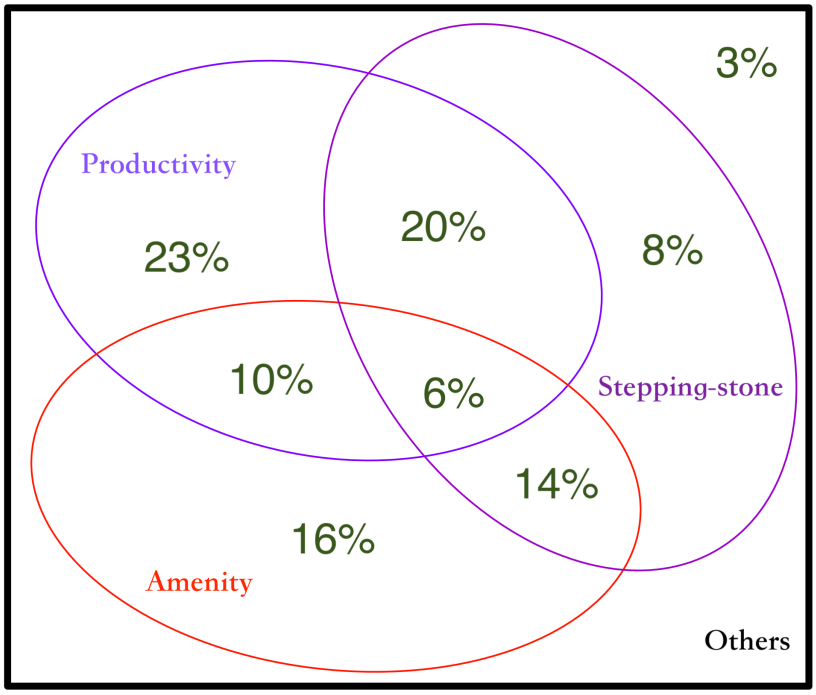
5.6.2 Motivation for Transitions and ECUTs

Following model validation, I use the model to relate each motivation type to both job transitions and ECUTs. The breakdown of pecuniary motivation is not directly observable in the data. However, the model highlights the role of stepping-stone motivation in shaping transitions and the resulting earnings dynamics.

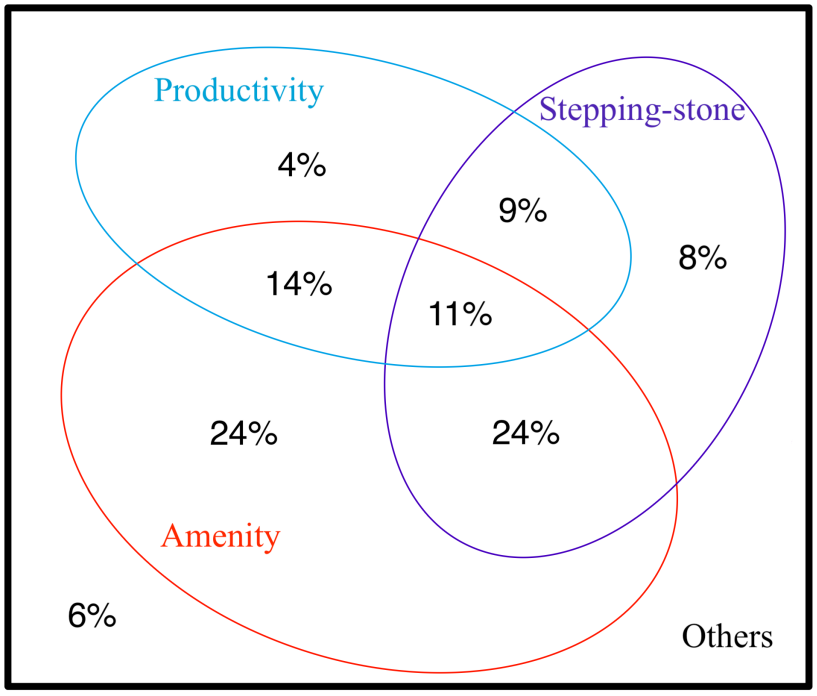
In Figure 9a, the box represents the universal set of transitions. Circles inside the box indicate the sets of transitions driven by previously defined motivations. Stepping-stone motivations, when combined with other factors, account for 48% of transitions and for 8% when they are the sole motivator. Transitions driven solely by productivity make up 23% of all transitions, but when combined with additional factors, productivity influences 59% of transitions. Non-pecuniary motivations affect 49% of transitions, with 16% driven exclusively by amenity considerations. Furthermore, 50% of transitions are driven by multiple factors, including 6% influenced by a combination of productivity, stepping-stone, and amenity motivations.

Figure 9b focus on the transitions with earnings cuts (ECUTs) and its distribution by different motivations. Specifically, stepping-stone motivations relate to 52% of ECUTs - 8% exclusively and 44% in combination with other motivations.[48] In contrast, 38% of ECUTs involve productivity. While non-pecuniary factors are the predominant driver of transitions involving earnings cuts - associated with 79% of ECUTs - stepping-stone motivations are the primary pecuniary driver in these cases.

[48]For transitions without earnings cuts, 46% involve stepping-stone motivations, 71% relate to productivity, and 30% are driven by amenity considerations.



(a) All Transitions



(b) Transitions with Earnings Cuts (ECUTs)

Figure 9. Share of Transitions by Motivations

Table 12 provides a different perspective by examining the share of ECUTs within each motivational category. Specifically, 24% of transitions driven by productivity involve earnings cutsbut when productivity is the exclusive motivator, the ECUT share drops to 7%, which explains the model's lower predicted ECUT share for transitions labeled as "payonly" in Table 11. In contrast, transitions motivated by stepping-stone employers exhibit a 40% ECUT share, which remains high at 38% for those driven solely by stepping-stone motivations. Transitions driven by non-pecuniary factors are associated with significantly higher ECUT shares compared to those driven by pecuniary considerations.[49] Overall, stepping-stone motivation emerges as a critical factor not only for transitions but also for earnings cuts, highlighting the significance of future opportunities in shaping both job mobility and wage dynamics.

Table 12. ECUT Share by Motivation

Motivations	Inclusively	Exclusively
Productivity	0.24	0.07
Stepping-stone	0.40	0.38
Amenity	0.60	0.57
Others	0.38	0.73

5.7 Counterfactual

To anatomize the influence of stepping-stone employers, I conduct three counterfactual exercises, each targeting a different aspect of employer heterogeneity in offer arrival rates, leaving other parameters unchanged.

In the first exercise, I eliminate differences in potential offer quantity by fixing the overall offer arrival rate constant at the average of total arrival rates in the baseline model. Offers remain heterogeneous in quality: once an offer arrives, it may originate from one of three employer groups, each with distinct productivity distributions. In the second counterfactual experiment, I neutralize variation in offer quality by setting the vector component $\overrightarrow{R_y} = (1/3, 1/3, 1/3)$. This adjustment maintains heterogeneity in arrival rates but unifies productivity distributions across received offers. Finally,

[49]The ECUT share for the transitions inclusively motivated by "Others" is 37.5%, as reported in Table 11, because this category indicates all transitions.

I remove heterogeneity in arrival rates altogether, assuming that workers search on-the-job with identical offer arrival rates, and all arrived offers are drawn from a unified productivity distribution, leaving employer differences confined to productivity, as in standard search models.

Table 13. ECUT Share of Counterfactuals

Motivations	Baseline	Quantity-Controlled	Quality-Controlled	No Stepping-stone
payonly	0.176	0.109	0.098	0.030
payplus	0.339	0.288	0.255	0.152
nopay	0.589	0.639	0.599	0.665
All (cutoff=0%)	0.375	0.364	0.314	0.292
All (cutoff=5%)	0.312	0.304	0.262	0.246

Table 13 reports the ECUT shares across three counterfactual scenarios, mirroring the structure of Table 11. The "Baseline" column restates the model's original results as a reference point. Across all transitions and within each motivation category, we observe a decline in the ECUT share. In the first counterfactual, "Quantity-Controlled," controlling for the heterogeneity in the quantity of offers results in a slight reduction in the ECUT share, though the effect is less pronounced compared to the second counterfactual, "Quality-Controlled." This pattern suggests that, while offer quantity heterogeneity influences ECUTs, variations in offer quality play a more significant role. In the third counterfactual, where both offer quantity and quality heterogeneities are neutralized, no stepping-stone motivation remains, leading to a minimal ECUT share of only 3% for pecuniary-driven transitions. For all transitions, the ECUT share falls below 30%, about 20% (7 percentage points) lower than the baseline. The ECUTs are driven primarily by non-pecuniary motivations. There are two main takeaways from the counterfactual results: First, the role of stepping-stone employers is mostly reflected by the heterogeneity in quality of offers that may arrive to the workers during on-the-job search. Second, stepping-stone motivation significantly contributes to transitions and ECUTs in the labor market, especially for those workers labeled for pecuniary reasons.

6 Conclusion

This paper provides an investigation into transitions, associated earnings dynamics, and highlights the role of stepping-stone employers in labor market dynamics. Using the LEHD and NSCG data, I confirm the prevalent ECUTs in U.S. and identify the motivations for transitions. The empirical evidence shows that, although non-pecuniary motivations do play a role, pecuniary motivations predominantly drive transitions. Even among workers who report financial gain as their sole reason for moving, ECUTs are frequent.

Further, the findings reveal that initial pecuniary motivations for job transitions align with higher future earnings growth and an increased likelihood of subsequent transitions. This pattern suggests that workers leverage certain transitions as strategic moves toward longer-term earnings potential rather than immediate gains. I identify a subset of firms that serve as "stepping-stones," offering workers improved transition opportunities toward more desirable employment outcomes. Finally, the theoretical model introduced in this paper provides a structured framework to interpret these findings. By modeling firms heterogeneous in job offer arrival rates, the model highlights that stepping-stone employers is an important pecuniary motivation for transitions and ECUTs in the labor market. Together, the empirical analysis and theoretical framework reveal that ECUTs are not merely an anomaly but rather an integral part of workers' forward-looking strategies to achieve improved career outcomes.

There are several potential sources of the observed heterogeneity in firms' transition rates. One is the differing importance of human capital accumulation across firms, as studied by Gregory (2020). Alternatively, Del Prato (2023) briefly discusses that certain firms may excel in signaling the abilities of their workers. This signaling advantage could be facilitated through social networks among coworkers (e.g. Fontaine, 2008; Bayer et al., 2008; Barwick et al., 2019), or through business interactions between firms, such as input-output relationships or firm-to-firm transactions (Cardoza et al., 2022; Komatsu, 2023). A future avenue could incorporate stepping-stone function into firm dynamics and relate these mechanism to demand side of labor market.

Census DMS Numbers
Project 2799: CBDRB-FY24-P2799-R11722

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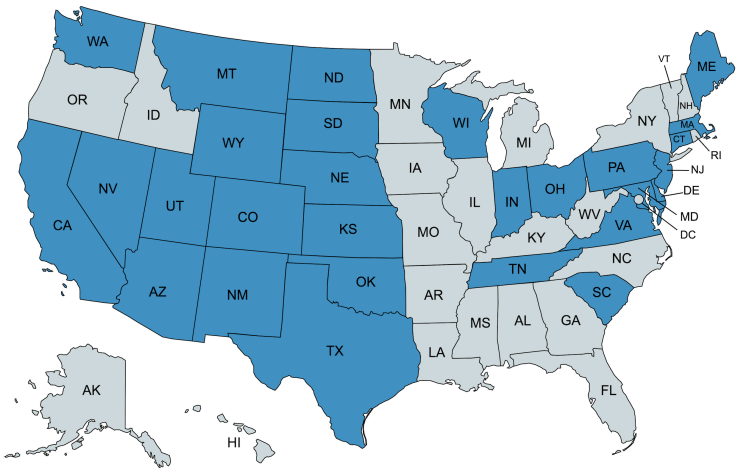
Appendix

A Datasets

A.1 Accessible States



28 accessible states are labeled in blue.

A.2 Statistics of the LEHD Dataset

Following the approach of Sorkin (2018), I implement two decomposition methodologies to achieve these aims. The decompositions serve two primary purposes. First, they facilitate an understanding of earnings dispersion within the annualized LEHD data analyzed in this study. Second, they yield estimates of firm fixed effects, which are subsequently employed to classify employers and identify "stepping-stone employers".

The first estimation is "ensemble decomposition" that follows the estimation by Card et al. (2018):

$$Var(log(w_{it})) = Cov(\alpha_i, log(w_{it})) + Cov(\psi_{j(i,t)}, log(w_{it})) + Cov(X_{it}\beta, log(w_{it})) + Cov(\varepsilon_{it}, log(w_{it})).$$

In this decomposition, the proportion of earnings variance attributable to firms is given by $\frac{Cov(\psi_{j(i,t)}, log(w_{it}))}{Var(log(w_{it}))}$. As indicated in Table A1, workers explain approximately 51% of the earnings variance, while firms explain about 24%. These results are closely

aligned with those from Sorkin (2018), where workers account for 57% and firms for 21% of the variance.

The second approach is the AKM decomposition:

$$Var(log(w_{it})) = Var(\alpha_i)+Var(\psi_{j(i,t)})+Var(X_{it}\beta)+Var(\varepsilon_{it})+2Cov(\alpha_i, \psi_{j(i,t)})+2Cov(\alpha_i+\psi_{j(i,t)}, X_{it}\beta).$$

Table A1 shows that the firm's contribution is approximately 15%, which is comparable to the 14% reported by Sorkin (2018) and the 12% reported by Song et al. (2019). The worker share in my sample (44%) is slightly lower than that in Sorkin (2018) (51%) and Song et al. (2019) (52%).

Appendix Table A1. LEHD: 2010-2019

	Sample	**Decomposed Share**
# Worker-year	601,300,000	
# Worker	107,100,000	
# Employer	544,000	
Mean of log earnings	10.6	
Variance of log earnings	0.78	
Ensemble Decomposition		
Worker	0.40	0.51
Employer	0.18	0.24
Variance Components		
Var(worker)	0.34	0.44
Var(employer)	0.12	0.15
Cov(worker, employer)	0.05	
Corr(worker, employer)	0.25	

A.3 Constructing the Linked NSCG-LEHD

I first link the quarterly LEHD data to each NSCG survey cycle year using the personal identity key in the crosswalk files. Each linked panel data covers the periods of the corresponding survey. Then I append these four linked panels together.

Before the appending, If a worker is observed in two consecutive surveys, I drop the last quarter of the first survey, which is also the first quarter of the second survey.

Note that workers may still have the last quarter of the survey if it's not followed by another survey.

A.4 Controlling Counties of Employers in the LEHD

To link the county of firms, I first need unique year-firm-county pair, which cannot be directly extract from the Employer-Characteristics Files (ECF). Because ECF are quarterly data, a firm may have multiple corresponding counties in the same year but different quarters.

There are 2 variables to identify "county": `MODE_ES_COUNTY_EMP` and `MODE_LEG_COUNTY_EMP`. While `MODE_ES_COUNTY_EMP` means that the information was sourced from the es202 data, `MODE_LEG_COUNTY_EMP` refers to the longitudinal employer geography (LEG) process that used to work towards assigning geographic information to the LEHD data. If a variable has the "LEG" naming convention, then it was assigned using this process. This paper uses `MODE_LEG_COUNTY_EMP` to identify and control counties of employers.

B More results about earnings dynamics after ECUT

B.1 Pecuniary motivation and future earning levels

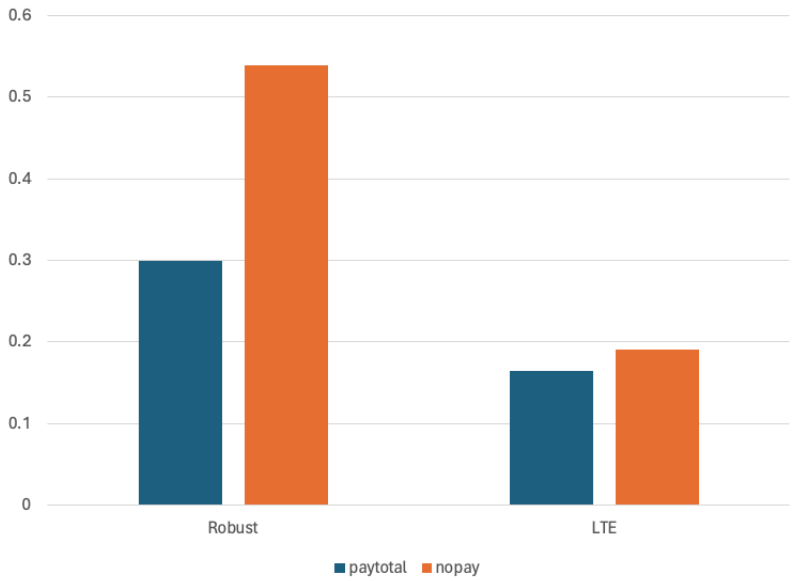
I begin with constructing "long-term earnings" to indicate future earning levels. Then I compare the change of estimated long-term earnings upon transitions for different motivations using the linked NSCG-LEHD dataset.

"Long-term earnings" at quarter t, LTE_t, is defined as the average quarterly log earnings over the subsequent four years, using a sample of workers with available records. The long-term earnings are then estimated based on the following specification:

$$LTE_{it} = \beta_1 x_{it} + \beta_2 x_i + \eta_t + \epsilon_{it}$$

where x_{it} is time-variant variables including the log earnings and earnings growth rate at quarter t, marital status, and polynomial of ages; x_i indicates the time-invariant variables including race and gender; η_t is year fixed effect.

In Figure A1, I compare the ECUT share measured by estimated long-term earnings, $\widehat{LTE}_t$, with the share calculated using a robust measure of ECUTs. I combine the categories "payonly" and "payplus" into a single category, "paytotal," which includes all movers motivated by pecuniary factors.



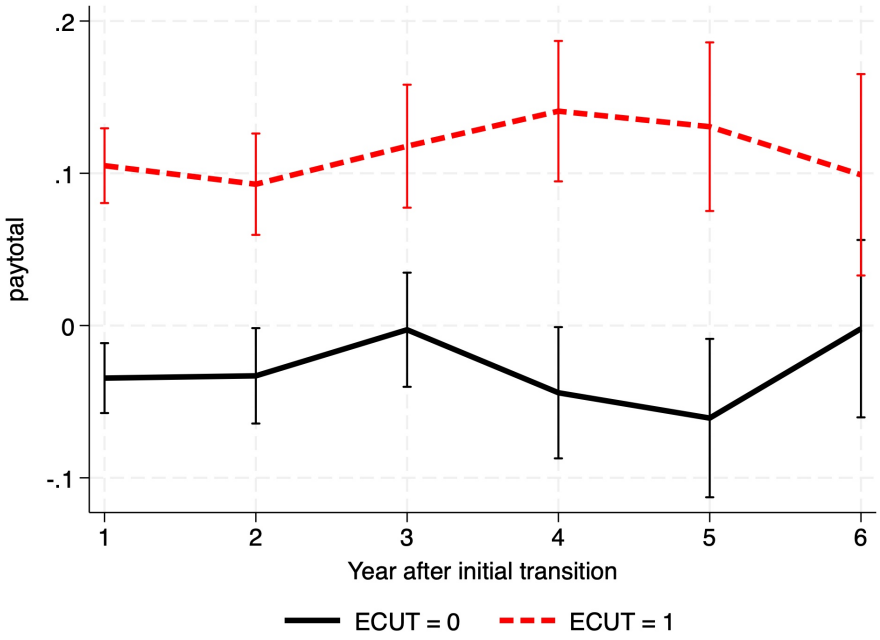
Appendix Figure A1. ECUT Share: Robust v.s. LTE

Compared to the share of ECUTs calculated using immediate earnings, a smaller proportion of movers experience a decline in $\widehat{LTE}_t$ following transitions, especially those who move for pecuniary reasons. Additionaly, among movers with immediate earnings declines, 29% also experience a reduction in $\widehat{LTE}_t$. In contrast, this conditional probability is only 10% for movers without immediate earnings cuts. Therefore, while earnings may initially decline following a transition, they typically recover and eventually exceed pre-transition levels.

B.2 Pecuniary motivation and future earning growths

To examine whether movers driven by pecuniary motives experience distinct earnings dynamics depending on the occurrence of an earnings cut (ECUT), I estimate regression 1 separately for two groups of movers: those who experience an earnings cut (ECUT=1) and those who do not (ECUT=0). If the hypothesis holds that workers who transition for pecuniary reasons but encounter an earnings cut anticipate higher future earnings, we would expect the coefficients β_1^τ for movers with ECUTs to exceed those for movers without ECUTs. Figure A2 provides evidence in support of this hypothesis.

For workers who experience earnings cuts during transitions, those motivated by pecuniary factors exhibit, on average, 11 percentage points higher wage growth compared to those driven by non-pecuniary factors. This wage growth premium remains



Appendix Figure A2. $\hat{\beta}_1^{\tau}$ and 90% Confidence Interval

stable over a 1-6 year period following the initial transition. In contrast, for workers who did not experience earnings cuts, the correlation between motivation and wage growth is either insignificant or slightly negative, suggesting that pecuniary motivation does not yield significantly different wage outcomes relative to non-pecuniary motivation. This implies that, for workers who already maintain or increase their wages upon transition, the initial reason for their move (pecuniary or non-pecuniary) does not appear to matter much in terms of future wage growth. Both groups tend to experience similar wage trajectories after the transition.

C Persistence and Dispersion of Transition Rates

$$\Pi_t^{EE} = \beta \Pi_{t-1}^{EE} + \epsilon_t$$

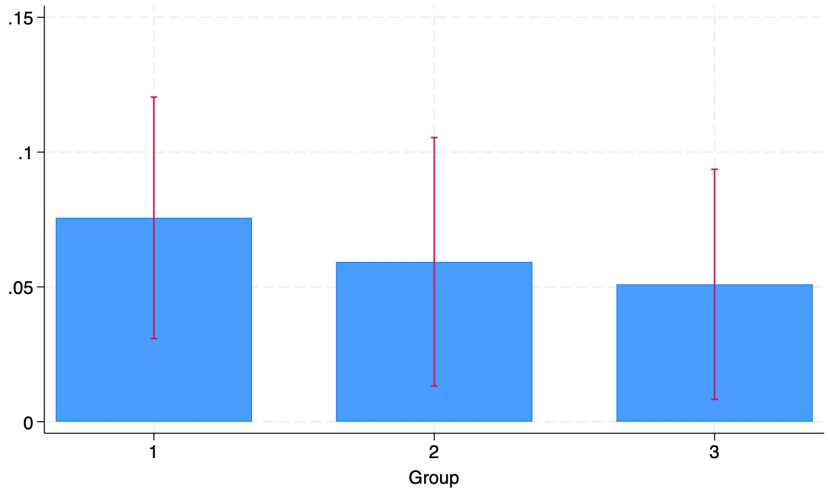
Figure A3 illustrates the group-specific moments from Table 10, each solid bar represents the weighted average transition rate for each employer group, with weights based on firm employment size. The error bars show one standard error within each employer group. Notably, the figure demonstrates a substantial dispersion of transition rates both within each employer group and across the overall distribution. In

Π_t	(1)	(2)	(3)	(4)
Π_{t-1}^{EE}	0.8754	0.8796	0.9015	0.9167
	(0.0003499)	(0.0003201)	(0.001156)	(0.000276)
Year FE	N	N	Y	Y
R^2	0.7502	0.7521	0.8355	0.8381
Observations	3110000	3110000	3110000	3110000

Following the disclosure policy of U.S. census, the number of observations are rounded numbers.

Appendix Table A2. Coefficients of AR(1) for transition rates

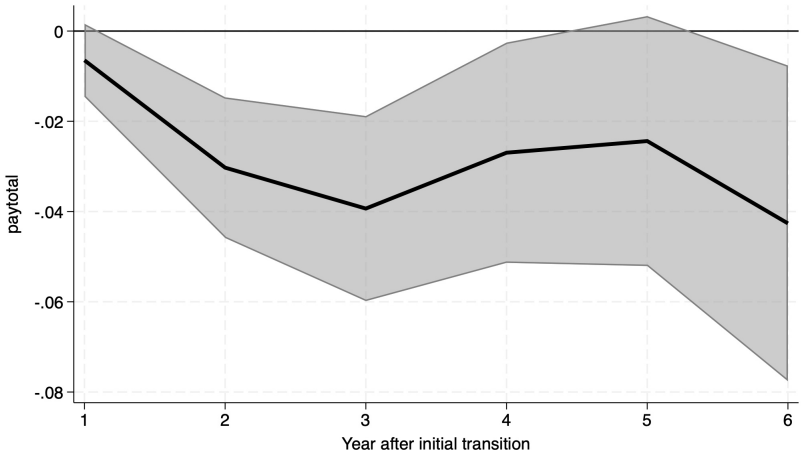
addition, employer group 3, which has the highest level of $\hat{\psi}_j$, exhibits the lowest mean transition rate, whereas employer group 1, with the lowest level of firm fixed effect, displays the highest mean transition rate.



Appendix Figure A3. Mean and standard deviation of EE Transition rates by employer groups

D Subsequent transitions and Working Conditions

Reported pecuniary motivations, alongside factors related to "working conditions," show a negative association with the likelihood of subsequent job transitions. Figure A4 illustrates a strong negative correlation between "working conditions" and the probability of future transitions.



Appendix Figure A4

Appendix Figure A5. $\hat{\beta}_1^{\tau}$ and 90% Confidence Interval

E Derivation of Joint Surplus

By definition, $S(x,\theta,\theta') = max\{W(x,\theta,\theta') - U(x) + J(x,\theta,\theta'), 0\}$. After plugging equations (6) and (7), we have

$$
\begin{aligned}
S(x,\theta,\theta') = \max\Bigg\{ & 0, u(w,\phi_y) + f(x,p_y) - w(x,\theta,\theta') + \beta\delta_x U(x) - U(x) \\
& + \beta(1-\delta_x)\Bigg[\tilde{\lambda}_y \sum_{g_z} r_{gg_z} \int_{\phi} \Bigg(\int\int\int_{\Omega_1} W(x,\theta_z,\theta) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \\
& + \int\int\int_{\Omega_2} [W(x,\theta,\theta_z) + J(x,\theta,\theta_z)] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \\
& + \int\int\int_{\Omega_3} [W(x,\theta,\theta') + J(x,\theta,\theta')] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \Bigg) dH(\phi_z) \\
& + (1-\tilde{\lambda}_y)\Bigg[(1-\rho)\Big(W(x,\theta,\theta') + J(x,\theta,\theta')\Big) \\
& + \rho \int_{\phi}\int\int\int \max\{W(x,\theta_{z'},\theta_u), U(x)\} dF_{g_{z'}} d\Lambda_{g_{z'}} d\Gamma_{g_{z'}} dH(\phi_{z'})\Bigg]\Bigg]\Bigg\}.
\end{aligned}
$$

Then replace the $W(x,\theta,\theta')$ and $J(x,\theta,\theta')$ with $S(x,\theta,\theta')$ and $U(x)$ using the definition,

$$
\begin{aligned}
&S(x,\theta,\theta') = \max\Bigg\{0, u(w,\phi) + f(x,p_y) - w(x,\theta,\theta') + \beta\delta_x U(x) - U(x) + \\
&\beta(1-\delta_x)\Bigg[\int_\phi \tilde{\lambda}_y \sum_{g_z} r_{gg_z}\Bigg(\int\int\int_{\Omega_1}\Big[U(x) + S(x,\theta,\theta') + \alpha[S(x,\theta_z,\theta) - S(x,\theta,\theta')]\Big]dF_{g_z}d\Lambda_{g_z}d\Gamma_{g_z} \\
&+ \int\int\int_{\Omega_2}[S(x,\theta,\theta_z) + U(x)]dF_{g_z}d\Lambda_{g_z}d\Gamma_{g_z} + \int\int\int_{\Omega_3}[S(x,y,\phi,y',\phi') + U(x)]dF_{g_z}d\Lambda_{g_z}d\Gamma_{g_z}\Bigg)dH(\phi_z) \\
&+ (1-\tilde{\lambda}_y)\Big[(1-\rho)\Big(S(x,\theta,\theta') + U(x)\Big) \\
&+ \rho\int_\phi\int\int\int[W(x,\theta_{z'},\theta_u) - U(x)]^+ dF_{g_{z'}}d\Lambda_{g_{z'}}d\Gamma_{g_{z'}}dH(\phi_{z'}) + \rho U(x)\Big]\Bigg]\Bigg\}
\end{aligned}
$$

Plugging equation (5) and replacing $U(x)$ in the above,

$$
\begin{aligned}
&S(x,\theta,\theta') = \max\Bigg\{0, u(w,\phi) + f(x,p_y) - w(x,\theta,\theta') - u(b_x) \\
&- \alpha\beta\int_\phi\Bigg(\tilde{\lambda}_u\sum_{g_z} r_{ug_z}\int\int\int\big[S(x,\theta_z,\theta_u)\big]^+ dF_{g_z}d\Lambda_{g_z}d\Gamma_{g_z}\Bigg)dH(\phi_z) + \\
&\beta(1-\delta_x)\Bigg[\int_\phi \tilde{\lambda}_y\sum_{g_z} r_{gg_z}\Bigg(\int\int\int_{\Omega_1}\Big[S(x,\theta,\theta') + \alpha[S(x,\theta_z,\theta) - S(x,\theta,\theta')]\Big]dF_{g_z}d\Lambda_{g_z}d\Gamma_{g_z} \\
&+ \int_{\Omega_2}[S(x,\theta,\theta_z)]dF_{g_z}(z) + \int_{\Omega_3}[S(x,\theta,\theta')]dF_{g_z}d\Lambda_{g_z}d\Gamma_{g_z}\Bigg)dH(\phi_z) \\
&+ (1-\tilde{\lambda}_y)\Big[(1-\rho)S(x,\theta,\theta') + \rho\alpha\int_\phi\int[S(x,\theta_{z'},\theta_u)]^+ dF_{g_{z'}}d\Lambda_{g_{z'}}d\Gamma_{g_{z'}}dH(\phi_{z'})\Big]\Bigg]\Bigg\}
\end{aligned}
$$

If the utility function is quasi-linear in wages, such that $u(w,\phi) = w + c(\phi)$, and

conjecture that the surplus function does not depend on the outside options, then

$$
\begin{aligned}
&S(x,\theta,\theta') = S(x,\theta) = \max\Bigg\{0, c(\phi) + f(x,p_y) - u(b_x) \\
&- \alpha\beta \int_{\phi} \Bigg(\tilde{\lambda}_u \sum_{g_z} r_{ug_z} \int\int\int \big[S(x,\theta_z)\big]^{+} dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \Bigg) dH(\phi_z) + \\
&\beta(1-\delta_x) \Bigg[\int_{\phi} \tilde{\lambda}_y \sum_{g_z} r_{gg_z} \Bigg(\int_{\Omega_1} \big[S(x,\theta) + \alpha[S(x,z,\phi_z) - S(x,\theta)]\big] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \\
&+ \int_{\Omega_2} S(x,\theta) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} + \int_{\Omega_3} S(x,y,\phi) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \Bigg) dH(\phi_z) \\
&+ (1-\tilde{\lambda}_y)(1-\rho) S(x,\theta) + (1-\tilde{\lambda}_y)\rho\alpha \int_{\phi} \int [S(x,\theta_{z'})]^{+} dF_{g_{z'}} d\Lambda_{g_{z'}} d\Gamma_{g_{z'}} dH(\phi_{z'}) \Bigg] \Bigg\}
\end{aligned}
$$

Recall that $\Omega_3(x,\theta,\theta') \equiv (\Omega_1 \cup \Omega_2)^{\complement}$, we can combine and simplify the integral terms with offer sets, such that

$$
\begin{aligned}
&S(x,\theta) = \max\Bigg\{0, c(\phi) + f(x,p_y) - u(b_x) \\
&- \alpha\beta\tilde{\lambda}_u \sum_{g_z} r_{ug_z} \int_{\phi} \int\int\int \big[S(x,\theta_z)\big]^{+} dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) + \\
&\beta(1-\delta_x) \Bigg[\alpha \sum_{g_z} \lambda_{gg_z} \Bigg(\int_{\phi} \int\int \int_{\Omega_1} [S(x,\theta_z) - S(x,\theta)] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} \Bigg) dH(\phi_z) \\
&[1 - \rho(1-\tilde{\lambda}_y)] S(x,\theta) + (1-\tilde{\lambda}_y)\rho\alpha \int_{\phi} \int\int\int [S(x,\theta_{z'})]^{+} dF_{g_{z'}} d\Lambda_{g_{z'}} d\Gamma_{g_{z'}} dH(\phi_{z'}) \Bigg] \Bigg\}
\end{aligned}
$$

This is the expression offered in the main text which also verifies that the joint surplus does not depend on the threat offer.

F Referenced Values for Initiation

Derive the referenced value of Beta distribution for scalar component: I initially choose the values close to the referenced values derived by the weighted mean ($\hat{E}_g$) and variance ($\hat{V}_g$) of the group g in the dataset. I back out the referenced values by:

$$\kappa_g = \frac{\hat{E}_g(1-\hat{E}_g)}{\hat{V}_g^2} - 1, \text{ and } \sigma_g = \kappa_g \left(\frac{1-\hat{E}_g}{\hat{E}_g} \right).$$

Derive the referenced value of Dirichlet distribution for vector component: Specifically, let $\hat{r}^j_{gg'}$ be the estimated flow ratio of firm j from group g to group g', i.e. $\hat{r}^j_{gg'} = \frac{\sum \mathbf{1}\{\text{EE movers to } g'\}}{\sum \mathbf{1}\{\text{EE movers}\}}$. Using the mean and variance of $\hat{r}^j_{gg'}$, we can derive the reference values $\hat{\gamma}_{gk}(k=1,2,3)$ for a Dirichlet distribution. Following

$$E(\hat{r}^j_{gk}) = \frac{\hat{\gamma}_{gk}}{\hat{\gamma}^0_g}, \text{ and } \operatorname{Var}(\hat{r}^j_{gk}) = \frac{\hat{\gamma}_{gk}(\hat{\gamma}^0_g - \hat{\gamma}_{gk})}{(\hat{\gamma}^0_g)^2(\hat{\gamma}^0_g+1)},$$

where $\hat{\gamma}^0_g = \sum_{k'} \hat{\gamma}_{gk'}$, we can derive

$$\hat{\gamma}_{gk} = \frac{E^2(p^j_k)[1-E(p^j_k)]}{Var(p^j_k)} - E(p^j_k) = \frac{E(\hat{r}^j_{gk})[E(\hat{r}^j_{gk}) - E((\hat{r}^j_{gk})^2)]}{E((\hat{r}^j_{gk})^2) - E^2(\hat{r}^j_{gk})}.$$

where $E(\hat{r}^j_{gg'})$ and $E((\hat{r}^j_{gg'})^2)$ are mean flow ratios and their squared form weighted by firm size in group g.