Earnings Cuts Upon Transitions and the Role of Stepping-stone Employers

Xiaonan Ma*

University of Rochester
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Abstract

This article studies the prevalence and drivers of earnings cuts upon transitions (ECUTs) in U.S. labor market. Using linked administrative-survey dataset, I identify the workers' reported motivations for transitions and study their relationship to ECUTs. I find that half of ECUTs are related to pecuniary motivation, and 29% of transitions motivated only by pecuniary reason still involve ECUTs, suggesting a potential tradeoff between current and future earnings during job transitions. Further analyses show that workers who transition for pecuniary reasons have higher future earnings growth and higher probability of subsequent transitions. I then argue that certain employers serve as "stepping-stones" by offering better prospects of moving to better employers. Pursuing such 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. Quantitative results suggest that stepping-stone employers, particularly those with higher arrival rates of quality offers, function as a critical pecuniary motivation for ECUTs and transitions.

JEL codes: E20, E24, J31, J60

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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 contribute to widening earnings inequality or declines in worker well-being. Examining the motivations underlying these ECUTs shed light on the mechanisms shaping labor market dynamics and the evolution of earnings trajectories.

Recent research has proposed several potential explanations for ECUTs. First, limitations in data structure may introduce measurement errors that overestimate the incidence of ECUTs (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; 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 such as 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 ECUTs. These datasets provide workers' self-reported motivations for transitions and their relation-

[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.

[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*.

ship with ECUTs. The empirical findings introduce an often-overlooked pecuniary motivation for job transitions: the prospect of future transitions to other employers. 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 employer-to-employer (EE) transitions. This pattern holds consistently across years and is largely stable across worker characteristics, including gender, education level, and age. Moreover, I show that the prevalence of ECUTs cannot be attributed primarily to difference across locations or measurement errors in transition timing.

The empirical analysis proceeds in three stages to examine the frequent ECUTs. First, I explore the driving factors behind transitions and their associated earnings cuts. The NSCG shows that the pecuniary reason is the most selected one for transitions, accounting for more than 60%. By linking the LEHD data with the NSCG, I show that non-pecuniary motivations alone do not fully explain the occurrence of ECUTs. Notably, half of the workers who experience ECUTs cite pecuniary reasons as either their sole or a contributing factor for transitioning, and 29% of those who report pecuniary motivations alone still incur ECUTs. The findings suggest that workers may perceive ECUTs as a strategic decision, aimed at future earnings growth through improved job matches.

Second, I extend the analysis 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 and earnings dynamics.

In the third empirical stage, I first examine the relationship between workers' transition motivations and their subsequent mobility. Prior research has established that job transitions are common and positively associated with long-term earnings growth (Topel and Ward, 1992). Moreover, early-career employer changes tend to result in wage gains (Borovičková and Macaluso, 2024). My findings extend this literature by showing that a substantial share of workers transition again shortly after their initial move. Notably, workers who report pecuniary motives for their transitions are 5 percentage points more likely to switch employers again within three years of their initial transitions.

Next, I study the role of employers as "stepping-stone" in ECUTs. The intuition is that, if employers' transition rates are persistent, workers may accept lower initial wages from employers that offer higher probabilities of transitioning to more desirable employers. Using LEHD data, I first confirm the persistence and substantial dispersion in firm-level transition rates. Regression results further indicate a negative relationship between a firm's transition rate to higher-paying firms and workers' earnings changes upon joining the firm.

Building on the empirical results, I develop the search model in Cahuc et al. (2006) to formalize and further examine the role of stepping-stone employers in labor market dynamics. In this framework, 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, with each element indicating the employer groups from which the offers are sent.

The heterogeneity of vectorized offer arrival rates makes some employers that provide better opportunities to workers career-wise and thus serve as "stepping-stones" for them. Specifically, vectorized arrival rates capture 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. The vector component represents the conditional probability of transitioning from the current employer group to other employer groups upon receiving an offer, thereby capturing the quality dimension of job opportunities. Within this framework, stepping-stone employers are defined as those offering a "better" arrival rate, characterized by either a higher scalar component (indicating a greater volume of offers), a more favorable vector component (implying an increased likelihood of offers originating from more productive employers), or a combination of both. Increasing the offer arrival rate from the employer group with low average productivity (low quality offer) may not make the offer more attractive as it could crowd out the probability of receiving offers from the employer group with high average productivity (high quality offer).

The model allows for a detailed decomposition of transition motivations into pecuniary and non-pecuniary drivers. Among pecuniary motivations, I distinguish between "productivity motivation" and "stepping-stone motivation." The former drives transitions to more productive employers. The stepping-stone motivation captures a worker's incentive to transition toward stepping-stone employers. Non-pecuniary motivations are further categorized into "amenity" and "others". Amenity-driven transitions reflect an increasing preferences for the new match, while the "others" category captures transitions motivated by factors outside the previously defined dimensions. This decomposition allows for evaluation of the model's fit through comparisons with self-reported motivations in the linked dataset. It also highlights the critical, yet often unobservable, role of stepping-stone employers in transitions and ECUTs.

The model is calibrated using LEHD data and employs a novel vector quantization algorithm to efficiently simulate the vectorized offer arrival rate. This approach allows the model to replicate key labor market moments effectively and align closely with the untargeted ECUT share, as well as its breakdown by reported motivations derived from the linked NSCG-LEHD data. Importantly, the model yields insights into the role of stepping-stone employers, which is not directly observable from the data. The analysis reveals that 48% of all transitions and 52% of transitions with earnings cuts involves stepping-stone motivations. Moreover, approximately 40% of transitions for stepping-stone employers are associated with earnings cuts. These results highlight the significance of stepping-stone motivations as a central driver of pecuniary incentives, influencing both transitions and broader earnings dynamics in the labor market.

To further examine the influence of stepping-stone employers, I conduct three counterfactual experiments. Specifically, I control for variations in the quantity, quality, and combined attributes of offer arrival rates. The exercise reveals that, in the absence of stepping-stone employers, the share of ECUTs is approximately 22% (or 8 percentage points) lower than the baseline. However, controlling only for heterogeneity in offer quantities results in a mere 1 percentage point decline in the ECUT share. These results highlight two key insights: (1) the impact of stepping-stone employers is driven primarily by differences in offer quality, and (2) stepping-stone motivation serves as a pivotal pecuniary driver of both job transitions and ECUTs.

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 research uses 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 NSCG to analyze ECUTs. To the best of my knowledge, this is the first study to examine ECUTs in U.S. with detailed worker characteristics, and their relationship with underling motivations for transitions.

This paper identifies and explores the drivers of ECUTs by analyzing self-reported reasons from the linked survey-administrative data. This methodology bridges multiple strands of literature on the determinants of transitions and the associated earnings cuts, 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 motivations reported for transitions and quantifying their impact on earnings dynamics.

The second strand of literature emphasizes pecuniary motivations as an explanation for ECUTs. It is established that workers' transitions are driven by expectations of future returns (Topel and Ward, 1992; Borovičková and Macaluso, 2024). Literatures that study the role of employers in the decision of transitions focus on their productivity. For instance, Postel-Vinay and Robin (2002) and Cahuc et al. (2006) introduce a sequential auction model in which workers may accept initial wage cuts to transition to higher-productivity employers, who offer steeper future wage growth. Since then, a growing body of research has enriched this wage-setting mechanism by incorporating additional dimensions of employer heterogeneity.[4]

This paper contributes to the sequential auction framework by introducing a novel dimension of employer heterogeneity: a vectorized offer arrival rate that captures both the quality and quantity of future job offers. This extension provides a new lens to understand "stepping-stone employers" as a pecuniary mechanism driving transitions 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 an employer attribute reflecting heterogeneity in meeting rates, approximated empirically through a firm's degree centrality within a labor flow network. 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 through heterogeneous, vectorized offer arrival rates. I further link this concept to pecuniary motivations for transitions and quantify its role in shaping labor market dynamics, while accounting for both pecuniary and non-pecuniary determinants of worker mobility.

Roadmap

The remainder of the paper is organized as follows. Section 2 provides an overview of the datasets. Section 3 examines the patterns of ECUTs, the reported motivations for transitions, and their relationships with future earnings dynamics. Section 4 provides suggestive evidence that some employers function as stepping-stones for workers. In Section 5, I develop a search model to formalize the concept of stepping-stone employers and quantify their role in transitions and ECUTs. Finally, Section 6 concludes.

[4] For example, Gregory (2020) examines how variation in firms' learning environments affects workers' human capital accumulation. Jarosch (2023) explores how differing separation rates across jobs affect workers' choices.

[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: the Longitudinal Employer-Household Dynamics, the National Survey of College Graduates, 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 LEHD and the linked NSCG-LEHD data cover 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 define a transition as occurring when a worker's current employer differs from their employer in the previous year. I classify transitions into two types: employer-to-employer (EE) transitions and employer-to-nonemployment-to-employer (ENE) transitions.[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 National Survey of College Graduates is a biennial survey of college graduates that has been conducted since the 1970s. It samples individuals who are living in U.S. during the survey reference week, have earned at least a bachelor's degree, and are younger than 76.[13] I utilize four survey cycles that together document respondents'

[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 popu-

answers from the week of October 1, 2010, to the week of February 1, 2019.

The questionnaire of the NSCG provides detailed information about labor participation. Specifically, the following questions in Part B of each questionnaire includes a series of questions designed to capture respondents' employment histories.

Question B1:

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

1. *Yes*
2. *No*

In Question B1, t_1 and t_2 are the starting and ending date of the survey, respectively. For example, in the 2013 survey cycle, t_1 refers to Oct. 1, 2010, and t_2 to Feb. 1, 2013. Similarly, in the 2019 cycle, t_1 represents February 1, 2017, while t_2 denotes February 1, 2019.[14] Table 1 shows that 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 and in same type of job*
2. *Same employer but in different type of job*
3. *Different employer but in same type of job*
4. *Different employer and 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. I focus on the latter one, which account for about three quarters of transitions.

lation 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.

[14]The reference periods for 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 Question B1 and the choice 1 of Question B2 will lead to questions in part C about other work-related experience, which will not be discussed in this paper.

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

From Table 1, we find that weekly working hours in NSCG are heavily concentrated around 40 hours, which is consistent with Bick et al. (2022). The reported annual salary is nominal and increasing. 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.

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

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*

Question B3 offers valuable insights into the motivations behind job transitions. First, the provided options capture a broad range of potential factors, including pecuniary reasons (pay or promotion opportunities)[17], amenities (e.g. working conditions, locations), individual reasons (e.g. family-related, school-related, changed interest or career), and other reasons (e.g. retire, laid off, some other reason).Second, the consistency and stability of Questions B1-B3 across all four survey waves enhance the reliability of the data. Notably, these surveys draw from the same dataset framework, the American Community Survey (ACS), ensuring a comparable respondent base. Third, the allowance for workers to report multiple reasons is particularly significant. This feature enables a richer understanding of the multifaceted nature of job transition decisions, a nuance that is absent in other major datasets such as the NLSY, CPS, PSID, and SIPP. 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.

2.3 The Linked NSCG-LEHD

To study the relationship between employment and reported reasons of transitions, I construct a quarterly panel from 2010Q1 to 2019Q1 by merging and appending four NSCG surveys to the LEHD data based on the unique protected identification key.[18]

I impose two restrictions on employment records in the linked dataset. First, I limit the analysis to a sample of "consistent movers" - workers 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.[19] Table 2 shows that imposing the consistency restriction reduces the linked sample size by approximately 20%, both in terms of total observations and the number of distinct workers.

Table 2. Summary of Linked NSCG-LEHD and Consistent Workers

	2013	**2015**	**2017**	**2019**	**All**
# Linked worker-quarter	461,000	372,000	335,000	412,000	1,581,000
# Linked workers	55,000	47,500	43,000	49,500	112,000
# Consistent worker-quarter	354,000	294,000	266,000	326,000	1,240,000
# Consistent workers	44,500	38,500	35,000	41,000	98,500

Second, to properly identify motivations for transitions, I restrict the sample to movers who change employers only once during each survey reference period. This restriction addresses cases where workers report multiple transitions within a single reference period, which could obscure the relationship between their stated motiva-

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

[19]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.

tions for transitions and their observed labor market behavior. As shown in Table 3, 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.

Table 3 presents summary statistics for all consistent workers and for movers who experienced a single transition during the survey reference period.[20] 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.[21]

The linked data offer two key insights into EE transitions and earnings dynamics. First, they leverage the NSCG that prompts workers to report the starting month and year of their principal job.[22] This allows for precise tracking of job transitions and the timing of employment changes.

[20] 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.

[21] 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.

[22] 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])?*

Table 3. 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
# Observations	229,000	173,000

Numbers of observations are rounded following disclosure policy of US census.

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. In Section 3.1, I will use this information to properly measure the share of transitions with earnings cuts (ECUT share).[23]

Second, the linked NSCG-LEHD 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.

[23] 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.

3 Earnings Dynamics and Transitions

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

3.1 ECUTs in U.S.

Using the annualized panel data from the LEHD, I define an earning cut upon transition (ECUT) as an incidence that a worker's first annualized earnings after a transition falls below her earning from the previous employer in the last year. To measure the prevalence of ECUTs, I calculate the share of ECUTs relative to all observed transitions each year. Figure 1 illustrates the annual ECUT shares, categorized by transition types as defined in Section 2. The ECUT share 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.

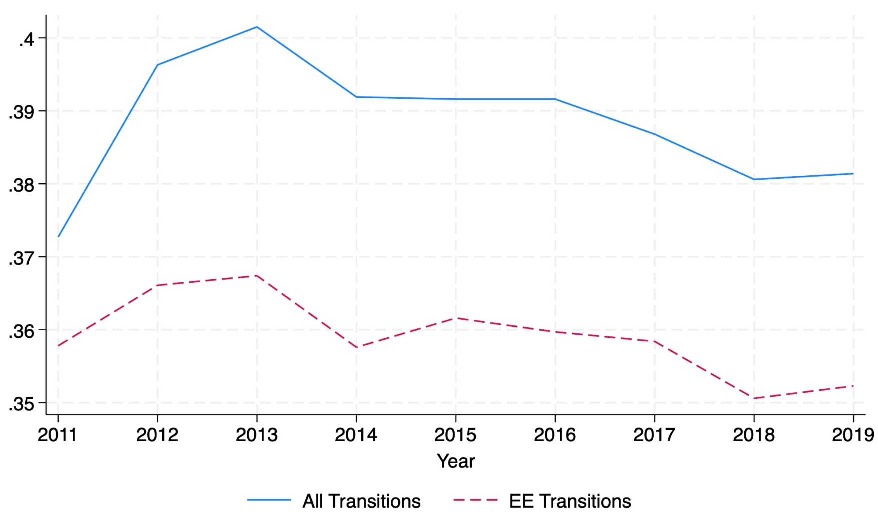


Figure 1. Annualized ECUT share

Furthermore, I examine the share of ECUTs across various worker characteristics. As shown in Panel A of Table 4, the ECUT share differs only marginally between college-educated and non-college-educated workers. Likewise, the gap in ECUT shares between male and female movers is negligible. Although workers under 40 exhibit lower ECUT share compared to their older counterparts, earnings cuts still account for over one-third of transitions among younger movers.[24]

On the intensive margin, the average change of earnings conditional on ECUTs is -29.13%, and the conditional pseudo median change if -24.12%.[25] In addition, I recalculate ECUT share using a more restrictive criterion for ECUT incidence. Specifically, when ECUT is defined as a drop in earnings of more than 5% upon transition, Table 4 shows that over a third of transitions still result in earnings cuts. These suggest that a significant proportion of ECUTs are not concentrated into minor reductions in earnings. Overall, Figure 1 and Panel A of Table 4 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.[26]. 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 may vary significantly across locations. For example, a worker moving from Manhattan to Rochester, New York State, may see a earnings decline of 10 percent, yet this may not constitute an "real" ECUT due to Rochester's lower cost of living.[27] If many transitions are of this nature, accounting for location changes would explain a substantial share of observed ECUTs.

To address this concerns, I focus on the workers whose employers before and after the transitions are located in the same county.[28] Panel B of Table 4 shows this county-controlled ECUT share. A comparison with the unconditional ECUT share in Panel A reveals that the shares are generally similar for the movers in the same counties, suggesting that change of locations is not the primary drivers of frequent ECUTs.

[24]Older workers exhibit a higher likelihood of experiencing ECUTs, potentially due to a greater propensity for transitions driven by non-pecuniary considerations. Ma (2024) examines the relationship between transition motivations and worker demographic characteristics, shedding light on this pattern.

[25]By the disclosure policy of FSRDC, researchers should calculate a pseudo-quantile (or pseudo-percentile). That is, take the mean value from a subset of observations around the percentile âĂŞ the true quantile and at least five observations on either side, for a total of at least 11 observations for a given quantile.

[26]Possible mechanisms behind this phenomenon are studied by Baum-Snow and Pavan (2012) and Roca and Puga (2017). However, this is not the focus of this paper.

[27]For cost-of-living data by county, metro area, or state, see MIT Living Wage Calculator.

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

Table 4. 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.

Another measurement error could be the timing of employment or transitions, 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 overestimate the measure of ECUT ratio if the new job begins at t, and an idereste if it starts at $t-1$. Consequently, the ECUT share presented in Table 4, based on annualized earnings, may be biased towards 50%.

To address the measurement issue and verify the ECUT shares in Table 4, I resort to the linked NSCG-LEHD dataset with reported job start dates. 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 5. 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	13,000	13,000	8,079,000

Number of transitions are rounded to thousands.

The ECUT share based on this robust measure is shown in the first column of Table 5, labeled "Robust Measure." For comparison, the second column of Table 5, 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 4.

Table 5 highlights two key insights. 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 consistency of ECUT share in robust measure and annualized panel supports the reliability of the annualized ECUT shares in Table 5.

In sum, ECUTs are persist with notable frequency across the U.S. labor market over the years, irrespective of worker characteristics. This ECUT share is hardly attributed to measurement errors, such as the move across locations or conflating of EE transitions with ENE transitions. In Appendix C, I also show that the change of working hours is unlikely to dominate the considerable share of ECUTs on extensive and intensive margin.

3.2 Transition Motivations and ECUTs

ECUTs are a prominent feature of the U.S. labor market, but what mechanisms underpin this phenomenon? Answering this question requires identifying the primary motivations behind transitions, particularly those involving ECUTs. If non-pecuniary factors dominate, then non-wage job attributes or individual-specific shocks may provide key explanations for ECUTs. Conversely, if pecuniary considerations are the main drivers, it becomes essential to pinpoint the specific financial factors - such as immediate wage adjustments or long-term earnings prospects - that account for the prevalence of ECUTs.

Using the linked NSCG-LEHD dataset, I find that pecuniary reasons emerge as the predominant reasons for changing employers. Figure 2 displays the distribution (proportion) 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, 65.4% of movers cite "pay or promotion opportunities" as a reason of changing employers. Nevertheless, amenities - such as working conditions (51.7%) and job location (36.3%) - also contribute meaningfully to these transitions. While individual reasons, such as a change in interests (33.1%) or family-related issues (15.7%), play a comparatively smaller role, they are not trivial in explaining transitions.

The bottom panel of Figure 2 focuses on cases where a single reason was indicated.

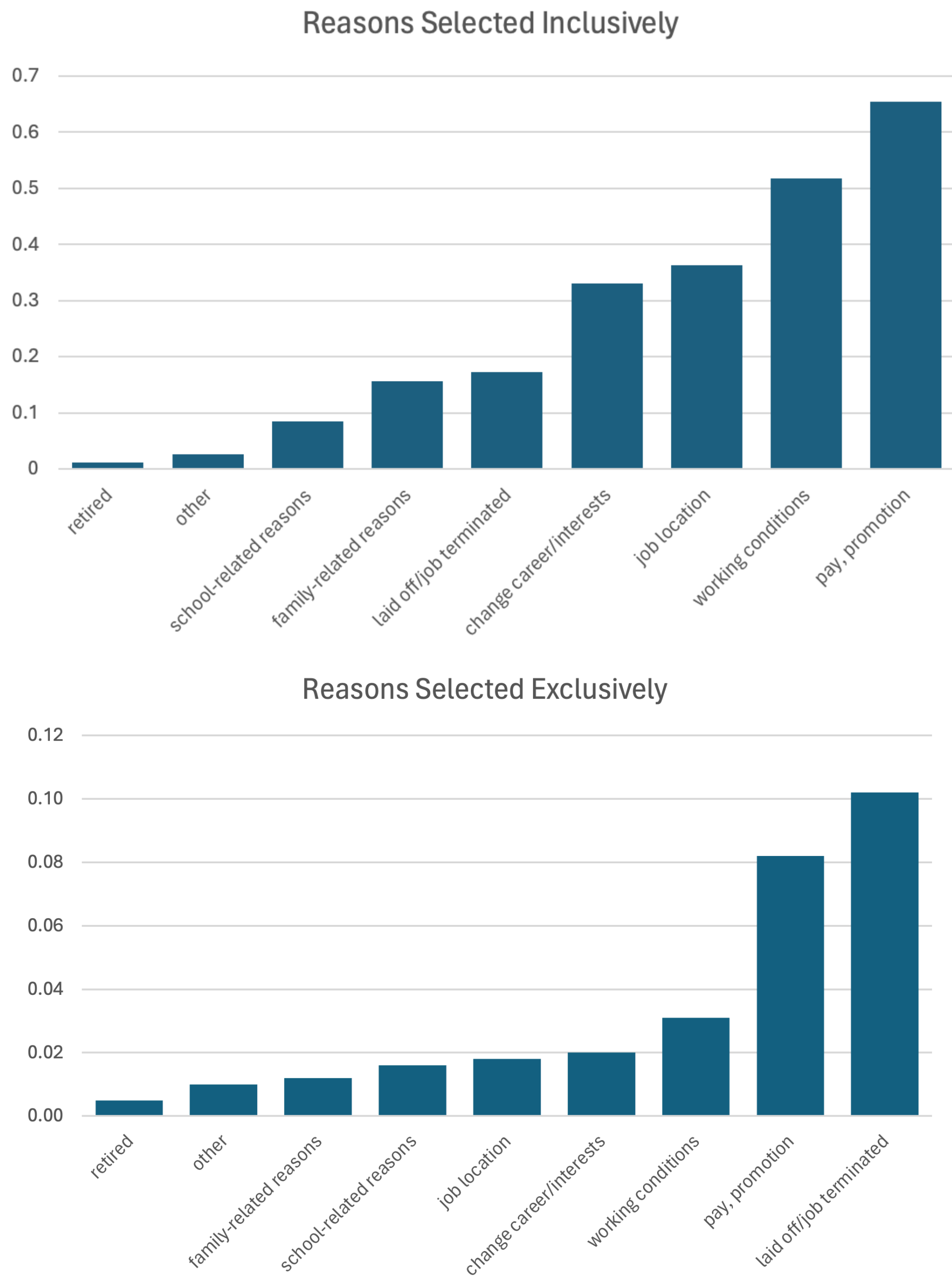


Figure 2. Reported Reasons for Transitions

Aside from the reason "laid off/job terminated", pecuniary reason is still the mostly selected reason, with 8.2% of movers indicating it as their exclusive reason for changing employers. In Appendix B, I show that the distribution of selected reasons from the public NSCG has similar patterns. These patterns are consistent across survey cycles and are robust to the use of weighted data.

I re-examine the distribution of pecuniary motivations with the following categories: “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. Figure 3 displays 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. 44.7% of transitions with earnings cuts involve both pecuniary and non-pecuniary reasons, and 6.2% of them occurring for exclusively 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%, and three quarters of them are related to pecuniary motivations.

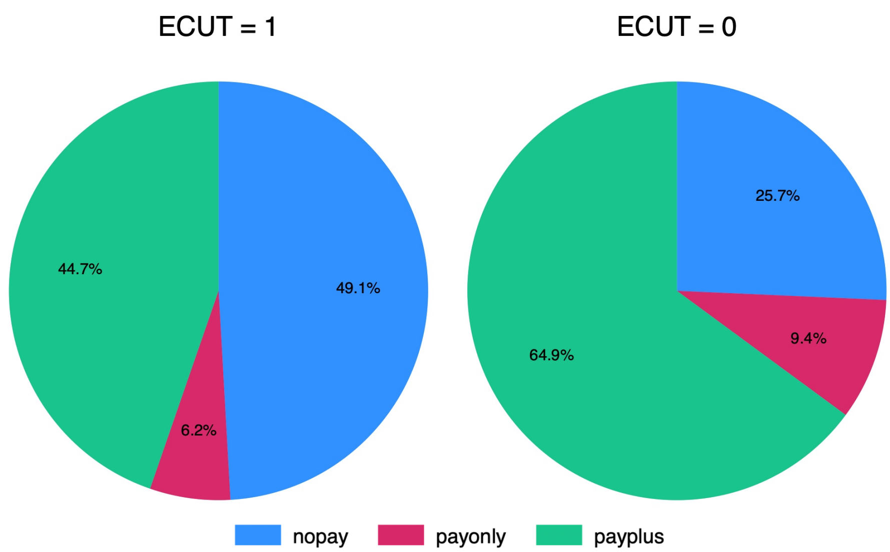


Figure 3. Motivations by Transitions with/without Earnings Cuts

Table 6 reports the share of ECUT by motivation category, as previously defined. The findings indicate that transitions driven by pecuniary motivations are associated with lower ECUT rates compared to those driven by non-pecuniary factors. Specifically, transitions motivated solely by non-pecuniary considerations exhibit the highest ECUT share at 53.9%. In contrast, transitions driven by a combination of pecuniary and non-pecuniary factors show a 29.7% share, while transitions motivated exclusively by pecuniary reasons account for a 28.8% share under the robust measure. The naive measure shows a broadly consistent pattern but indicates slightly higher ECUT shares for pecuniary-driven transitions and marginally lower shares for non-pecuniary transitions. These findings underscore the predominant role of pecuniary motivations in driving transitions and highlight their significance in the context of ECUTs. [29]

Table 6. ECUT Share by Motivations

Motivations	Robust Measure	Naive Measure	Total Transitions
payonly	0.288	0.400	1,100
payplus	0.297	0.396	7,400
nopay	0.539	0.508	4,500

Data: Linked NSCG-LEHD

3.3 Transition Motivations and Earnings after ECUTs

The findings suggest that workers may account for future earnings prospects in their decision-making, balancing trade-offs between current and future earnings. In the following, I will investigate whether post-transition earnings align with these forward-looking transition motivations.

I apply OLS regression to show that pecuniary motivation relates to higher post-transtion earning growths. Consider a worker i, who is employed by 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.[30] 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'.[31] I define the indicator variable, $D_{it}^{paytotal} = 1$, if worker i reports pecuniary motivation for the transition (denoted "paytotal", including "payonly" and "payplus").

[29] Workers may also accept lower earnings for higher job security, as studied by Gregory (2020). In Appendix C, I use the reported job security satisfaction from the NSCG to show that the changes in job security satisfaction have moderate effect on the extensive and intensive margin of earnings cuts.

[30] 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.

[31] 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 $t-2$.

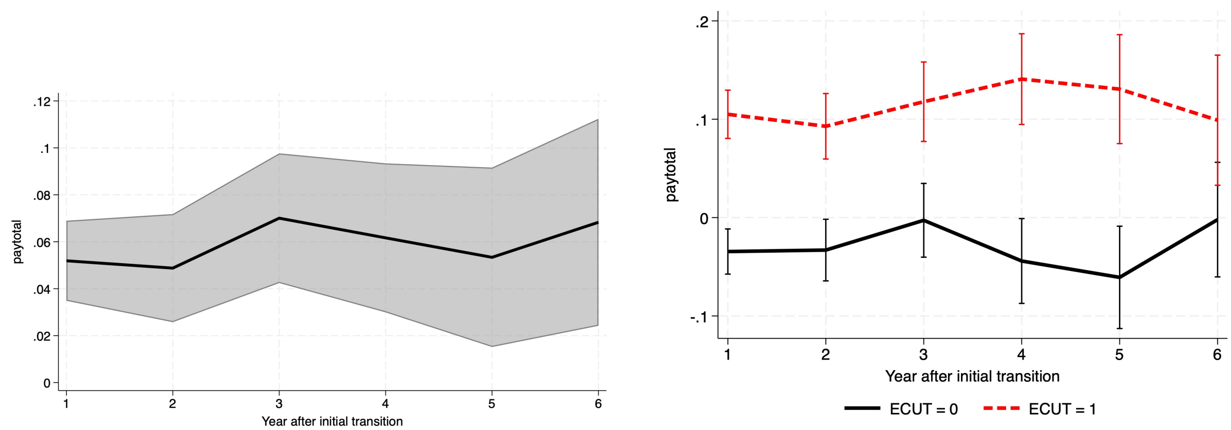
I estimate the following regression, where the dependent variable is the log wage ratio $log(\frac{w_{it+\tau}}{\tilde{w}_{it}})$:

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

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., 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 4a shows that workers who transitioned for pecuniary reasons consistently experienced about 6% higher wage growth compared to those who transitioned for non-pecuniary reasons. The wage growth premium fluctuates slightly across different time horizons. Overall, the results indicate that the motivations behind transitions are consistent with post-transition earnings trajectories, suggesting a strategic transition for pecuniary motivations.

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. As supported by Figure 4b, this effect is particularly pronounced for workers who experienced ECUTs. Particularly, movers 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 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.[32]



(a) All movers

(b) Movers by ECUT

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

4 Stepping-stone Employers

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

The previous section established the alignment between workers' stated transition motivations and their post-transition earnings. Building on this, I first demonstrate the positive correlation between pecuniary motivation and subsequent transition rates. To establish the role of stepping-stone employers, which depend on firm-level heterogeneity in transition rates, I show the persistence and dispersion of these rates across firms. Finally, I analyze whether the transitions to these stepping-stone employers may offer a plausible explanation for the prevalence of ECUTs.

4.1 Transition Motivations and Subsequent Transitions

Workers often undergo additional transitions within a relatively short period following an initial move. Table 7 presents the unconditional probability of subsequent transitions with the number of years since the initial transition increases. If transitions involving stepping-stone employers reflect a form of pecuniary motivation, we would

[32] Appendix D also calculate an alternative ECUT share measured by expected long-term earnings to suggest this strategic consideration.

expect a positive correlation between pecuniary motivation and subsequent transition rates. This hypothesis will be empirically tested in the following regression.

Table 7. Unconditional probability of subsequent transitions

Year(s) after initial transition	1	2	3	4	5	6
Unconditional prob.	0.057	0.200	0.350	0.445	0.517	0.558
Observations	10,500	8,400	7,000	5,300	4,200	2,600

Dataset: Linked NSCG-LEHD

The regressor of the specification (2) 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.

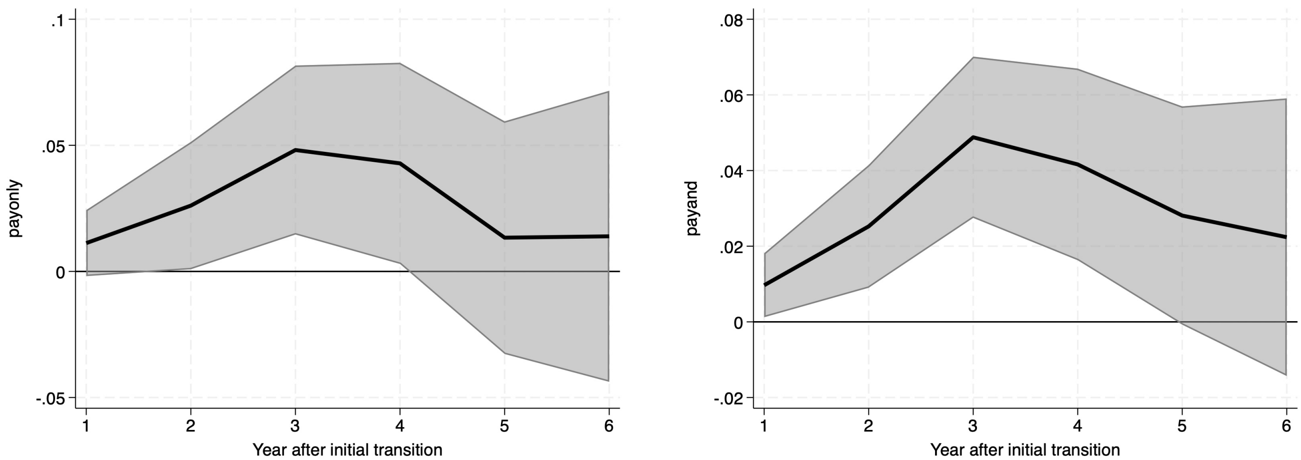
$$\mathbb{I}\{j_{t+\tau} \neq j_t\} = \beta_1^\tau D_{it}^{pay} + \beta_2^\tau X_{it} + \beta_3^\tau Z_{jt} + \alpha_i^\tau + \lambda_j^\tau + \eta_t^\tau + \epsilon_{ijt}^\tau, \tag{2}$$

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."[33]

The estimation results reveal a positive correlation between pecuniary motivations for the initial job transition and the likelihood of subsequent transitions. Specifically, Figure 5a 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 5b, where

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



(a) Indicator: payonly

(b) Indicator: payand

Figure 5. $\hat{\beta}_1^\tau$ and 90% Confidence Interval From Regression (2)

the sample size is larger. However, we observe that, in either panel, the effect peaks at 5% in year three and then diminishes.

4.2 Transition Rates on Firm Level

I construct a firm-year panel by aggregating the LEHD data by firm ID and year. The firm-level EE transition rates, denoted by Π_t^j, are defined 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 11 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.

To establish the persistence of firm-level transition rates, I estimate 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.[34] Table 8 presents the results of various specifications. Columns (1) shows the results of simple OLS

[34]In Appendix E, 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.

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.

Table 8. 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.

4.3 Transition Rates and Earnings Dynamics Upon Transitions

The post-transition earnings growth encompasses both the growth within employer following the transition and the gains from the employers after subsequent transitions.[35]

The intuition behind the role of stepping-stone employers in ECUTs is that workers may accept lower initial wages from current employers 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:

$$\log w_{it} = \alpha_i + \psi_{j(it)} + X_{it}\beta + \varepsilon_{it} \tag{3}$$

[35]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.

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.[36]

I partition the estimated firm fixed effects, $\hat{\psi}_j$, into three distinct groups.[37] Firms in Group 3 offer the highest wages, followed by those in Group 2, with firms in Group 1 offering the lowest wages. Figure 6 illustrates the average flow ratio of workers who make EE transitions across these groups. A majority of workers transitioning within 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%.

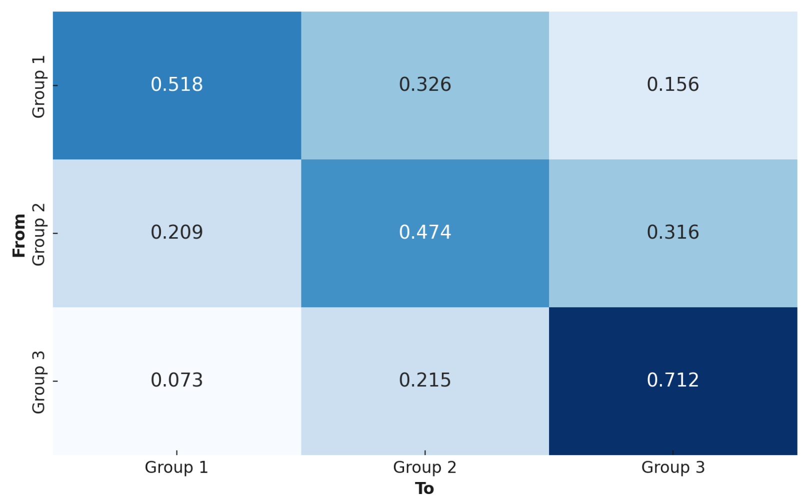


Figure 6. Labor Flow Ratio Between Firm Groups

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^{up}_{jt} 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:

$$\Delta \log(w_{it}) = \beta_1^{up} \pi^{up}_{j(i)t} + \beta_2 x_{it} + \beta_3 z_{j(i)t} + \alpha_i + \eta_t + \epsilon_{ijt}, \tag{4}$$

[36]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.

[37]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.

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.[38]

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}.[39] The second approach leverages these three-year average transition rates as instruments in a Two-Stage Least Squares (2SLS) 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 estimated coefficients in Table 9 are in line 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 9. 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.

[38]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.

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

4.4 Discussion

One possible concern 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 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 (4) suggest that this concern is unlikely to be significant.

In summary, this section provides suggestive evidence that some firms serve as "stepping-stones" for workers by providing higher probability of moving to high-paying firms. Such "stepping-stone employers" could be an additional pecuniary motivation for transitions which result in workers' initial earnings cuts.

5 Model

Previous sections have shown that the presence of stepping-stone employers, alongside other factors, shapes transitions and earnings dynamics in labor market. 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. In this framework, jobs (matches) and offers vary across three dimensions: employer's productivity, employer's offer arrival rates, and match-specific preferences. A central feature of the model is the heterogeneous and vectorized structure of offer arrival rates, which captures the role of stepping-stone employers. This setup facilitates a quantitative decomposition of workers' transition motivations, highlighting the contribution of stepping-stone employers to labor market 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 unemployment benefit.

(ii) An exogenous separation shock, δ_x, contingent on the worker's type, occurs and

transitions a fraction of employed workers into unemployment the next period.[40]
(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 employer characteristics. Employers send take-it-or-leave-it offers.
(iv) Upon receiving an offer, a worker draws her match-specific preference, $\phi \sim H(\phi)$, and decides whether to move, renegotiate, or maintain the status quo.[41]
(v) If no offer arrives during the period, the worker may experience a reallocation (Godfather) shock that forces a transition either to a new employer or to unemployment.[42]

Workers

Workers are infinitely lived and heterogeneous with respect to their time-invariant ability type, $x \in X$. At any point in time, a worker is either employed or unemployed. An employed worker derives per-period utility $u(w, \phi)$. In contrast, an unemployed worker receives per-period utility $u(b_x, 0)$, where b_x reflects unemployment benefits that depends on the worker's ability type.

Employers

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

Introducing employer groups 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 arrival rates, such that $p_y \sim F_g$ and $\overrightarrow{\lambda_y} \sim \Lambda_g \times \Gamma_g$.

I define 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 further decompose the vectorized arrival rate into two distinct components, such that

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

[40]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.

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

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

The first scalar 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, $\overrightarrow{R_y} \equiv [r_{gg'}]_{G\times 1}$, which follows another group-specific distribution, Γ_g. Each element, $r_{gg'} \equiv \frac{\lambda_{gg'}}{\sum \lambda_{g\cdot}}$, indicates a conditional probability or weight that, given an offer has arrived at employer g, the offer comes from employer g'. Therefore, when the productivity distribution differ across employer groups, the vector component reflects the quality of offers.

I define the arrival rates similarly for unemployed workers with a subscript u but make them predetermined, 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 sending 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 on 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, as outlined by Cahuc et al. (2006) and Postel-Vinay and Robin (2002). In this model, wages are determined through a bargaining process between employers and workers, where the worker's outside option is represented by a threat offer. Let θ denote a matched offer between a worker and an employer of type y. This offer is characterized by the employer's attributes p_y, the vectorized offer arrival rate $\overrightarrow{\lambda}_y$, and the worker's job-specific preference ϕ. Formally, the matched offer can be expressed as $\theta = (p_y, \overrightarrow{\lambda}_y, \phi)$. Similarly, a threat offer from another employer of type y' is given by $\theta' = (p_{y'}, \overrightarrow{\lambda_{y'}}, \phi')$. If the worker's outside option is unemployment, the corresponding threat offer is denoted as 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's bargaining power in the negotiation.

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 new 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. This dynamics is influenced by the interaction between employer types and workers' preference draws across current and potential offers. Finally, in *Case 3*, the contract remains unchanged, and wages stay constant.

5.2 Value Functions

Workers and employers are assumed to discount future with the same rate β. An unemployed worker in type x has value

$$U(x) = u(b_x, 0) + \beta\Bigg((1-\tilde{\lambda}_u)U(x) + \tilde{\lambda}_u \sum_{g_z} r_{ug_z} \mathbb{E}_{\theta_z|g_z}\big[\max\{W(x,\theta_z,\theta_u), U(x)\}\big]\Bigg). \quad (5)$$

The first term inside the brackets represents the expected continuation value when no job offer is received. The second term captures the expected value of receiving a new offer θ_z, which is sent by an employer of type $z = (g_z, p_z, \overrightarrow{\lambda_z})$ and is associated with a match-specific preference ϕ_z.[43] Here, $\tilde{\lambda}_u$ denotes the probability that an offer arrives, while r_{ug_z} represents the conditional probability of receiving an offer θ_z from an employer belonging to group g_z. The expectation operator integrates over the distribution of employer characteristics and job-specific preferences associated with the offer.[44]

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

[43] The employer group g affects the worker's decision only indirectly, as it determines the distribution of productivity levels and vectorized offer arrival rates. Conditional on productivity, arrival rates, and match preferences, the employer group does not enter directly into the worker's decision-making process.

[44] Formally, the expectation is given by

$$\mathbb{E}_{\theta_z|g_z}\big[\max\{W(x,\theta_z,\theta_u), U(x)\}\big] = \int\iiint max\{W(x,\theta_z,\theta_u), U(x)\} dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z).$$

Similar expectation operators are used throughout for notational convenience, with full derivations provided in Appendix G.

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

$$
\begin{aligned}
&W(x,\theta,\theta') = u(w(x,\theta,\theta'),\phi_y) + \beta\Bigg\{\delta_x U(x) + (1-\delta_x)\Bigg[\\
&\tilde{\lambda}_y \sum_{g_z} r_{gg_z}\Bigg(\mathbb{E}_{\theta_z\in\Omega_1|g_z}[W(x,\theta_z,\theta)] + \mathbb{E}_{\theta_z\in\Omega_2|g_z}[W(x,\theta,\theta_z)] + \mathbb{E}_{\theta_z\in\Omega_3|g_z}[W(x,\theta,\theta']\Bigg) \\
&+ \quad (1-\tilde{\lambda}_y)\Bigg((1-\rho)W(x,\theta,\theta') + \rho\sum r_{ug_{z'}}\mathbb{E}_{\theta_{z'}|g_{z'}}[\max\{W(x,\theta_{z'},\theta_u),U(x)\}]\Bigg)\Bigg]\Bigg\}.
\end{aligned} \tag{6}
$$

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 separation shock, δ_x, 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 (*Case 1*: $\theta_z \in \Omega_1$), or use the offer to renegotiate (*Case 2*: $\theta_z \in \Omega_2$). In either case, her negotiation threat offer gets updated. If the new outside offer is not good enough (*Case 3*: $\theta_z \in \Omega_3$), 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 type of the reallocated new employer is assumed to drawn from the same distribution that is faced by unemployed workers, because their threat offers are θ_u in this scenario.

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

$$
\begin{aligned}
J(x,\theta,\theta') =& f(x,p_y) - w(x,\theta,\theta') + \beta(1-\delta_x)\Bigg[(1-\tilde{\lambda}_y)(1-\rho)J(x,\theta,\theta') + \\
&\tilde{\lambda}_y \sum r_{gg_z}\Bigg(\mathbb{E}_{\theta_z\in\Omega_2|g_z}[J(x,\theta,\theta_z)] + \mathbb{E}_{\theta_z\in\Omega_3|g_z}[J(x,\theta,\theta')]\Bigg)\Bigg].
\end{aligned} \tag{7}
$$

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

Using the definition of joint surplus along with the bargaining protocol, Appendix

G derives the joint surplus as below:

$$
\begin{aligned}
S(x,\theta) = \max\Bigg\{0,\quad & c(\phi_y) + f(x,p_y) - b_x - \beta\alpha\tilde{\lambda}_u \sum r_{ug_z}\mathbb{E}_{\theta_z|g_z}[S(x,\theta_z)] + \\
& \beta(1-\delta_x)\Big[\alpha\tilde{\lambda}_y \sum r_{gg_z}\mathbb{E}_{\theta_z\in\Omega_1|g_z}[S(x,\theta_z) - S(x,\theta)] + \\
& (1-\tilde{\lambda}_y)\rho\alpha \sum r_{ug_{z'}}\mathbb{E}_{\theta_{z'}|g_{z'}}[S(x,\theta_{z'})] + \big(1-\rho(1-\tilde{\lambda}_y)\big)S(x,\theta)\Big]\Bigg\}.
\end{aligned}
\tag{8}
$$

The joint surplus first reflects current total flow surplus $c(\phi_y) + f(x,p_y) - b_x$. From Appendix G, 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. $S(x,\theta,\theta') = S(x,\theta)$.[45] 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. Value functions (5)-(7) solve worker's and employer's optimization problems;
2. Workers and employers split the total surplus that satisfy the equation (8) based on the sequential auction framework;
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 Motivations for Transitions

The decision of transition is directed by the *Case 1* in wage contract: workers make transitions if and only if the newly joint surplus is high enough so that, given a constant bargaining power, the worker will eventually enjoy more surplus. Based on the

[45] I assume $c' > 0$. In the following calibration, $c(\phi) = \phi$.

factors that would affect the joint surplus of a match, I categorize motivation for a transition from employer y to employer y' 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)-(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 Theoretical Results

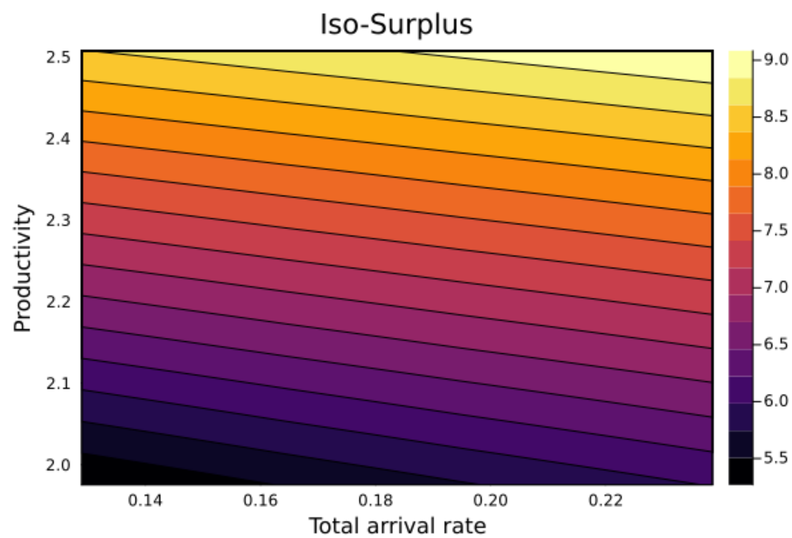
Joint surplus, $S(x, \theta)$, is key to worker's decisions. The proposition below describes the monotonicity of $S(x, \theta)$ with respect to amenity, productivity, and total offer arrival rate in the offer type.[46]

[46] Appendix H shows the proofs.

Proposition 1. *Joint surplus, $S(x,\theta)$, is increasing with match specific preference (ϕ), employer productivity (p), and total arrival rate ($\tilde{\lambda}$):*

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

Hence, 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.[47]



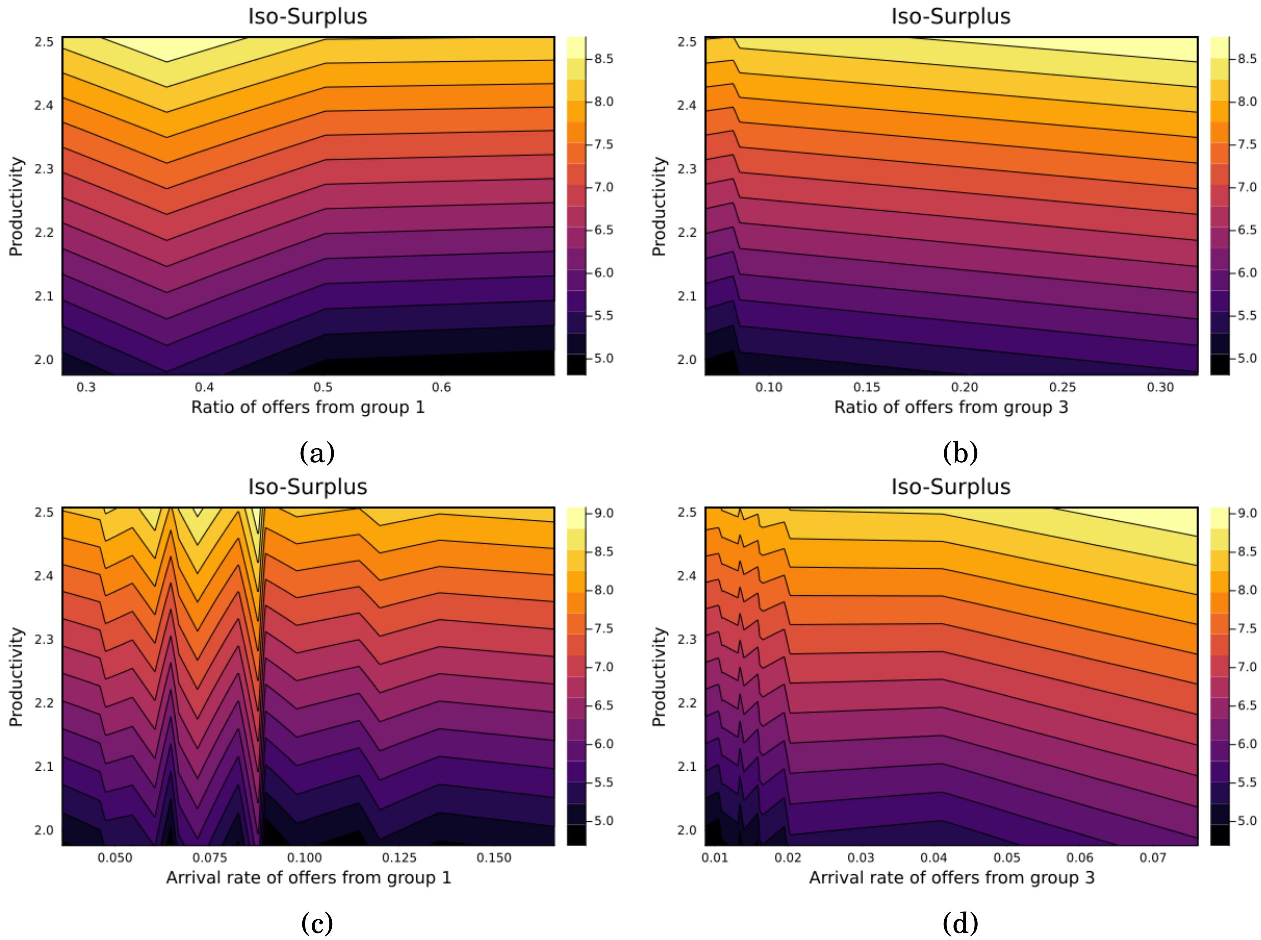
*Joint surplus of a match in employer group 2.

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.[48] All figures show the joint surplus value in group 2.

[47] Del Prato (2023) explores the heterogeneity of total offer arrival rate and displays a similar plot.

[48] 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"[49]. 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.[50] 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

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

arrival rates from specific employer groups may be 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.

5.6 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%. Fifteen parameters are calibrated internally using the Simulated Method of Moments (SMM). Table 10 summarizes the parameters and the 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. There are four distinct worker types, corresponding to the four educational levels in the LEHD dataset.[51] 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 $(0, \bar{\phi})$. The utility function is assumed to be linear in both wages and job amenities, such that the match-specific preference function is given by $c(\phi) = \phi$.

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 from the LEHD data. The flow value for unemployed workers is normalized to $b = 1.0$. Additionally, the reallocation

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

shock parameter is calibrated to match the overall average employer-to-employer (EE) transition rate.

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.[52]

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., $\Lambda_g \sim$ Beta(κ_g, σ_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.[53] 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 modeled as following a Dirichlet distribution, $Dir(\overrightarrow{\gamma_g})$, with group-specific parameters $\overrightarrow{\gamma_g} = (\gamma_{g1}, \gamma_{g2}, \gamma_{g3})$ for employer group g.[54] The calibration of $\overrightarrow{\gamma_g}$ is based on the estimated labor flow ratios between the three employer groups, as illustrated in Figure 6. 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 I 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

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

[53] Appendix I shows the derivation of the referenced value used for the initial selection.

[54] 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.

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, with the number of clusters corresponding to a pre-specified number of grid points. Third, I extract the centroids of each cluster. Since k-means clustering minimizes within-cluster variance, these centroids serve as representative approximations of different segments of the distribution and can be 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, maintaining a probabilistic alignment between the original distribution and its discretized representation.

5.7 Quantitative Results

5.7.1 Model Validations

As shown in Table 11, 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, $b/\mathbf{E}(w)$. 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 12, 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"). Overall, the simulated ECUT shares generated by the model align closely with the observed shares in the linked NSCG-LEHD data. The model underestimates the ECUT share for the "pay-only" category, because many workers transitioning for higher "productivity" do

Table 10. 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 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 11. 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 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)

not experience earnings cuts, as illustrated in the first row of Table 13. [55]

Additionally, the model aligns well with the observed ECUT shares reported in Table 4. It estimates that 37.5% of EE transitions involve ECUTs, closely matching the observed share of 36.3% for EE transitions within the same county. Similarly, the model generates 31.2% of transitions associated with earnings declining more than

[55] This discrepancy could be mitigated by revising the production function $f(x, p_y)$. The current linear specification may lead to a rapid increase in joint surplus as productivity rises. Nonetheless, relaxing the linearity assumption would come at the cost of the model's simplicity.

Table 12. 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

*In the first column, 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%, closely mirroring the observed rate of 32.1%. Furthermore, the model replicates comparable ECUT shares across both high-ability workers and the broader workforce, reinforcing the patterns documented in Table 4. Subsequent analyses will examine motivations and transitions across all worker types to ensure comprehensive insights.

5.7.2 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 uncovers the significance of stepping-stone motivation in shaping transitions and the resulting earnings dynamics.

Table 13 continues to examine the share of ECUTs by each motivational category. Specifically, 24% of transitions driven by productivity involve earnings cuts but 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 12. 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.[56] 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 shap-

[56]The ECUT share for the transitions inclusively motivated by "Others" is 37.5%, as reported in Table 12, because this category indicates all transitions.

ing both job mobility and wage dynamics.

Table 13. 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

Figure 9 account for motivation for transitions and ECUTs. The box of Figure 9a represents the universal set of transitions. Circles inside the box indicate the sets of transitions driven by previously defined motivations. Specifically, 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.

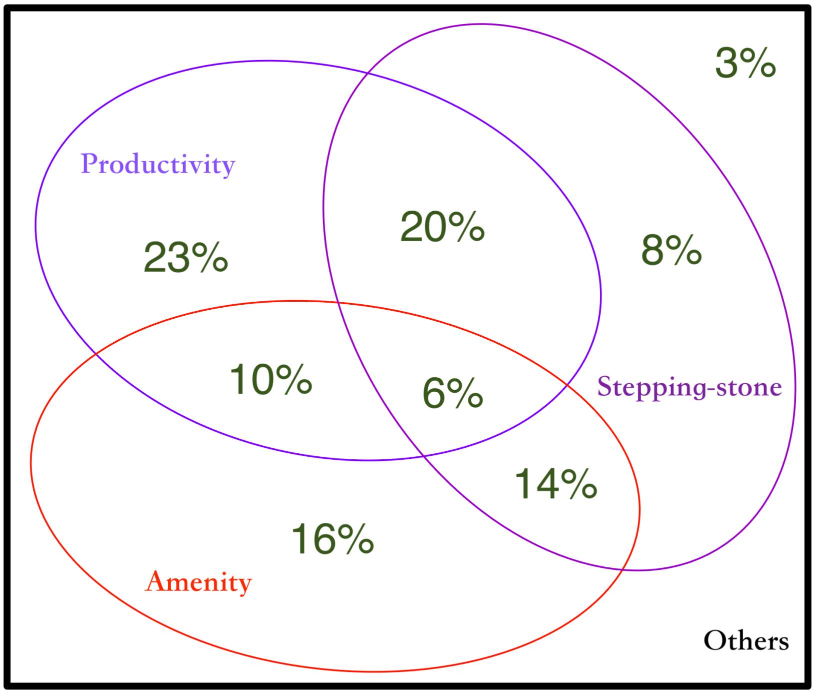
Figure 9b focus on the transitions with earnings cuts (ECUTs) and its distribution by different motivations. Stepping-stone motivation is related to 52% of ECUTs - 8% exclusively and 44% in combination with other motivations.[57] In contrast, 38% of ECUTs involve productivity. While non-pecuniary factors 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.

5.8 Counterfactual

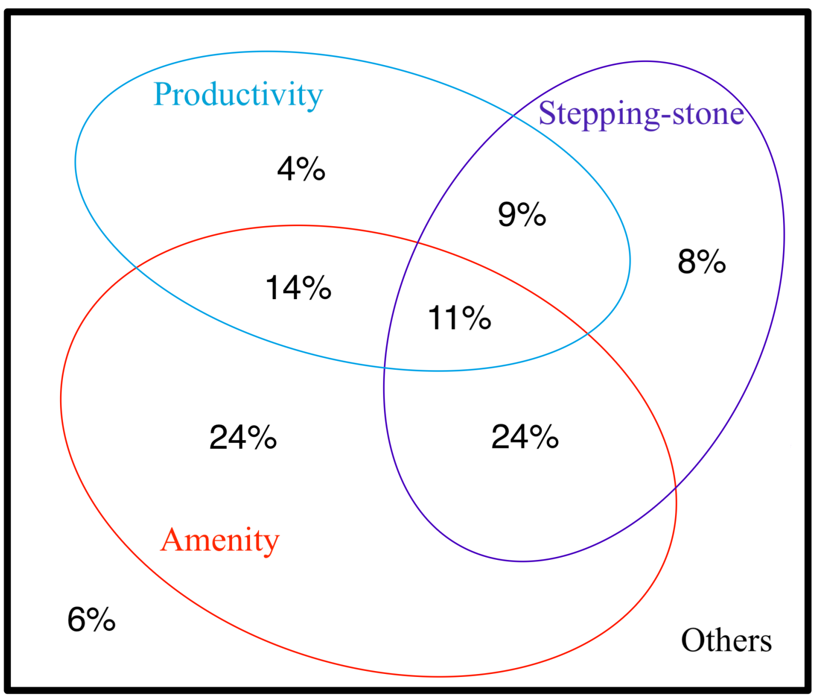
To analyze the influence of stepping-stone employers, I conduct three counterfactual exercises, each targeting a different aspect of employer heterogeneity in offer arrival rates, leaving other parameters unchanged.

In the first exercise, I eliminate differences in potential offer quantity by fixing the overall offer arrival rate constant at 0.218, which is the average of total arrival

[57] 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. Accounting of Motivations for Transitions and ECUTs

rates in the baseline model.[58] 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, 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 14. 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 14 reports the ECUT shares across three counterfactual scenarios, mirroring the structure of Table 12. 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 to 29.2%, about 20% (7 percentage points) lower than the baseline. However, controlling only for heterogeneity in offer quantities results in a mere 1 percentage point decline in the ECUT share (36.4%).

[58] This is close to the calibrated meeting rate for employed workers, 0.238, in Herkenhoff et al. (2024).

In sum, these counterfactual findings underscore two key insights. First, stepping-stone employers exert their primary influence mainly through the quality dimension of offers. Because workers can reject unfavorable offers, variations in the quantity of offers play a secondary role compared to differences in offer quality in governing workers' decisions. Second, the stepping-stone motivation represents a crucial pecuniary driver behind transitions and ECUTs. This is oft-overlooked in the literature and hardly directly observed from the data. But this model shows the prevalence of its impact in labor market.

6 Conclusion

This paper studies the prevalent ECUTs in U.S. labor market. Using the LEHD and NSCG data, I identify the motivations for transitions and highlight the role of stepping-stone employers in ECUTs. 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.

The empirical analysis of this paper shows that pecuniary motivations predominantly drive transitions. Even among workers who report financial gain as their sole reason for moving, ECUTs are frequent. Further, the regressions suggest that workers leverage certain transitions as strategic moves toward longer-term earnings potential rather than immediate gains. Hence, I argue that some firms are "stepping-stone employers" that offer workers improved opportunities of moving toward higher-paying firms. Finally, the theoretical model in this paper provides a structured framework to interpret these findings. By modeling firms heterogeneous in vectorized offer arrival rates, I emphasize that stepping-stone employers, particularly those with higher arrival rates of quality offers, is an important pecuniary motivation for transitions and ECUTs in the labor market.

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 this mechanism to demand side of labor market.

Census DMS Numbers
Project 2799: CBDRB-FY24-P2799-R11722, CBDRB-FY24-P2799-R11760, CBDRB-FY25-P2799-R11945

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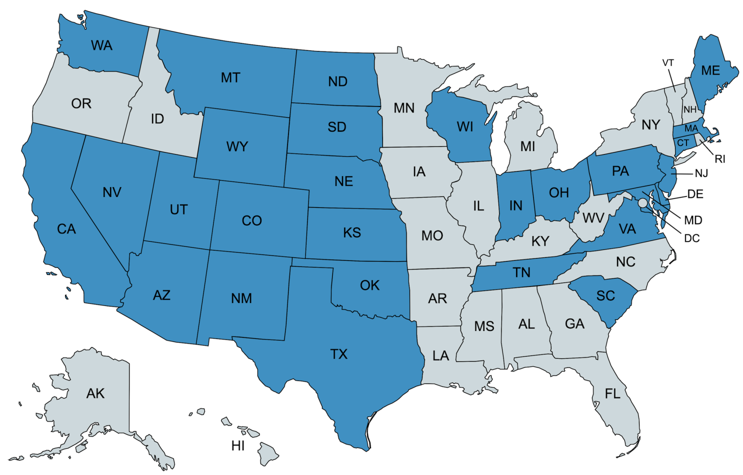
Appendix

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.

This paper uses `MODE_LEG_COUNTY_EMP` to identify and control counties of employers. There are 2 variables that could be used 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.

B Distribution of Reasons Selected from Public NSCG

Table A1

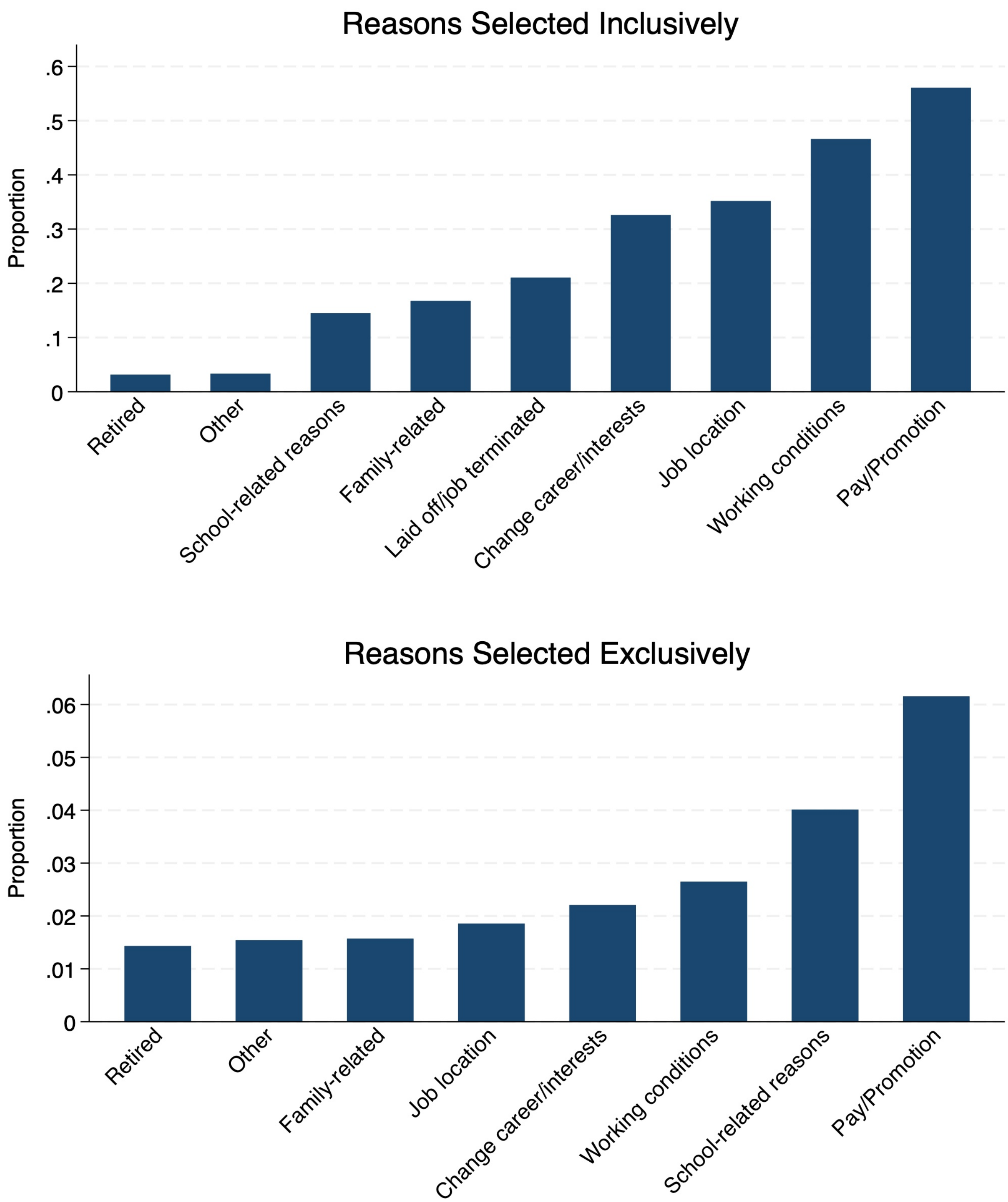
The bottom panel of Figure A1 focuses on cases where a single reason was indicated, excluding "layoff or job termination" as a motivation. 12% of all EE movers choose "layoff or job terminated" as their sole reason for transitions.

C Change of Job Security and ECUTs

The change of job security upon transitions may cause ECUTs. While this factors is not directly reported through the Question B3 in NSCG, Question A28 and C6 provide information about their job security in terms of satisfaction and subjective importance.

Question A28:
Thinking about your principal job held during the week of February 1, please rate your satisfaction with that job's...
(1-Very satisfied, 2-Somewhat satisfied, 3-Somewhat dissatisfied, 4-Very dissatisfied)

1. *Salary*
2. *Benefits*



Appendix Figure A1. Reported Reasons for Transitions

3. *Job security*
4. *Job location*
5. *Opportunities for advancement*
6. *Intellectual challenge*
7. *Level of responsibility*
8. *Degree of independence*
9. *Contribution to society*

Question C6:

When thinking about a job, how important is each of the following factors to you? (1-Very important, 2-Somewhat important, 3-Somewhat unimportant, 4-Very unimportant)

1. *Salary*
2. *Benefits*
3. *Job security*
4. *Job location*
5. *Opportunities for advancement*
6. *Intellectual challenge*
7. *Level of responsibility*
8. *Degree of independence*
9. *Contribution to society*

I focus on workers who respond in at least two consecutive survey cycles, enabling the measurement of changes in perceived job security associated with job transitions. Among these transitions, 31.7% are accompanied by an increase in job security satisfaction, as reported by workers.

To examine the relationship between changes in job security satisfaction during transitions and ECUTs, I regress the earnings changes on the difference of job security satisfaction upon transitions ($\triangle$jbsec), while controlling for workers' reported importance of job security, change of working hours ($\triangle$hour), and polynomial terms of age. In the first column of Table A2, the dependent variable is the log change of earnings upon transitions. Although the coefficient on $\triangle$jbsec is negative, suggesting that higher job security satisfaction is associated with slower earnings growth upon transitions, this result is statistically insignificant.

Similarly, the second column of Table A2 indicates that higher job security satisfaction is positively associated with the likelihood of ECUTs. However, the magnitude of this effect is modest; for instance, a one-unit increase in job security satisfaction raises the probability of an ECUT by only one percent. These results imply that while workers tend to experience ECUTs when transitioning to employers with greater job security satisfaction, the effect is statistically weak or economically negligible.

	(1)	(2)
	Δearnings	ECUT
Δjbsec	-0.0499	0.0135*
	(0.0532)	(0.008)
Δhour	0.0203***	-0.0077***
	(0.0052)	(0.0008)
R^2	0.0065	0.0487
Observations	3,300	

Appendix Table A2. Working hours and job security upon transitions

In addition, Table A2 further shows that more working hours is positively related to earnings changes upon transitions and negatively associated with the likelihood of ECUTs.

D More results about earnings dynamics after ECUT

D.1 Pecuniary motivation and future earning levels

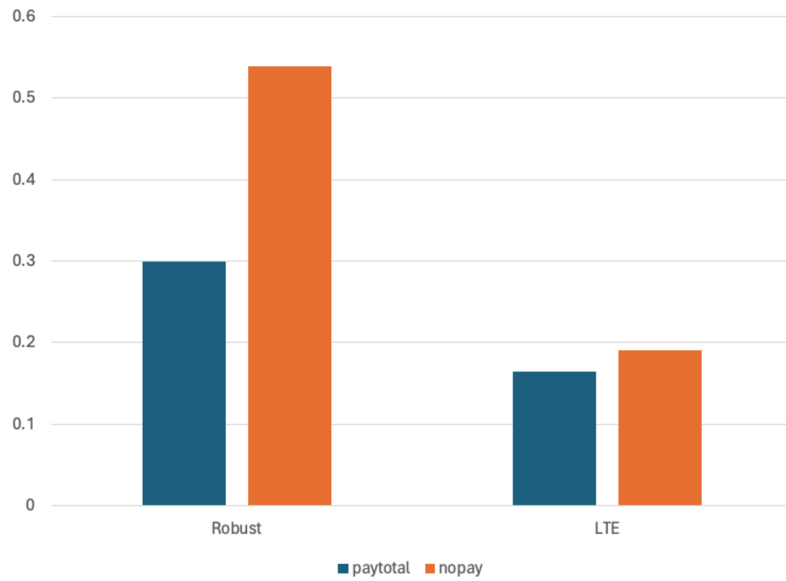
I begin with constructing "long-term earnings" to indicate future earning levels. Then I estimate the expected long-term earnings of each period given the characteristic of workers and employers. Finally, I compare the change of expected long-term earnings upon transitions for different motivations using 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 expected 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 A2, 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 A2. 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. Additionally, 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.

E Persistence and Dispersion of Transition Rates

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

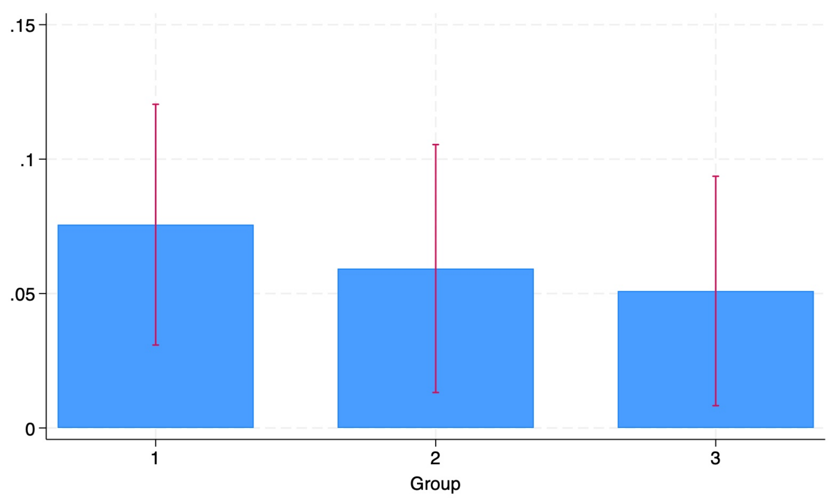
Figure A3 illustrates the group-specific moments from Table 11, each solid bar represents the weighted average transition rate for each employer group, with weights based on firm employment size. The error bars show one standard error within each

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 A3. Coefficients of AR(1) for transition rates

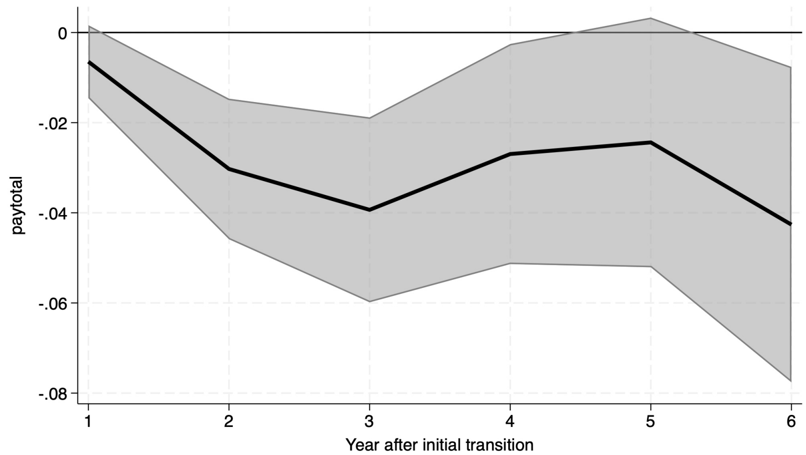
employer group. Notably, the figure demonstrates a substantial dispersion of transition rates both within each employer group and across the overall distribution. In addition, employer group 3, which has the highest level of $\hat{\psi}_j$, exhibits the lowest mean transition rate, whereas employer group 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

F 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

G 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,

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

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

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

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

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

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

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

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

H Proof of Monotonicity of $S(x, \theta)$

The proof is inspired by the appendix supplement to Jarosch (2023). The joint surplus function $S(x, \theta)$ is given as:

$$
\begin{aligned}
S(x,\theta) = \max \Bigg\{ 0,\, & c(\phi_y) + f(x, p_y) - b_x \\
& - \beta\alpha\tilde{\lambda}_u \sum r_{ug_z} \iiiint S(x,\theta_z) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) \\
& + \beta(1-\delta_x)\Bigg[\alpha\tilde{\lambda}_y \sum r_{gg_z} \iiiint_{\Omega_1} [S(x,\theta_z) - S(x,\theta)] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) \\
& \quad + (1-\tilde{\lambda}_y)\rho\alpha \sum r_{ug_z} \iiiint S(x,\theta_z) dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) \\
& \quad + [1-\rho(1-\tilde{\lambda}_y)] S(x,\theta) \Bigg] \Bigg\}.
\end{aligned} \tag{9}
$$

where $\theta = (p_y, \overrightarrow{\lambda_y}, \phi)$. Ω_1 is the set of offers θ_z that motivate transitions from the current contract θ, i.e. $\Omega_1(\theta) = \{\theta_z \mid S(x,\theta_z) > S(x,\theta)\}$. The following derive monotonicity with respect to ϕ, p, and $\tilde{\lambda}_y$.

First, we want to prove that $S(x, \theta)$ is strictly increasing in ϕ when $S(x, \theta)$ is strictly positive. To show this, we firstly construct the following mapping

$$
\begin{aligned}
\mathbb{T}\hat{S}(x,\theta) = & c(\phi) + \beta(1-\delta_x)\Bigg[[1-\rho(1-\tilde{\lambda}_y)]\hat{S}(x,\theta) + \\
& \alpha\tilde{\lambda}_y \sum r_{gg_z} \iiiint_{\Omega_1(\theta)} [\hat{S}(x,\theta_z) - \hat{S}(x,\theta)] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z) \Bigg].
\end{aligned} \tag{10}
$$

Here $\hat{S}(x, \theta)$ is a strictly positive term of $S(x, \theta)$. Note that the equation (10) has omitted terms that are irrelevant to the change of ϕ. Then we only need to show (i) the mapping is contraction and (ii) it maps weakly increasing into strictly increasing functions. The mapping operator $\mathbb{T}$ is a contraction because it satisfies Blackwell's sufficient conditions.

Denote

$$\check{S}(x,\theta) \equiv [1-\rho(1-\tilde{\lambda}_y)]\hat{S}(x,\theta) + \alpha\tilde{\lambda}_y \sum r_{gg_z} \iiiint_{\Omega_1(\theta)} [\hat{S}(x,\theta_z) - \hat{S}(x,\theta)] dF_{g_z} d\Lambda_{g_z} d\Gamma_{g_z} dH(\phi_z)$$
$$= [1-\rho(1-\tilde{\lambda}_y)]\hat{S}(x,\theta) + \alpha\tilde{\lambda}_y \int_{\Omega_1(\theta)} [\hat{S}(x,\theta_z) - \hat{S}(x,\theta)] d\Xi(\theta_z)$$

where $\Xi(\theta_z)$ simply denote the draw of offer type tuple that captures its productivity, arrival rates, and amenity. We want to show that when $\hat{S}(x,\theta)$ is non-decreasing in ϕ then $\check{S}(x,\theta)$ is non-decreasing in ϕ. Consider two offers θ_1 and θ_2 that are only different in their amenities ϕ_1 and ϕ_2, respectively. Let $\phi_1 < \phi_2$, then if $\hat{S}(x,\theta)$ is non-decreasing in ϕ, we have

$$\begin{aligned}
&\check{S}(x,\theta_2) - \check{S}(x,\theta_1) = \\
&\left(\hat{S}(x,\theta_2) - \hat{S}(x,\theta_1)\right)\left(1-\rho\left(1-\tilde{\lambda}_y\right) - \tilde{\lambda}_y\alpha\int_{\Omega_1(\theta_2)} d\Xi(\theta_z)\right) \\
&\quad - \tilde{\lambda}_y\alpha\left(\int_{\Omega_1(\theta_1)\setminus\Omega_1(\theta_2)} \hat{S}(x,\theta_z)\, d\Xi(\theta_z) - \hat{S}(x,\theta_1)\int_{\Omega_1(\theta_1)\setminus\Omega_1(\theta_2)} d\Xi(\theta_z)\right) \\
&\geq \left(\hat{S}(x,\theta_2) - \hat{S}(x,\theta_1)\right)\left(1-\rho\left(1-\tilde{\lambda}_y\right) - \tilde{\lambda}_y\alpha\left[\int_{\Omega_1(\theta_2)} d\Xi(\theta_z) + \int_{\Omega_1(\theta_1)\setminus\Omega_1(\theta_2)} d\Xi(\theta_z)\right]\right) \\
&= \left(\hat{S}(x,\theta_2) - \hat{S}(x,\theta_1)\right)\left(1-\rho\left(1-\tilde{\lambda}_y\right) - \tilde{\lambda}_y\alpha\int_{\Omega_1(\theta_1)} d\Xi(\theta_z)\right) \geq 0
\end{aligned} \tag{11}$$

Then it becomes easy to show that if $\hat{S}(x,\theta)$ is weakly increasing in ϕ, the mapping $\mathbb{T}\hat{S}(x,\theta)$ is strictly increasing in ϕ, such that

$$\mathbb{T}\hat{S}(x,\theta_2) = c(\phi_2) + \beta(1-\delta_x)\check{S}(x,\theta_2) > c(\phi_1) + \beta(1-\delta_x)\check{S}(x,\theta_1) = \mathbb{T}\hat{S}(x,\theta_1) \tag{12}$$

where $c(\phi)$ is assumed to be increasing with ϕ. This completes the proof of monotonicity of $S(x,\theta)$ with respect to ϕ. The proofs for productivity p_y and total arrival rate $\tilde{\lambda}_y$ are almost analogous and therefore omitted.

I 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

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

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.