Unemployment Insurance Employment Outcomes (UIEO): The Composition and Re-employment Dynamics of UI Claimants

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Abstract

We document the composition and labor market outcomes of workers who claim and collect unemployment insurance (UI). Using comprehensive administrative data on weekly UI claims in several states, we describe the demographic, job, and employer characteristics of UI claimants. We link these claims to their earnings and job histories in the Longitudinal Employer-Household Dynamics (LEHD) data to measure their pre- and post-unemployment spell earnings, earnings changes, and mobility across states and industries. We highlight the heterogeneity in earnings gains and losses by workers' unemployment spell characteristics, demographics, re-employment types, and mobility. These new measures reveal the joint importance of the worker and employer in shaping re-employment outcomes, highlight how outcomes vary with mobility and unemployment duration, and facilitates further study of the role of social insurance in cyclical labor market recoveries and the trajectories of displaced workers.

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1 Introduction

The Great Recession and COVID-19 recession elevated unemployment insurance (UI) to a central policy instrument for stabilizing the U.S. labor market, renewing interest in its effects and tradeoffs. A growing empirical literature has leveraged large administrative datasets to study UI, yet important measurement challenges and data constraints continue to limit both academic analysis and publicly available statistics on program participation and outcomes. In this paper, we use newly assembled administrative data from several U.S. states that link high-frequency UI claims to longitudinal quarterly earnings and employment records from the Longitudinal Employer-Household Dynamics (LEHD) program. These data provide one of the most comprehensive views to date of UI recipients and enables a detailed characterization of their demographic attributes, job and employer characteristics, benefit receipt, and post-displacement labor market trajectories.

We link weekly initial and continuing UI claims from several states to quarterly earnings in LEHD. As LEHD is derived from UI earnings records, it spans the entirety of UI-covered employment. We thus have complete coverage of UI-eligible employment and earnings histories for the claimants within our sample regardless of their state of employment. The weekly frequency of paid claims gives us the ability to measure unemployment spells with much more precise timing than typical quarterly or annual administrative earnings data. We also know for these claims that the worker is unemployed rather than non-employed (potentially out of the labor force and not seeking work), and that the worker was subject to involuntary separation via layoff rather than having quit their job. This detail allows us to observe displaced workers and their unemployment spells with unprecedented accuracy in a framework that also allows us to track them longitudinally for significant spans of time. Each claimant can be linked to their quarterly earnings history in LEHD which allows us to measure their earnings, employer characteristics, and employment duration both before and after each spell. We focus on documenting workers' unemployment duration, earnings, earnings dynamics, and mobility.

We highlight the utility of our data for research on UI as well as its potential for the

production of public-use statistics on the UI population and their outcomes. To this end, these data have several advantages. Since we have the universe of regular weekly UI claims, these data are comprehensive within the states for which we have coverage. Existing sources of information about the UI system as a whole come from individual states or from the U.S. Department of Labor's Employment and Training Administration. Our UI claims are the source data for these tabulations. While these sources have timely information on claims and some information about their composition, they are limited in detail and lack information on outcomes. With the underlying microdata on individual claimants and collectors, we can understand at a detailed level who claims and collects UI. Further, we can use these data linked with workers' earnings and job histories to measure the outcomes of workers as they become re-employed following a UI spell. Relative to UI claims and earnings data available from individual states, the LEHD program provides the ability to track earnings outcomes for individuals who move across state lines. Eventual incorporation with the Self-employment Jobs Frame will also allow us to track outcomes for workers who move out of UI-covered employment into self-employment.

In addition to administrative data, publicly-available longitudinal survey data that can be used to track workers' outcomes and UI participation also have important limitations. First, they are limited by sample size, whereas we can track the universe of UI-covered employment. For example, the Current Population Survey (CPS), the most commonly used survey for studying UI, samples 60,000 households per month, most of whom are continuously employed or out of the labor force. Second, measurement of UI receipt (and transfer income in general) is notoriously difficult in surveys (Meyer et al., 2009).[1] Survey data is also limited in the length of its panel and rarely provides details about the employer's characteristics aside from industry. The CPS basic monthly data allows for measuring monthly transitions, but the rotation group structure limits the ability to track workers' earnings and employment outcomes beyond one year. We track workers over longer time-horizons with LEHD, allowing for the measurement of long-run employment outcomes following an unemployment spell. Of

[1]For example, the Survey of Income and Program Participation (SIPP) warns users of measurement error issues for UI income in 2020: https://www.census.gov/programs-surveys/sipp/tech-documentation/user-notes/2021-usernotes/volat-unemp-comp-during-covid19-pand.html.

course, these data are also subject to limitations. Since we rely on administrative records, we lack detail about the job search status and workers' reasons for nonemployment (quit, layoff, etc.) that are typically available in survey data, and affect eligibility for UI, which we cannot observe for those who don't collect.[2]

Our preliminary results are based on UI claims in 2020 from six states.[3] This was an unprecedented time period for the labor market as well as for UI policy, and our data allow for a uniquely detailed perspective on it. We document substantial heterogeneity in earnings losses and gains across claimant subgroups, shaped by differences in unemployment spell duration, re-employment type, and geographic and industry mobility. We highlight that variation in earnings outcomes is sensitive to several measures of mobility, including re-employment to a new firm in comparison to recall, re-employment to a new industry, or to an employer in a new state. We also document that recall is pervasive in 2020 and the associated earnings and re-employment outcomes of recalled workers differs substantially from those who find re-employment elsewhere, consistent with Fujita and Moscarini (2017) and Gertler et al. (2022). Mobility across industry and state of employment are also associated with significant dispersion in outcomes relative to workers who did not move. Earnings gains and losses from displacement can be substantial and have a strong industry and unemployment duration component. We also document substantial heterogeneity in earnings outcomes which vary based on worker and job characteristics such as age and earnings in the pre-spell job.

Our measures of UI collectors and their characteristics contribute to a growing literature measuring the UI system, its coverage, and heterogeneity in participation using survey and administrative data. In terms of participation and coverage, Kuka and Stuart (2025) and Skandalis et al. (2022) document disparities in UI take-up and recipiency by race. Forsythe and Yang (2021) study changes in UI coverage before and during the COVID-19 pandemic along similar demographic dimensions. Ganong et al. (2020) document the distribution of replacement rates and statutory benefits of workers from the expansion of UI in the CARES

[2]We can measure monetary eligibility but this affects our ability to identify separation eligibility and other factors such as availability for work that define labor force status and determine UI eligibility.

[3]Data spanning a longer time horizon and from additional states is forthcoming.

Act. Our results provide similar detail on the heterogeneity of claimants, with the ability to also track and measure their re-employment outcomes. A long literature has focused on the labor market effects of UI policy, summarized by Schmieder and Von Wachter (2016). This literature has seen a renewed interest in the wake of the unprecedented expansion of UI benefits during the COVID-19 pandemic. We bring new administrative data with precise measurement of the timing, duration, and collection of UI benefits along with the infrastructure to measure workers' outcomes. While our focus here is not on causal analysis of UI policy, we document outcomes along relevant dimensions for future work on the causal impacts of UI policy, such as benefit amount, duration/timing, and employer and worker heterogeneity.

We also contribute to a large literature measuring the cost of job loss. Administrative data on earnings has been instrumental in facilitating the measurement of long-run labor market effects, such as in Jacobson et al. (1993); Lachowska et al. (2020); Guvenen et al. (2021). Relative to these studies, which mostly utilize annual tax data, we have much more precise information about timing and joblessness. For instance, to measure nonemployment in annual tax data with certainty requires full-year nonemployment, which selects on a very small fraction of long-term unemployed workers. Identifying displaced workers in administrative data is also challenging because most of the time one cannot differentiate layoffs from quits. Similar to our data, 1099-G forms from the Internal Revenue Service (IRS) are a comprehensive administrative source for receipt of government benefits including UI, but annual frequency makes it difficult to elicit the timing or duration of unemployment and which jobs preceded or followed the unemployment spell. For example, differentiating a worker who is recalled from temporary layoff following an unemployment spell and also makes a subsequent job transition during the same calendar year vs. a worker who is laid off from a job and finds a new job with a different employer is difficult with annual or even quarterly data. Our results provide additional precision in identifying involuntary joblessness and sufficient detail to better understand the heterogeneity in transitions and costs – or in some instances, gains – from job loss.

These new facts about UI claimants and recipients and their re-employment outcomes

provide vital information for understanding the interaction of worker heterogeneity, UI policy, and job loss. This broad detail at the worker and employer level is vital to inform theoretical and empirical research on UI. Models of frictional job search and unemployment have increasingly emphasized the importance of heterogeneity in workers and firms. Our results point to important sources of variation in re-employment outcomes such as recall, industry, and duration-dependence, which we hope will inform future developments in theoretical and empirical research. These data give additional detail to UI claimants and outcomes during a time period with unprecedented variation in UI policy, which we hope will provide fruitful avenues for future causal analysis.

2 Unemployment Insurance Policy Context and Data

In this section, we briefly describe the institutional context for UI during the COVID-19 pandemic and how it differed from normal UI policies. We then describe our data and its construction for our analysis.

2.1 Unemployment Insurance Policy During the Pandemic

During normal times, UI is funded by payroll taxes and administered by the states. Regular UI is available for workers who were employed in a UI-covered job, lost their job through no fault of their own (i.e., were laid off as opposed to quit), and are able and available to work. In addition, states require a minimum work history in a UI-covered job as a condition of eligibility. While all workers who fit these criteria are eligible to receive UI, they must file a claim to receive UI benefits. Many eligible workers do not claim UI due to anticipated re-employment, informational barriers, and the perceived value of receiving benefits, among other factors.[4] The states determine the generosity of UI benefits, including the weekly benefit amount (WBA) and the maximum duration of benefits. Most states

[4]These are categories from the 2018 UI supplement to the Current Population Survey (CPS), which asked displaced workers why they did not apply for benefits.

allow up to 26 weeks of UI benefits. In our sample, maximum potential benefit duration for regular UI ranges from 20 weeks in Missouri to 26 weeks in the other five states. The average weekly benefit amount in our sample is $328. See Appendix A.1 for additional program-level details for each state in our sample. In addition to regular UI, the Extended Benefits (EB) program provides an additional 13-20 weeks of UI benefits for unemployed workers who exhaust regular UI and are covered by a state with an elevated unemployment rate.[5]

At the onset of the COVID-19 Recession, Congress expanded eligibility for UI and created several additional programs to assist unemployed workers. The Pandemic Extended Unemployment Compensation (PEUC) program followed a familiar playbook from previous recessions. PEUC provided additional weeks of UI for workers who exhausted their regular UI benefits after June 2019, were not eligible for other UI programs, and were available for work except for cases when COVID-19 made it not possible. At its inception in March 2020, PEUC provided up to 13 weeks of UI benefits beyond regular UI. This maximum potential duration was subsequently expanded to 24 weeks in December 2020 and then 53 weeks in March 2021. States could choose to opt out of this program at any time.

The most substantial expansion in UI during the pandemic recession was the Pandemic Unemployment Assistance (PUA) program, which marked the largest expansion of eligibility for UI in the U.S. since the Social Security Act of 1935. PUA provided UI benefits for workers not typically eligible for regular UI: independent contractors, freelancers, and self-employed workers who could not find work due to the pandemic. In addition, unemployed workers in UI-covered jobs who would otherwise not be eligible for benefits or who exhausted regular, PEUC, and EB benefits could receive PUA benefits. PUA initially provided up to 39 weeks of benefits starting in March 2020 and was expanded to provide 50 weeks in December 2020 and 79 weeks in March 2021. In addition to providing additional weeks of UI benefits, Congress increased weekly benefits by $600 on top of all other UI benefits through the Federal Pandemic Unemployment Compensation (FPUC) program starting in April 2020. This benefit top-off was later reduced to $300 in August 2020. Finally, a small program

[5]EB becomes available for participating states when the Insured Unemployment Rate (IUR) exceeds a given "trigger" threshold. Not all states adopt the same insured unemployment rate (IUR) and total unemployment rate (TUR) triggers. See Bell et al. (2021) for more details.

called Mixed Earner Unemployment Compensation (MEUC) provided an additional $100 per week in participating states for workers with at least $5,000 in self-employment income in 2019. The UI claims data we received from the states does not contain information on FPUC or MEUC and these supplemental benefits are not reflected in the weekly benefit amounts in our data.

2.2 Data

We combine data on weekly UI claims from six states with quarterly data on the near universe of employment and earnings from 49 states in the LEHD program at the U.S. Census Bureau.[6] The claims data consist of claims for regular UI, as well as claims for PEUC, EB, and some PUA claims. For all states, we are able to separately identify claims for regular UI, PEUC, and EB. For PUA claims, we rely on program-specific parameters to tag these payments when PUA claims are included alongside other types of UI claims. In practice, this only affected data from Missouri. For example, the minimum PUA benefit was equal to 50% of the average weekly benefit amount for regular UI in each state, which in Missouri was $133. We assume all claims in Missouri that paid exactly $133 each week are PUA claims. Because PUA payments could be higher than this amount, it is possible that we are not identifying all PUA claims in Missouri. This did not affect the other states in our sample because they handled PUA claims in separate systems from other types of UI claims.

For accepted claims, we group the raw weekly claims data received from the states into UI spells. We define a UI spell as the set of continuous claims made by the same claimant and UI account number. We stitch together claims made within 21 days of each other in the same spell, including when the claimant transitions between UI programs. Gaps shorter than 21 days can appear in the data for a variety of reasons, such as the need to apply for extended UI benefits under a second program (e.g., PEUC) after exhausting benefits from a first program (e.g., regular UI). A given worker can make multiple claims for UI benefits at any point in time and can receive multiple payments in the same week during a UI spell.

[6] The states in our sample with UI claims are Connecticut, Missouri, Ohio, Oklahoma, Utah, and Virginia.

Each claimant is assigned a Protected Identification Key (PIK) that serves as a unique person identifier while obscuring their personally identifiable information. Along with the PIK and firm UI account number, a spell consists of a start date, number of weeks paid, average weekly benefit amount (over weeks paid), and an end date. Using the PIK, we can match individuals to other data in the Census environment to capture demographic characteristics, including date of birth, age, sex, race/ethnicity, education, and place of residence. We link to the LEHD Individual Characteristics File (ICF) to provide this information.

For each UI spell, we attach information on the PIK's employment before and after the spell to the extent that we observe these jobs. We use the LEHD Job History File (JHF) to link the individual to their quarterly earnings history in LEHD, which provides individual earnings records for any person-firm combination (job). These wage records come from state UI systems and, by definition, should comprise the universe of UI eligible earnings. Using the SEIN (State Employment Identification Number, a firm identifier) attached to a worker in a quarter, we can observe the employment and earnings history on either side of an unemployment spell, as well as the characteristics of the employer (such as state or industry). It is important to note that we have weekly information on the length and timing of UI collection, but this may not correspond to the length of the unemployment spell (if benefits expire), and quarterly earnings can overlap this spell timing significantly.

Figure 1 outlines the timing for an example UI spell and associated earnings. We denote the quarter in which the UI spell starts as t_S and the quarter in which it ends, potentially the same quarter, as t_E. We look for the most recent job in the quarter prior to t_S to find the most recent job. To measure prior earnings, we look for the most recent quarter and full-quarter of earnings. Full-quarter (FQ) earnings are measured in an interior quarter of a job which has at least three consecutive quarters of positive earnings. This ensures the earnings measure is from a period where the job existed for the full duration of the quarter, eliminating partial-quarter earnings. We look for earnings in the eight-quarter span prior to the spell start. Similarly, we look for post-UI employers in the eight-quarter span after t_E. Note that while the end of the pre-UI job spell is likely to coincide with the start of the UI spell, it is possible for the post-UI job spell to not coincide with the end of the UI spell,

especially if the worker exhausted UI benefits. We look at adjacent quarters to the UI spell for the pre- and post-employer spell as opposed to the quarter of the spell since for many UI spells, the worker may have earnings from one or both jobs within the same quarter. For most of our analysis, we use the sample of UI spells where we can link the spell to a pre- and post- UI spell full-quarter observation. This excludes some UI spells with short tenure in either job.

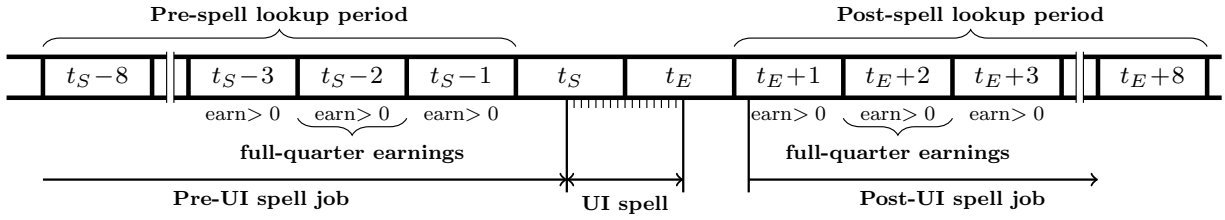


Figure 1: Timing of a UI spell and quarterly earnings records

3 Results

3.1 Coverage

Our data consists of the universe of regular UI claims in each of six states for the year 2020. As a validation exercise, we compare our sample to the published aggregate initial and continuing claims time-series from the U.S. Department of Labor's Employment and Training Administration (DOL ETA). Our claims are the source data for these series. After harmonizing claims timing across states and stitching together UI spells, we can closely replicate the time-series for both initial and continued claims. Figure 2 shows that our time-series of all UI claims is nearly identical to the DOL ETA published series.

We link our weekly claims series to quarterly earnings records in LEHD. LEHD is built from states' UI wage records, which should coincide with the near-totality of UI-covered employment. That said, there are instances such as linkage error, where we might fail to match a prior employment spell and earnings to a paid UI claim. When looking at outcomes,

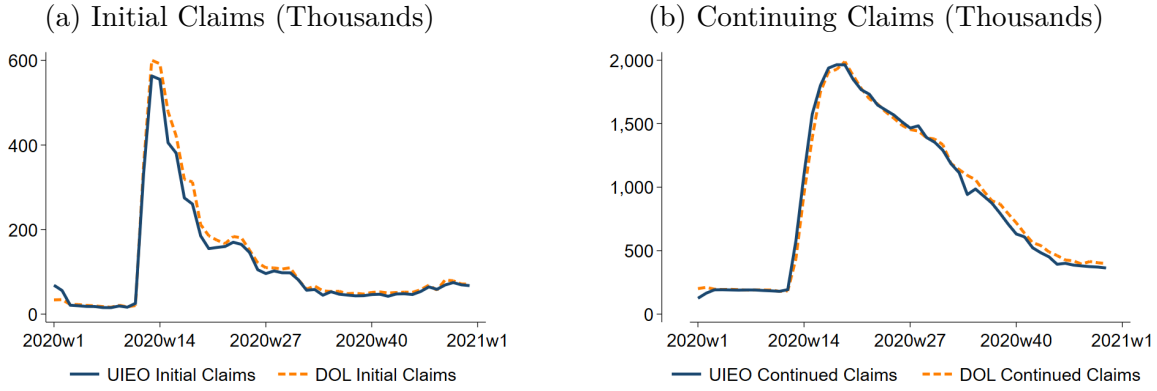


Figure 2: UI Claims Time Series

Note: Initial and continuing claims for Connecticut, Missouri, Ohio, Oklahoma, Utah, and Virginia. DOL claims are obtained from the U.S. Department of Labor Employment and Training Administration.

we restrict the sample in our main analysis to claim spell observations for which we observe full-quarter earnings at some point in the eight-quarter window preceding the UI spell as well as the eight-quarter window following the UI spell.[7] There are many short job spells in the data, and restricting spells to those with three consecutive quarters of employment in a single job both before and after the UI spell could induce selection into our sample.

In Table 1 we document the share of spells we observe for various worker demographic characteristics, separately for all UI spells and for those where we observed full-quarter earnings before and after the spell ("FQ Matched"). From our initial sample of 5.91 million initial weekly and 44.9 million continued weekly claims, we have 4,044,000 UI spells with a positive weekly benefit collection and linked to a valid PIK.[8] Of these 4 million UI spells, we have matched a full-quarter earnings observation prior- and post-spell for 3.2 million spells. We can see that the matched sample has a higher share of prime-age workers. The biggest difference between samples is the much smaller share of older workers in the matched sample,

[7]Full-quarter earnings is measured from the interior quarter of a consecutive three-or-more quarter spell with positive earnings. This ensures continuous employment throughout the quarter and excludes partial-quarter measures of quarterly earnings.

[8]We restrict the sample to those with a valid PIK, age between 15 and 80 at the start of the spell, and with no more than 12 jobs in the JHF in the 8 quarters surrounding the UI spell.

Table 1: Sample Summary Statistics

Demographic	Category	Share of All Spells	Share of FQ Matched	% Difference
Age	< 22	0.061	0.061	-1.2%
	22-24	0.067	0.070	3.3%
	25-34	0.240	0.244	1.7%
	35-44	0.215	0.217	1.0%
	45-54	0.195	0.202	3.4%
	55-59	0.095	0.097	1.7%
	60-64	0.072	0.067	-7.5%
	65 +	0.054	0.043	-19.8%
Sex	F	0.505	0.508	0.6%
	M	0.495	0.492	-0.6%
Race	White	0.742	0.755	1.7%
	Nonwhite	0.258	0.245	-4.9%
Ethnicity	Hispanic	0.083	0.084	1.2%
	Non-Hispanic	0.917	0.916	-0.1%
Sample Size		4,044,000	3,207,000	

Note: All Spells refers to all UI spells with a valid person link (PIK), with a strictly positive weekly benefit amount, age between 15 and 80 at the start of the spell, and with no more than 12 jobs in the 8 quarters before and after each spell. FQ Matched refers to the subset of All Spells with a linked employer with positive full-quarter (FQ) earnings in both the pre- and post-UI spell jobs.

consistent with the fact that many older workers who were laid off during 2020 left the labor force. We also see substantially fewer racial minority workers in the matched sample. We outline the differences in occupation and industry shares between samples in Appendix A.2.

3.2 Characteristics of UI collectors and their Outcomes

We observe the demographic, employer, and job-level characteristics of workers experiencing a UI spell during 2020. In terms of demographics, we observe age, race, ethnicity, sex, and education.[9] Figure 3 shows that the claimant population is dominated by prime age workers, between 25 and 55. For these workers, earnings outcomes from a UI spell are

[9]Note that education is heavily imputed in LEHD, with only about 20% of workers covered by observed educational attainment from surveys.

moderately negative. However, the earnings changes of younger and older workers who experience a UI spell are much more extreme. Earnings changes are monotonically decreasing in age, and largest in magnitude for the youngest workers, who on average experience gains, and the oldest workers, who on average experience the steepest losses. Some of these large earnings gains among the youngest workers are likely attributable to early-career transitions and may be unique to the 2020 UI policy context. Earnings are also heterogeneous by sex, ethnicity, race, and education. Figure 4 shows that men experienced slightly larger earnings losses than women. Figure 5 and 6 show that, in contrast with earnings losses for other race and ethnicity groups, Hispanic and Asian workers experienced slight earnings gains after a UI spell.

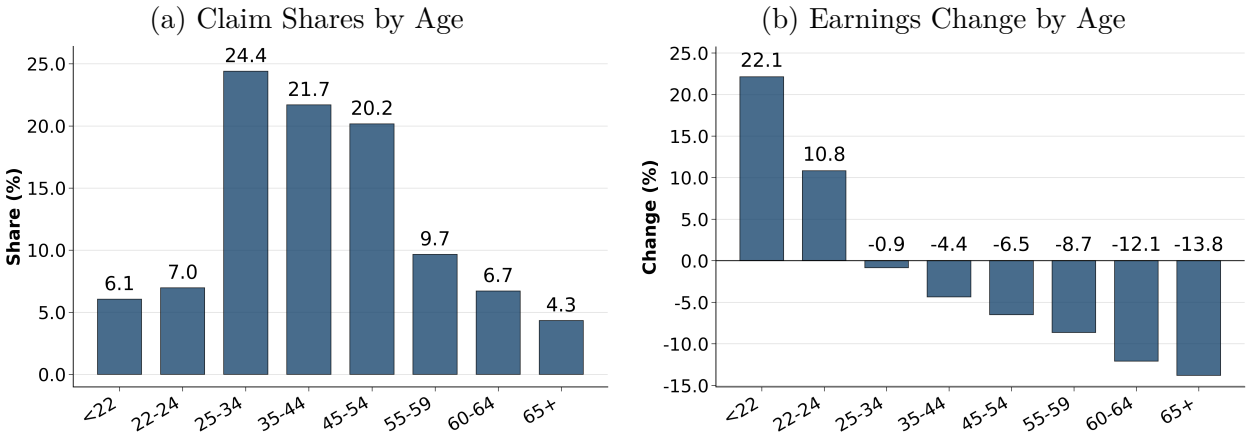


Figure 3: Age Group

Note: Share of UI claims and average earnings changes by recipient age at the start of the UI spell. Sample excludes workers younger than 15 and older than 80.

Table 2 reports the full set of re-employment outcomes by demographic characteristics of the worker. We report the average UI spell duration, average weekly benefit amount, percentage change in earnings, and the share of spells which involved re-employment to the same employer (recall), the share that changed sectors, and the share that changed state of employment.[10] We see that benefit amounts are increasing in age. Recall share is

[10]We refer to re-employment to the same employer after the UI spell as a recall. We use this terminology

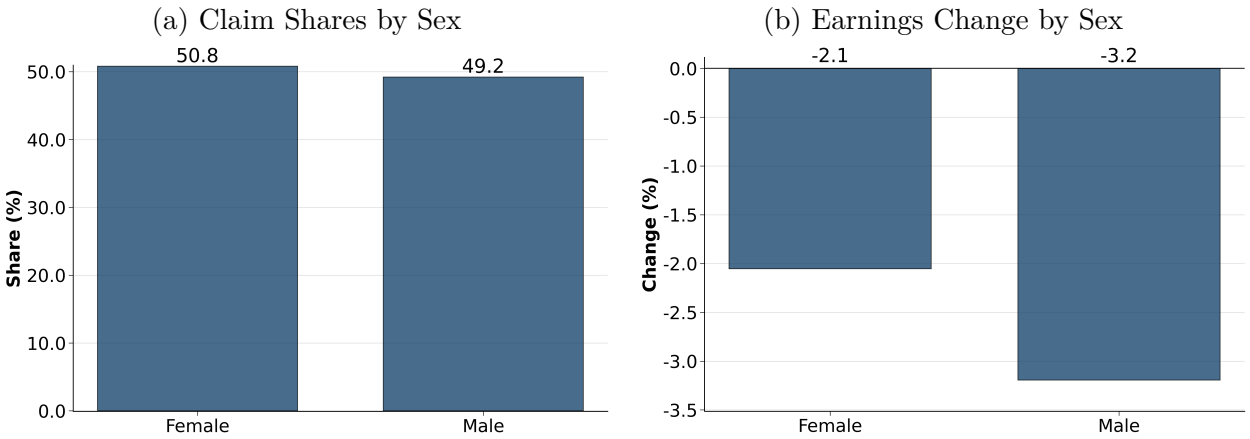


Figure 4: Sex

Note: Share of UI claims and average earnings changes by recipient sex.

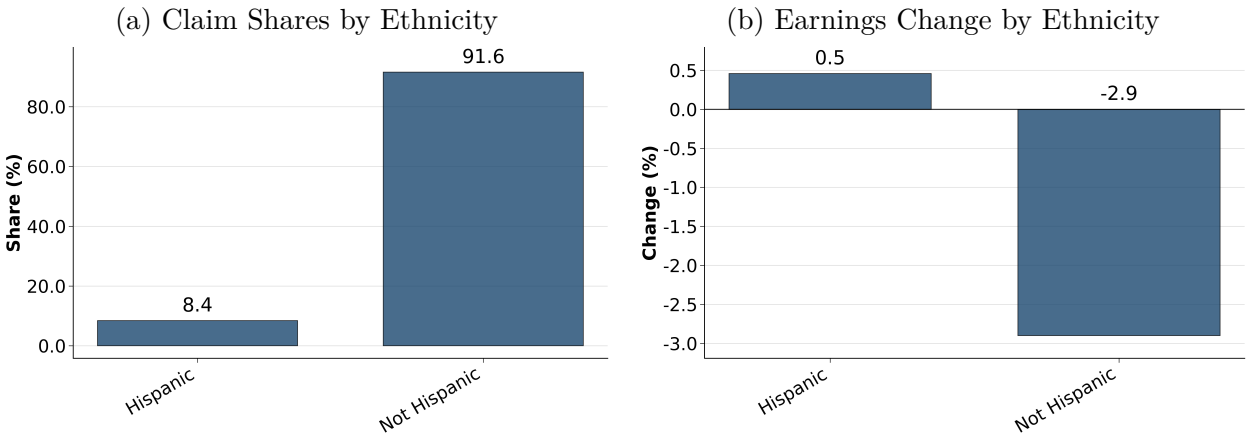


Figure 5: Ethnicity

Note: Share of UI claims and average earnings changes by recipient ethnicity.

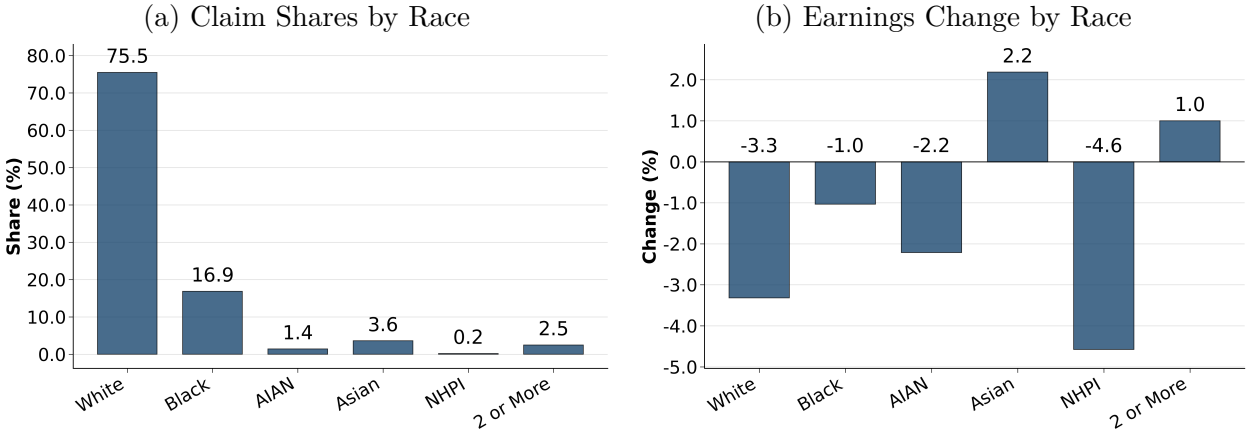


Figure 6: Race

Note: Share of UI claims and average earnings changes by recipient race. AIAN refers to American Indian or Alaska Native, NHPI refers to Native Hawaiian or Other Pacific Islander.

increasing in age and both sectoral and geographic mobility are decreasing in age. In most groups, the majority of claimants in our sample return to the same employer. This is in line with past estimates of recall rates but could be related to specific dynamics in 2020 (Katz and Meyer, 1990; Gertler et al., 2022). Benefits are lower for women than men and duration is slightly longer. Black workers' average benefits are smaller than white workers' benefit amounts, consistent with Skandalis et al. (2022). Black workers also experience longer unemployment durations than other race groups. Black workers also exhibit lower recall probability than other racial groups, and have slightly higher rates of sectoral mobility. On average, Asian workers saw earnings gains following UI spells. These workers also had relatively low rates of sectoral mobility but high rates of geographic mobility compared to other race groups. College-educated workers were slightly more likely to change state of employment than workers with lower levels of education.

somewhat loosely because we cannot measure whether the employer intends the layoff to be temporary, the expectation of an offer to return to work, or an actual offer of work after a pre-specified amount of time.

Table 2: Outcomes by Worker Demographics

Demo	Category	Share (%)	WBA ($)	Duration (Wks)	Earnings (% Chg)	Recall (%)	Δ Sector (%)	Moved (%)
Age	< 22	6.1	175	10.7	+22.1	44.4	40.7	5.5
	22-24	7.0	253	11.3	+10.8	46.8	38.4	7.7
	25-34	24.4	321	11.7	-0.9	55.0	30.7	6.4
	35-44	21.7	350	11.5	-4.4	62.3	24.9	5.1
	45-54	20.2	364	11.1	-6.5	67.7	21.2	4.5
	55-59	9.7	362	11.2	-8.7	71.4	18.8	3.9
	60-64	6.7	358	11.2	-12.1	76.1	15.8	3.2
	65 +	4.3	299	12.8	-13.8	78.6	14.4	2.8
Sex	Female	50.8	297	12.0	-2.1	61.4	26.1	4.6
	Male	49.2	361	10.8	-3.2	62.5	25.6	5.8
Race	White	75.5	338	10.9	-3.3	64.1	24.3	4.9
	Black	16.9	289	13.6	-1.0	52.2	33.1	6.1
	AIAN	1.4	340	10.1	-2.2	64.1	25.0	4.5
	Asian	3.6	313	12.8	+2.2	65.7	21.2	6.8
	NHPI	0.2	336	12.1	-4.6	55.4	31.3	6.0
	2 or More	2.5	303	11.8	+1.0	55.3	31.0	5.9
Ethnicity	Hispanic	8.4	316	12.5	+0.5	57.9	28.3	6.4
	Not Hisp.	91.6	329	11.3	-2.9	62.3	25.6	5.1
Education	< HS	14.0	312	12.2	-1.9	60.0	26.8	5.3
	HS	30.9	327	11.3	-3.2	63.9	24.5	4.6
	Some Col.	32.4	329	11.3	-2.6	62.0	25.8	5.0
	College +	22.6	338	11.3	-2.2	60.4	27.2	6.0

Note: WBA refers to the mean weekly benefit amount in 2020 dollars. Recall refers to the share of each group that is re-employed by the same employer. Δ Sector refers to the share who are re-employed in a different employer NAICS sector after their UI spell. Moved refers to the share of each cell who experienced a change in the state of their employment (not necessarily residence) after their UI spell. AIAN refers to American Indian or Alaska Native, NHPI refers to Native Hawaiian or Other Pacific Islander. Educational attainment is heavily imputed in LEHD.

3.3 Job and Employer Characteristics of UI Collectors

We report the same UI spell and re-employment outcome statistics by characteristics of the job and employer. Some states collect occupation information from UI claimants. Table 3 reports self-reported two-digit SOC codes for the UI collector's previous job for the four states where we have occupation information.[11] Occupation-level data on unemployed workers in the U.S. typically comes from surveys with limited sample sizes, making inferences about outcomes difficult to assess. Our ability to observe this information and link it to LEHD, therefore, is a uniquely important feature of our data. We also report outcome statistics by the NAICS sector of the pre-UI spell job in Table 4. Note that there is substantial heterogeneity in the mean weekly benefit amount, reflecting broad earnings disparities across both sectors and occupations. UI spell duration, earnings changes, and mobility also vary quite significantly across sectors and occupations.

Our sample contains workers for whom we observe both pre- and post-spell full-quarter earnings, so we also show the two-digit NAICS sector for both the worker's origin (pre-UI) and destination (post-UI) employment. Specifically, we build a transition matrix displaying the probability of a worker moving from one sector to another. Figure 7 reports the transition matrix of origin and destination consolidated NAICS sectors for our sample. We report the transition probability from each origin two-digit NAICS sector to a destination sector. The diagonal elements, shaded in blue, reflect the proportion of workers from each sector who are re-employed in the sector after their UI spell. The off-diagonal values, in green shades, reflect the share of workers in an origin sector (row) that is re-employed in a new destination sector (column). We see from this matrix that most workers stay in the same sector after re-employment. It is clear that certain sectors have relatively higher probabilities of attracting workers out of unemployment than others, evidenced by columns with heavier green shades. These include Retail Trade (44-45), Administrative, Support, Waste Management and Remediation Services (56), and Healthcare and Social Assistance (62). This pattern indicates that workers across many sectors are likely to find re-employment in these specific areas if they change sectors after unemployment. The transition matrix does

[11] These states are Missouri, Ohio, Utah, and Virginia.

Table 3: Outcomes by Occupation of Worker

Occupation	Share (%)	WBA ($)	Duration (Wks)	Earnings (% Chg)	Recall (%)	Δ Sector (%)	Moved (%)
11: Mgmt	4.5	372	11.2	-9.2	55.7	31.0	7.4
13: Bus/Fin	1.9	376	11.5	-5.0	50.7	37.6	7.4
15: Comp/Math	1.1	380	10.8	-2.0	40.7	45.0	10.5
17: Arch/Eng	1.0	426	8.5	-2.8	64.7	23.2	7.2
19: Science	0.3	324	10.4	+1.4	50.5	37.0	10.0
21: Comm/SocSvc	0.6	296	11.5	-2.3	50.0	33.2	5.9
23: Legal	0.2	358	11.4	-4.4	48.4	33.9	7.3
25: Educ/Library	2.0	261	11.6	-0.5	65.3	23.7	3.9
27: Arts/Media	1.4	312	12.2	-4.4	58.2	32.4	7.6
29: Health Pract	3.1	367	8.6	-2.0	68.6	14.1	4.6
31: Health Supp	2.9	296	9.9	-1.0	60.2	20.7	3.4
33: Protective	0.4	286	10.6	-1.1	50.3	37.5	7.8
35: Food Service	7.3	241	13.6	-0.2	58.7	26.1	4.5
37: Bldg/Grounds	1.5	265	11.5	-3.3	63.6	26.6	3.5
39: Personal Care	2.5	255	11.1	-0.9	66.5	22.3	4.0
41: Sales	5.5	288	11.3	+0.8	57.3	30.4	4.9
43: Office/Admin	6.0	293	11.3	-2.4	55.2	34.9	5.0
45: Farm/Forest	0.2	316	9.1	-4.4	66.3	25.1	4.6
47: Constr/Extract	4.5	400	8.9	-6.7	68.2	15.9	5.7
49: Maint/Repair	2.6	373	9.3	-2.5	65.7	23.5	4.4
51: Production	9.5	364	8.7	-3.0	74.6	18.3	2.4
53: Transport/Move	3.9	324	10.5	-4.3	64.4	26.2	5.2
99: Unknown/Other	37.0	336	12.8	-2.3	61.4	26.2	5.7

Note: Occupation is self-reported by the claimant. WBA refers to the mean weekly benefit amount in 2020 dollars. Recall refers to the share of each group that is re-employed by the same employer. Δ Sector refers to the share who are re-employed in a different employer NAICS sector after their UI spell. Moved refers to the share of each cell who experienced a change in the state of their employment (not necessarily residence) after their UI spell.

Table 4: Outcomes by Origin Industry of Worker

NAICS Sector	Share (%)	WBA ($)	Duration (Wks)	Earnings (% Chg)	Recall (%)	Δ Sector (%)	Moved (%)
11: Agric/Forest	0.2	307	10.6	-6.3	64.5	32.0	7.3
21: Mining/Oil&Gas	0.7	473	13.1	-24.8	45.5	44.1	15.1
22: Utilities	0.1	432	8.5	-10.6	67.1	32.4	6.3
23: Construction	6.7	411	9.8	-6.4	65.9	16.5	6.4
31-33: Manufacturing	16.7	391	8.2	-6.2	78.9	14.6	2.5
42: Wholesale	3.3	384	11.3	-7.2	57.6	37.1	5.5
44-45: Retail	10.5	275	11.5	+5.2	56.1	29.7	5.0
48-49: Transport	4.7	336	11.7	-4.8	64.6	25.9	6.0
51: Information	1.3	353	12.5	-7.3	51.1	44.0	7.8
52: Finance/Ins	1.4	392	11.7	-10.6	39.4	44.7	8.6
53: Real Estate	1.2	341	13.6	-8.2	48.3	45.1	7.5
54: Professional	3.9	377	12.4	-5.7	47.2	37.7	10.4
55: Mgmt Companies	1.7	376	10.8	-6.0	62.1	39.9	5.9
56: Admin/Support	7.1	304	13.1	-0.1	45.0	40.6	7.2
61: Education	4.1	312	10.3	-5.8	71.8	20.3	4.5
62: Healthcare	13.5	322	10.4	-0.9	64.1	16.7	3.7
71: Arts/Recreation	2.8	278	13.3	-0.9	64.8	30.6	5.6
72: Accom/Food	14.7	248	15.1	+0.7	55.7	27.8	5.4
81: Other Services	4.2	286	12.7	-1.5	65.0	27.9	4.6
92: Public Admin	1.2	342	9.3	-2.0	68.1	28.9	3.4

Note: WBA refers to the mean weekly benefit amount in 2020 dollars. Recall refers to the share of each group that is re-employed by the same employer. Δ Sector refers to the share who are re-employed in a different employer NAICS sector after their UI spell. Moved refers to the share of each cell who experienced a change in the state of their employment (not necessarily residence) after their UI spell.

not reflect the relative size differences across sectors, only the shares of workers within each sector who stay or move. To get a better picture of the transition dynamics across sectors, we report the net flow of claimant jobs into and out of each sector, both in terms of total jobs and in percentage changes. Table 5 reports counts of the pre- and post-UI spell jobs in each sector. The net flows of workers across sectors is then given by the net difference between origin and destination job counts as well as the percentage change in jobs for that sector. Transportation and Warehousing (48-49), Administrative and Support Services (56), and Healthcare attracted a significant number of net jobs. Accommodation and Food Services (72) experienced a very large net decline in jobs among UI recipients. The flows into and out of these specific sectors in 2020 align with contemporaneous accounts of the response to the pandemic and the resulting disruptions to restaurants, bars, and hotels.

Table 5: Sector Net Flows - All Transitions (Including Same-Sector)

Sector	Pre-UI Emp	Post-UI Emp	Net Change	% Change
11: Agric/Forest	6,600	7,650	+1,050	+15.9%
21: Mining/Oil&Gas	21,000	14,350	-6,650	-31.7%
22: Utilities	3,350	4,200	+850	+25.4%
23: Construction	215,250	217,750	+2,500	+1.2%
31-33: Manufacturing	541,050	527,000	-14,050	-2.6%
42: Wholesale	105,650	102,900	-2,750	-2.6%
44-45: Retail	335,500	346,800	+11,300	+3.4%
48-49: Transport	149,950	175,150	+25,200	+16.8%
51: Information	41,050	37,300	-3,750	-9.1%
52: Finance/Ins	47,550	52,750	+5,200	+10.9%
53: Real Estate	37,900	38,100	+200	+0.5%
54: Professional	126,700	133,100	+6,400	+5.1%
55: Mgmt Companies	55,900	51,550	-4,350	-7.8%
56: Admin/Support	217,500	239,400	+21,900	+10.1%
61: Education	132,400	144,300	+11,900	+9.0%
62: Healthcare	436,950	457,250	+20,300	+4.6%
71: Arts/Recreation	87,650	80,950	-6,700	-7.6%
72: Accom/Food	469,900	399,350	-70,550	-15.0%
81: Other Services	134,100	129,500	-4,600	-3.4%
92: Public Admin	38,900	45,500	+6,600	+17.0%

Note: Pre-UI Emp is the count of UI spells in our sample with a pre-spell job in this sector. Post-UI Emp is the count of UI spells that end with employment in that sector. Net Change is the number of net jobs gained or lost over all spells and sector transitions.

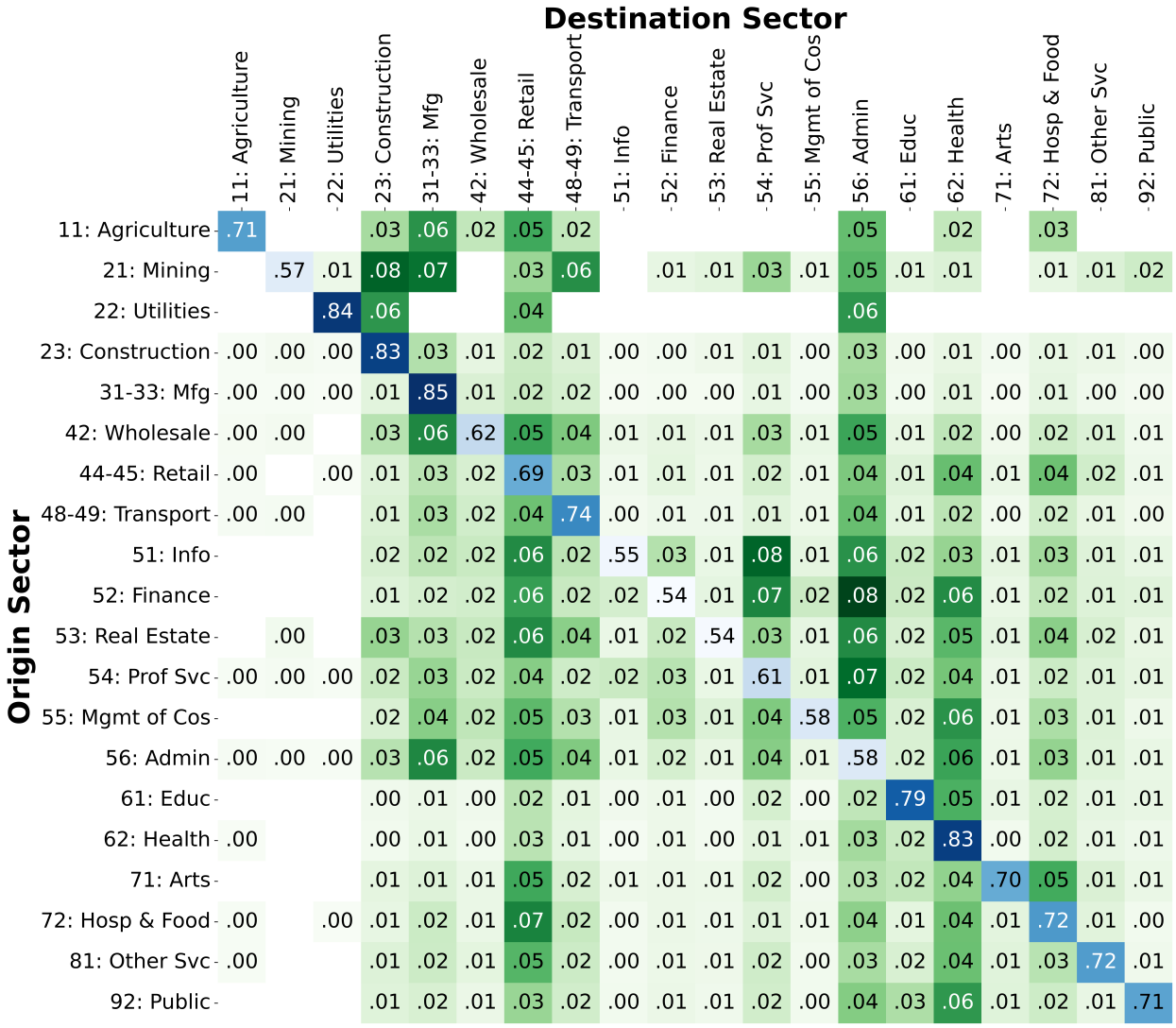


Figure 7: Sector Transition Matrix

Note: Each cell represents the fraction of recipients in the indicated origin sector (row) that moved to the indicated destination sector (column) following a UI spell. Blank cells suppressed due to insufficient observations.

In Figure 8 we also report the associated mean earnings gain or loss of the workers in each origin-destination cell, using a symmetric percent change measure (Davis et al. (1996) growth rate). Diagonal elements reflect the average earnings change for workers who are re-employed in the same sector. Average earnings changes are quite large for workers who become employed in a different sector, reflected in the off-diagonal elements of the matrix. Workers leaving sectors like Mining and Manufacturing experienced large earnings decreases when moving out of the sector. In contrast, workers from Educational Services (61), Arts, Entertainment, and Recreation (71) and Hospitality and Food Services (72) saw earnings gains when switching to jobs in many other sectors.

3.4 Earnings Level

We next document how post-UI outcomes differ according to the worker's pre-UI earnings level. Table 6 reports outcomes across quarterly earnings bins, reflecting the closest full-quarter earnings observation prior to the UI spell deflated to 2020 dollars. We plot several of these columns over the earnings distribution in subsequent figures. Figure 9a plots the distribution of UI spells across quarterly earnings level bins. Figure 9b plots the average earnings change following a UI spell across pre-spell quarterly earnings bins. Earnings changes are monotonically decreasing in prior earnings level. This pattern is consistent with workers falling off of a so-called "wage ladder" when displaced. Figure 9c plots the average weekly duration of the UI spells across the distribution of pre-spell quarterly earnings. On average, shorter UI spells are more common among higher earners.

Earnings level and different measures of mobility are strongly correlated. Figure 10a plots the share of the UI spells in each pre-spell quarterly earnings bin that were re-employed by the same employer. This recall rate is increasing in the pre-spell earnings level: higher earners were more likely to return to the same employer than workers with lower earnings. Figure 10b plots the share of the UI spells that changed sectors in re-employment. Workers at the bottom of the earnings distribution were more likely to be re-employed in a different sector following a layoff. Unlike employer and sector mobility, the pattern of geographic

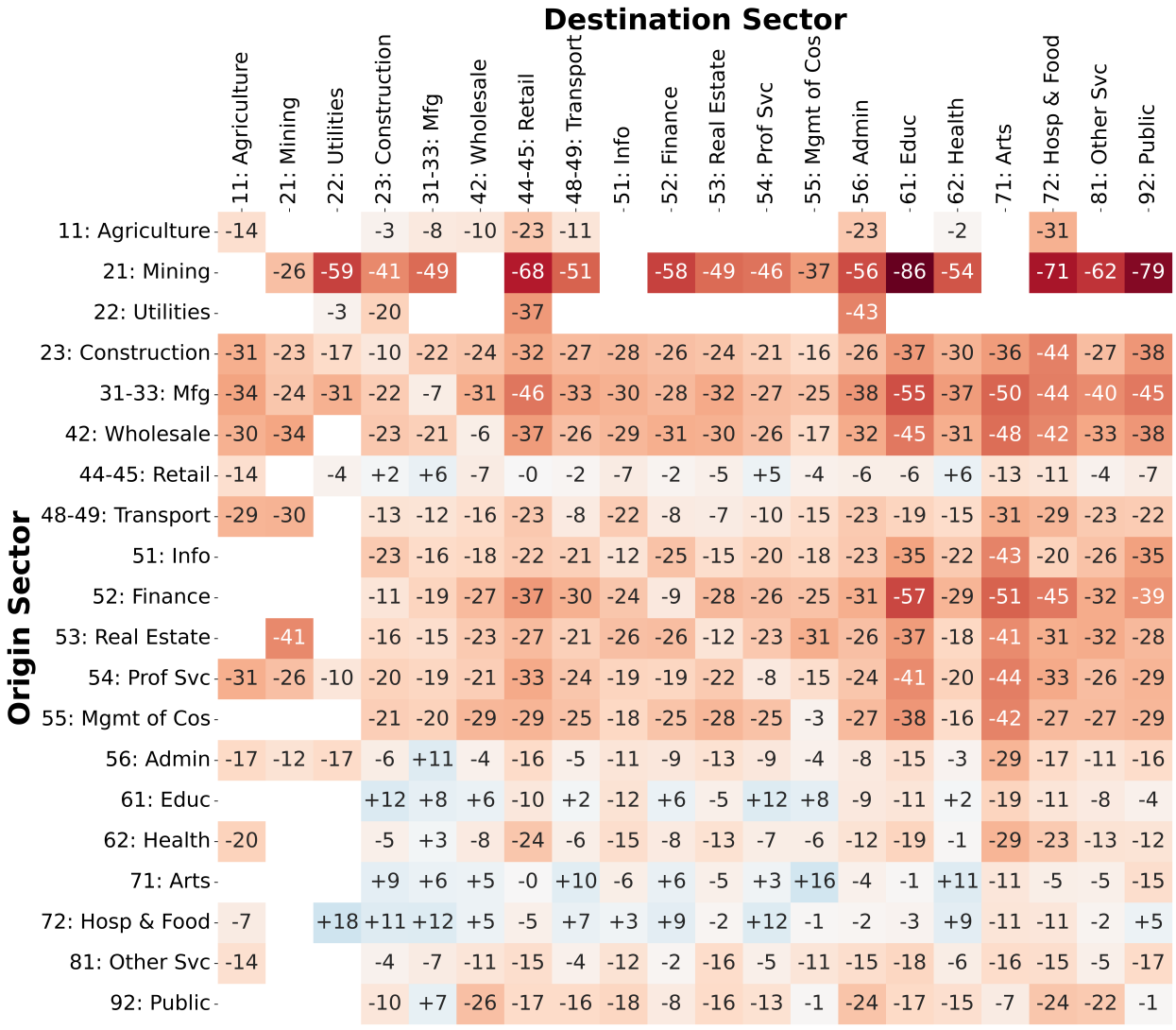


Figure 8: Sector Transition Matrix: Earnings Changes

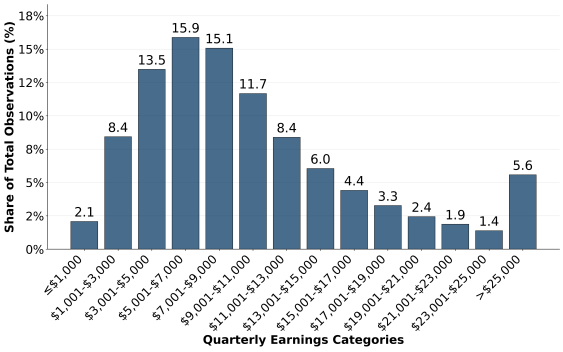
Note: Each cell shows the mean earnings change for the recipients in the indicated origin sector (row) that moved to the indicated destination sector (column) following a UI spell. Earnings changes are calculated as symmetric percent changes (i.e., Davis et al. (1996) growth rates). Blank cells suppressed due to insufficient observations.

Table 6: Outcomes by Prior Earnings Level

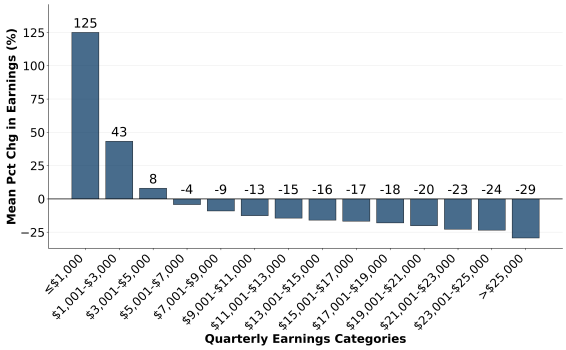
Earnings Category	Share (%)	Earnings (% Chg)	Duration (Weeks)	Weekly Benefit ($)	Recall (%)	Δ Sector (%)	Moved (%)
≤$1,000	2.1	+125.0	11.3	170	44.6	40.7	7.3
$1,001–$3,000	8.4	+43.2	12.7	162	51.6	34.8	5.1
$3,001–$5,000	13.5	+8.0	13.3	201	55.2	31.1	4.5
$5,001–$7,000	15.9	-4.3	12.6	258	57.9	29.2	4.5
$7,001–$9,000	15.1	-9.1	11.7	319	62.2	26.4	4.4
$9,001–$11,000	11.7	-12.6	11.0	371	65.9	23.2	4.6
$11,001–$13,000	8.4	-14.5	10.6	413	68.0	21.0	4.9
$13,001–$15,000	6.0	-16.0	10.2	444	68.6	20.0	5.3
$15,001–$17,000	4.4	-16.8	9.8	463	69.3	18.9	5.7
$17,001–$19,000	3.3	-18.0	9.7	474	69.3	18.6	6.2
$19,001–$21,000	2.4	-20.2	9.5	477	69.5	18.2	6.6
$21,001–$23,000	1.9	-22.9	9.2	476	70.0	18.0	6.9
$23,001–$25,000	1.4	-23.5	9.1	477	70.3	17.7	7.1
>$25,000	5.6	-29.4	8.9	484	68.2	19.6	9.0

Note: WBA refers to the mean weekly benefit amount in 2020 dollars. Recall refers to the share of each group that is re-employed by the same employer. Δ Sector refers to the share who are re-employed in a different employer NAICS sector after their UI spell. Moved refers to the share of each cell who experienced a change in the state of their employment (not necessarily residence) after their UI spell. All earnings are reported in quarterly values. All monetary values deflated to 2020 dollars.

(a) Earnings Distribution



(b) Earnings Changes over the Earnings Distribution



(c) UI spell Duration over the Earnings Distribution

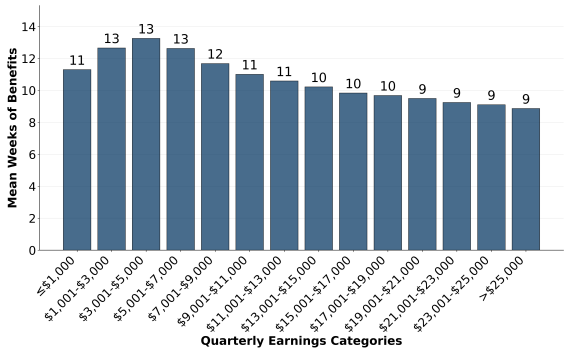


Figure 9: Earnings Level Before UI Spell

Note: Earnings changes are calculated as symmetric percent changes (i.e., Davis et al. (1996) growth rates). Earnings reported in these figures are quarterly earnings amounts in 2020 dollars.

mobility by earnings is not monotone.[12] Figure 10c plots the share of the UI spells in each earnings bin that changed their state of employment after the UI spell. Mobility across states exhibits a "U-shaped" pattern: both low and high earners were more likely to find employment in a different state than were workers in the middle of the earnings distribution. This pattern demonstrates the power of multi-state UI claims data. State labor market information offices know about the pool of unemployed workers in their own state but do not observe their re-employment outcomes for the set of workers taking jobs in other states. For states interested in retaining talent in their labor market, the fact that both low and high earners are more likely to seek employment across state lines means a single strategy for retention may not be successful.

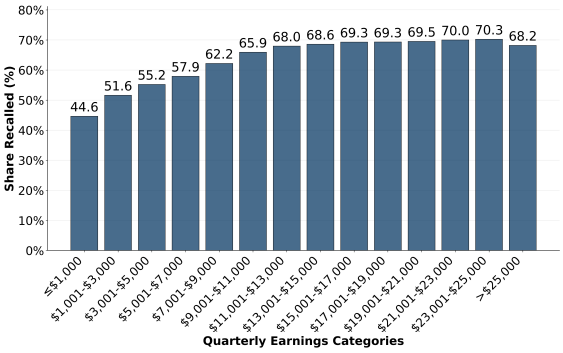
3.5 Spell Duration

One of the strengths of weekly claims data is that we can precisely identify the length of each UI spell. It is important to note, however, that we cannot always determine the length of an *unemployment* spell, which is the time an unemployed worker remains out of work and can include the time after UI benefits are exhausted. Benefit exhaustion mostly occurs at 20, 26, or 39 weeks in our sample, but can occur at other durations, for instance if the worker had a recent previous UI spell, via Extended Benefits being triggered in the state, or if the UI spell continued past the December 27, 2020, extension of PEUC from 13 to 24 weeks. During economic downturns, such as our sample period, benefit exhaustion is more common as both unemployment spells and UI spells tend to be longer. At the same time, UI benefits are usually extended for additional weeks to help unemployed workers find jobs, as was the case in 2020. There are many ways in which the causal relationship between extended UI benefits and longer UI spells is confounded during these times, and so we reiterate here that the analyses presented below do not represent the causal effect of UI policy.

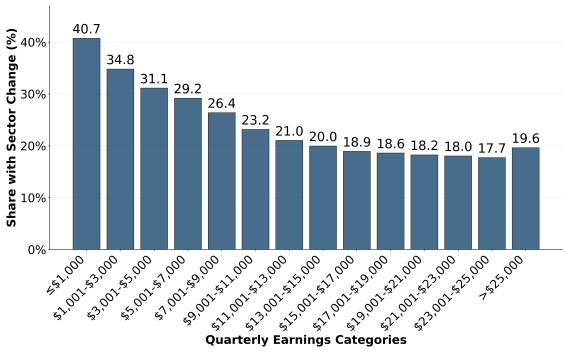
The weekly precision in our data is particularly important when we consider the distribution of UI spell lengths in our sample. Unemployment can be a very short phenomenon, and

[12]Note that this geography relates to the location of the *employer* and not the residence of the worker.

(a) Recall Rate over the Earnings Distribution



(b) Sector Mobility Rate over the Earnings Distribution



(c) State Mobility Rate over the Earnings Distribution

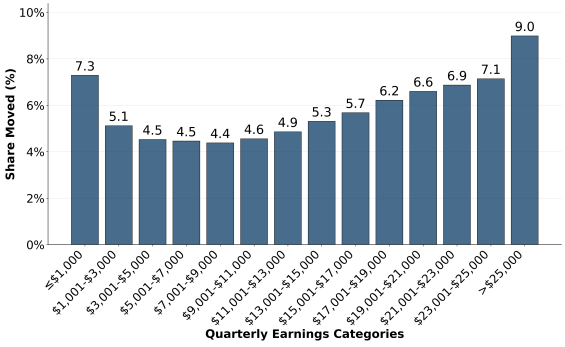


Figure 10: Earnings Level Before UI Spell: Mobility

Note: Recall refers to workers re-employed by the same employer. Sector change refers to workers re-employed in a different employer NAICS sector after their UI spell. Moved refers to workers who experienced a change in the state of their employment (not necessarily residence) after their UI spell. All earnings are reported in quarterly values. All monetary values deflated to 2020 dollars.

its incidence can easily be missed in monthly and quarterly data. Figure 11a shows the share of UI spells in our sample that last for a given number of weeks. Half of the spells in our sample are less than eight weeks in length. With quarterly data, researchers typically rely on observing at least one or two quarters of nonemployment in order to classify workers as being out of work. Our data show that, while necessary with quarterly data, this approach results in a small subset of UI spells being studied: 30% of spells in our sample last at least 13 weeks (i.e., one quarter) and only 12% last for at least 26 weeks. In non-recessionary times, spells of these lengths are likely much less frequent as regular benefits typically end after 26 weeks in most states.

Figure 11b shows that while they may be infrequent, longer UI spells are associated with increasingly worse re-employment outcomes. For a set of short spell durations in our sample, the average earnings change is *positive*.[13] However, longer duration spells have increasingly worse outcomes in terms of earnings losses. These losses get larger in magnitude around durations related to benefit expiration (e.g., 26 and 41 weeks). These UI spells likely ended in exhaustion of benefits rather than re-employment. The real length of these unemployment spells may have been longer than the UI spell and thus had worse outcomes.

Appendix Table 12 reports the values represented in these figures. It is important to note that these results do not point to a causal relationship. There are potentially a number of mechanisms that account for this duration relationship, including selection, duration dependence, moral hazard, and UI policies. One example of the potentially multi-faceted relationship of duration with outcomes is that while earnings change outcomes are mostly monotone in duration, the average earnings of the workers prior to their UI spell is not. The mean of average earnings in the worker's previous job is "U-shaped" in duration, at its highest for short duration spells and long duration spells, as seen in Figure 12a.

[13]This is likely the result of some positive selection of UI spells due to requiring full-quarter earnings in the pre- and post-spell jobs. When we relax this full-quarter restriction to consider spells with any positive pre- and post-spell earnings, changes become more negative and there is no region with significant earnings gains.

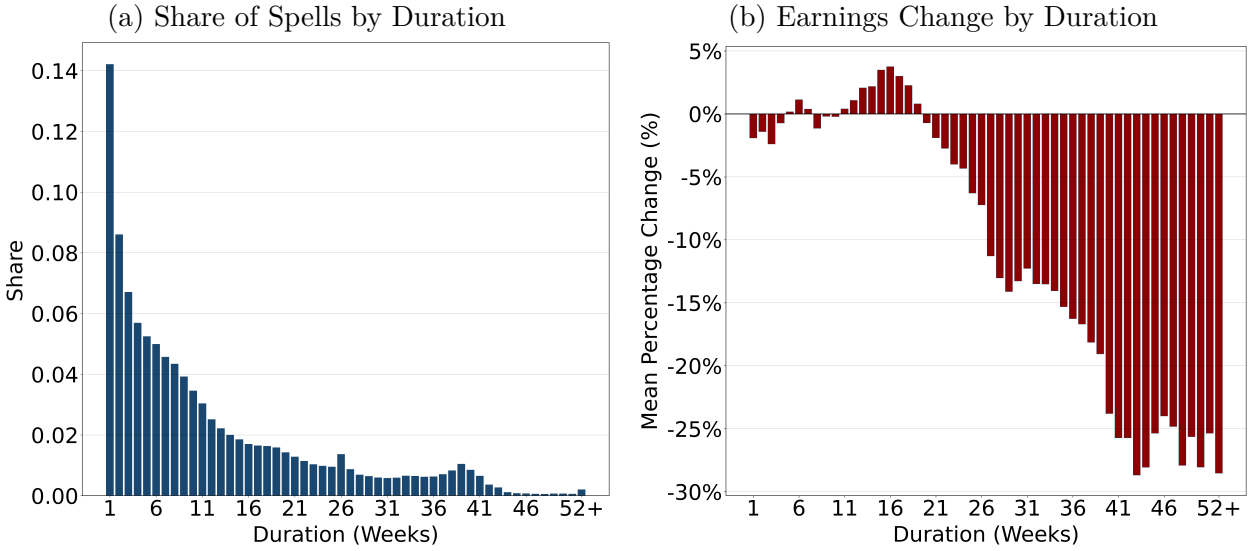


Figure 11: Duration in Weeks

Note: Earnings changes are calculated as symmetric percent changes (i.e., Davis et al. (1996) growth rates).

3.6 Mobility and the Distribution of Earnings Changes

While most of our results have focused on the mean outcomes of UI spells grouped by worker or job characteristics, it is important to note the distribution of these outcomes as well. In this section we examine the distribution of earnings changes workers experience following a UI spell. Figure 13 shows the distribution of earnings changes for all spells in our sample. Note that there is significant density at 0, which represents the ±5% earnings change bin.

As highlighted in prior sections, there is substantial variation in rates of recall, sector mobility, and state mobility across UI spells. We also consider how re-employment outcomes vary based on mobility. We first report means of weekly benefit amount, prior earnings level, earnings change, and mobility metrics separately by whether the worker was recalled, changed sector, and changed state of employment. Table 7 reports outcome measures by these different types of mobility.

In the following figures, we document a common pattern across different measures of

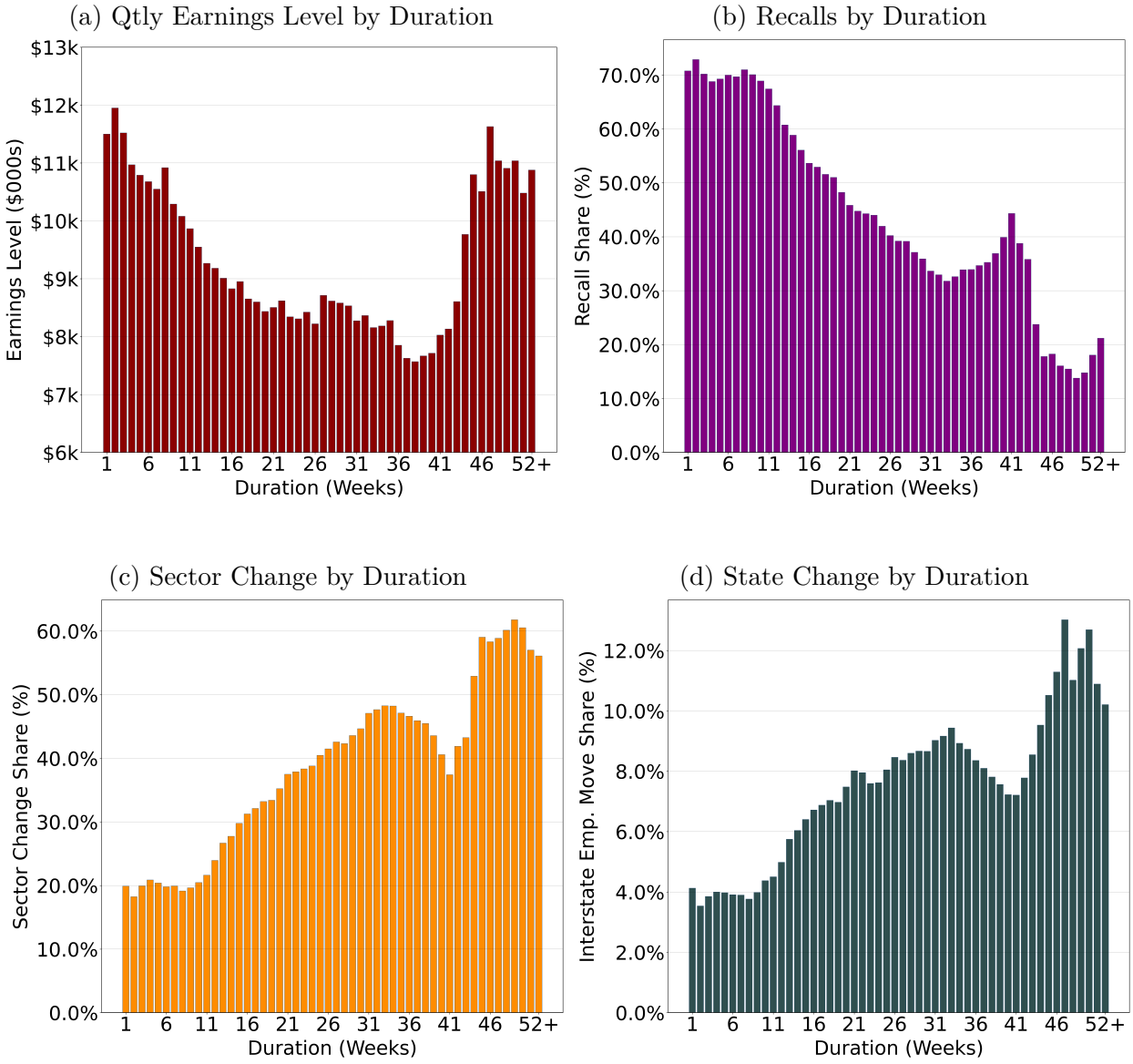


Figure 12: Mobility by Duration

Note: Recall refers to workers re-employed by the same employer. Sector change refers to workers re-employed in a different employer NAICS sector after their UI spell. "Interstate Emp. Move" refers to workers who experienced a change in the state of their employment (not necessarily residence) after their UI spell. All earnings are reported in quarterly values. All monetary values deflated to 2020 dollars.

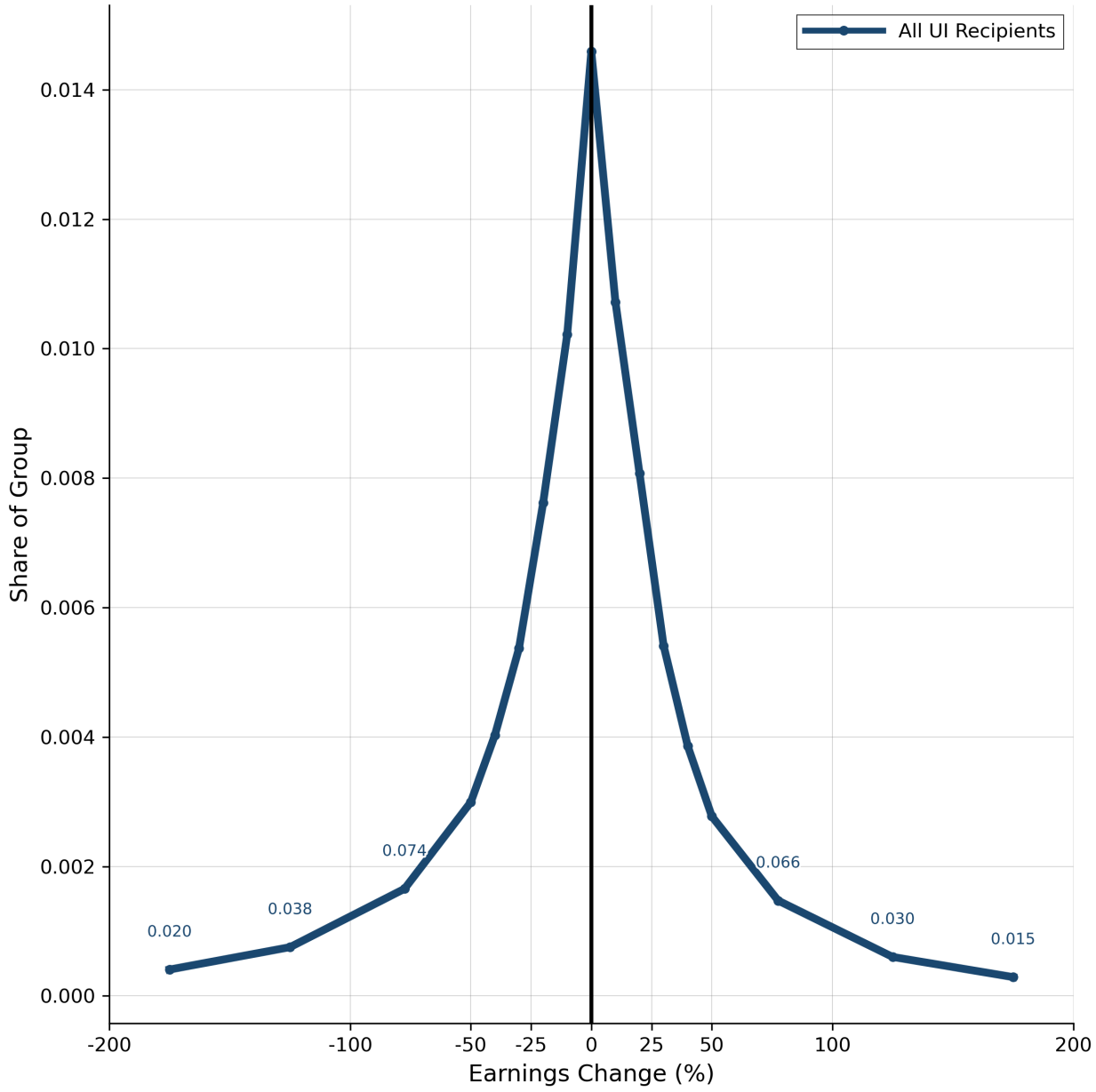


Figure 13: Earnings Change Distribution

Note: Points from -50 to 50 are the midpoints of 10% bins ranging from $[-55\%, -45\%]$ to $[45\%, 55\%]$. Points outside of this range are the midpoints of the $\pm[55\%, 100\%]$, $\pm[100\%, 150\%]$, and $\pm[150, 200\%]$ bins. Levels of the points were adjusted to reflect the density of observations if bin sizes were identical. Actual shares are reported in the numbers above each point. Earnings changes are the symmetric percent change in real full-quarter earnings (i.e., Davis et al. (1996) growth rate). All monetary values deflated to 2020 dollars.

Table 7: Mobility Table

Mobility	Share (%)	Pre-Spell Earnings ($)	Earnings (% Chg)	Recall (%)	Δ Sector (%)	Moved (%)
Recalled	62.0	11,440	-4.9	100.0	0.7	—
Not Recalled	38.0	8,208	+1.1	—	66.7	13.6
Same Sector	74.2	11,010	-3.9	82.9	—	2.4
Changed Sector	25.8	7,911	+1.1	1.7	100.0	13.0
Same State	94.8	10,180	-2.9	65.3	23.7	—
Changed State	5.2	10,720	+2.9	—	65.2	100.0

Note: WBA refers to the mean weekly benefit amount in dollars. Recall refers to the share of each group that is re-employed by the same employer. Δ Sector refers to the share who are re-employed in a different employer NAICS sector after their UI spell. Moved refers to the share of each cell who experienced a change in the state of their employment (not necessarily residence) after their UI spell. All monetary values deflated to 2020 dollars.

mobility: each type of mobility is associated with wider dispersion of outcomes. There is more variance in earnings changes following a UI spell for those who change employers, sectors of employment, or state of employment, than for those who did not move. Figure 14 plots the distribution of earnings changes by whether the worker was re-employed by the same employer (recall) or by a new firm. The distribution of earnings changes for recalled workers is widely dispersed, but much less so than for those who change employers. In addition, we observe both positive and negative earnings changes for recalled workers as well. Among those who changed employers, more workers experienced large positive changes in earnings than large earnings losses, reflected in the shares at each tail. By contrast, for those who were recalled, the share of workers experiencing large negative changes outnumbered the share with large gains.

Figure 15 plots the distribution of earnings changes across UI spells separately for workers who remained in the same sector after unemployment and those who changed sectors. We see similar patterns in the distribution of movers and stayers based on industry sector as we did with employers (recall). Movers had much higher dispersion, but also had a higher share of large earnings gains compared with those who didn't move. More non-movers had large earnings losses than had large gains, but they had far fewer large changes and a more compressed distribution of earnings changes compared with those changing sectors.

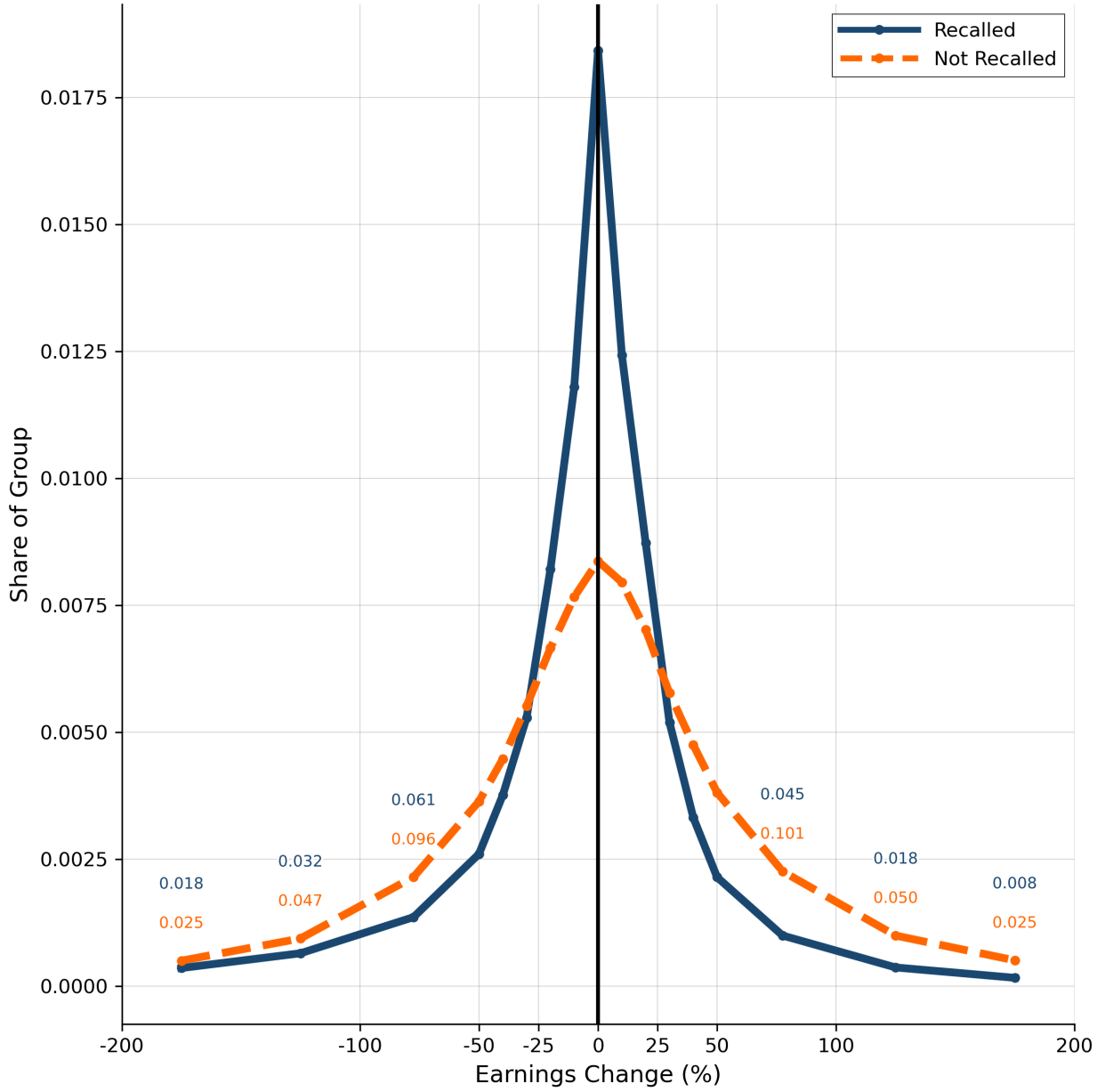


Figure 14: Earnings Change by Recall

Note: Points from -50 to 50 are the midpoints of 10% bins ranging from $[-55\%, -45\%]$ to $[45\%, 55\%]$. Points outside of this range are the midpoints of the $\pm[55\%, 100\%]$, $\pm[100\%, 150\%]$, and $\pm[150, 200\%]$ bins. Levels of the points were adjusted to reflect the density of observations if bin sizes were identical. Actual shares are reported in the numbers above each point. Our earnings percent change measure is the symmetric percent change in real full-quarter earnings (i.e., Davis et al. (1996) growth rate). All monetary values deflated to 2020 dollars.

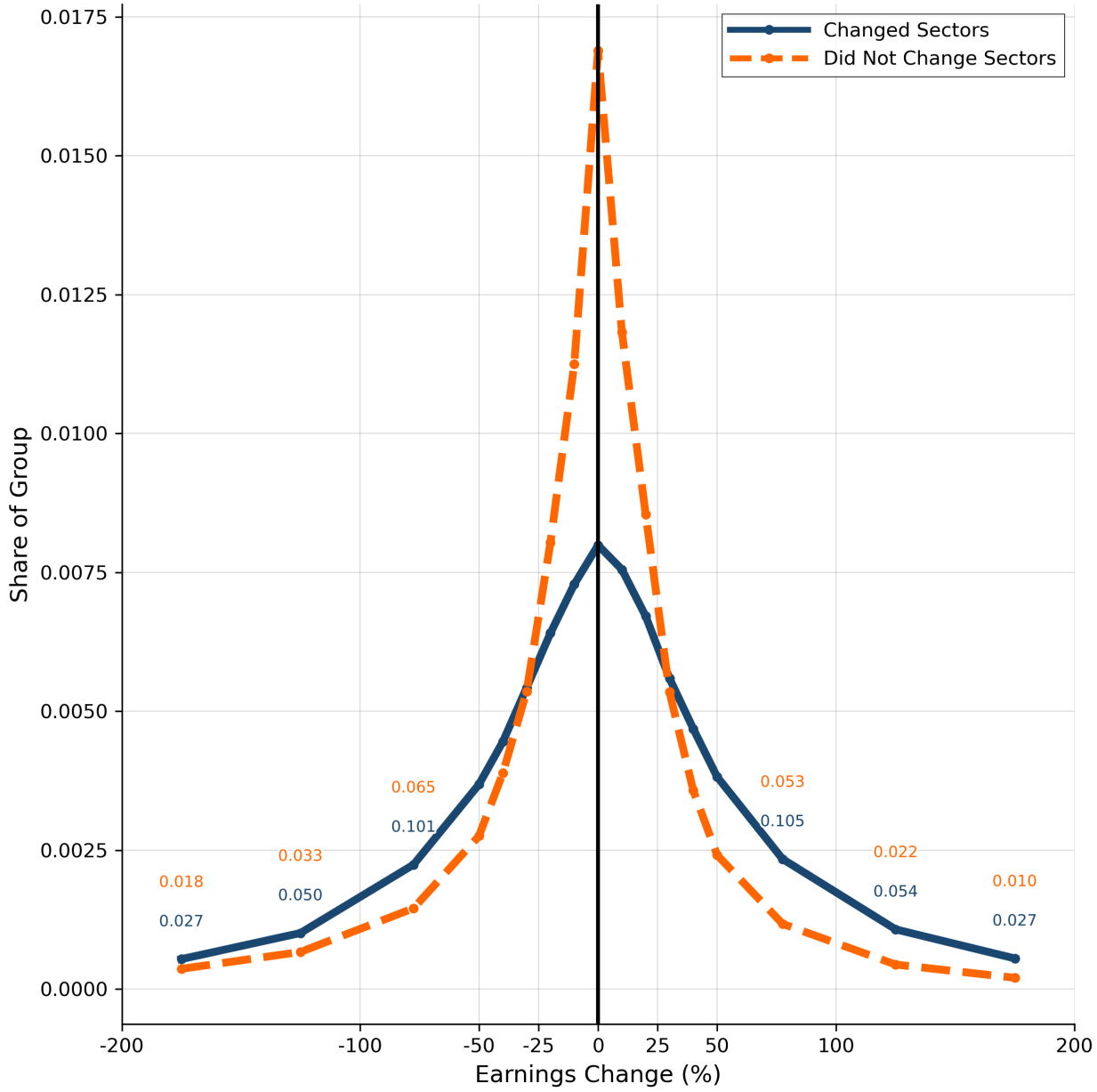


Figure 15: Earnings Change by Sector Transition

Note: Points from -50 to 50 are the midpoints of 10% bins ranging from $[-55\%, -45\%]$ to $[45\%, 55\%]$. Points outside of this range are the midpoints of the $\pm[55\%, 100\%]$, $\pm[100\%, 150\%]$, and $\pm[150, 200\%]$ bins. Levels of the points were adjusted to reflect the density of observations if bin sizes were identical. Actual shares are reported in the numbers above each point. Our earnings percent change measure is the symmetric percent change in real full-quarter earnings (i.e., Davis et al. (1996) growth rate). All monetary values deflated to 2020 dollars.

Figure 16 plots the distribution of earnings changes across UI spells by whether the worker was re-employed in the same state as their original employment prior to the layoff, or if they moved to an employer in another state. Note that this does not necessarily mean the worker changed their location or state of residence. We again see the familiar theme around mobility and the distribution of outcomes. Movers had much higher dispersion, but there also was a higher share of workers experiencing large earnings gains relative to the share with large earnings losses. More non-movers had large earnings losses than had large gains, but they had far fewer large changes overall and a more compressed distribution of earnings changes compared with workers whose state of employment changed.

We also examine differences in outcomes by the timing of re-employment. Specifically, we compare workers who were immediately re-employed after their UI spell with those where we observe re-employment more than one quarter after the end of their UI spell. Figure 17 plots the distribution of earnings changes for these two groups. Workers immediately transitioning to work were more likely to experience no earnings change and exhibit a tighter distribution of earnings changes compared to those who took longer to return to work.

4 Discussion

These results underscore the heterogeneity in post-unemployment earnings trajectories across workers' demographics, occupations, and industries. Younger workers often experience earnings gains after re-employment, reflecting upward mobility, while older workers face steep losses, consistent with evidence on scarring effects of job displacement later in life. These patterns suggest that UI and job displacement interacts strongly with life-cycle considerations. Outcomes also vary widely in the characteristics of the pre-UI spell job such as the earnings level, occupation, and industry. These patterns hint at different wage-premia across job types influencing earnings losses either from transitions out of these jobs, or by falling off the job ladder. We hope to explore the role of employer characteristics and these dynamics in future work.

Mobility, in terms of employers, sectors, and states of employment, is another central

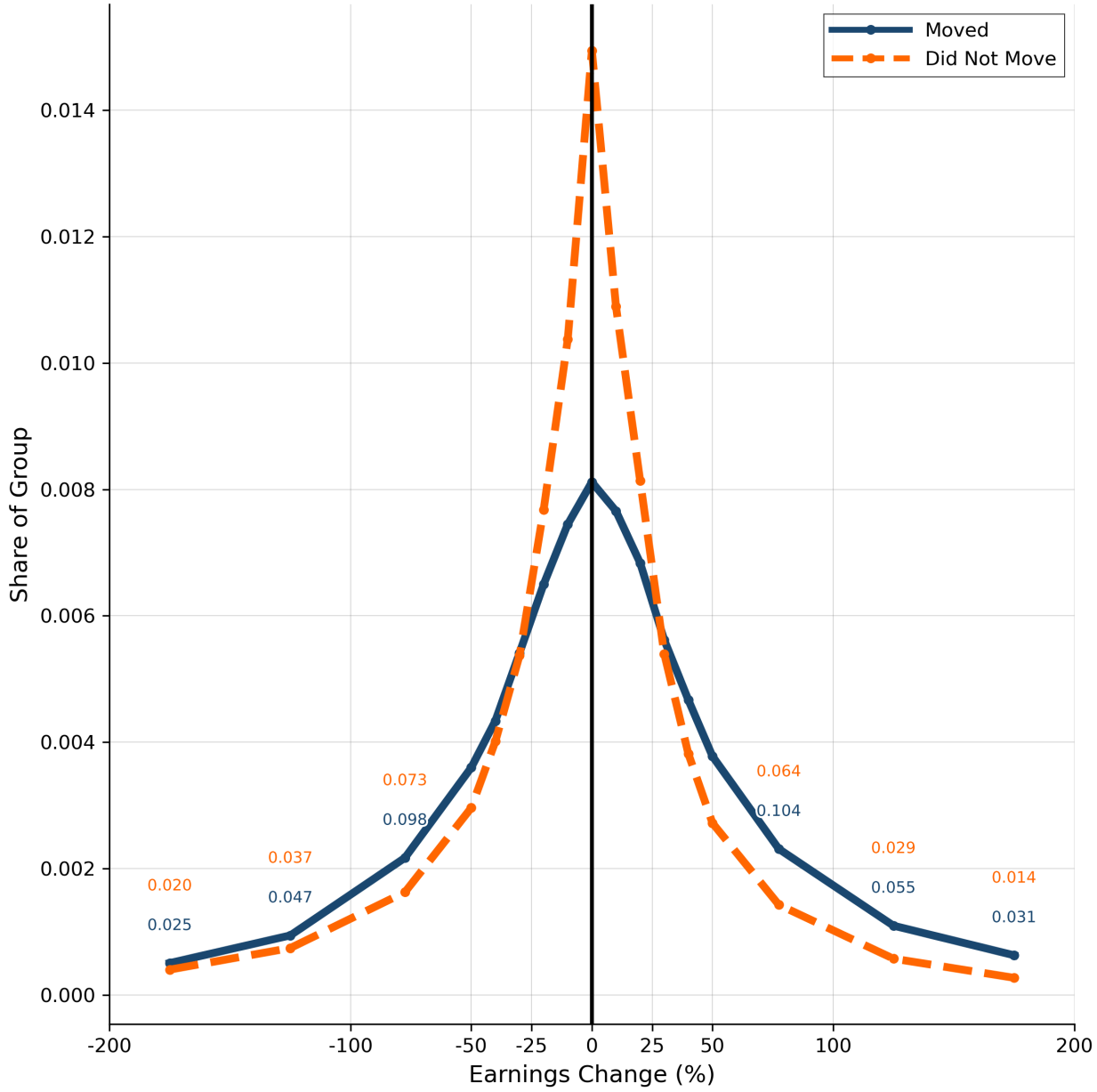


Figure 16: Earnings Change by Mobility of State of Employment

Note: Points from -50 to 50 are the midpoints of 10% bins ranging from $[-55\%, -45\%]$ to $[45\%, 55\%]$. Points outside of this range are the midpoints of the $\pm[55\%, 100\%]$, $\pm[100\%, 150\%]$, and $\pm[150, 200\%]$ bins. Levels of the points were adjusted to reflect the density of observations if bin sizes were identical. Actual shares are reported in the numbers above each point. Our earnings percent change measure is the symmetric percent change in real full-quarter earnings (i.e., Davis et al. (1996) growth rate). All monetary values deflated to 2020 dollars.

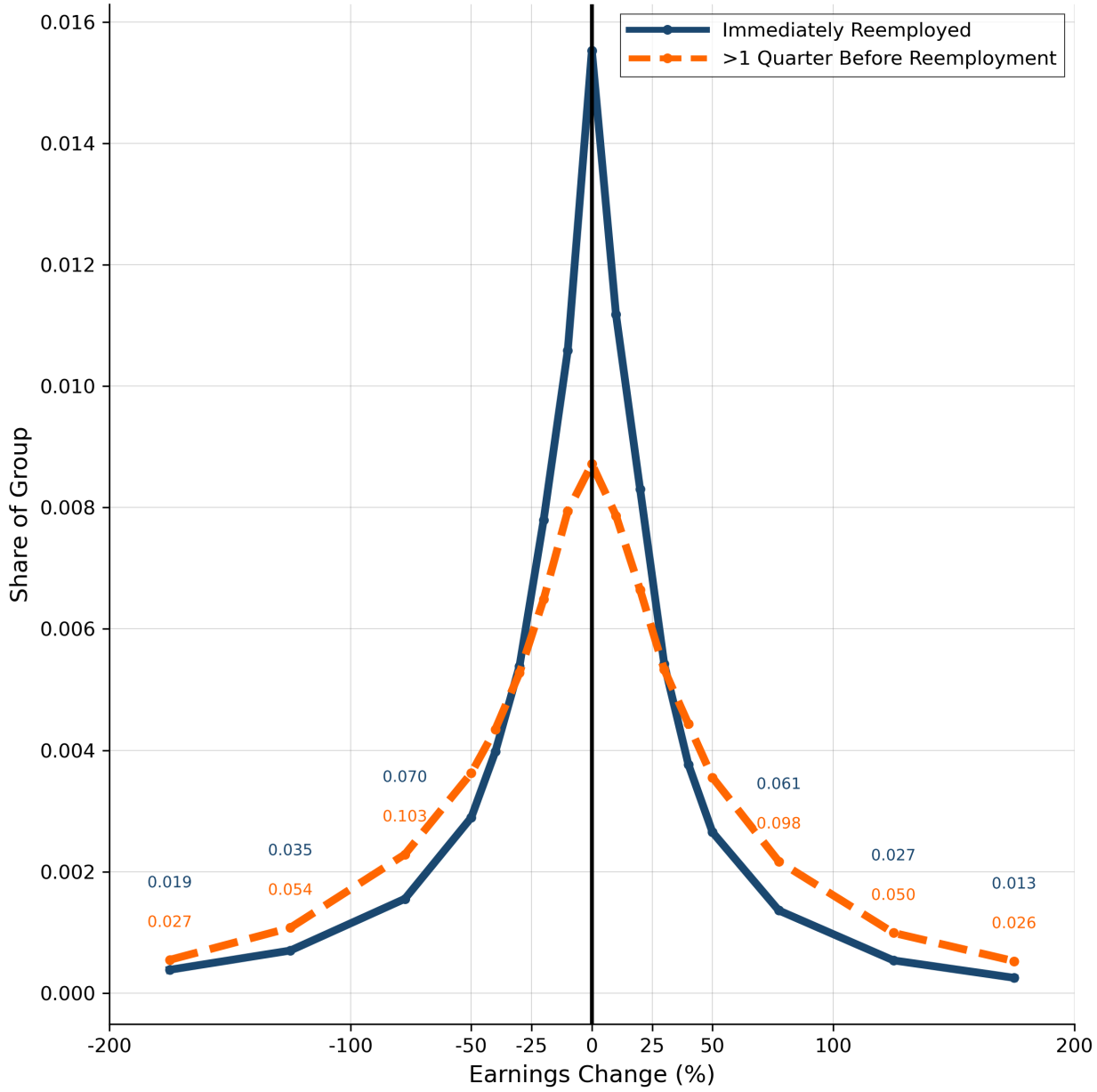


Figure 17: Earnings Change by Re-employment Timing

Note: Points from -50 to 50 are the midpoints of 10% bins ranging from $[-55\%, -45\%]$ to $[45\%, 55\%]$. Points outside of this range are the midpoints of the $\pm[55\%, 100\%]$, $\pm[100\%, 150\%]$, and $\pm[150, 200\%]$ bins. Levels of the points were adjusted to reflect the density of observations if bin sizes were identical. Actual shares are reported in the numbers above each point. Our earnings percent change measure is the symmetric percent change in real full-quarter earnings (i.e., Davis et al. (1996) growth rate). All monetary values deflated to 2020 dollars.

feature of our results that is crucial for interpreting earnings outcomes following a UI spell. Workers re-employed by their prior employers experienced less earnings dispersion, both in terms of gains and losses, compared to those who transitioned to new firms, industries, or states. This pattern aligns with prior work showing that recalls play a stabilizing role in downturns, particularly during the pandemic recession (Katz and Meyer, 1990; Fujita and Moscarini, 2017; Gertler et al., 2022). The differential earnings dispersion for recalls is an important addition to this existing set of papers which largely focus on re-employment dynamics and not earnings. At the same time, our sectoral transition matrix documents substantial flows across industries in 2020, with net losses in accommodation and food services and gains in sectors such as transportation and healthcare. These reallocation patterns highlight how UI spells can facilitate labor reallocation, though sometimes with a substantial loss in earnings.

Lastly, the role of duration in influencing re-employment outcomes and the possibility of duration dependence appears prominently in our results. Longer unemployment spells are associated with progressively larger earnings losses and lower recall rates, echoing a central theme in the job search and unemployment duration literature. Our ability to observe duration with precise weekly claims timing highlights how starkly duration relates to unemployment outcomes. These findings also reinforce the importance of considering UI benefit duration policies in light of the trade-off between providing insurance during longer spells and the erosion of re-employment prospects over time. It is important to stress that these associations are not causal, and future work can disentangle the role of selection, moral hazard, and asymmetric information in these patterns.

The ability to track workers through linked claims and earnings data enables a more precise characterization of the costs of job loss and the detailed heterogeneity of employment outcomes than previously possible with survey or annual administrative data. At the same time, several limitations merit discussion. These pilot data are restricted to a subset of states and to a single year marked by extraordinary labor market disruption. Additionally, while our linkage to LEHD earnings provides rich longitudinal coverage, it excludes non-UI-covered employment such as informal work or self-employment. Additional UI claims data

to expand the years and states covered, plus linkages with the Self-Employment Jobs Frame are promising expansions to address these limitations.

5 Conclusion

We link weekly UI claims data from 2020 for six states with LEHD data to create the most comprehensive view to date of unemployed workers and their outcomes during and after the COVID-19 Recession. There is substantial heterogeneity in worker outcomes by demographic and job characteristics. Average earnings gains following a UI spell are declining with age, suggesting that job loss later in life has a large scarring effect. Both men and women experience a small earnings decline at re-employment, with men experiencing a slightly larger drop off. Earnings changes at re-employment also differ with occupation. Workers in science and sales occupations had slight positive changes in earnings following a UI spell. At the same time, those separating from management and construction/extraction occupations faced steep earnings declines once re-employed.

Our results also point to the important role of unemployment duration for post-separation outcomes. Individuals out of work for longer periods of time experienced larger earnings declines at re-employment, in line with the existing literature (e.g., Kroft et al., 2013; Schmieder et al., 2016). Our weekly claims data allow us to trace out this correlation at a granular level. We observe steeper earnings declines for workers remaining jobless at important UI program benefit thresholds. At the same time, however, there is substantial worker- and job-level heterogeneity in average UI spell durations which underscores that the relationship between unemployment duration and earnings we document is correlational and not causal.

Finally, we document substantial variation in outcomes across different types of mobility. We show that variation in earnings changes following job loss is much less disperse for workers returning to the same employer compared to those who did not, consistent with the macro-stabilizing role of recalls in 2020 (Gertler et al., 2022). Mobility across sectors is another key source of the variation in outcomes experienced by workers. In line with anecdotal commentary from the time, we observe meaningful average earnings gains for workers leaving

the hospitality and food sector in the wake of the pandemic. The mobility of employment across state lines was also most prominent for both the lowest- and highest-earning workers in our sample.

These initial estimates illustrate the promise of the UIEO program for advancing both research and measurement of the UI system and the outcomes of displaced workers. In particular, these data allow us to observe rich individual-level heterogeneity and labor market outcomes that neither program-level administrative data nor surveys can produce.

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A Additional Tables and Figures

A.1 State UI Policies

Table 8: State UI Details

State	Eligibility (Weeks)	Min WBA ($)	Max WBA ($)	Avg WBA ($)	Min DUA/PUA WBA ($)
Connecticut	26	15	649-724*	398.64	200
Missouri	20	35	320	265.97	133
Ohio	26	157	757	377.84	189
Oklahoma	26	16	539	386.15	194
Utah	26	28	746	424.48	213
Virginia	26	33	378	315.42	158
State	PUA End (2021)	PEUC End (2021)	MEUC End (2021)	FPUC End (2021)	
Connecticut	Sept. 6	Sept. 6	Sept. 6	Sept. 6	
Missouri	June 12	June 12	June 12	June 12	
Ohio	Sept. 6	Sept. 6	June 26	June 26	
Oklahoma	June 26	June 26	June 26	June 26	
Utah	June 26	June 26	June 26	June 26	
Virginia	Sept. 6	Sept. 6	Sept. 6	Sept. 6	

Note: WBA refers to weekly benefit amount in dollars. Average WBA and Min. Disaster Unemployment Assistance WBA are taken from Dept. of Labor Employment and Training Administration Unemployment Insurance Program Letter No. 26-20 at https://www.dol.gov/sites/dolgov/files/ETA/advisories/UIPL/2020/UIPL_11-20.pdf. The Connecticut WBA formula includes number of dependents, allowing an additional $15 per dependent for up to 5 dependents. The $649 maximum reported here is for an individual with no dependents. All monetary values deflated to 2020 dollars.

A.2 Sample

These tables report the differences between the sample of "All" UI spells with a valid PIK, strictly positive weekly benefit amount, age between 15 and 80 at the start of the spell, and with no more than 12 jobs in the 8 quarters before and after each spell and our matched sample. Our FQ Matched sample, from which most of our outcomes are tabulated, refers to the subset of All Spells with a linked employer with positive full-quarter earnings in both

the pre- and post-UI spell jobs. We show the selection in our FQ Matched sample by pre-UI spell occupation, and by pre- and post-UI spell industry.

Table 9 outputs the share of workers in each sample by their occupation before the UI spell. Occupations like architecture and engineering, healthcare practitioners, and production workers are more likely to be in the matched sample, likely due to having more stable employment. Occupations like Building and Grounds Cleaning and Personal Care and Service are less likely to be in the FQ Matched sample. Table 10 shows a similar pattern in NAICS 2 digit sectors. Looking at sector of employment before the UI spell, those laid off from Manufacturing and Healthcare are a greater share of the FQ Matched sample. Workers laid off from Admin/Support (56) and Agriculture/Forestry (11) are less likely to be in the FQ Matched Sample. Table 11 shows the variation in samples by sector of employment after the UI spell. It is worth noting that the sector after UI spell is not available for about 10.5% of observations in the All Spells sample. This is the share of the All Spells sample that does not have any employment in the 8 quarters after the UI spell. This skews the % Difference higher for this table, but we see similar variation by sector, with higher shares in sectors like Manufacturing (31-33) and Management (55), and lower shares in Administrative and Support Services (56).

A.3 Duration

We report in Table 12 how earnings and re-employment outcomes vary with the length of the UI spell, in weeks. We document the mean of earnings change and the mean of the Pre-UI spell quarterly earnings, the share recalled, share that changed sectors, and share that moved employer state by the UI spell duration.

Table 9: Sample: Occupation Before UI Spell

SOC Occupation	Share of All Spells	Share of FQ Matched	% Difference
11: Mgmt	0.043	0.045	3.4%
13: Bus/Fin	0.019	0.019	3.4%
15: Comp/Math	0.010	0.011	2.5%
17: Arch/Eng	0.010	0.010	9.4%
19: Science	0.003	0.003	-0.9%
21: Comm/SocSvc	0.006	0.006	-1.7%
23: Legal	0.002	0.002	-0.2%
25: Educ/Library	0.019	0.020	5.6%
27: Arts/Media	0.015	0.014	-6.7%
29: Health Pract	0.027	0.031	13.1%
31: Health Supp	0.027	0.029	6.0%
33: Protective	0.004	0.004	-1.0%
35: Food Service	0.069	0.073	6.8%
37: Bldg/Grounds	0.018	0.015	-12.3%
39: Personal Care	0.029	0.025	-14.0%
41: Sales	0.055	0.055	-0.0%
43: Office/Admin	0.059	0.060	1.1%
45: Farm/Forest	0.002	0.002	-8.2%
47: Constr/Extract	0.046	0.045	-1.9%
49: Maint/Repair	0.026	0.026	1.7%
51: Production	0.086	0.095	9.8%
53: Transport/Move	0.040	0.039	-2.8%
99: Unknown/Other	0.384	0.370	-3.7%

Note: All Spells refers to all UI spells with a valid person link (PIK), with a strictly positive weekly benefit amount, age between 15 and 80 at the start of the spell, and with no more than 12 jobs in the 8 quarters before and after each spell. FQ Matched refers to the subset of All Spells with a linked employer with positive full-quarter earnings in both the pre- and post-UI spell jobs.

Table 10: Sample: Industry Before UI Spell

NAICS Sector	Share of All Spells	Share of FQ Matched	% Difference
11: Agric/Forest	0.002	0.002	-10.4%
21: Mining/Oil&Gas	0.007	0.007	-0.3%
22: Utilities	0.001	0.001	4.4%
23: Construction	0.067	0.067	0.4%
31-33: Manufacturing	0.149	0.169	12.9%
42: Wholesale	0.032	0.033	3.0%
44-45: Retail	0.106	0.105	-1.6%
48-49: Transport	0.047	0.047	-1.1%
51: Information	0.013	0.013	1.6%
52: Finance/Ins	0.015	0.015	0.5%
53: Real Estate	0.012	0.012	-4.1%
54: Professional	0.040	0.040	-1.3%
55: Mgmt Companies	0.016	0.018	7.5%
56: Admin/Support	0.079	0.068	-13.9%
61: Education	0.039	0.041	5.7%
62: Healthcare	0.128	0.136	6.2%
71: Arts/Recreation	0.027	0.027	2.9%
72: Accom/Food	0.144	0.147	1.8%
81: Other Services	0.043	0.042	-1.9%
92: Public Admin	0.012	0.012	4.1%
Info. Not Available	0.021	0.000	-100.0%

Note: All Spells refers to all UI spells with a valid person link (PIK), with a strictly positive weekly benefit amount, age between 15 and 80 at the start of the spell, and with no more than 12 jobs in the 8 quarters before and after each spell. FQ Matched refers to the subset of All Spells with a linked employer with positive full-quarter (FQ) earnings in both the pre- and post-UI spell jobs.

Table 11: Sample: Industry After UI Spell

NAICS Sector	Share of All Spells	Share of FQ Matched	% Difference
11: Agric/Forest	0.003	0.003	-0.6%
21: Mining/Oil&Gas	0.004	0.005	14.4%
22: Utilities	0.001	0.002	19.0%
23: Construction	0.061	0.068	11.8%
31-33: Manufacturing	0.137	0.164	20.3%
42: Wholesale	0.027	0.032	17.4%
44-45: Retail	0.100	0.108	8.5%
48-49: Transport	0.051	0.055	6.4%
51: Information	0.010	0.012	14.2%
52: Finance/Ins	0.014	0.017	15.8%
53: Real Estate	0.010	0.012	13.0%
54: Professional	0.037	0.042	11.9%
55: Mgmt Companies	0.014	0.016	18.6%
56: Admin/Support	0.081	0.075	-7.2%
61: Education	0.039	0.045	15.5%
62: Healthcare	0.123	0.143	16.1%
71: Arts/Recreation	0.022	0.025	12.9%
72: Accom/Food	0.113	0.125	10.2%
81: Other Services	0.036	0.040	12.5%
92: Public Admin	0.012	0.014	17.8%
Info. Not Available	0.105	0.000	-100.0%

Note: All Spells refers to all UI spells with a valid person link (PIK), with a strictly positive weekly benefit amount, age between 15 and 80 at the start of the spell, and with no more than 12 jobs in the 8 quarters before and after each spell. FQ Matched refers to the subset of All Spells with a linked employer with positive full-quarter (FQ) earnings in both the pre- and post-UI spell jobs.

Table 12: Outcomes by Spell Duration

Duration	Share (%)	Pre-Spell Earnings ($)	Earnings (% Chg)	Recall (%)	Δ Sector (%)	Moved (%)
1 wk	14.2	11,500	-1.9	70.8	19.9	4.1
2 wks	8.6	11,950	-1.4	72.9	18.2	3.5
3 wks	6.7	11,520	-2.4	70.2	19.9	3.9
4 wks	5.7	10,970	-0.7	68.8	20.9	4.0
5 wks	5.2	10,790	+0.2	69.3	20.4	4.0
6 wks	5.0	10,680	+1.1	70.0	19.8	3.9
7 wks	4.6	10,550	+0.4	69.7	19.9	3.9
8 wks	4.3	10,920	-1.2	71.0	19.1	3.8
9 wks	3.9	10,290	-0.2	70.1	19.7	4.0
10 wks	3.5	10,080	-0.2	68.9	20.5	4.4
11 wks	3.0	9,867	+0.4	67.4	21.6	4.5
12 wks	2.5	9,548	+1.1	64.4	23.9	5.0
13 wks	2.2	9,267	+2.1	60.8	26.7	5.7
14 wks	2.0	9,182	+2.2	58.9	27.7	6.0
15 wks	1.9	9,011	+3.5	56.1	29.8	6.4
16 wks	1.7	8,830	+3.7	53.6	31.3	6.7
17 wks	1.6	8,953	+3.0	52.9	32.1	6.9
18 wks	1.6	8,654	+2.3	51.6	33.2	7.0
19 wks	1.6	8,600	+0.8	51.0	33.4	7.0
20 wks	1.4	8,437	-0.7	48.2	35.2	7.5
21 wks	1.3	8,506	-1.9	45.9	37.5	8.0
22 wks	1.1	8,621	-2.7	44.8	37.9	8.0
23 wks	1.0	8,344	-4.0	44.3	38.3	7.6
24 wks	1.0	8,309	-4.3	44.0	38.8	7.6
25 wks	0.9	8,425	-6.3	42.0	40.5	8.0
26 wks	1.4	8,222	-7.2	40.2	41.5	8.5
27 wks	0.9	8,714	-11.3	39.2	42.6	8.4
28 wks	0.7	8,616	-13.0	39.2	42.3	8.6
29 wks	0.6	8,582	-14.1	37.1	43.6	8.7
30 wks	0.6	8,533	-13.3	35.9	44.7	8.7
31 wks	0.6	8,276	-12.3	33.7	47.1	9.0
32 wks	0.6	8,367	-13.5	33.0	47.7	9.2
33 wks	0.7	8,158	-13.5	31.8	48.3	9.4
34 wks	0.6	8,186	-14.1	32.6	48.2	8.9
35 wks	0.6	8,280	-15.3	33.9	47.1	8.7
36 wks	0.6	7,853	-16.3	33.9	46.6	8.4
37 wks	0.7	7,629	-16.7	34.7	45.9	8.1
38 wks	0.8	7,570	-18.1	35.3	45.5	7.8
39 wks	1.0	7,668	-19.1	36.9	43.6	7.6
40 wks	0.8	7,714	-23.8	39.9	40.6	7.2
41 wks	0.6	8,029	-25.7	44.3	37.4	7.2
42 wks	0.4	8,134	-25.7	38.8	41.9	7.8
43 wks	0.3	8,607	-28.7	35.8	43.3	8.5
44 wks	0.1	9,767	-28.1	23.8	52.9	9.5
45 wks	0.1	10,800	-25.4	17.8	59.1	10.5
46 wks	0.1	10,510	-24.0	18.3	58.3	11.3
47 wks	0.1	11,630	-24.8	16.1	58.9	13.0
48 wks	0.1	11,040	-27.9	15.5	60.2	11.0
49 wks	0.1	10,910	-25.6	13.8	61.8	12.1
50 wks	0.1	11,040	-28.1	14.8	60.5	12.7
51 wks	0.1	10,480	-25.4	18.1	57.0	10.9
52+ wks	0.2	10,880	-28.5	21.2	56.1	10.2

Note: Recall refers to the share of each group that is re-employed by the same employer. Δ Sector refers to the share who are re-employed in a different employer NAICS sector after their UI spell. Moved refers to the share of each cell who experienced a change in the state of their employment (not necessarily residence) after their UI spell. The average duration of spells in the 52+ week category is about 56 weeks. All monetary values deflated to 2020 dollars.