Self-Insurance in Turbulent Labor Markets

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Abstract

We study how workers' wealth and skills shape recovery from job displacement in turbulent labor markets. Unemployment depletes liquid assets, while turbulent transitions may place workers in jobs where accumulated skills transfer poorly. We develop and quantify a heterogeneous-agent directed-search model with incomplete markets, skill dynamics, and heterogeneous job tiers. Reemployment is a multidimensional allocation problem: skills determine where workers are most productive, while wealth shapes which job tier they can pursue. Workers self-insure through savings and tier mobility, so incomplete markets distort asset-skill sorting and make low-wealth workers more likely to downgrade. In U.S. data, persistent wage losses after turbulent transitions concentrate among low-wealth workers who move to lower tiers. The calibrated model reproduces these patterns and generates negative duration dependence in reemployment wages through wealth-driven downgrading. Policy counterfactuals show that unemployment insurance delivers larger welfare gains, whereas targeted vacancy subsidies generate larger output gains.

JEL: D31, E21, E24, J24, J31, J63, J64.

Keywords: self-insurance; job displacement; turbulence risk; precautionary savings; directed search; job tiers; skill loss; unemployment insurance.

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Wealth plays an essential role in shaping labor-market outcomes. Much of the literature highlights wealth's long-run effects through education, parental transfers, health, or neighborhood quality. We offer a different perspective: the interaction of wealth and skills can have long-term effects by amplifying transitory shocks. Unemployment depletes liquid assets, forcing poorer workers to accept available jobs to replace lost income, while wealthier workers can afford to wait for a more suitable job. These changes can have persistent effects when reemployment entails choosing among heterogeneous jobs that differ in how they reward skills, how quickly they can be accessed, and the employment risks they carry. Without complete insurance, even a short unemployment spell can generate lasting differences in job mobility and wages.

We organize this job heterogeneity into broad categories, or *job tiers*, with distinct technological and risk–return profiles. Tiers differ in productivity, separation risk, and search frictions, and offer different trade-offs between wages and job-finding probabilities. Moving across tiers is costly. This parsimonious segmentation is consistent with Ahn, Hobijn and Şahin (2023), who show that U.S. labor-market dynamics are well approximated by primary and secondary segments with distinct employment-stability profiles. The essential feature of a tier is not simply that jobs pay different wages. Productivity differences create a technological sorting force: workers' skills determine where they are most productive. At the same time, differences in job-finding rates, separation risks, and mobility costs create a wealth-dependent sorting force: liquid assets determine how much search risk workers can bear and which tiers they can access. Choosing where to search is therefore a multidimensional allocation problem in skills and wealth.

This allocation problem becomes especially consequential after job displacement. During unemployment, workers draw down liquid assets to smooth consumption. As liquidity declines, they become less able to sustain selective search and place greater value on rapid reemployment. This is the precautionary-search mechanism emphasized by Eeckhout and Sepahsalari (2024). In sorting terms, risk aversion and incomplete insurance create a preference complementarity between liquid wealth and job productivity: workers with more assets can better bear unemployment risk while pursuing higher-productivity jobs. In our environment, it operates both within tiers, through the wage–job-finding trade-off, and across tiers, through the choice of job segment. Low-wealth workers are therefore more likely to move toward lower-tier jobs that are easier to access, whereas wealthier workers can search longer and bear the costs of returning to high-tier employment.

Displacement can also affect workers' skills. Some separations are *turbulent*: they reduce the value of skills accumulated before displacement, as in Ljungqvist and Sargent (1998) and Baley, Ljungqvist and Sargent (2023, 2025). In the model, turbulence manifests as skill loss at separation; in the data, we proxy for it with the low ex post transferability of occupational skills. Importantly, skill loss and tier mobility are distinct margins: turbulence changes the worker's human capital, whereas tier mobility changes where her remaining skills are employed. Wealth cannot undo the direct consequences of skill loss, but it allows workers to smooth consumption and sustain search. Thus, a turbulent worker whose skills decline may face lower returns in high-tier employment, yet greater wealth enables them to persist in high-tier search rather than downgrading to a lower-productivity job. Viewed through this lens, turbulence risk can arise from broader structural change, including import competition (Traiberman, 2019), technological acceleration (Violante, 2002; Braxton and Taska, 2023), and rapid sectoral shifts (Grigsby and Zorzi, 2026). Our analysis shows how liquid wealth shapes recovery from the resulting turbulent displacement.

Two complementarities govern this multidimensional allocation problem. First, a technological complementarity between worker skill and job productivity makes high-tier employment particularly valuable for high-skilled workers. Second, risk aversion and incomplete insurance generate a preference complementarity between liquid wealth and job productivity: wealthier workers can better bear the unemployment risk of pursuing higher-productivity jobs. Mobility costs reinforce this wealth dependence by making access to high-tier jobs directly conditional on liquid resources. When the two complementarities point in the same direction, they reinforce sorting across tiers. After displacement, however, they may conflict. A high-skilled worker has a technological motive to search in a high-productivity job tier, but asset depletion during unemployment strengthens the self-insurance motive to search in a safer, easier-to-access low-productivity tier. Conversely, turbulence can reduce a wealthy worker's skill sufficiently that the technological motive to return to the high-productivity tier weakens. Skill loss therefore changes the return to tier choice, while asset depletion changes workers' willingness and ability to bear the risks and costs of accessing those tiers. Their interaction makes wage scarring depend on wealth.

We call the reallocation component driven by liquidity constraints *precautionary tier mobility*. It adds an across-tier allocation margin to the established precautionary-search logic: workers adjust not only the wage-job-finding trade-off they target within a tier, but also the tier in which they search and ultimately employ their skills. By affecting where workers employ their remaining skills after displacement, liquidity constraints can turn a transitory unemployment spell into a persistent wage scar. In the U.S. data, persistent wage losses after turbulent transitions concentrate among low-wealth workers who move to lower tiers, while wealthier workers recover much of their initial losses. We quantify this mechanism and examine how economy-wide unemployment insurance and targeted vacancy subsidies affect the resulting allocation.

Contributions First, on the theory side, we bring liquid wealth and workers' skills together in an incomplete-markets directed-search model with heterogeneous job opportunities. One strand of the literature studies wealth-dependent search, including search while unemployed and employed (Lise, 2013; Krusell, Mukoyama and Şahin, 2010), job quality, sorting, and mismatch (Griffy, 2021; Eeckhout and Sepahsalari, 2024; Herkenhoff, Phillips and Cohen-Cole, 2024; Huang and Qiu, 2026), and on-the-job wage progression (Chaumont and Shi, 2022). A complementary strand studies wealth-dependent mobility along job ladders (Kaas, Lalé and Siassi, 2026), across costly or risky job and occupational transitions (Hawkins and Mustre-del Río, 2017; Clymo, Denderski and Harvey, 2022; Caratelli, 2024; Repele, 2026; Pellegrini, 2026; Clymo, Denderski, Mercan and Schoefer, 2026), and across sectors and locations (Soenarjo, 2024; Zanella, 2025).

We build directly on these wealth-dependent search and mobility forces. Relative to models in which assets alone govern sorting, we introduce worker skill as a second dimension of heterogeneity. This creates a multidimensional allocation problem governed by two distinct sorting forces: a preference complementarity between liquid wealth and job productivity, and a technological complementarity between worker skill and job productivity. Because displacement affects assets and skills differently, these forces may point toward different tiers. Incomplete insurance can therefore distort skill allocation across jobs, linking workers' financial positions to persistent post-displacement wage losses.

Second, on the empirical and quantitative side, we provide new evidence on how liquid wealth and occupational reallocation shape wage recovery after job loss. We combine employment and wealth histories from the NLSY79 with O*NET occupational requirements. We construct job tiers from occupations' overall skill intensity and proxy turbulence with transitions involving low ex post skill transferability, measured by the angular distance between pre- and post-displacement occupational requirements (Gathmann and Schönberg, 2010; Autor, 2013; Baley, Figueiredo and Ulbricht, 2022). Turbulence need not involve a tier change: skill transferability and tier mobility are distinct empirical phenomena. Our measurement is also related to Huang and Qiu (2026), who use the same data sources to study wealth-dependent worker–job mismatch.

We document three facts: (1) wage losses are larger following turbulent transitions; (2) they are largest among workers who downgrade; and (3) they are persistent primarily among those with little liquid wealth at separation. These facts sharpen existing literature on post-displacement losses (Jacobson, LaLonde and Sullivan, 1993; Davis and von Wachter, 2011; Burdett, Carrillo-Tudela and Coles, 2020) by showing that long-run wage consequences depend critically on workers' liquid wealth: persistent scars concentrate among low-wealth workers who move to lower tiers. The wealth gradient is therefore concentrated precisely where the model's allocation margin operates. Our findings also connect to the literature on occupation-specific human capital (Kambourov and Manovskii, 2009; Fujita, 2018; Postel-Vinay and Sepahsalari, 2023), occupational downgrading (Huckfeldt, 2022), and job security after displacement (Jarosch, 2023; Figueiredo, Marie and Markiewicz, 2026).

The calibrated model accounts for several salient untargeted patterns. It reproduces the greater persistence of wage losses among low-wealth workers following turbulent transitions and concentrates the wealth gradient among tier switchers; workers who remain in the same tier experience the direct skill-loss penalty but gradually recover. As an additional test of the mechanism, we examine its dynamic implications for reemployment wages. The model generates negative duration dependence in reemployment wages as asset depletion lowers wage targets and increases tier downgrading. It accounts for about half of the aggregate semielasticity in the data and closely matches it among tier switchers. This channel is consistent with evidence that households draw down liquid balances after job loss (Andersen *et al.*, 2023), and that wealth and credit access affect unemployment duration (Fontaine, Jensen and Vejlin, 2024; Herkenhoff, Phillips and Cohen-Cole, 2024).

Lastly, on the policy side, we compare unemployment insurance with subsidies to vacancy creation in the high-productivity tier. Macro search models show that unemployment insurance can improve allocation by allowing workers to wait for more productive jobs (Marimon and Zilibotti, 1999; Acemoglu and Shimer, 1999, 2000), while related work studies how insurance and liquidity affect search and reemployment outcomes (Chetty, 2008; Braxton, Herkenhoff and Phillips, 2024). We add sorting across job tiers as a policy margin. The two policies operate differently. Unemployment insurance relaxes liquidity constraints, allowing low-wealth, highly skilled workers to access jobs where their skills yield higher returns. Vacancy subsidies instead expand high-productivity job opportunities more broadly. Thus, unemployment insurance changes who can access high-productivity jobs, whereas vacancy subsidies change how many such jobs are available. The former delivers larger welfare gains, while the latter produces larger output gains.

1 Model

We develop an incomplete-markets directed-search model in which workers differ in liquid assets and skills, and jobs belong to tiers with distinct technological and risk–return profiles. Following job loss, workers choose how much to save, which wage–job-finding trade-off to target within a tier, and which tier to search in. Reemployment is therefore a multidimensional allocation problem: skills determine where workers are most productive, while wealth shapes which opportunities they can access and how selectively they can search.

The distinction between skills and tiers is central. Skills summarize workers' accumulated human capital and evolve over time, while tiers are job segments that unemployed workers choose where to search. Workers may redirect search across tiers, possibly at a mobility cost, but cannot choose their skill level. The equilibrium therefore allocates workers with different assets and skills across job tiers through technological returns, search risk, and incomplete insurance.

1.1 Environment

Time is infinite and discrete. A continuum of ex ante identical workers interacts with a continuum of potentially operating firms.

Preferences. Workers are risk-averse and value consumption c_t according to $\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t u(c_t)$, where $u' > 0$ and $u'' < 0$. The effective discount factor is $\beta \equiv \hat{\beta}(1-\rho_r)$, where $\hat{\beta} \in (0,1)$ is the subjective discount factor and $\rho_r \in (0,1)$ is a constant retirement probability.

Workers. Workers are either employed or unemployed. Unemployed workers search for a job and receive home production b. Employed workers supply one unit of labor inelastically and receive wage w, taxed at rate $\tau \in [0,1)$. Workers save or borrow liquid assets a at gross return $R > 1$, subject to $a' \geq \underline{a}$, where $\underline{a} < 0$ captures financial-market incompleteness. Workers jointly own firms and receive equal per-capita dividends π.[1] In addition to employment status, workers differ in skill level $x_i \in \{x_l, x_h\}$ and asset holdings a. Employed workers are additionally characterized by their job tier and wage; unemployed workers retain a reference tier that determines the cost of redirecting search. Retiring workers exit and are replaced by low-skilled unemployed entrants, who share their assets equally.

[1]Free entry drives the value of newly posted vacancies to zero, but current operating profits net of vacancy expenditures—and hence dividends—need not be zero; see Appendix A.5.

Technology and job tiers. Worker–firm pairs operate in one of two tiers, $k \in \{A, B\}$. Vacancies are homogeneous within a tier. Across tiers, jobs differ in productivity, separation risk, vacancy-creation cost, and matching efficiency. Tier A is more productive than Tier B, $y_A > y_B$; in the calibration, it is also more stable, more costly to create, and harder to access. A firm in tier k matched with a worker of skill i produces $f_{ik} \equiv f(x_i, y_k)$. We assume increasing differences between worker skill and job productivity, so that the return to skill is higher in more productive jobs:

$$f(x_h, y_A) - f(x_l, y_A) \ > \ f(x_h, y_B) - f(x_l, y_B), \tag{1}$$

so that skills yield higher returns in the more productive tier.[2] This technological complementarity creates a sorting force toward high-tier employment for high-skilled workers.

Skill dynamics. Skills evolve with employment and displacement:

(i) *Upgrades.* Low-skilled employed workers become high-skilled with probability γ^u;

(ii) *Separations.* A job with worker skill i in tier k ends with probability λ_{ik};

(iii) *Turbulence.* Conditional on layoff, a high-skilled worker loses skills with probability γ_k^d.

Labor markets. A firm seeking a worker with skill i in tier k posts a vacancy at cost κ_k. Search is directed. Submarkets are indexed by worker skill, job tier, and assets (i, k, a). At the beginning of each period, firms simultaneously announce the wage they offer, w. Workers observe bundles of wages and job-finding probabilities across all submarkets in each tier and choose the submarket (w, θ) they wish to apply for. Market tightness is the vacancy–applicant ratio, $\theta \equiv v/u$. Within each submarket, firms and workers are randomly matched using a CRS matching function $m_k(u, v)$, with tier-specific matching efficiency. Thus, a worker applying to submarket θ finds a job with probability $p_k(\theta)$ and a firm fills a vacancy with probability $q_k(\theta)$, where $p_k(\theta) = m_k(u, v)/u$ and $q_k(\theta) = m_k(u, v)/v = p_k(\theta)/\theta$.

Unemployed workers may redirect search across tiers. A worker whose reference tier is k can search in tier k' by paying a one-time monetary cost $\mathcal{M}_{kk'}$, with $\mathcal{M}_{kk} = 0$. Redirecting search changes the productivity, job-finding probability, separation risk, and future skill risk associated with reemployment.

[2] In the calibration, $f(x_i, y_k) = x_i y_k$, which satisfies this condition whenever $x_h > x_l$ and $y_A > y_B$.

1.2 Value functions

We now describe firms' and workers' value functions. For simplicity, we index value functions by worker skill $i \in \{l, h\}$ and job tier $k \in \{A, B\}$, instead of explicitly carrying these states.[3]

Value of a vacancy. Let V_{ik} be the vacancy value in tier k aimed at a worker with skill i, and let $J_{ik}(w)$ be the value of the corresponding filled job at wage w. The vacancy value is

$$V_{ik} \;=\; -\kappa_k \;+\; \beta \max_{\theta} \left\{ q_k(\theta) J_{ik}(w(\theta)) + (1 - q_k(\theta)) V_{ik} \right\}, \qquad \forall (k, i). \tag{2}$$

Free entry makes firms indifferent across active vacancy-posting submarkets: wage differences are offset by differences in vacancy-filling probabilities and match values.

Value of a filled job. The value of a filled job with a high-skilled worker ($i = h$) at wage w is

$$J_{hk}(w) \;=\; f_{hk} \;-\; w \;+\; \beta \left[\lambda_{hk} V_{hk} \;+\; (1 - \lambda_{hk}) J_{hk}(w) \right], \tag{3}$$

whereas the value of a filled job with a low-skilled worker ($i = l$) at wage w is

$$J_{lk}(w) \;=\; f_{lk} \;-\; w \;+\; \beta \left[\lambda_{lk} V_{lk} \;+\; (1 - \lambda_{lk})((1 - \gamma^u) J_{lk}(w) \;+\; \gamma^u J_{hk}(w')) \right]. \tag{4}$$

Here, $w' \equiv w + (f_{hk} - f_{lk})$ is the wage following a skill upgrade, equal to the initial wage plus the associated increase in productivity.[4] The value of high-skilled jobs in (3) embeds the risk of an exogenous separation at rate λ_{hk}. In contrast, the value of low-skilled jobs in (4) considers both the risk of an exogenous separation at rate λ_{lk} and the risk of a skill upgrade at rate γ^u. Consequently, firms that employ low-skilled workers factor in the potential output and the corresponding wage increases when determining job value.

Inner value of unemployment in tier k. Let $U_{ik}(a)$ be the value of an unemployed worker with skill i searching for a job in tier k with assets a. Let $E_{ik}(a, w)$ be the value of a worker with skill x_i employed in tier k at wage w and with assets a.

Given the wage-tightness menu (w, θ) offered by firms, an unemployed worker chooses

[3] For brevity, we drop the asset, skill, and tier indices of submarkets.

[4] We assume that an upgrade raises the worker's wage one-for-one with the increase in productivity to avoid introducing a separate wage-renegotiation problem following skill upgrading. Alternative surplus-sharing rules could be accommodated, but would add an additional non-central wage-setting mechanism.

savings a' and a submarket θ to maximize:

$$U_{ik}(a) = \max_{a',\theta} u(c) + \beta \left[p_k(\theta)E_{ik}(a', w(\theta)) + (1 - p_k(\theta))\mathcal{U}_{ik}(a')\right] \tag{5}$$

$$c + a' = Ra + b + \pi, \quad a' \geq \underline{a} \tag{6}$$

subject to the borrowing limit $a' \geq \underline{a}$. With endogenous probability $p_k(\theta)$, the worker finds a job and obtains the value of employment E_{ik} in the same tier, and with the complementary probability $1 - p_k(\theta)$, the worker remains unemployed. The optimal savings and submarket choices are functions of assets a, skill i, and tier k. While unemployed, a worker receives the value of home production b and decides how much to save and consume.

Outer value of unemployment. Before embarking on a job search, unemployed workers select the tier in which to search for jobs during the next period. The timing is as follows. Unemployed workers first draw preference shocks for working in each tier, ϵ_A and ϵ_B. The shocks ϵ_A and ϵ_B are i.i.d. standard type-I extreme-value random variables, normalized to have mean zero. The parameter $\nu > 0$ governs their scale.[5]

Second, given their preferences, asset holdings, and skill levels, they decide whether to switch by paying the switching cost or remain in the same tier. Tier choice reflects systematic differences in continuation values—driven by skills, assets, mobility costs, and tier-specific opportunities—together with idiosyncratic tastes. If paying the mobility cost would violate the borrowing constraint, the alternative tier is infeasible. After making the mobility decision, they determine their savings and the submarket to which they will apply. Thus, the outer value of being unemployed is

$$\mathcal{U}_{ik}(a) = \mathbb{E}\left[\max_{k' \in \{A,B\}} U_{ik'}(a - \mathcal{M}_{kk'}) + \nu\epsilon_{k'}\right], \qquad k \in \{A, B\}, \tag{7}$$

subject to the borrowing limit. Following McFadden (1973), the distributional assumptions on preference shocks[6] imply that the share of unemployed workers with assets a switching from tier k to k', denoted by $\mu_{ikk'}(a)$, is

$$\mu_{ikk'}(a) = \frac{\exp\left(U_{ik'}(a - \mathcal{M}_{kk'})/\nu\right)}{\sum_{r \in \{A,B\}} \exp\left(U_{ir}(a - \mathcal{M}_{kr})/\nu\right)}, \qquad k, k' \in \{A, B\}. \tag{8}$$

[5] Our use of extreme-value shocks connects to models in which worker mobility is shaped by idiosyncratic preference shocks and moving costs (Kennan and Walker, 2011; Giannone, Li, Paixao and Pang, 2023).

[6] See Appendix A for all the derivations.

For any destination tier that is infeasible because the worker cannot cover the mobility cost without violating the borrowing constraint, we set the corresponding choice probability to zero and normalize the remaining probabilities over the feasible alternatives.

Thus, switching rates take the familiar logit form—ratios of exponentially tilted continuation values—and vary smoothly with assets. The taste shocks smooth tier choice but do not, by themselves, generate systematic sorting by wealth. The parameter ν governs the relative importance of systematic value differences and idiosyncratic tastes: as $\nu \to 0$, continuation values dominate and tier choices become nearly deterministic; as $\nu \to \infty$, taste shocks dominate and choice probabilities converge across worker types. For intermediate values, as in our calibration, tier choice varies smoothly with workers' assets and skills.

Value of employment. Employed workers make saving decisions, subject to their budget

$$c + a' \;=\; Ra + (1-\tau)w + \pi, \quad a' \geq \underline{a} \tag{9}$$

where the worker's consumption and saving decisions are based on the after-tax wage and the assets saved from the previous period.

The value of being a low-skilled employed worker in tier k at wage w is:

$$E_{lk}(a,w) \;=\; \max_{c,a'} \; u(c) + \beta(1-\lambda_{lk})\Big[(1-\gamma^u)E_{lk}(a',w) + \underbrace{\gamma^u E_{hk}(a',w')\Big]}_{\text{skill upgrade}} + \beta\lambda_{lk}\mathcal{U}_{lk}(a')$$

where $w' = w + (f_{hk} - f_{lk})$. A low-skilled employed worker in tier k gains utility from consumption and discounts the future at rate β. Following a separation, the worker can reconsider the tier in which to search next period. Otherwise, they will stay in their current job. With probability γ^u, they receive a skill upgrade and their wage increases to a new value w' that accounts for the skill upgrade.

The value for a high-skilled employed worker in tier k with assets a and wage w equals:

$$E_{hk}(a,w) \;=\; \max_{c,a'} \; u(c) + \beta(1-\lambda_{hk})E_{hk}(a',w) \;+\; \beta\lambda_{hk}\Big[(1-\gamma^d_k)\mathcal{U}_{hk}(a') + \underbrace{\gamma^d_k\mathcal{U}_{lk}(a')}_{\text{skill downgrade}}\;\Big]$$

The value accounts for turbulence risk, reflected in the probability γ^d_k of suffering a skill downgrade after a layoff, which happens at rate λ_{hk}.

1.3 Worker Masses and Distributions

Let $\Gamma^E_{ik}(a,w)$ denote the mass distribution of employed workers over assets and wages in skill–tier cell (i,k), and let $\Gamma^U_{ik}(a)$ denote the corresponding mass distribution of unemployed workers over assets. Then, the masses of employed and unemployed workers by skill and tier are computed as

$$e_{ik} \equiv \int_a \int_w d\Gamma^E_{ik}(a,w), \qquad u_{ik} \equiv \int_a d\Gamma^U_{ik}(a), \tag{10}$$

and the total masses of employed and unemployed workers are

$$e \equiv \sum_{i\in\{l,h\}} \sum_{k\in\{A,B\}} e_{ik}, \qquad u \equiv \sum_{i\in\{l,h\}} \sum_{k\in\{A,B\}} u_{ik}. \tag{11}$$

1.4 Stationary Equilibrium

Given a gross interest rate R and a value of home production b, a stationary equilibrium consists of worker and firm value functions $\{V_{ik}, J_{ik}, \mathcal{U}_{ik}(a), U_{ik}(a), E_{ik}(a,w)\}$; consumption $c_{ik}(a)$ and saving $a'_{ik}(a)$ policies for all workers; the mobility policy given tier, assets and skills $(\mu_{ikk'(a)})$ and submarket choice $(\theta_{ik}(a))$ for the unemployed workers; wage-tightness profiles $(w(\theta_{ik}), \theta_{ik})$; tax rate τ; tier-skill distribution of employed workers over wages and assets $\Gamma^E_{ik}(a,w)$; and tier-skill distribution of unemployed workers over assets $\Gamma^U_{ik}(a)$ such that the following conditions hold:

1. Consumption $c_{ik}(a)$ and saving policies $a'_{ik}(a)$ maximize workers' values;
2. Submarket choices $\theta_{ik}(a)$ maximize unemployed workers' values by trading off wages and job-finding rates;
3. Free entry condition holds for firms, so that vacancies earn zero expected profit, i.e., $V_{ik} = 0 \; \forall(i,k)$;
4. Tier-choice probabilities $\mu_{ikk'}(a)$ solve the outer unemployment problem and consistently reallocate unemployed workers across tiers;
5. The distributions $\Gamma^U_{ik}(a)$ and $\Gamma^E_{ik}(a,w)$ are invariant under the full law of motion induced by saving, search, employment, skill, retirement, and tier-choice policies.

The equilibrium maps workers' asset-skill pairs into search choices and, ultimately, job tiers. High skill raises the technological return to Tier A, while liquid wealth expands workers' ability to finance mobility costs and sustain selective search. Sorting is therefore positive but imperfect: high-skill, high-wealth workers are more likely to search in Tier A, while low-skill, low-wealth workers are more likely to search in Tier B.

1.5 Model Solution

The equilibrium is block recursive: conditional on the interest rate R, wage–tightness schedules do not depend on the distribution of workers and vacancies across submarkets (Shi, 2009; Menzio and Shi, 2011). We first solve the wage–tightness menus, then the worker problem, and finally the stationary distribution and simulated worker histories used for the quantitative analysis.[7]

1.6 Three Self-Insurance Mechanisms

Workers self-insure along three margins: precautionary savings, within-tier search, and across-tier mobility. The first two are familiar from incomplete-markets search models. The third—precautionary tier mobility—is the allocation margin this paper emphasizes: workers choose not only how much to save and how selectively to search within a tier, but also which tier to search. Because assets evolve during unemployment, the three margins interact. We illustrate these mechanisms using policy functions from the calibration in Section 3.

1.6.1 Precautionary Savings

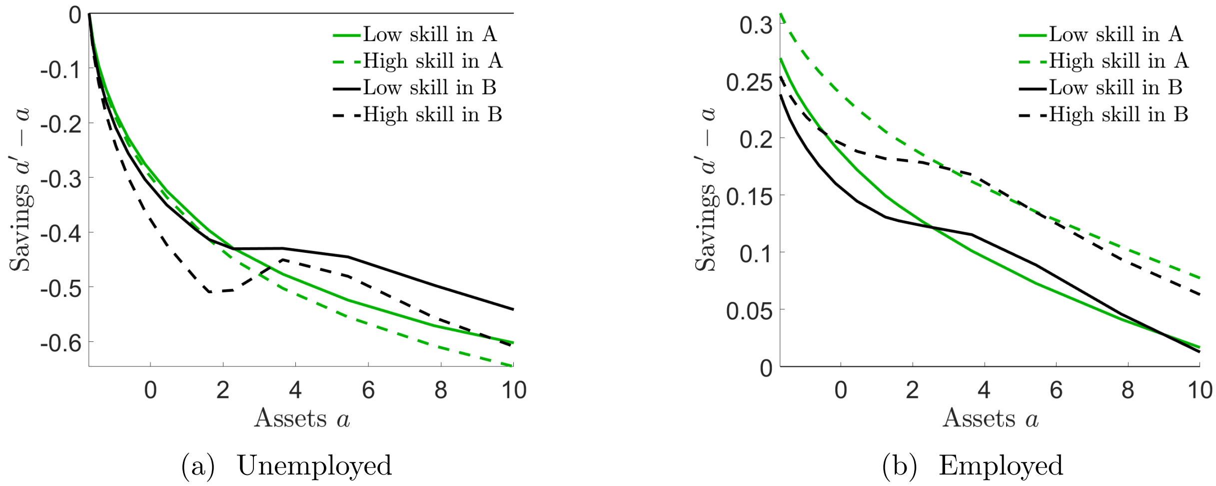
Workers smooth consumption over time by adjusting their asset holdings. Figure 1 plots net asset accumulation, $a' - a$, as a function of current asset holdings. Employed workers save, whereas unemployed workers dissave. The intensity of the precautionary motive, captured by the slope of $a' - a$, varies systematically with employment status, skill level, and job tier. Conditional on assets, high-skilled unemployed workers draw down wealth more rapidly because they anticipate higher reemployment wages, while high-skilled employed workers accumulate larger precautionary buffers.

1.6.2 Precautionary Within-Tier Search

Conditional on a tier, unemployed workers choose along a wage–job-finding menu generated by free entry. Figure 2 shows that wealthier workers target higher wages (Panel a) with

[7] Appendix B describes the computational algorithm.

Figure 1: Saving Policies



Note: Net saving equals the change in asset holdings between periods, $a' - a$. The savings of employed workers are evaluated at the group's average wage. Parametrization from Table 1.

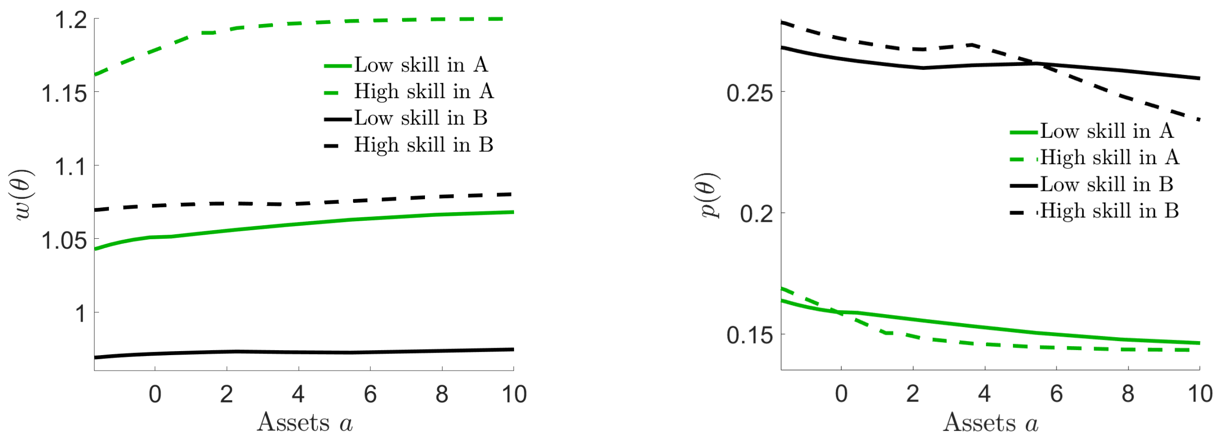
lower job-finding probabilities (Panel b), whereas low-wealth workers prioritize faster reemployment. As unemployment depletes assets, workers move toward lower wages and higher job-finding rates, generating negative duration dependence in reemployment wages (Eeckhout and Sepahsalari, 2024). The skill ranking of job-finding rates also varies with wealth, reflecting differences in the opportunity cost of unemployment.

1.6.3 Precautionary Across-Tier Mobility

Having analyzed within-tier behavior, we now turn to the across-tier allocation margin. Figure 3 plots switching probabilities by origin tier, skill, and assets. The policies reveal multidimensional sorting. Conditional on skill, the probability of searching in Tier A rises with wealth because richer workers can finance mobility costs and sustain the lower job-finding probabilities associated with high-productivity jobs. Conditional on wealth, high-skilled workers have a stronger technological motive to search in Tier A, where their skills yield higher returns. The central tension arises when these dimensions point to different tiers, most notably for highly skilled, low-wealth workers: their skills favor Tier A, but limited self-insurance pushes them toward faster reemployment in Tier B.

This generates sharp wealth asymmetries. At low asset levels, over 20% of the unemployed in A downgrade, while essentially none in B can afford to upgrade because of switching costs. At high wealth levels, downgrades vanish, and nearly half of unemployed workers

Figure 2: Wage and Job Search Policies



(a) Wage policy (b) Job-finding-rate policy

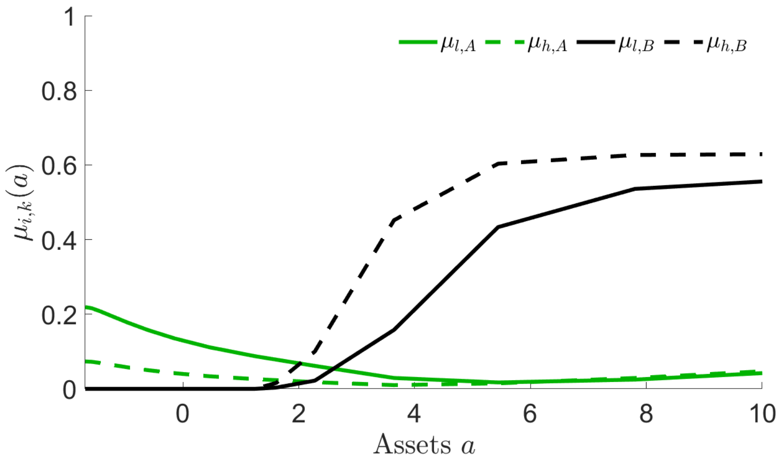
Note: Equilibrium wages and job-finding rates for unemployed workers in Tier A (green) and Tier B (black). Solid lines for low-skilled unemployed; dashed lines for high-skilled unemployed. Parameters in Table 1.

in B upgrade to A. For example, a low-skilled worker in A at the borrowing constraint can increase her job-finding probability by 68% by downgrading to B, but suffers a 7% wage loss. Conversely, a wealthy, highly skilled worker in B can move to A, trading a 40% lower job-finding probability for a 12% wage gain. We call this mechanism *precautionary tier mobility*. Workers adjust not only their savings and within-tier wage targets, but also the tier in which they search. Importantly, within- and between-tier choices interact: rich workers can afford to wait for better matches within a tier and to apply to more productive tiers, thereby securing more favorable trade-offs between wages and job-finding rates.[8]

Figure 4 maps the tier-mobility policies into the steady-state allocation. The distribution exhibits positive but imperfect multidimensional sorting. Conditional on wealth, high-skilled workers are more concentrated in Tier A, where their skills yield the highest returns. Conditional on skill, wealthier workers are also more concentrated in Tier A because they can finance mobility costs and sustain selective search. The off-diagonal groups are equally informative. Some high-skilled, low-wealth workers remain in Tier B despite the high return to their skills in Tier A, while some low-skilled, high-wealth workers are allocated to Tier A despite weaker technological gains. Skills shape the productivity return to tier choice; wealth shapes access.

[8]The benchmark abstracts from on-the-job search to isolate reallocation following unemployment. In the NLSY79 sample, job-to-job transitions occur at similar rates across wealth groups. The model therefore focuses on the EUE allocation margin without implying that mobility while employed is unimportant.

Figure 3: Tier Mobility Policy



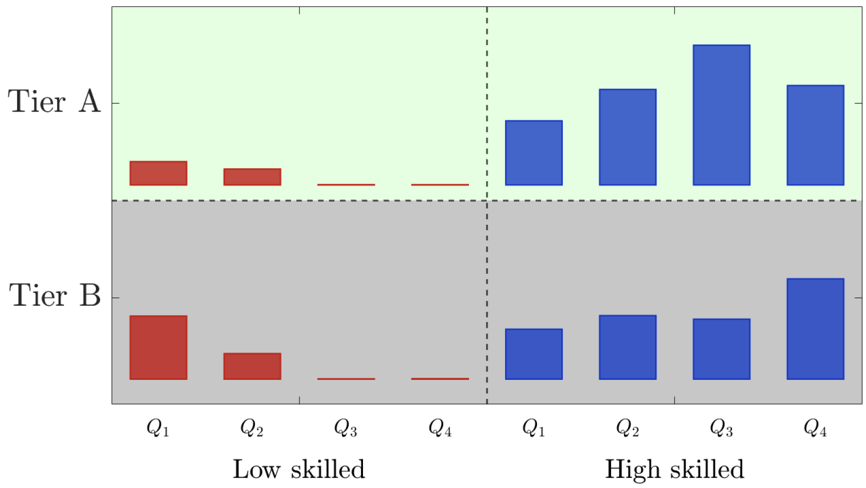
Note: Equilibrium tier mobility rates $\mu_{i,k}(a)$. Green: downgrades from Tier A to B. Black: upgrades from Tier B to A. Solid lines = low-skilled workers. Dashed lines = high-skilled workers. Parameters in Table 1.

Three forces shape this allocation. Taste shocks create residual heterogeneity and smooth the discrete tier choice, but do not generate systematic sorting by wealth. Mobility costs create a direct resource barrier to upward reallocation and therefore reinforce wealth dependence, but they do not by themselves generate the preference complementarity. That complementarity arises from risk aversion and incomplete insurance: because low-wealth workers value rapid reemployment more, the wage–job-finding trade-off makes high-productivity, harder-to-access jobs relatively more attractive as wealth rises. Borrowing constraints amplify the wealth gradient. Precautionary tier mobility thus reflects the interaction of preference-based sorting, technological differences across jobs, and costly mobility.

2 Identifying Job Tiers and Turbulence Risk

To discipline the model, we require empirical counterparts for its two central empirical objects: (i) tier mobility and (ii) turbulence shocks. To operationalize these components, and following evidence that human capital is largely occupation-specific (Kambourov and Manovskii, 2009; Postel-Vinay and Sepahsalari, 2023), we treat occupations as the empirical analog of "jobs" in the model. Occupations can be viewed as combinations of tasks that require distinct skills (Autor, 2013). These skill requirements provide empirical proxies for broad productivity differences (Acemoglu and Autor, 2011; Deming and Kahn, 2018), which define job tiers in the model and the risk of human capital loss, since skills used in one

Figure 4: Equilibrium Sorting



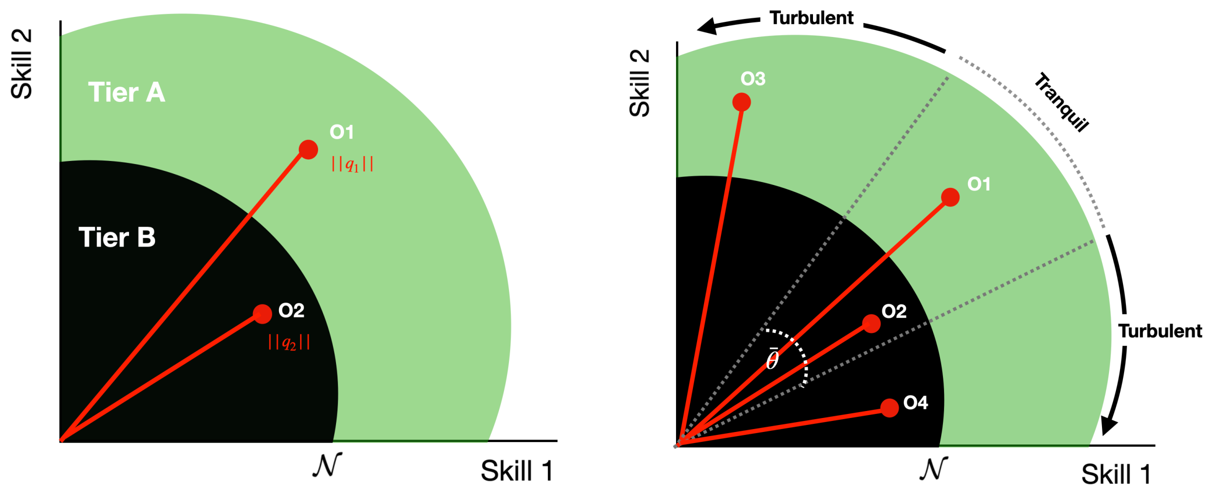
Note: Steady-state worker mass by skill, job tier, and quartile of the unconditional asset distribution. Bars report skill–tier–asset cell masses, normalized by the largest cell. Q_1–Q_4 rank workers from the lowest to the highest asset quartile.

occupation may not fully transfer to another. Accordingly, we combine occupation-level information from the U.S. Department of Labor's O*NET project with individual-level data from the NLSY79 to measure occupational skill requirements, then use these to construct empirical measures of job tiers and turbulence risk. All data details are in Appendix C.

2.1 Occupational Skill Requirements

We represent each occupation at the 3-digit level as a vector of required skills, $q \in \mathbb{R}^J$ (Poletaev and Robinson, 2008; Gathmann and Schönberg, 2010). Our empirical measure of skill requirements is based on the O*NET project, which characterizes occupations using 277 descriptors of required worker attributes and skills. Following Guvenen, Kuruscu, Tanaka and Wiczer (2020) and Baley, Figueiredo and Ulbricht (2022), we aggregate these descriptors into four ($J = 4$) broad skill dimensions—math, verbal, social, and technical. To make them comparable, we normalize each skill dimension to percentile ranks. Each 3-digit occupation is thus represented by a four-element skill requirement vector, which we use to construct our empirical objects for (i) job tiers, based on the overall skill intensity captured by the vector's norm, and (ii) turbulence risk, based on differences in skill composition across occupations and workers' tenure in an occupation.

Figure 5: Job Tiers and Skill-Mix Changes



(a) Job Tiers (b) Skill-mix Changes

Note: Panel (a) shows the tier definition for the case of 2 skills ($J = 2$). Tier A (green segment) groups occupations with a norm of the skill requirement vector above the median ($||q||_1 \geq \mathcal{N}$); Tier B (black segment) groups occupations below the median ($||q||_1 < \mathcal{N}$). Panel (b) shows the classification of skill-mix changes. Skill-mix changes with angular distance below $\bar{\theta}$ are tranquil (e.g., between O1 and O2). Skill-mix changes with angular distance above $\bar{\theta}$ are turbulent (e.g., between O1 and O3 or O4).

2.2 Job Tiers

Motivated by evidence that occupational skill requirements strongly correlate with productivity and wages (Acemoglu and Autor, 2011; Deming and Kahn, 2018), we define job tiers using the Manhattan norm, $\|q\|_1$, which summarizes an occupation's overall skill intensity. Let $\mathcal{N}$ denote the median Manhattan norm across 3-digit occupations. We classify occupations with $\|q\|_1 \geq \mathcal{N}$ as Tier A and those with $\|q\|_1 < \mathcal{N}$ as Tier B.[9]

Figure 5a illustrates our empirical approach to job tiers for the case where $J = 2$. The x-axis represents the required level of skill 1, and the y-axis represents the required level of skill 2. Occupations with a norm above the median are classified as Tier A (green segment), while those with a norm below the median are classified as Tier B (black segment). In the example, occupation $O1$ with $\|q_1\|_1 \geq \mathcal{N}$ is in Tier A, while occupation $O2$ with $\|q_2\|_1 < \mathcal{N}$ is in Tier B. Upward and downward transitions across these segments correspond to tier mobility in the model.

To validate our empirical measure of job tiers, we combine the O*NET skill measures

[9] The resulting tier classification is robust to using the Euclidean norm instead.

with individual-level data from NLSY79 and assign each worker-occupation pair to Tier A or Tier B using the 3-digit census occupation codes and the norm threshold. The distribution is balanced, with roughly half of all worker–job pairs falling into each tier. Wage differences across tiers are substantial: average hourly wages in Tier A are about 0.48 log points higher than in Tier B. After controlling for worker characteristics, the difference remains 0.19 log points.[10] These findings support the validity of our occupation-based definition of job tiers.[11]

Using the O*NET skill vector norm to construct job tiers has three advantages. First, unlike wages, required skill vectors are not mechanically constructed from individual wages, avoiding a tier definition based on the outcome we later study. Second, a median split yields balanced tier sizes, helping preserve statistical power in estimating mobility patterns. Third, alternative definitions—such as k-means clustering of occupations or partitioning by wage premia—produce very similar tier classifications. We thus maintain the norm-based median split throughout.

2.3 Turbulence Risk

In our model, turbulence is an exogenous skill loss in human capital that occurs at separation. In the data, we proxy this shock using realized transitions between occupations with low skill transferability. Because we do not observe the exact moment at which skills are lost, we follow the standard approach in the displacement literature and classify turbulence based on the angular distance between pre- and post-unemployment occupational skill vectors. This provides an empirically grounded measure of low ex post skill transferability, not a direct observation of skill destruction.

Tenure and skill transferability To measure turbulence risk empirically, we label an Employment to Unemployment to Employment (EUE) transition as turbulent if two conditions hold. The first condition requires that the worker be tenured, defined as having at least two years of experience in an occupation. This ensures that the worker has accumulated occupation-specific skills that are at risk of being lost.[12] This tenure restriction also addresses

[10] The set of controls includes age, age squared, labor market experience, gender, race, education, ability, industry, and year and month fixed effects. Results are reported in Table C.2.

[11] Relative to workers in Tier B, workers in Tier A also own twice as much liquid wealth and have greater labor market experience and occupational tenure.

[12] The two-year cutoff follows prior work in the literature (Fujita, 2018) and evidence that wage returns to occupational tenure peak in the second year (Figure C.1a). Workers with less than two years of tenure are considered untenured. They are excluded from the turbulence measurement, since they are unlikely to have accumulated substantial occupation-specific human capital.

concerns that some unemployed workers may selectively change occupations after learning about their abilities across skills.[13] Our occupational-tenure restriction serves a purpose similar to the employer-tenure restrictions commonly used in the displacement literature: it focuses attention on workers who have had time to accumulate job- or occupation-specific human capital (Davis and von Wachter, 2011; Jarosch, 2023).

The second condition requires that, conditional on tenure, skill transferability between pre- and post-unemployment occupations is low. The idea is that accumulated skills are more likely to be lost when the post-unemployment occupation has a markedly different skill mix than the occupation at separation. To measure skill transferability across occupation pairs, we follow Gathmann and Schönberg (2010) and compute angular distance using the Euclidean inner product and its associated norm:

$$\theta(q_1, q_2) \;=\; \cos^{-1}\left(\frac{q_1 \cdot q_2'}{||q_1||_2||q_2||_2}\right). \tag{12}$$

Angular distance captures changes in skill composition, not merely levels, and is therefore the standard measure of occupation-specific skill transferability. When the required skill sets differ considerably, the human capital accumulated in the previous occupation may transfer poorly. Accordingly, we classify any EUE transition involving a move from an occupation with q_1 to an occupation with q_2 as *turbulent* if and only if $\theta \geq \bar{\theta}$, reflecting low skill transferability. Otherwise, it is *tranquil*.

Figure 5b illustrates this construction in the case of two skill dimensions. Moving from occupation O_1 to O_2 entails a slight change in skill composition and thus is considered tranquil. Instead, moving from occupation O_1 to O_3 or O_4 entails a radical shift in skill composition and is therefore labeled turbulent. These transitions are the empirical basis for identifying turbulence risk: large changes in skill mix are classified as turbulent, while smaller changes are considered tranquil.

Angular threshold Following Baley, Figueiredo and Ulbricht (2022), we set $\bar{\theta} = 14.8°$, the threshold at which transitions above the cutoff have zero market-weighted average correlation in skill requirements. Among tenured EUE transitions, we classify moves with $\theta \geq \bar{\theta}$ as turbulent and those with $\theta < \bar{\theta}$ as tranquil. Tranquil transitions may still involve

[13] The underlying assumption is that such learning is most relevant in the early stages of repeated performance observation, as shown by Baley, Figueiredo and Ulbricht (2022). Consistent with this, we find that the probability of switching occupations declines steeply during the first 30 months before leveling off (Figure C.1b).

an occupational change, but not a sufficiently large change in skill mix. We interpret low skill transferability as a form of skill loss. Using this cutoff, approximately 7.8% of EUE transitions in our sample are classified as turbulent, 22.8% as tranquil, and the remainder correspond to untenured workers whom we do not consider at risk of human capital loss.

Notably, the angular-distance threshold used to classify transitions is fixed independently of workers' wealth, consistent with the model's treatment of turbulence as a shock the worker does not directly choose. Because the classification uses the realized post-unemployment occupation, however, occupational choice may partly reflect workers' liquid wealth and the opportunities available to them. We therefore interpret angular distance as a measure of low ex post skill transferability rather than as a direct observation of skill destruction. Table C.1 shows that workers in turbulent and tranquil transitions have broadly comparable age and tenure profiles, although workers experiencing turbulent transitions enter unemployment with lower wages and liquid wealth. Crucially, turbulent transitions are associated with a 13% decline in wages upon reemployment, compared with only a 2% decline following tranquil transitions. Together with the concentration of wage losses among workers who downgrade tiers, this evidence supports the interpretation that low-transferability transitions contain an important adverse human-capital component.

2.4 Turbulence Risk and Tier Mobility

Turbulence and tier mobility are distinct margins. In the model, turbulence is an exogenous skill-loss shock at separation, whereas tier mobility is an endogenous response to liquidity and job-finding considerations. The empirical measures mirror this distinction: angular distance captures changes in the composition of occupational skill requirements, while tier transitions capture movements across broad productivity groups. A transition may therefore involve both margins—for example, a worker may experience a large change in skill mix while also downgrading to a lower-productivity tier.

Turbulence need not involve a tier change. The empirical occupation space is richer than the model's: occupations differ both in the overall intensity of their skill requirements, which defines tiers, and in their composition, which determines skill transferability. Thus, a worker moving between two occupations in the same tier with very different skill mixes is classified as turbulent but does not change tiers. The model counterpart of such a transition is a skill-loss shock followed by reemployment in the same broad productivity tier. The model can therefore represent turbulence without tier mobility, while abstracting from richer occupational heterogeneity within tiers.

3 Calibration

This section describes the model calibration using U.S. data. We follow a two-step strategy. First, we discipline parameters standard in the labor search literature using well-established empirical benchmarks to ensure comparability with previous work. Second, because our framework features endogenous tier mobility and turbulence shocks that are not present in standard models, we discipline the additional parameters using newly constructed moments from O*NET and the NLSY79. This separation makes transparent which moments capture the model's novel features and which reproduce well-known aggregate labor-market facts.

3.1 Functional forms

We adopt standard functional forms for preferences, technology, and matching. Preferences are represented by a CRRA utility function, $u(c) = c^{1-\sigma}/(1-\sigma)$, where σ is the coefficient of relative risk aversion. Output is produced with a multiplicative technology, $f(x_i, y_k) = x_i y_k$ where x_i denotes worker skill and y_k denotes job productivity. The numeraire is one unit of output. Labor market matching follows the CES form in Menzio and Shi (2011), yielding a job-finding rate, $p_k(\theta) = \chi_k \theta/(1+\theta^\alpha)^{\frac{1}{\alpha}}$. Here χ_k captures tier-specific matching efficiency, while α governs the curvature of the matching function and hence how the elasticity of the job-finding rate with respect to market tightness varies with θ.

3.2 Externally calibrated parameters

Of the 25 parameters to calibrate, 14 are fixed outside of the model and summarized in Part I of Table 1. One model period corresponds to one month. Accordingly, we set the discount factor to $\hat{\beta} = 0.9965$ and the retirement probability to $\rho^r = 0.0021$, which implies an effective monthly discount factor of $\beta = \hat{\beta}(1-\rho^r) = 0.9944$. The retirement probability corresponds to an average working life of 40 years. We set the net monthly risk-free interest rate to $r = 0.003$, consistent with an annual rate of 3.7%. The corresponding gross return is $R = 1 + r$. We set the coefficient of relative risk aversion to $\sigma = 2$, a standard value in the literature.

The skill upgrading probability is set to $\gamma^u = 0.041$, consistent with the definition of becoming tenured after two years (recall Section 2.3). Since $1/\gamma^u \approx 24$, this implies that the average waiting time for a skill upgrade is 24 months.

Table 1: Parametrization

Parameter	Definition	Value	Parameter	Definition	Value
I. Externally calibrated					
$\hat{\beta}$	discount factor	0.9965	ρ_r	retirement probability	0.0021
r	interest rate	0.003	σ	relative risk aversion	2
γ^u	prob. of upgrade	0.041	x_l	low-skilled productivity	1
Tier specific					
y_B	Tier-B productivity	1 (norm.)	$\mathcal{M}_{AB}$	switching cost to B	0 (norm.)
λ_h^A	high-skill separation	0.016	λ_h^B	high-skill separation	0.019
λ_l^A	low-skill separation	0.025	λ_l^B	low-skill separation	0.037
γ_A^d	turbulence risk	0.180	γ_B^d	turbulence risk	0.280
II. Internally calibrated					
χ_A	matching efficiency	0.247	χ_B	matching efficiency	0.322
κ_A	vacancy creation cost	0.220	κ_B	vacancy creation cost	0.028
α	matching elasticity	0.770	b	home production	0.350
$\underline{a}$	borrowing constraint	-1.68	y_A	Tier-A productivity	1.159
x_h	skill return	1.100	$\mathcal{M}_{BA}$	switching cost to A	0.910
ν	taste-shock dispersion	1.203			

Tier-specific parameters. We now turn to job-tier-specific parameters. We normalize Tier-B productivity (y_B) and low skill (x_l) to unity. We also normalize the mobility cost from Tier A to Tier B to zero, $\mathcal{M}_{AB} = 0$. To inform the model about the separation and turbulence risk, we combine worker-level data from the NLSY79 with occupation-level data from O*NET. Worker-job pairs are assigned to Tier A or Tier B based on the tier definition in Section 2.2.

To discipline the tier- and skill-specific separation rates λ_{ik}, we estimate the probability of transitioning from employment to unemployment separately by tier and occupational tenure, using tenured and untenured workers as the empirical counterparts of high- and low-skilled workers.[14] We obtain separation rates of $\lambda_l^A = 2.5\%$ and $\lambda_l^B = 3.7\%$ for low-skilled workers, and $\lambda_h^A = 1.6\%$ and $\lambda_h^B = 1.9\%$ for high-skilled workers. Separation rates are lower in Tier A than in Tier B for both skill groups, and lower for high-skilled workers within each tier. This ordering is consistent with labor-market segments that differ systematically in job stability (Ahn, Hobijn and Şahin, 2023), with lower-quality jobs carrying greater separation risk (Jarosch, 2023; Repele, 2026), and with human capital associated with greater employment stability (Cairó and Cajner, 2018).

[14] Separation rates are predicted at the means of the covariates from a logit model including age, cumulative labor market experience, gender, ethnicity, industry, education, time fixed effects, as well as a job-tier dummy. We estimate models separately for tenured and untenured workers.

Table 2: Target Moments

Moment	Model	Data	Moment	Model	Data
Unemp. duration (months)	5.11	6.18	Employed in A / total	0.54	0.50
Elasticity of UE to tightness*	0.23	0.28	Outside option $\mathbb{E}[b/w]^*$	0.36	0.40
Asset–wage correlation	0.46	0.26	Negative asset holders (%)	9.20	10.28
Skill premium in A	1.12	1.12	Skill premium in B	1.10	1.08
Switchers to A (% EUE in B)	10.92	12.93	Switchers to B (% EUE in A)	8.46	9.72
Experienced workers (A/B)	1.16	1.21			

*Note: All data moments are from the NLSY79, except those marked with *, which are from Shimer (2005). Skill premia are $\mathbb{E}[w_h^k]/\mathbb{E}[w_l^k]$ for $k \in \{A, B\}$.*

Finally, to discipline turbulence risk γ_k^d by tier, we compute the fraction of tenured workers who undergo an EUE transition and are reemployed in an occupation with a substantially different skill composition, as defined in Section 2.3. Based on this measure, we find that 18% of tenured workers in Tier A and 28% in Tier B experience a turbulence shock at separation, corresponding to turbulence risks of $\gamma_A^d = 0.18$ and $\gamma_B^d = 0.28$, respectively.

3.3 Internally calibrated parameters

In the second step, we use the Simulated Method of Moments (SMM) to calibrate the remaining eleven parameters (listed in Part II of Table 1) by matching empirical targets. We jointly calibrate the parameters using a search algorithm over the parameter space that minimizes the distance between the empirical and simulated moments. Table 2 compares model-generated moments with their empirical counterparts. The model reproduces the data well across both aggregate and tier-specific statistics. The largest discrepancy is the asset–wage correlation, which is 0.46 in the model and 0.26 in the data, indicating that the model generates stronger wealth sorting in wages than observed empirically. We therefore interpret the quantitative strength of the wealth channel with caution and complement the targeted moments with untargeted evidence on mobility and post-displacement wage paths.

The following discussion describes which moments primarily discipline each parameter; because the parameters are jointly estimated, these mappings are not one-to-one.[15] We use the borrowing constraint $\underline{a}$ to target the share of workers with negative liquid wealth.[16] Following Shimer (2005), we use the flow value of home production, b, to match the upper

[15] Implementation details are provided in Appendix B.4.

[16] We measure financial positions using net liquid wealth, defined as the reported market value of easily tradable assets (savings, stocks, bonds, mutual funds, business assets, vehicles, and farms) minus debts in these categories (Chetty, 2008; Lise, 2013; Griffy, 2021). Housing is excluded as highly illiquid.

bound of the income replacement rate observed in the U.S. labor market. The elasticity of the matching function, α, influences the elasticity of unemployment-to-employment (UE) flows with respect to market tightness. The Tier A productivity parameter, y_A, and the skill return, x_h, jointly determine the average skill premium in both Tiers A and B.

The taste-shock dispersion ν and the upward mobility cost $\mathcal{M}_{BA}$ jointly govern tier choice and wealth-dependent sorting, but through distinct channels. The mobility cost creates a direct resource barrier to upgrading and therefore has its largest effect at low asset levels, while ν governs how strongly tier choices respond to systematic differences in continuation values across assets and skills. Together, these parameters are primarily disciplined by the Tier-A employment share and the asset–wage correlation. The matching efficiencies χ_A and χ_B are then disciplined by directional tier-switching rates conditional on origin tier: moves to Tier B account for 8.46% of relevant EUE transitions in the model and 9.72% in the data, while moves to Tier A account for 10.92% and 12.93%, respectively. Finally, the vacancy creation costs κ_A and κ_B determine the number of vacancies in each tier, thereby affecting the share of experienced workers and the average unemployment duration.

Magnitude of the upward mobility cost The upward mobility cost is $\mathcal{M}_{BA} = 0.91$. Following Giannone, Li, Paixao and Pang (2023), we interpret this parameter as the resource component of a broader mobility friction, rather than as a single transition expense. Modeling this component as a monetary cost allows us to isolate how cash on hand affects occupational mobility, the mechanism of interest in our setting. The cost parsimoniously captures direct and opportunity costs associated with upward mobility, including retraining expenditures and earnings foregone while acquiring new skills (Andrieu, Jamet, Marcolin and Squicciarini, 2019), geographic relocation (Kennan and Walker, 2011), and the time devoted to searching and applying for better jobs (Faberman, Mueller, Şahin and Topa, 2022). Since a model period is one month and the calibrated nonemployment flow value is $b = 0.35$, the cost corresponds to $\mathcal{M}_{BA}/b = 0.91/0.35 = 2.60$ months of the nonemployment flow value. Using the targeted outside-option ratio, $\mathbb{E}[b/w] = 0.36$, this is equivalent to approximately $2.60 \times 0.36 = 0.94$ months of average earnings, or \$1.9 thousand in 2000 USD.[17]

[17] The magnitude is consistent with external estimates: Andrieu *et al.* (2019) report direct retraining costs across OECD countries of approximately \$1.2 thousand for transitions requiring limited training and \$2.3 thousand for those requiring moderate training, expressed in 2000 USD.

4 Wealth, Reallocation, and Wage Scarring

We examine how liquid wealth influences labor market outcomes following job loss, combining reduced-form evidence from the NLSY79 with model-based analysis. We begin by documenting that post-unemployment wages depend not only on the transition type—turbulent versus tranquil—but also on workers' liquid wealth at the time of separation. We then show that the model quantitatively replicates these wage patterns and that wealth-driven mobility across job tiers accounts for the observed heterogeneity in wage losses along the wealth distribution. Finally, we provide suggestive empirical evidence consistent with this mechanism.

4.1 Wages after Job Loss

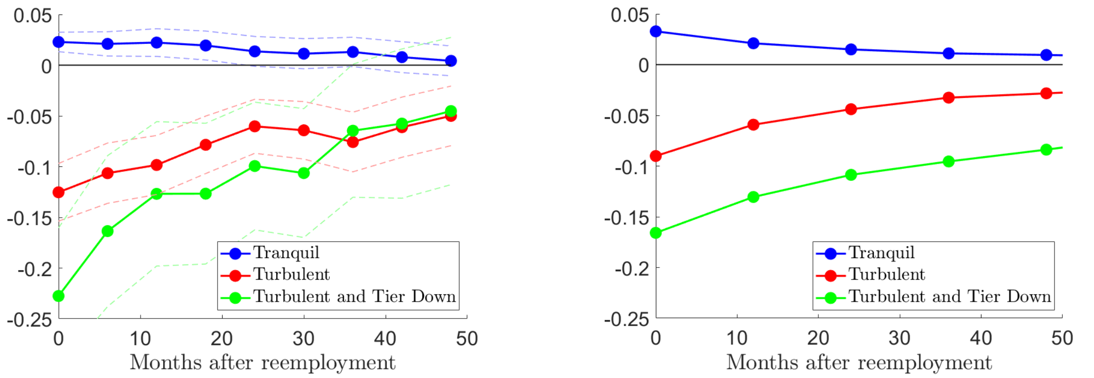
We use individual-level data from the NLSY79, focusing on workers with high occupational tenure who subsequently experience unemployment. This sample provides a natural empirical analog to the model's high-skill workers facing job loss. We classify each EUE transition as *tranquil* or *turbulent* depending on whether the worker switches to an occupation with low skill transferability upon reemployment. We also record whether workers move upward (from Tier B to A) or downward (from Tier A to B) across job tiers.

Our main outcome variable is residual wage growth, defined as the log change in real hourly wages j months after reemployment relative to the pre-separation wage, for $j \in \{0, \ldots, 48\}$, residualized with respect to age and its square, cumulative labor-market experience, race, gender, education, industry and time fixed effects, as well as the log wage in the last job.[18] We also control for ability proxied by scores on the Armed Services Vocational Aptitude Battery (ASVAB) following Prada and Urzúa (2017).

The Role of Turbulence Risk We begin by showing that we can replicate well-documented findings in the literature. Figure 6a plots average residual wage growth at reemployment and every six months thereafter for tranquil transitions (blue line), turbulent transitions (red line), and turbulent transitions with a tier downgrade (green line). In line with Fujita (2018), we find that workers experiencing turbulent transitions have larger wage losses than those in tranquil ones: wages fall by about 12% at reemployment, compared to a 3% gain for tranquil transitions, and remain 5% lower after 4 years. Importantly, as in Huckfeldt (2022),

[18] The model's skill state captures occupation-specific human capital rather than general labor-market experience. For this reason, in the empirical wage specifications, we control for cumulative experience, measured as months worked since first employment.

Figure 6: Wages after Job Loss: Tranquil versus Turbulent Transitions



(a) Data

(b) Model

Note: The figure plots average residual wage growth at reemployment and every six months thereafter, both in the data (Panel a) and in the model (Panel b). The sample covers EUE transitions observed from 1979 to 2016 in NLSY79. Dotted lines report 95% confidence intervals.

wage declines are concentrated during turbulent transitions involving a tier downgrade, with wages dropping by 22% upon reemployment.

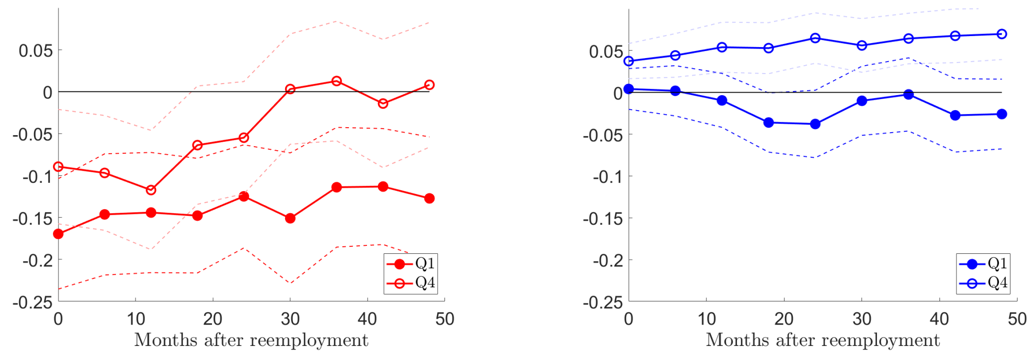
Figure 6b shows the model counterpart. As in the data, turbulent transitions that also involve a tier downgrade experience larger wage declines that persist for four years after reemployment. This provides an untargeted check on the model, since these wage paths are not used in the calibration.

The Role of Wealth Next, we examine how liquid wealth shapes wage dynamics following unemployment. Following Chetty (2008) and Griffy (2021), we use net liquid wealth as a proxy for liquidity constraints at job loss. We measure liquid wealth at separation using the closest pre-unemployment interview and classify workers in the bottom 25% of the liquid wealth distribution before displacement as low-wealth (Q1, constrained), and those in the top 25% as rich (Q4, unconstrained).[19]

Figure 7 replicates Figure 6 but conditions on transition type and liquid wealth at separa-

[19]See Footnote 16 for the definition of liquid wealth. In the NLSY79 data, we observe wealth at survey interviews rather than on the exact date of displacement. We use the closest pre-unemployment observation, ensuring that measured wealth precedes the unemployment spell and is not mechanically affected by asset depletion during the spell. Because interviews are not perfectly synchronized with separations, interpret the measure as a ranking of workers' pre-displacement liquidity rather than as exact cash on hand on the separation date. At separation, the bottom quartile Q1 holds about $3.4 thousand, the middle quartiles Q2-Q3 around $9 thousand, and the top quartile Q4 about $101 thousand. Assets are converted to 2000 dollars using the Consumer Price Index.

Figure 7: Wages after Job Loss by Wealth: Data



(a) Turbulent (b) Tranquil

Note: The figure plots average residual wage growth at reemployment and every six months thereafter. Panel (a) shows turbulent transitions, and Panel (b) shows tranquil transitions. Q1 and Q4 denote the first and fourth quartiles of the household liquid wealth distribution at the start of the unemployment spell. The sample covers EUE transitions observed from 1979 to 2016 in NLSY79. Dotted lines report 95% confidence intervals.

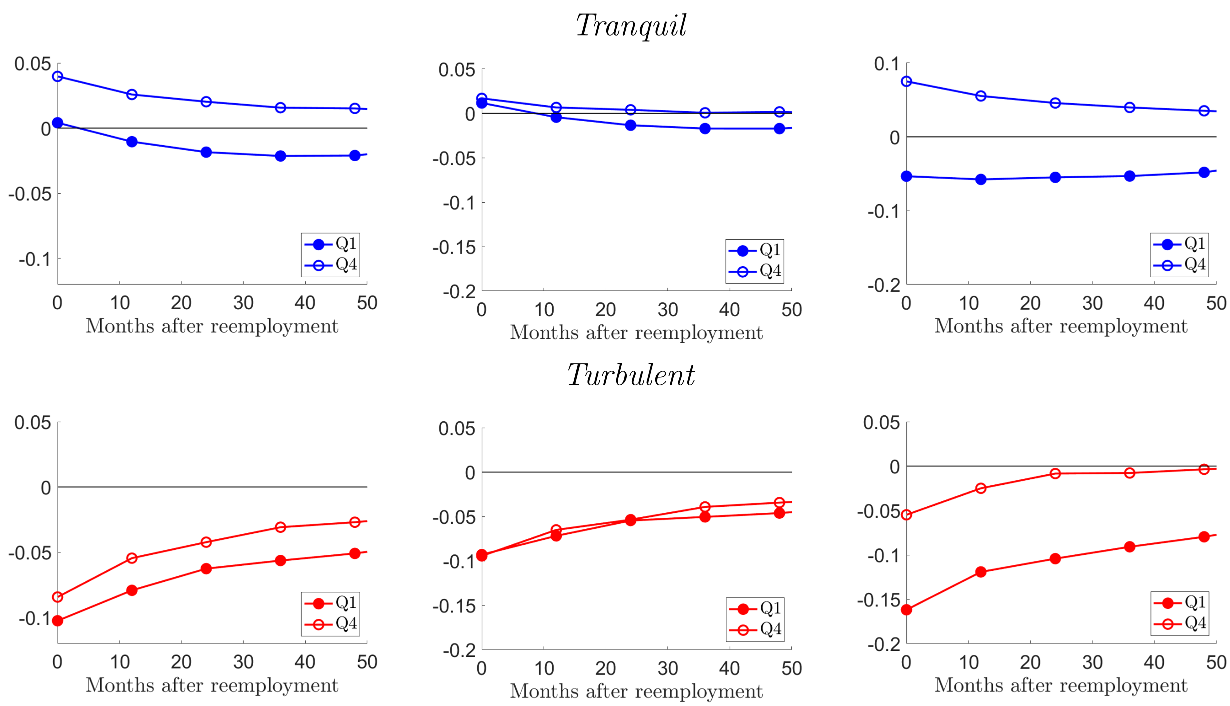
tion. The point estimates suggest a pronounced interaction between wealth and turbulence, although the confidence intervals are wide and the wealth differences should be interpreted as suggestive.[20] In turbulent transitions (Panel a), both poor and rich workers suffer significant initial wage losses. However, rich workers recover fully within four years, whereas low-wealth workers suffer 6% larger wage losses upon reemployment and remain about 16% below pre-unemployment levels on average. In tranquil transitions (Panel b), wealth differences are more muted. Low-wealth workers exhibit no significant wage change after four years, while rich workers experience an average gain of 4%.[21]

Although post-unemployment wage trajectories are not directly targeted, the model reproduces the scarring patterns observed in the data (Figure 8a). In particular, it captures the wealth gradient following turbulent transitions: low-wealth workers experience larger and more persistent wage losses, while wealthy workers nearly recover to their pre-unemployment wages within four years.

[20]The wide confidence intervals largely reflect the relatively small number of tenured turbulent EUE transitions once the sample is further split by liquid-wealth quartile and post-reemployment horizon.

[21]These patterns are robust to several alternative specifications reported in Appendix C.5, including additional income controls, alternative tenure and unemployment-spell restrictions, and different definitions of turbulence and liquid wealth. We also find no evidence that the Q1–Q4 wage-growth gap varies systematically with prior job tenure: the interaction with top-quartile wealth is insignificant both upon reemployment and 48 months later ($p = 0.58$ and $p = 0.26$).

Figure 8: Wages after Job Loss by Wealth: Model

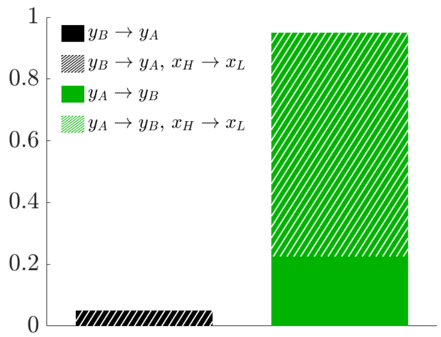


(a) All (b) Same Tier (c) Different Tier

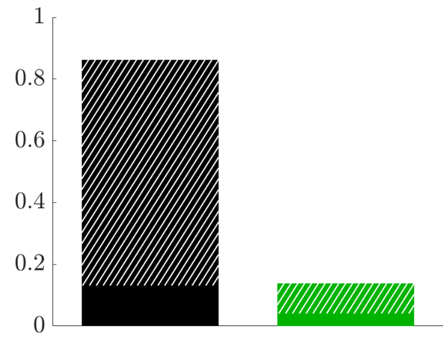
Note: Average wage growth at reemployment and at six-month intervals thereafter in the model under the baseline calibration. The top row shows tranquil transitions and the bottom row turbulent transitions. Panel (a) includes all EUE transitions, Panel (b) those in which workers are reemployed in the same tier, and Panel (c) those in which workers change tiers upon reemployment. Q1 and Q4 denote the first and fourth quartiles of the liquid-wealth distribution at the start of the unemployment spell.

The Role of Tier Mobility Panels 8b and 8c split the same transitions between workers who are reemployed in the same tier and those who change tiers. The wealth gradient is concentrated among tier switchers, indicating that tier mobility is the main channel through which liquid wealth amplifies and prolongs wage losses in the model. Turbulent workers who remain in the same tier lose about 10% upon reemployment and gradually recover, reflecting the direct effect of skill loss. Among tier switchers, by contrast, wage paths differ sharply by wealth. Rich turbulent workers lose about 5% upon reemployment and fully recover within three years, whereas poor turbulent workers lose about 15% and remain roughly 10% below their pre-unemployment wage after four years.

Figure 9: Tier Mobility, Wealth and Turbulence



(a) Low-wealth at separation (Q1)



(b) High-wealth at separation (Q4)

Note: Among EUE transitions involving a tier change, the figure reports the shares that upgrade to Tier A or downgrade to Tier B. Tier upgrades in black bars and tier downgrades in green. Panel (a) shows transitions for poor workers in Q1, and Panel (b) shows transitions for the rich in Q4. Hatched areas denote turbulent transitions.

4.2 Wealth-Driven Mobility

Wealth-driven mobility is the central mechanism linking turbulence to persistent scarring by sorting unemployed workers across job tiers. The model generates larger and more persistent wage losses for poor workers who experience a turbulence shock at separation because they are more likely to be sorted into jobs in which their remaining skills yield lower returns. In contrast, rich workers hit by the same shock tend to recover their initial wage losses because they are more likely to preserve or regain access to Tier A jobs. Figure 9 shows the equilibrium shares of EUE transitions that change tier, distinguishing between upgrades to Tier A (black bars) and downgrades to Tier B (green bars), for poor (Panel a) and rich (Panel b). Among workers who change tiers at reemployment, most low-wealth workers downgrade from A to B, whereas most rich workers upgrade from B to A. This asymmetry is particularly pronounced after turbulent separations, when skill losses occur. The figure thus illustrates how wealth influences the direction of tier mobility and, in turn, the persistence of wage scarring: rich workers recover more quickly by upgrading to high-paying jobs. In contrast, poor workers face persistent losses as they transition to lower-wage opportunities.

Inspecting the Mechanism To isolate the contribution of wealth-sensitive tier mobility to post-unemployment wage dynamics, we conduct two counterfactual exercises. The first removes the systematic dependence of tier choice on workers' assets and skills, while the second removes heterogeneity across tiers altogether. These exercises isolate the roles of systematic worker sorting and heterogeneity across job tiers.

The first counterfactual sets the preference-shock scale ν to a large value. As $\nu \to \infty$, idiosyncratic preference shocks dominate systematic differences in continuation values, so tier choices become effectively independent of assets and skills (see Figure D.1a). Turbulent workers still experience larger wage losses than tranquil workers, but the differential recovery across wealth groups disappears: poor and rich workers face similar initial declines and nearly identical wage paths over the subsequent 48 months. Turbulence still generates wage losses, but it no longer produces wealth-dependent scars through systematic tier selection.

The second counterfactual eliminates heterogeneity across tiers by setting all Tier B parameters equal to their Tier A counterparts (see Figure D.1b). Workers may still adjust their within-tier wage-job-finding trade-off as a function of wealth, as in standard precautionary-search models, but liquidity no longer affects the productivity segment entered after displacement through an across-tier allocation margin. Turbulent workers consequently experience similar wage losses across wealth groups. Without a lower-paying tier to downgrade into, constrained workers bear the full 10% skill-loss penalty at reemployment, which gradually dissipates over time.

The counterfactuals show that wealth-sensitive tier mobility is the principal amplification mechanism behind heterogeneous wage recovery in the benchmark model. After a turbulence shock, wealthy workers can sustain selective search and remain in or move toward Tier A, partially offsetting the initial skill loss. Liquidity-constrained workers are more likely to move toward Tier B, where jobs are found more quickly but wages are lower. This precautionary downgrading transforms a transitory skill-loss shock into a persistent wage scar.

Suggestive Evidence The model predicts a nonlinear relationship between assets and tier mobility, with the largest differences between low- and high-wealth workers. We therefore compare Q1 and Q4, which clearly contrast pre-displacement liquidity.

We estimate separate logistic regressions for tier mobility among workers initially in Tier A and Tier B. Among workers initially in Tier A, the outcome equals one ($Y_i^A = 1$) if worker i downgrades to Tier B upon reemployment and zero ($Y_i^A = 0$) if she remains in Tier A. Analogously for workers in Tier B. For each model $k \in \{A, B\}$, we estimate:

$$\text{(13)} \qquad \log\left(\frac{p_i^k}{1-p_i^k}\right) = \alpha_k + \beta_k Q4_i + \delta_k' \mathbf{X}_i, \qquad \text{where } p_i^k = \Pr(Y_i^k = 1 \mid Q4_i, \mathbf{X}_i).$$

Here $Q4_i$ is an indicator equal to one for workers in the fourth (top) wealth quartile and zero for those in the first (bottom) quartile. The vector $\mathbf{X}_i$ includes individual-level controls, including age and its square, gender, race, prior labor market experience, the angular distance between previous and current occupations, and month and year fixed effects. Results are reported in Table 3. Among workers initially in Tier A, those in the top wealth quartile ($Q4$) have a 4.9 percentage-point lower predicted probability of downgrading to Tier B than workers in the bottom quartile ($Q1$). Among workers initially in Tier B, they have a 3.1 percentage-point higher predicted probability of upgrading to Tier A. These estimates are conditional correlations rather than causal effects, but they are consistent with the model's mechanism: greater liquid wealth is associated with less downward mobility and more upward mobility following unemployment.

Table 3: Wealth and Tier Mobility

	Downgrading ($A \to B$)	Upgrading ($B \to A$)
Rich (Q4)	-0.0487^{***}	0.0309^{**}
	(0.0105)	(0.0124)
Observations	3,182	4,243

Note: The table reports average marginal effects of being in the top (Q4) relative to the bottom (Q1) quartile of the pre-displacement liquid-wealth distribution, estimated from logistic regression models. Column 1 estimates the probability of downgrading among workers initially in Tier A; Column 2 estimates the probability of upgrading among workers initially in Tier B. We control for age and its square, gender, race, prior labor-market experience, angular distance between the pre- and post-unemployment occupations, and month and year fixed effects. Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.3 Unemployment Duration

In our framework, wealthier workers can sustain longer searches for high-wage jobs, while poorer workers accept lower wages to reenter employment faster. This wealth–duration relationship is consistent with Card, Chetty and Weber (2007), who show that a lump-sum transfer reduces job-finding rates, and Chetty (2008), who finds that the response of job-finding to unemployment benefits declines with liquid wealth. In our data, workers in the top wealth quartile remain unemployed about 31% longer than those in the bottom quartile after turbulent transitions and 40% longer after tranquil transitions.[22] The model reproduces this gradient, although at a smaller magnitude, with unemployment durations 10–12% longer for wealthy workers. We next show that the same wealth-driven search mechanism also generates negative duration dependence in reemployment wages.

[22] Duration is residualized using the same set of controls described earlier.

Negative duration dependence Directed-search models with precautionary savings distinguish between two sources of duration dependence. In the cross-section, workers targeting higher wages face lower job-finding probabilities, implying positive duration dependence. Over time, however, unemployed workers deplete their assets and redirect search toward lower-wage submarkets with higher job-finding probabilities, generating negative duration dependence, as observed in the data. Our model reproduces this pattern and clarifies how it varies across workers. We estimate the empirical relationship between reemployment wages and unemployment duration by regressing

$$\log(w_i) \;=\; \gamma\, dur_i \;+\; \delta' \mathbf{X}_i \;+\; \epsilon_i, \tag{14}$$

where w_i is the reemployment wage, dur_i is the duration of the unemployment spell, and $\mathbf{X}_i$ is the same control vector used in the empirical analysis.

Table 4 shows negative duration dependence in both the data and the model. The semielasticity is -0.0050 in the data and -0.0022 in the model, which accounts for about half of the aggregate relationship.[23] Among tier switchers, the model closely matches the empirical elasticity (-0.0039), as asset depletion induces downgrading to Tier B.

Table 4: Duration Dependence of Reemployment Wages

Sample	**Data**	**Model**
All transitions	-0.0050 (.0009)	-0.0022
Transitions with tier switch	-0.0039 (.0015)	-0.0039

Note: The table reports the coefficient γ from the regression in (14). The sample consists of EUE transitions among tenured workers observed in the NLSY79 from 1979 to 2016; the second row further restricts the sample to workers who change tiers. Controls include age and age squared, labor-market experience, gender, race, education, ability, previous wage, and year and month fixed effects. Robust standard errors, clustered at the individual level, are reported in parentheses.

Tier mobility therefore amplifies the standard within-tier duration-dependence channel. As assets decline, workers both lower their wage targets within tiers and become more likely to downgrade. A one-tier model retains the first force but misses the second. The wealth gradient in wage recovery and the additional duration dependence generated by tier switching thus arise from the same interaction between asset depletion and job allocation.

[23]These estimates are similar to those in Eeckhout and Sepahsalari (2024).

5 Policy Analysis

Our framework links liquid assets, unemployment duration, and reemployment quality through tier mobility. We compare two interventions on a common fiscal scale: economy-wide unemployment insurance (UI), which relaxes workers' liquidity constraints, and targeted job-creation subsidies (JC), which expand high-tier vacancies. The benchmark holds separation risks and tier attributes fixed, abstracts from skill depreciation during unemployment, and excludes on-the-job search. The exercises therefore isolate the EUE allocation channel rather than provide a comprehensive ranking of optimal policies.

5.1 Unemployment Insurance

We first consider an unemployment insurance (UI) scheme that provides a transfer ϕ to unemployed workers in addition to home production b. By relaxing liquidity constraints, UI partially substitutes public insurance for private self-insurance. The policy is financed through a proportional tax τ on labor income, and the equilibrium is recomputed for each value of ϕ subject to the balanced-budget condition, $\tau\overline{w}e = \phi u$, where e and u denote total employment and unemployment, and the average wage $\overline{w}$ is

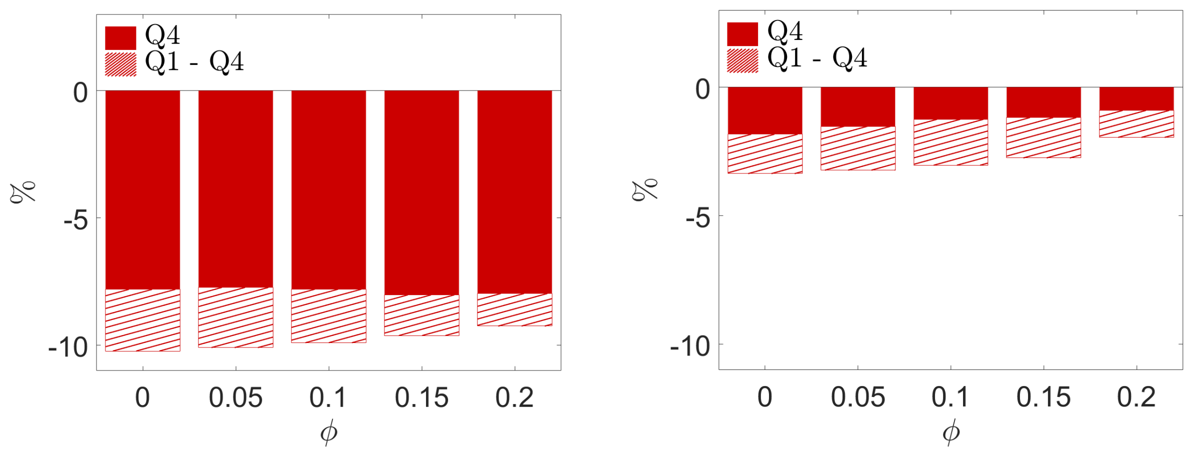
$$\overline{w} \equiv \frac{1}{e} \sum_{i\in\{l,h\}} \sum_{k\in\{A,B\}} \int_a \int_w w \, d\Gamma^E_{ik}(a, w). \tag{15}$$

Figure 10 quantifies how different steady-state levels of the UI transfer shape reemployment outcomes following turbulent transitions. We consider five values in the interval $\phi \in [0, 0.2]$. The maximum transfer corresponds to an expenditure-to-output ratio of 1.5%. Panel (a) shows the short-term wage response—average wage growth upon reemployment relative to the pre-separation wage, $\log(w_1/w_0)$. Panel (b) depicts the long-term effect—average wage growth four years after reemployment, $\log(w_{48}/w_0)$. Solid bars represent the rich, while hatched bars indicate the differential effects on poor workers.[24]

Two results stand out. First, in the short term, a more generous UI allows poor workers to search longer and secure higher-quality matches, narrowing the wage gap upon reemployment. Rich workers, already well insured, show little change. Second, in the long run, UI dampens wage scars, substantially reducing persistent earnings losses among poor workers. These effects underscore UI's role in mitigating the consequences of turbulence by providing insurance against income risk.

[24] Rich and poor correspond to the wealth levels Q4 and Q1 in the respective steady states.

Figure 10: Wage Growth After Turbulent Transitions for Different UI



(a) Short Term: $\log(w_1/w_0)$ (b) Long Term: $\log(w_{48}/w_0)$

Note: Wage growth following turbulent EUE transitions for various levels of ϕ. Relative to the pre-separation wage, Panel (a) shows average wage growth upon reemployment, and Panel (b) shows four years after reemployment. Solid bars report outcomes for Q_4 workers. Hatched segments report the $Q_1 - Q_4$ differential, so the total bar height gives the outcome for Q_1 workers.

5.2 Job Creation Programs

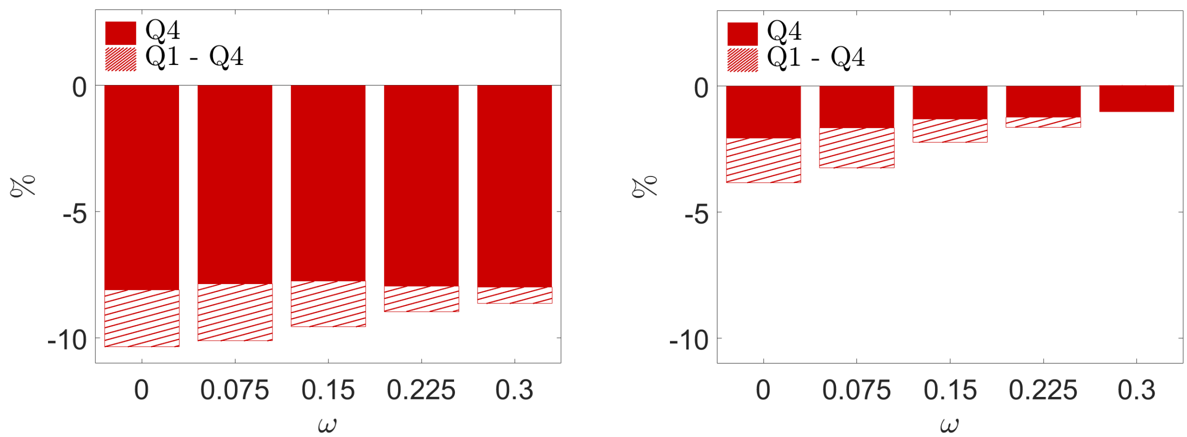
While UI provides public insurance on the worker side, job-creation (JC) subsidies act on the labor market demand side. We consider a subsidy covering a fraction ω of the vacancy-creation cost κ_A in Tier A, so firms pay $(1-\omega)\kappa_A$ per vacancy. By lowering posting costs, the policy stimulates vacancy creation in the high-productivity tier and indirectly affects workers' savings and search decisions. The policy is financed through the same proportional tax τ on labor income, with the balanced-budget condition $\tau\overline{w}e = \omega\kappa_A v_A$, where v_A denotes the equilibrium number of vacancies posted in Tier A:[25]

$$v_A \equiv \sum_{i\in\{l,h\}} \int_a \theta_{iA}(a)\, d\Gamma^U_{iA}(a). \tag{16}$$

Figure 11 illustrates how varying the vacancy subsidy affects post-unemployment wage dynamics. We consider five values in the interval $\omega \in [0, 0.3]$, where the maximum subsidy corresponds to an expenditure-to-output ratio of 1.5%.

[25] Under the vacancy subsidy, firms pay $(1-\omega)\kappa_A$ per vacancy, whereas the underlying resource cost remains κ_A. Accordingly, firm profits subtract the firm-paid cost, while aggregate resource accounting subtracts the full vacancy-creation cost.

Figure 11: Wages After Turbulent Transitions for Tier-A Vacancy Subsidy ω



(a) Short Term: $\log(w_1/w_0)$

(b) Long Term: $\log(w_{48}/w_0)$

Note: Wage growth following turbulent EUE transitions for various levels of ω. Relative to the pre-separation wage, Panel (a) shows average wage growth upon reemployment, and Panel (b) shows four years after reemployment. Solid bars report outcomes for Q_4 workers. Hatched segments report the $Q_1 - Q_4$ differential, so the total bar height gives the outcome for Q_1 workers.

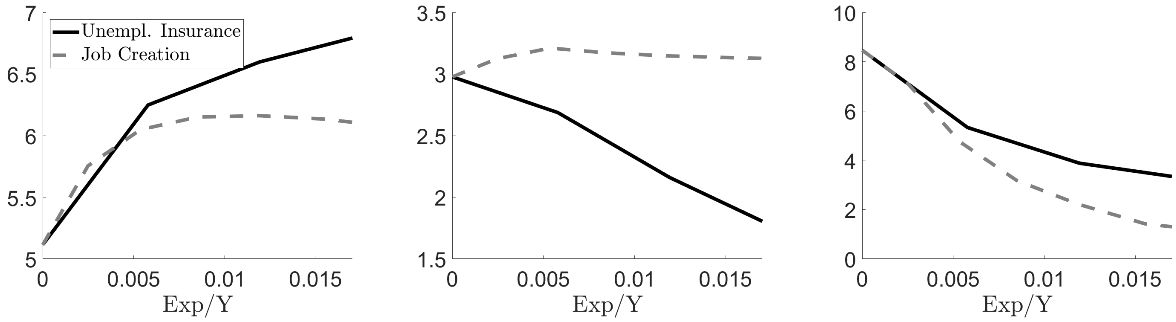
At baseline, poor workers experiencing turbulent transitions suffer steeper wage losses. As subsidies rise, this gap narrows sharply. Panel (a) shows that on-impact wage differences are nearly eliminated, as higher vacancy creation increases job availability in high-tier positions. Panel (b) reveals that long-run scars are also substantially reduced, with poor workers' wage trajectories converging toward those of rich workers.

Both policies reduce precautionary downgrading, but through different margins. UI allows low-wealth workers to sustain selective search, whereas JC improves access to high-productivity vacancies. In the benchmark, aggregate unemployment duration rises under both policies because more workers search in the harder-to-access high-productivity tier.

5.3 Macroeconomic and Welfare Effects of Policies

We now examine how the two policies manifest in the aggregate through the three self-insurance margins emphasized in our framework and how they translate into aggregate welfare and efficiency outcomes. We evaluate the aggregate implications of unemployment insurance (UI) and job creation (JC) policies on a common fiscal scale, expressing expenditures as a share of output.

Figure 12: Three Precautionary Mechanisms: UI vs. JC



(a) Unempl. Duration (b) Average Assets (c) Downgrades (%EUE)

Note: Panel (a) shows average unemployment duration; Panel (b) shows average assets; and Panel (c) shows the share of turbulent EUE transitions resulting in a tier downgrade. Black solid lines correspond to unemployment insurance (UI) and gray dashed lines to the job creation program (JC). Both policies are expressed as government expenditure relative to total output.

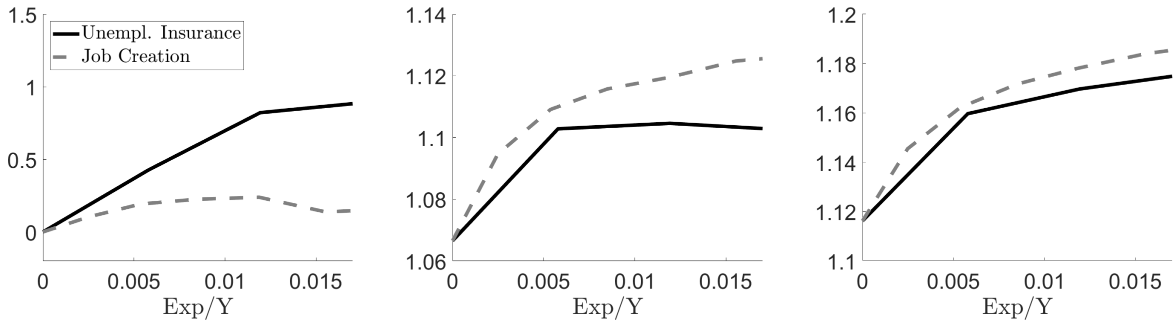
Precautionary mechanisms Figure 12 decomposes the aggregate responses into the three self-insurance margins emphasized in our framework: unemployment duration, asset accumulation, and job-tier downgrades.[26] Panel (a) shows that UI lengthens unemployment spells as insured workers can afford to search longer and be more selective. JC also increases duration because more workers move to Tier A, which has a lower job-finding rate than Tier B, even though the job-finding rate at Tier A increases with subsidies. Panel (b) shows that UI crowds out private savings, lowering average assets as public insurance substitutes for precautionary buffers, while JC leaves asset accumulation broadly unchanged or slightly higher. Panel (c) shows that both policies reduce downgrades among turbulent EUE transitions, but through different routes: UI stabilizes workers' search behavior, and JC expands the availability of high-tier vacancies.

Welfare, output, and wages Figure 13 compares aggregate welfare, total output, and average wages as functions of fiscal expenditure.[27] As seen in Panel (a), UI delivers larger welfare gains at all spending levels because it directly insures income risk and reduces the need for precautionary buffers. JC also improves welfare, but more modestly and with stronger diminishing returns, since its effects operate indirectly through employment and

[26] We present the results disaggregated by tier in Figure D.2 and Figure D.3.

[27] Welfare is measured as steady-state consumption-equivalent variation (CEV) relative to the benchmark economy. Following Krusell, Mukoyama and Şahin (2010), we hold the benchmark distribution of asset holdings fixed to ensure welfare is evaluated from the perspective of the same agents. This approach isolates the welfare impact of policy changes from any compositional effects arising from shifts in the asset distribution.

Figure 13: Welfare, Output and Wages: UI vs. JC



(a) Welfare (b) Total output (c) Avg. Wage

Note: Panel (a) shows welfare gains relative to baseline; Panel (b) shows total output; Panel (c) shows average wage. Black solid lines represent unemployment insurance (UI), and pink dashed lines represent the job creation program (JC). Both policies are expressed as expenditure relative to output (Exp/Y).

wages rather than through direct insurance.

Output effects favor JC. Panel (b) shows that total output rises more steeply under JC, as lower vacancy costs stimulate job creation and employment in high-productivity matches. UI also raises output at low benefit levels, but the gains flatten as longer unemployment spells and higher taxes offset the reallocation gains. Both policies raise wages by favoring mobility into Tier A.[28]

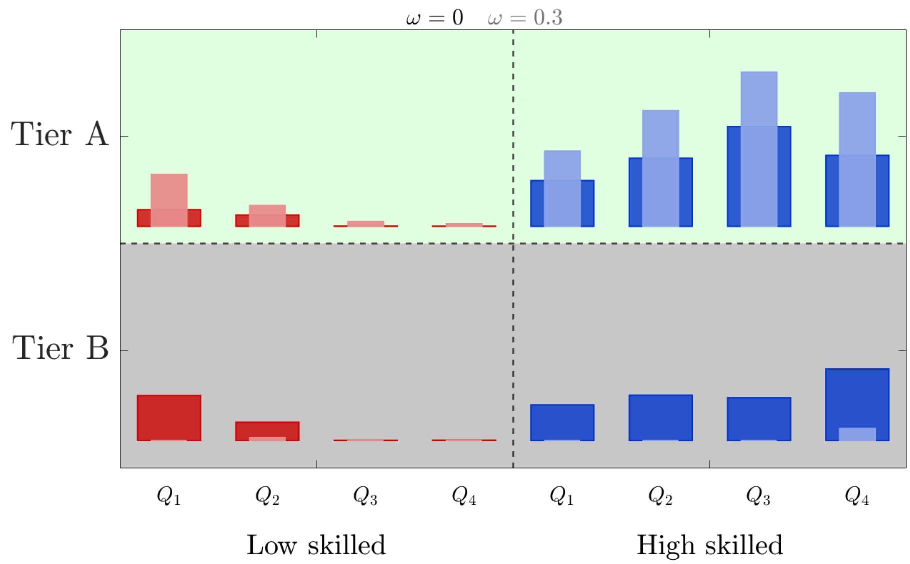
5.4 Sorting and Distributional Effects

The aggregate responses conceal how each policy reshapes workers' allocation across the skill–wealth distribution. Because tier choice depends jointly on skills and liquid assets, a similar increase in Tier-A employment can arise from very different reallocations. We therefore compare the baseline and counterfactual steady-state distributions across skills, job tiers, and asset quartiles. These comparisons reveal whether a policy broadly expands high-productivity employment or instead changes which workers gain access to it.

Figure 14 compares the vacancy-subsidy baseline, $\omega = 0$ (dark bars), with the counterfactual, $\omega = 0.30$ (light bars). By lowering vacancy-creation costs in Tier A, the subsidy expands the supply of high-productivity jobs. The resulting reallocation is broad: workers shift toward Tier A across skill and asset groups, while the asset composition within each skill group changes relatively little. The policy therefore operates mainly through the availability of high-productivity opportunities.

[28] We present the results disaggregated by tier in Figure D.4 and Figure D.5.

Figure 14: Equilibrium Sorting under a Vacancy Subsidy



Note: Steady-state worker distribution by skill, job tier, and asset quartile under the vacancy-subsidy baseline ($\omega = 0$, dark bars) and the counterfactual ($\omega = 0.3$, light bars). Bars are jointly normalized by the largest cell displayed across the baseline and counterfactual distributions.

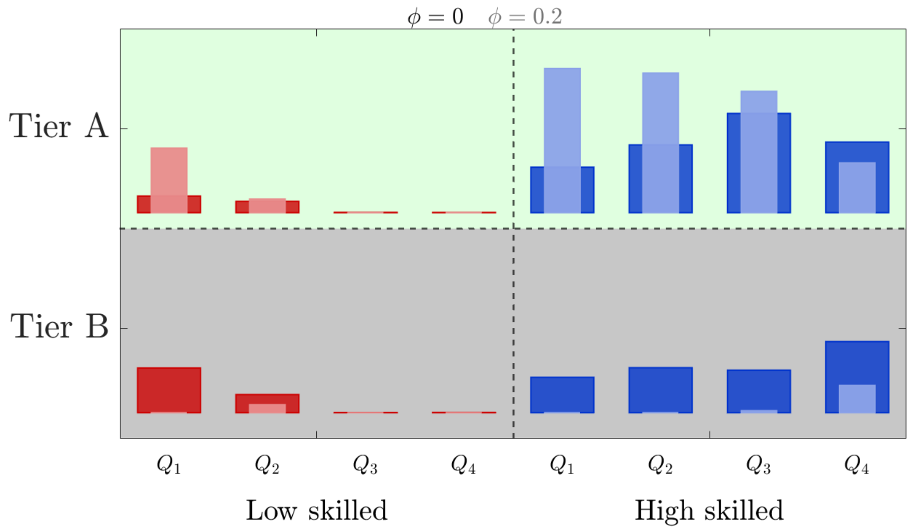
Figure 15 compares the unemployment-insurance baseline, $\phi = 0$ (dark bars), with the counterfactual, $\phi = 0.20$ (light bars). UI produces a more targeted compositional change. Relaxing liquidity constraints allows low-wealth workers to sustain selective search and avoid precautionary downgrading. The effect is strongest among low-wealth, high-skilled workers. Their skills yield high returns in Tier A, but their limited self-insurance capacity makes searching there difficult. UI partially substitutes for limited liquid wealth and reallocates these workers toward the jobs where their skills are most productive.

The counterfactuals reveal two distinct policy margins. Vacancy subsidies expand high-productivity employment, while unemployment insurance improves access for constrained workers. Accordingly, UI delivers larger welfare gains, whereas vacancy subsidies generate larger output gains.

6 Final Thoughts

We study how liquid wealth shapes workers' recovery from turbulent job displacement by affecting tier mobility. Combining new empirical evidence with a structural model, we show that persistent wage losses after turbulent separations concentrate among low-wealth workers who move to lower tiers. These findings underscore the central role of self-insurance in shap-

Figure 15: Equilibrium Sorting under Higher Unemployment Insurance



Note: Steady-state worker distribution by skill, job tier, and asset quartile under the UI baseline ($\phi = 0$, dark bars) and the counterfactual ($\phi = 0.2$, light bars). Bars are jointly normalized by the largest cell displayed across the baseline and counterfactual distributions.

ing labor-market reallocation and the persistence of earnings inequality after displacement. More broadly, post-displacement allocation reflects the interaction of technological complementarity between worker skill and job productivity and preference-based sorting generated by liquid wealth, so that incomplete insurance can distort where workers' remaining skills are ultimately employed.

Our findings also speak to the broader debate surrounding technological change and labor-market inequality. Skill-biased technical change and automation have contributed to rising wage inequality (Acemoglu and Restrepo, 2022), while financial support and retraining can insure workers against technological displacement (Braxton and Taska, 2025). Beraja and Zorzi (2025) further show that incomplete insurance can distort technological adoption. We add a distinct allocation margin: when technological or sectoral change raises turbulence risk, liquid wealth shapes not only how long displaced workers can search, but also where they employ their remaining skills.

Our framework is deliberately parsimonious; it isolates the post-displacement allocation mechanism during unemployment. Extensions could allow workers to rebuild skills through retraining (Humlum, Munch and Plato, 2025), introduce life-cycle heterogeneity in the cost of displacement (Bartal, Bécard and Bertheau, 2026), and incorporate multiple assets, recall, and changing skill demand (Larkin, 2019; Leenders, 2024; Hanks, 2025).

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Conflict of Interest

The authors declare no conflicts of interest.

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Self-Insurance in Turbulent Labor Markets

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and Alireza Sepahsalari

Online Appendix

Not for Publication

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A Proofs and Derivations

A.1 Solution to the firm problem

We derive the wage–tightness menus offered in each skill–tier submarket. We first express the value of a filled job as a function of wage, then combine it with free entry.

Values of filled jobs. Free entry implies that posting a vacancy has zero value in every active submarket. Using (2), the corresponding free-entry condition is

$$J_{ik}(w) \;=\; \frac{\kappa_k}{\beta q_k(\theta)}, \qquad i \in \{l,h\}, \quad k \in \{A,B\}. \tag{A.1}$$

Thus, differences in productivity across active submarkets are offset by differences in wages and vacancy-filling rates.

For a high-skilled worker, substituting $V_{hk} = 0$ into (3) gives

$$J_{hk}(w) \;=\; \frac{f_{hk} - w}{1 - \beta(1 - \lambda_{hk})}. \tag{A.2}$$

For a low-skilled worker, substituting $V_{lk} = 0$ into (4) and using the upgrading rule $w' = w + f_{hk} - f_{lk}$, so that $f_{hk} - w' = f_{lk} - w$, gives

$$J_{lk}(w) \;=\; \frac{(1 + \widehat{\gamma}^u_k)(f_{lk} - w)}{1 - \beta(1 - \lambda_{lk})(1 - \gamma^u)}, \qquad \widehat{\gamma}^u_k \equiv \frac{\beta(1 - \lambda_{lk})\gamma^u}{1 - \beta(1 - \lambda_{hk})}. \tag{A.3}$$

The term $\widehat{\gamma}^u_k$ summarizes how the possibility of future skill upgrading affects the value of a low-skilled match.

Wage–tightness menus. Combining (A.1) with (A.2) gives the wage–tightness menu for high-skilled workers,

$$w_{hk}(\theta) \;=\; f_{hk} - \frac{\widetilde{\kappa}_{hk}}{q_k(\theta)}, \qquad \widetilde{\kappa}_{hk} \equiv \frac{\kappa_k[1 - \beta(1 - \lambda_{hk})]}{\beta}. \tag{A.4}$$

Similarly, combining (A.1) with (A.3) gives the menu for low-skilled workers,

$$w_{lk}(\theta) \;=\; f_{lk} - \frac{\widetilde{\kappa}_{lk}}{(1 + \widehat{\gamma}^u_k) q_k(\theta)}, \qquad \widetilde{\kappa}_{lk} \equiv \frac{\kappa_k[1 - \beta(1 - \lambda_{lk})(1 - \gamma^u)]}{\beta}. \tag{A.5}$$

The menus capture the trade-off between wages and job-finding probabilities. A worker who selects a tighter submarket finds a job more quickly but accepts a lower wage. From the firm's perspective, the associated vacancy takes longer to fill but generates a larger flow surplus.

A.2 Workers' optimality conditions

Assets. Let $\xi^s_{ik} \geq 0$ denote the multiplier on the borrowing constraint for a worker with employment status $s \in \{u, e\}$. The envelope conditions for the inner unemployment and employment values are $U_{ik,a}(a) = Ru_c(c^u_{ik})$ and $E_{ik,a}(a, w) = Ru_c(c^e_{ik})$. Differentiating the outer unemployment value yields

$$\mathcal{U}_{ik,a}(a) \;=\; R \sum_{k' \in \{A,B\}} \mu_{ikk'}(a) u_c(c^u_{ik'}(a - \mathcal{M}_{kk'}))\,. \tag{A.6}$$

The Euler equation for an unemployed worker searching in tier k is

$$u_c(c^u_{ik}) \;=\; \beta R \left[p_k(\theta) u_c({c^e_{ik}}') + (1 - p_k(\theta)) \sum_{k' \in \{A,B\}} \mu_{ikk'}(a') u_c({c^u_{ik'}}') \right] + \xi^u_{ik}. \tag{A.7}$$

For a low-skilled employed worker,

(A.8)

$$u_c(c^e_{lk}) \;=\; \beta R \left\{ (1 - \lambda_{lk}) \left[(1 - \gamma^u) u_c({c^e_{lk}}') + \gamma^u u_c({c^e_{hk}}') \right] + \lambda_{lk} \sum_{k' \in \{A,B\}} \mu_{lkk'}(a') u_c({c^u_{lk'}}') \right\} + \xi^e_{lk}.$$

For a high-skilled employed worker,

(A.9)

$$u_c(c^e_{hk}) \;=\; \beta R \left\{ (1 - \lambda_{hk}) u_c({c^e_{hk}}') + \lambda_{hk}(1 - \gamma^d_k) \sum_{k' \in \{A,B\}} \mu_{hkk'}(a') u_c({c^u_{hk'}}') + \lambda_{hk} \gamma^d_k \sum_{k' \in \{A,B\}} \mu_{lkk'}(a') u_c({c^u_{lk'}}') \right\}$$

In each case, complementary slackness requires $\xi^s_{ik}(a' - \underline{a}) = 0$. Primes denote next-period consumption in the relevant labor-market state.

Submarket choice. Conditional on searching in tier k, an unemployed worker chooses a point on the wage–tightness menu. The first-order condition is

$$p_k'(\theta)\left[E_{ik}(a', w_{ik}(\theta)) - \mathcal{U}_{ik}(a')\right] + p_k(\theta) E_{ik,w}(a', w_{ik}(\theta))\, w_{ik}'(\theta) \;=\; 0. \tag{A.10}$$

The first term captures the gain from a higher job-finding probability, while the second captures the utility cost of the lower wage associated with a tighter submarket.

A.3 Unemployed value function $\mathcal{U}$: derivation

Let $\epsilon_{k'}$ be i.i.d. mean-zero type-I extreme-value shocks. Equivalently, their cdf is $F(\epsilon) = \exp\{-\exp[-(\epsilon + \gamma_{\text{EM}})]\}$, where $\gamma_{\text{EM}} \simeq 0.57721$ is the Euler–Mascheroni constant.

For an unemployed worker with skill i, reference tier k, and assets a, let $W_{k'} \equiv U_{ik'}(a - \mathcal{M}_{kk'})$. The random outer value is

$$Z \;\equiv\; \max_{k' \in \{A,B\}} \{W_{k'} + \nu \epsilon_{k'}\}. \tag{A.11}$$

The maximum is itself a type-I extreme value, with mean $\nu \log \sum_{k'} \exp(W_{k'}/\nu)$. Therefore,

$$\mathcal{U}_{ik}(a) \;=\; \nu \log \left[\sum_{k' \in \{A,B\}} \exp\left(\frac{U_{ik'}(a - \mathcal{M}_{kk'})}{\nu} \right) \right]. \tag{A.12}$$

Without the mean-zero normalization, the expression would contain the additive constant $\nu\gamma_{\text{EM}}$. This constant does not affect tier choices or choice probabilities because it is common across alternatives. We nevertheless remove it to keep value-function levels normalized consistently. Infeasible alternatives are omitted from the sum.

A.4 Switching probability

Let $W_{k'} \equiv U_{ik'}(a - \mathcal{M}_{kk'})$. Under i.i.d. type-I extreme-value shocks, the probability that a worker with skill i and reference tier k chooses destination tier k' is

$$\mu_{ikk'}(a) \;=\; \Pr\left(W_{k'} + \nu\epsilon_{k'} \geq W_r + \nu\epsilon_r,\ \forall r \in \{A,B\}\right) \;=\; \frac{\exp(W_{k'}/\nu)}{\sum_{r \in \{A,B\}} \exp(W_r/\nu)}. \tag{A.13}$$

Substituting for $W_{k'}$ gives

$$\mu_{ikk'}(a) \;=\; \frac{\exp\left(U_{ik'}(a-\mathcal{M}_{kk'})/\nu\right)}{\displaystyle\sum_{r\in\{A,B\}} \exp\left(U_{ir}(a-\mathcal{M}_{kr})/\nu\right)}, \tag{A.14}$$

which is equation (8). Infeasible alternatives receive probability zero, and the probabilities are renormalized over the feasible set.

A.5 Profits

Firms receive operating profits from filled jobs and incur costs when posting vacancies. Let $\Gamma^E_{ik}(a,w)$ denote the stationary mass distribution of employed workers in skill–tier cell (i,k). Aggregate operating profits are

$$\Pi^{\text{op}} \;=\; \sum_{i\in\{l,h\}} \sum_{k\in\{A,B\}} \int_a \int_w (f_{ik}-w)\, d\Gamma^E_{ik}(a,w). \tag{A.15}$$

Let $\Gamma^U_{ik}(a)$ denote the stationary mass distribution of unemployed workers who search in tier k. Since tightness is the vacancy–searcher ratio, vacancies in skill–tier submarket (i,k) are $v_{ik} = \int_a \theta^*_{ik}(a)\, d\Gamma^U_{ik}(a)$. Aggregate vacancy-posting expenditures are therefore

$$\Pi^{\text{vac}} \;=\; \sum_{i\in\{l,h\}} \sum_{k\in\{A,B\}} \kappa_k v_{ik}. \tag{A.16}$$

Profits distributed to households are

$$\pi \;=\; \Pi^{\text{op}} - \Pi^{\text{vac}}. \tag{A.17}$$

Because the population is normalized to one, π is also per-capita dividend income.

The free-entry condition (A.1) implies that the expected value of posting an additional vacancy is zero in every active submarket. It does not imply that current operating profits net of current vacancy expenditures are zero in each skill–tier cell: filled jobs generate profit flows over their entire duration, whereas vacancy costs are paid when vacancies are posted.

Under the Tier-A vacancy subsidy, firms pay $(1-\omega)\kappa_A$ per vacancy and the government finances the remaining share $\omega\kappa_A$. The underlying resource cost remains κ_A, so the subsidy changes the financing of vacancy creation but not its real resource cost.

A.6 Welfare measure

We compare the benchmark steady state, denoted by 0, with a counterfactual policy steady state, denoted by P. Welfare is evaluated using the benchmark distribution of initial worker states.

Individual welfare. For a worker with skill i, labor-market status $s \in \{E, U\}$, tier k, and initial state z, define expected discounted consumption utility under policy P (either UI through ϕ or JC through ω) as

$$\mathcal{W}_{ik}^{s,P}(z) \equiv \mathbb{E}_P \left[\sum_{t=0}^{\infty} \beta^t \frac{(c_t^P)^{1-\sigma}}{1-\sigma} \,\middle|\, s, i, k, z \right]. \tag{A.18}$$

The consumption-equivalent variation $\lambda_{ik}^s(z|P)$ is the permanent proportional change in benchmark consumption that makes the worker indifferent between the benchmark and the policy:

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t u\big((1 + \lambda_{ik}^s(z|P))c_t^0\big) \,\middle|\, s, i, k, z \right] = \mathcal{W}_{ik}^{s,P}(z). \tag{A.19}$$

Under CRRA utility,

$$\lambda_{ik}^s(z|P) = \left(\frac{\mathcal{W}_{ik}^{s,P}(z)}{\mathcal{W}_{ik}^{s,0}(z)} \right)^{\frac{1}{1-\sigma}} - 1. \tag{A.20}$$

A positive value indicates that the worker prefers the policy economy. The objects $\mathcal{W}_{ik}^{s,P}$ incorporate the consumption consequences of endogenous employment, savings, skill, and tier transitions but exclude the additive tier-preference shocks themselves.

Aggregate welfare. Aggregate welfare among unemployed and employed workers is

$$\Lambda^U(P) = \sum_{i \in \{l,h\}} \sum_{k \in \{A,B\}} \int_a \lambda_{ik}^U(a|P)\, d\Gamma_{ik}^{U,0}(a), \tag{A.21}$$

$$\Lambda^E(P) = \sum_{i \in \{l,h\}} \sum_{k \in \{A,B\}} \int_a \int_w \lambda_{ik}^E(a, w|P)\, d\Gamma_{ik}^{E,0}(a, w). \tag{A.22}$$

Because the benchmark mass distributions jointly integrate to one, economy-wide welfare is

$$\Lambda(P) \; = \; \Lambda^U(P) + \Lambda^E(P). \tag{A.23}$$

This measure averages individual consumption-equivalent variations using the benchmark distribution and therefore compares policies from the perspective of the same initial population.

B Computational Appendix

This appendix describes the numerical solution and estimation of the model. Block recursivity allows us to solve the wage–tightness menus and worker policy functions before computing the stationary distribution. The algorithm therefore proceeds in three steps. First, free entry determines a wage–tightness menu for each skill–tier submarket. Second, a nested fixed-point algorithm solves workers' consumption, saving, submarket, and tier-choice policies. Third, we iterate the induced law of motion to obtain the stationary distribution and simulate worker histories.

For policy counterfactuals, we embed these steps in an outer tax loop. For each value of the unemployment insurance transfer ϕ or vacancy subsidy ω, we update the proportional labor-income tax until the government budget constraint is satisfied.

B.1 Solution algorithm

Step 1: Wage–tightness menus. For each skill $i \in \{l, h\}$ and tier $k \in \{A, B\}$, free entry and the firm problem yield the analytical wage–tightness menus derived in Appendix A.1:

$$w_{hk}(\theta) \;=\; f_{hk} - \frac{\widetilde{\kappa}_{hk}}{q_k(\theta)}, \qquad w_{lk}(\theta) \;=\; f_{lk} - \frac{\widetilde{\kappa}_{lk}}{(1+\widehat{\gamma}_k^u)q_k(\theta)}. \tag{B.1}$$

We evaluate these menus on a grid for market tightness and retain feasible points with positive wages and probabilities in $[0, 1]$. The associated job-finding probability is $p_k(\theta) = \theta q_k(\theta)$. Because the menus depend only on primitives, not on the cross-sectional distribution, we compute them once for each parameter vector.

Under the Tier-A vacancy subsidy, the firm-paid cost entering the Tier-A menu is $(1 - \omega)\kappa_A$. The Tier-B menu is unchanged.

Step 2: Worker policies. We discretize assets on $[\underline{a}, \overline{a}]$ and wages on the set generated by the wage–tightness menus. Employed value functions are defined over assets and wages, $E_{ik}(a, w)$, whereas the inner and outer unemployment values, $U_{ik}(a)$ and $\mathcal{U}_{ik}(a)$, depend on assets, skill, and the worker's reference tier but not on a current wage.

We solve the worker problem using a nested fixed point. The inner loop applies the Endogenous Grid Method to update consumption and saving policies conditional on the current search policies. For employed workers, the continuation values incorporate separation, skill upgrading, and displacement-induced skill loss. For unemployed workers, they incorporate the probability of finding a job in the chosen submarket and the option to reconsider the search tier after an unsuccessful search.

The outer loop updates labor-market choices. Conditional on destination tier k', an unemployed worker chooses market tightness along $w_{ik'}(\theta)$. Given the resulting inner values, tier-choice probabilities are updated using

$$\mu_{ikk'}(a) \;=\; \frac{\exp\left(U_{ik'}(a-\mathcal{M}_{kk'})/\nu\right)}{\sum_{r\in\{A,B\}} \exp\left(U_{ir}(a-\mathcal{M}_{kr})/\nu\right)}. \tag{B.2}$$

Alternatives that violate the borrowing constraint after paying the mobility cost are assigned probability zero, and probabilities are renormalized over the feasible alternatives.

We alternate between the inner and outer loops until the value and policy functions converge. We use Howard improvement between full policy updates to accelerate convergence. The solution produces consumption and saving policies for employed and unemployed workers, optimal market tightness and wages within each destination tier, and tier-choice probabilities for every unemployment state.

Step 3: Stationary distribution and simulation. Given the policy functions, we construct the transition operator over employment status, skill, reference tier, assets, and, for employed workers, wages. We iterate this operator until the distribution converges. We then use the stationary distribution to compute aggregate and tier-specific moments.

For outcomes that depend on complete worker histories, including unemployment duration, tier transitions, and post-displacement wage dynamics, we simulate a panel from the stationary equilibrium. The simulation uses the same transition probabilities and policy functions as the stationary-distribution calculation.

Government-budget loop. In the benchmark without policy interventions, $\tau = 0$. For a counterfactual policy, begin from an initial tax rate $\tau^{(0)}$. At iteration n, solve Steps 1–3 at $\tau^{(n)}$, compute the stationary tax base and policy expenditure, and update the tax rate implied by the relevant balanced-budget condition:

$$\tau^{\mathrm{UI}}\overline{w}e \;=\; \phi u, \qquad \tau^{\mathrm{JC}}\overline{w}e \;=\; \omega\kappa_A v_A. \tag{B.3}$$

The loop stops when the difference between the updated and previous tax rates is below the tolerance used in the computation. To improve numerical stability, the tax update can be damped according to $\tau^{(n+1)} = (1-\zeta)\tau^{(n)} + \zeta\tau^{\text{new}}$, where $\zeta \in (0,1]$ is the relaxation parameter.

B.2 Stationary distribution

The individual state records employment status $s \in \{E, U\}$, skill $i \in \{l, h\}$, tier $k \in \{A, B\}$, and assets a. Employed workers are additionally characterized by their wage w. For unemployed workers, k denotes the reference tier that determines the cost of redirecting search.

Let $\Gamma^E_{ik}(a, w)$ and $\Gamma^U_{ik}(a)$ denote unnormalized stationary mass distributions. Their integrals equal the corresponding population masses and satisfy

$$\text{(B.4)} \qquad \sum_{i\in\{l,h\}} \sum_{k\in\{A,B\}} \left[\int_a \int_w d\Gamma^E_{ik}(a,w) + \int_a d\Gamma^U_{ik}(a) \right] = 1.$$

Employed-worker transitions. A low-skilled worker employed in tier k remains low-skilled with probability $(1-\lambda_{lk})(1-\gamma^u)$, upgrades with probability $(1-\lambda_{lk})\gamma^u$, and separates with probability λ_{lk}. A high-skilled worker remains employed and high-skilled with probability $1-\lambda_{hk}$. Upon separation, the worker retains high skill with probability $\lambda_{hk}(1-\gamma^d_k)$ and loses skill with probability $\lambda_{hk}\gamma^d_k$.

Conditional on remaining employed, next-period assets follow the relevant employed saving policy. If a low-skilled worker upgrades, the wage changes according to the upgrading rule in the main text. Upon separation, the worker becomes unemployed with reference tier equal to the tier of the displaced job.

Unemployed-worker transitions. An unemployed worker with skill i, reference tier k, and assets a chooses destination tier k' with probability $\mu_{ikk'}(a)$. Conditional on that choice, the worker selects tightness $\theta^*_{ik'}(a-\mathcal{M}_{kk'})$ and finds a job with probability $p_{k'}(\theta^*_{ik'}(a-\mathcal{M}_{kk'}))$.

A successful search generates employment in tier k' at the wage associated with the chosen submarket. Following an unsuccessful search, the worker remains unemployed, carries next-period assets determined by the unemployment saving policy, and enters the next period with k' as the reference tier. Thus, tier choice and job finding must be applied jointly; tier-choice probabilities alone do not describe the law of motion of unemployment.

Retirement and entry. With probability ρ_r, a worker retires and is replaced by a low-skilled unemployed entrant. Entrants are assigned the initial asset position and reference-tier distribution used in the computation. Assets left by retirees are redistributed according to the inheritance rule specified in the main text. The subjective discount factor used in the value functions is adjusted for retirement through $\beta = \widehat{\beta}(1 - \rho_r)$.

Transition operator. Let s index a point in the discretized state space and let $P(s'|s)$ denote the transition probability implied by the saving, search, tier-choice, skill, separation, and retirement rules. Asset policies generally fall between grid points; we allocate probability to adjacent points using linear interpolation. We treat wage transitions analogously when necessary.

Stacking the employed and unemployed mass distributions in the vector Γ, the law of motion is

$$\Gamma' = P(\Psi)\Gamma, \tag{B.5}$$

where Ψ collects the converged policy functions. The stationary distribution solves

$$\Gamma^* = P(\Psi)\Gamma^*, \qquad \mathbf{1}'\Gamma^* = 1. \tag{B.6}$$

We obtain Γ^* by iterating (B.5) from an initial distribution until the maximum absolute change in cell masses is below the distributional tolerance.

The distributions $\Gamma^E_{ik}(a, w)$ and $\Gamma^U_{ik}(a)$ used elsewhere in the paper are the corresponding marginals of Γ^*.

B.3 Simulation

We initialize simulated workers by drawing from the stationary distribution and then apply the model's transition probabilities and policy functions period by period. For each worker, we record assets, employment status, skill, reference and employment tiers, wages, unemployment duration, and realized tier transitions. To reduce the influence of initial conditions, we discard the first T_{burn} periods and compute simulated moments from the remaining observations.

The baseline results use $N_{\text{sim}} = 6{,}000$ simulated workers over $T_{\text{sim}} = 500$ retained periods, following a burn-in of $T_{\text{burn}} = 500$ periods. We use common random numbers across parameter vectors and policy experiments so that changes in simulated moments primarily reflect changes in parameters rather than simulation noise.

B.4 SMM calibration details

Let Θ denote the vector of eleven internally calibrated parameters and let g^d and $g^m(\Theta)$ denote the vectors of empirical and model moments reported in Table 2. We choose Θ to minimize

$$\widehat{\Theta} \; = \; \arg\min_{\Theta \in \mathcal{P}} \left[g^m(\Theta) - g^d \right]' \mathcal{W} \left[g^m(\Theta) - g^d \right] , \tag{B.7}$$

where $\mathcal{P}$ is the parameter space and $\mathcal{W}$ is the weighting matrix.

The eleven targeted moments are unemployment duration, the Tier-A employment share, the elasticity of unemployment-to-employment flows with respect to tightness, the average outside-option ratio, the asset–wage correlation, the share of workers with negative assets, the skill premium in each tier, the ratio of experienced workers across tiers, and the two directional tier-switching shares. All parameters are determined jointly; the parameter–moment discussion in the main text describes which moments primarily discipline each parameter rather than one-to-one identification.

Weighting matrix. The calibration uses an identity matrix.

Global and local search. We conduct a global search over $\mathcal{P}$ using a Sobol sequence with $N_{\text{Sobol}} = 50{,}000$ parameter vectors. For each vector, we solve the model, compute the stationary distribution and simulated moments, and evaluate (B.7). Starting from the best Sobol candidate, we then use the Nelder–Mead simplex algorithm to refine the solution. The optimization stops when both the parameter tolerance and the objective-function tolerance are below 10^{-4}.

C Data Appendix

C.1 Data Description

For the empirical analysis, we use data from the NLSY79, a nationally representative longitudinal survey of 12,696 individuals who were between 14 and 22 years old when they were first interviewed in 1979. We use a cross-sectional sample comprising 6,111 respondents, designed to represent the non-institutionalized civilian population living in the United States in 1979, with ages ranging from 14 to 22 as of December 31, 1978. From the core sample, we exclude individuals who served in the military for more than two years because their military experience does not represent the standard civilian labor-market experience. We further exclude respondents who are weakly attached to the labor market, defined as those who have been out of a job for more than 10 years.

Workers' employment histories The NLSY79 interviewed individuals annually from 1979 to 1993 and biennially from 1994 to 2016. The NLSY79 recorded labor force status weekly throughout the sample period, even in the later period when interviews were conducted biennially. Following Baley, Figueiredo and Ulbricht (2022), we use the NLSY79's Work History Data file to construct a monthly panel. This file records each respondent's work history week by week, including weekly labor status and hours worked. While an individual may hold more than one job, we focus on the primary job in a given month, defined as the one for which the individual worked the most hours. Using a mapping that links jobs across consecutive interviews, we construct a monthly panel of primary-job employment spells and nonemployment spells.

For each primary job, we retain information on the hourly wage, occupation, and industry codes. Before merging occupation and industry information with the employment panel, we clean occupational and industry titles using the approach outlined in Guvenen, Kuruscu, Tanaka and Wiczer (2020). For each job, we assign the occupation and industry codes most often observed during the employment spell. In the NLSY79, occupation titles are described by the 3-digit Census occupation code. Because this classification system changed over time[29], before cleaning, we converted all the occupational codes across the years into the *occ1990dd* occupation system developed by Dorn (2009), which has the advantage of being time-consistent.[30]

[29]Until 2000, NLSY79 reports occupation codes in the Census 1970 3-digit occupation code. After this year, occupation codes are reported in the Census 2000 3-digit occupation code.

[30]The crosswalk files between the Census classification codes and the *occ1990dd* occupation aggregates

Following Kambourov and Manovskii (2008), we mitigate measurement error by assigning each job the modal occupation code for its spell and classifying a switch as genuine only when it coincides with an employer change. Using this definition, we find that about 52% of EUE transitions involve an occupation switch, in line with the 45–67% range reported by Huckfeldt (2022) for the CPS Displaced Worker Supplement. Among EUE transitions without an occupational switch, around 35% are recalls to a previous employer, close to the 40% share reported by Fujita and Moscarini (2017) using the SIPP. These results confirm that even under a more traditional coding-based approach, our measurement strategy delivers credible benchmarks and a consistent mapping to the model's distinction between turbulent transitions (involving low ex post skill transferability) and tranquil ones.

Assets The NLSY79 contains detailed questions on household asset holdings and liabilities from 1985 onwards. The wealth information is not observed at the same frequency as the labor market data; asset data are collected at interview dates, yielding at most one observation per year. The NLSY79 defines all assets as the amount the respondent would reasonably expect someone to pay if the asset were sold in its current condition. Respondents report the market value of their assets at the time of the interview; we assign this information to that calendar month and leave all others blank. We use the CPI reported by the BLS to convert each asset's market value to 2000 dollars. From the detailed information reported in the NLSY, we create five categories of net assets—residential property, financial assets, business assets, vehicles, and others—as follows:

- Residential Property = "Market value of residential property r/spouse own" - "Amount of mortgages and back taxes r/spouse owe on residential property"
- Financial assets = "Total market value of stocks/bonds/mutual funds" + "Total amount of money assets like savings accounts of r/spouse"+ "Total amount of money in assets like IRAs or Keogh of r/spouse"+"Total amount of money in assets like CDs, loans or mortgages of r/spouse"
- Business assets = "Total market value of farm/business/other property r/spouse own"- "Total amount of debts on farm/business/other property r/spouse owe"
- Vehicles = "Total market value of vehicles including automobiles r/spouse own"- "Total amount of money r/spouse owe on vehicles including automobiles"

created by Autor and Dorn (2013) can be found at http://www.ddorn.net/data.

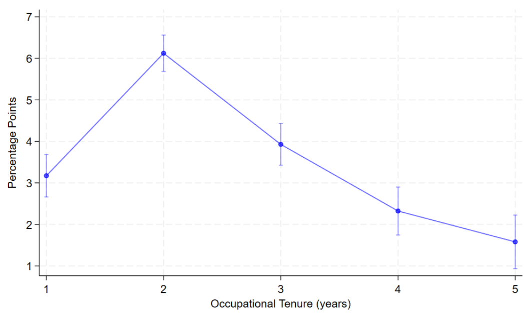
- Others = "Total market value of all other assets each worth more than \$500"-"Total amount of other debts over \$500 r/spouse owe"

We then define *Liquid Wealth* as the sum of business assets, financial assets, vehicles, and other assets, all net of debts. Following Lise (2013), we trim the top and bottom one-half of one percent of the distribution of the assets to reduce the influence of outliers.

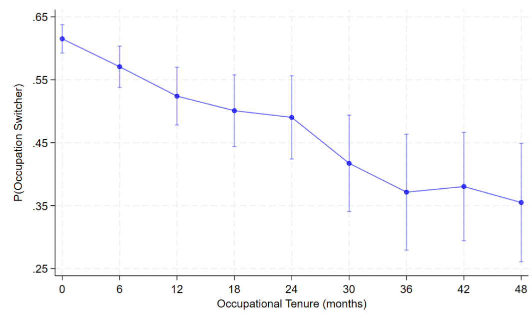
C.2 Turbulence Risk

Figure C.1 supports our tenure classification. Wage returns to occupational tenure are concentrated in the first two years, while occupational switching declines sharply during the first 30 months and then stabilizes. We therefore classify workers with less than two years of tenure as untenured and later switches with low skill transferability as potentially turbulent.

Figure C.1: Occupational Tenure and Mobility



(a) Returns to Occupational Tenure



(b) Occupational Mobility

Note: Panel (a) plots the wage return to working an additional year in an occupation during the first five years of employment in that occupation. Estimates control for individual characteristics (age and its square, labor market experience, gender, race, educational attainment, and ability), year, and month fixed effects. Panel (b) plots the probability of switching occupations from a logit regression that includes the same controls. Both panels use EUE transitions observed from 1979 to 2016 in the NLSY79.

C.3 Summary Statistics

The following table provides summaries of EUE transitions and worker characteristics at separation:

C.4 Wage differences

Table C.2 shows that our occupation-based definition of job tiers captures economically meaningful wage differences. Column 1 reports a substantial unconditional wage gap between tiers: workers in Tier A have log hourly wages about 0.48 log points higher than workers in Tier B. Column 2 shows that this difference remains sizable at 0.19 log points after controlling for age and its square, labor-market experience, gender, race, education, ability, industry, and year and month fixed effects.

Table C.1: Summary Statistics

	All	Untenured	Tranquil	Turbulent
EUE transitions	37,131	25,782	8,450	2,899
% of total	100	69.4	22.8	7.8
Worker characteristics at separation				
Age (years)	29.7	26.8	36.7	35.3
Job tenure (years)	1.4	0.5	3.2	3.5
Occupational tenure (years)	2.5	0.7	7.0	5.6
Labor market experience (years)	8.3	5.7	14.8	12.8
Hourly wage (2000 dollars)	11.5	9.5	17.2	11.9
Liquid wealth (thousands, 2000 dollars)	28.9	20.1	43.5	29.1
Wage growth at reemployment Δw (in %)	1%	4%	−2%	−13%

Notes: Average characteristics of EUE transitions observed from 1979 to 2016 in NLSY79.

Table C.2: Wage Differences Across Tiers

	(1) No controls	(2) Controls
Tier A	0.477***	0.189***
	(0.013)	(0.012)
Observations	1,059,962	1,059,962

Notes: The table presents OLS estimates of wage differences between workers employed in Tier A and Tier B jobs. The dependent variable is log hourly wages. Tier A is an indicator equal to one for workers employed in Tier A and zero for workers employed in Tier B. Column 1 reports the specification without controls. Column 2 controls for age and its square, cumulative labor-market experience, gender, race, industry, education, ability, and year and month fixed effects. Standard errors, clustered at the individual level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

C.5 Robustness Checks

In this section, we show that the empirical findings are robust to:

(i) unemployment benefits and spousal income as controls (Figure C.2),

(ii) different thresholds for occupational tenure τ (Figure C.3),

(iii) excluding short unemployment spells (Figure C.4),

(iv) restricting the sample to EUE transitions of workers with high job tenure in the previous job (at least two years) to better isolate involuntary separations from quits and selective firings (Figure C.5),

(v) a more traditional definition of turbulence-based occupational mobility across 3-digit occupation codes, in contrast to our baseline turbulence measure based on angular distances in the space of occupational skills requirements (Figure C.6), and

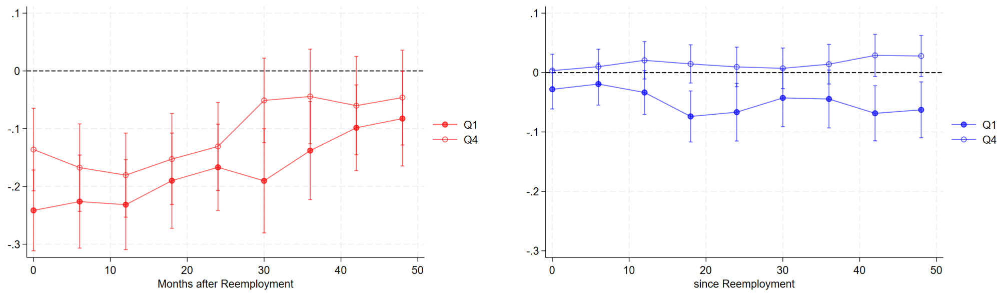
(vi) different definitions of liquid wealth (Figure C.7).

In all figures, we plot average residual wage growth at reemployment and every six months thereafter. The left plot shows turbulent transitions, defined as workers who switch to a new occupation with low skill transferability, i.e., those classified as experiencing a turbulent transition following an unemployment spell. The right plot shows tranquil transitions, defined as workers who, after unemployment, either return to their previous occupation or move to one with high skill transferability. Q1 and Q4 denote the first and fourth quartiles of the household liquid wealth distribution at the start of the unemployment spell. The sample covers EUE transitions observed from 1979 to 2016 in NLSY79.

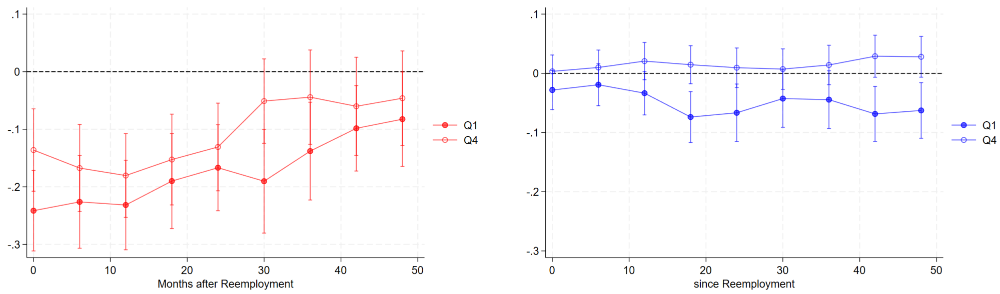
Across these alternative specifications, the wealth gradient is concentrated among turbulent transitions. Low-wealth workers experiencing low-transferability occupational moves suffer persistent wage losses, whereas high-wealth workers recover much of the initial decline. These exercises establish the robustness of the conditional pattern, but they do not eliminate the possibility that realized occupational choice contributes to the turbulence classification.

We also decompose the baseline wage paths according to whether reemployment occurs within the worker's pre-displacement tier or in a different tier. Figure C.8 reports this decomposition separately for turbulent and tranquil transitions.

Figure C.2: Robustness Check: Additional Controls

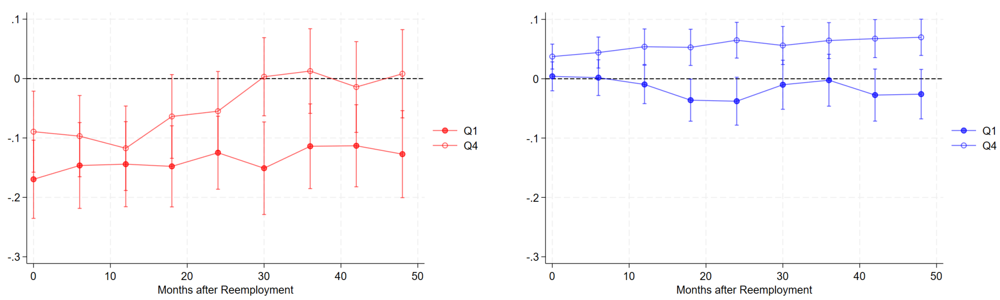


(a) Spousal Income

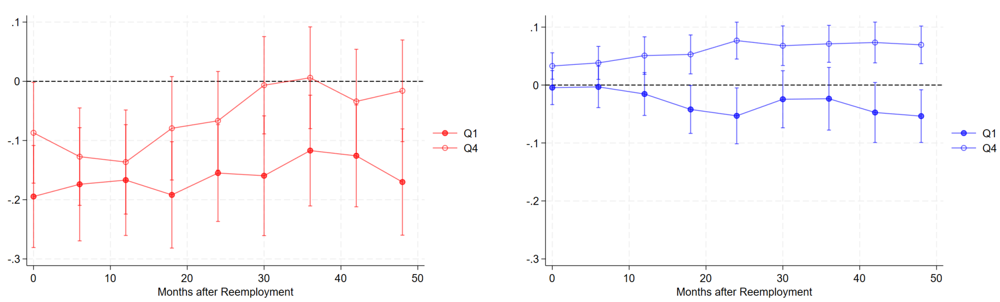


(b) Unemployment Benefits

Figure C.3: Robustness Check: Alternative Occupational Tenure Threshold (τ)

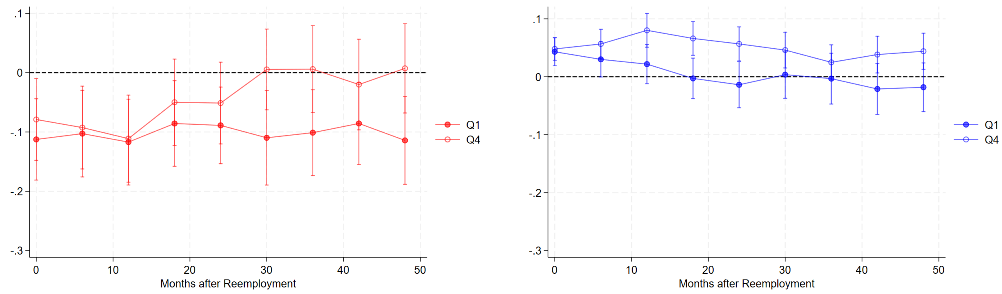


(a) Tenure Threshold Set at One Year

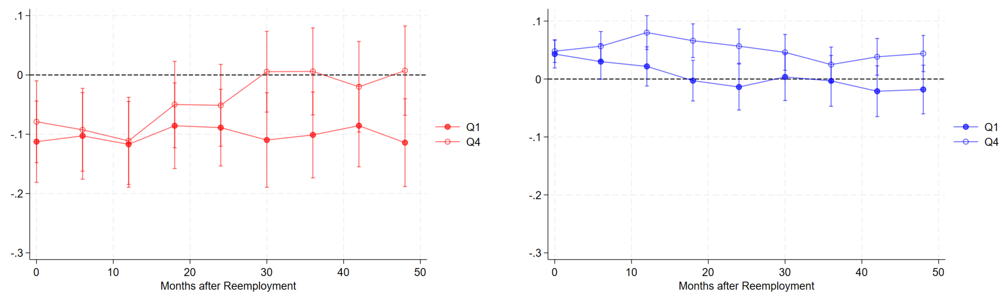


(b) Tenure Threshold Set at Three Years

Figure C.4: Robustness Check: Excluding Short Unemployment Spells



(a) Excluding Spells Lasting 1 Month



(b) Excluding Spells Lasting Less Than 2 Months

Figure C.5: Robustness Check: Restrict to Workers with High Job Tenure

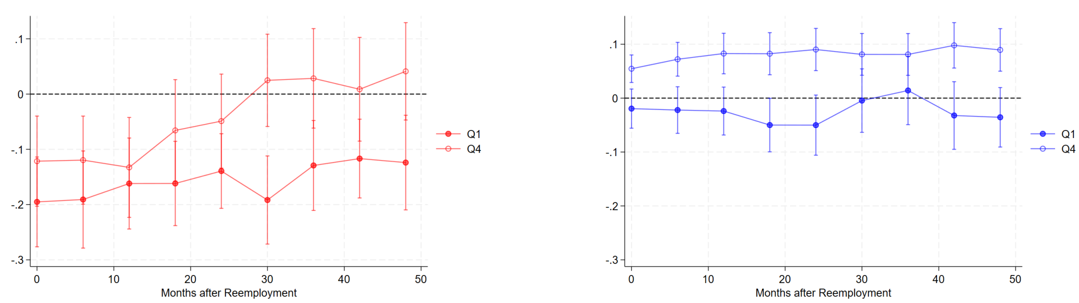


Figure C.6: Robustness Check: Switching Across 3-digit Occupations

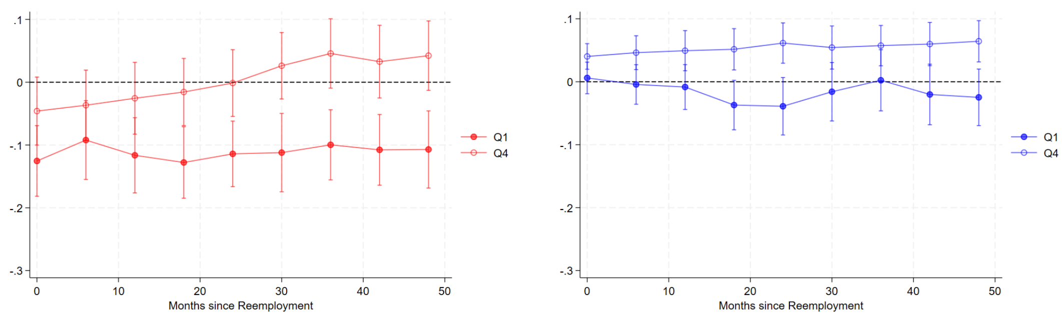
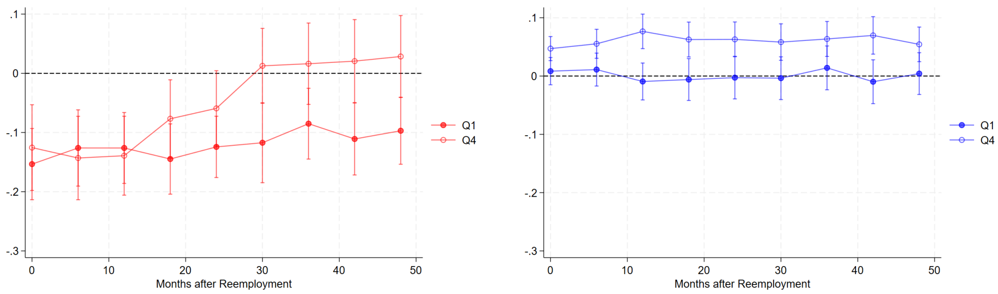
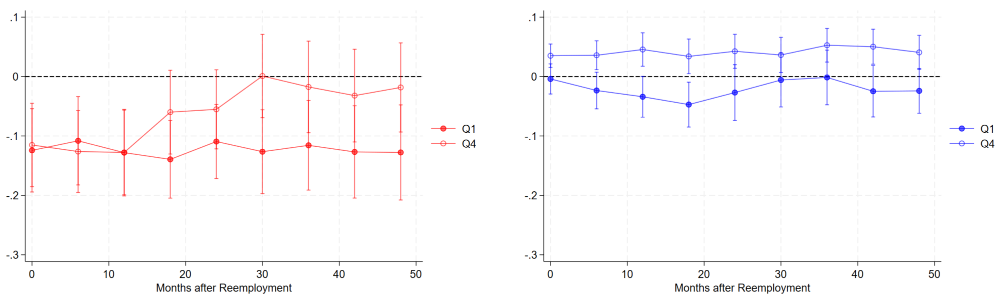


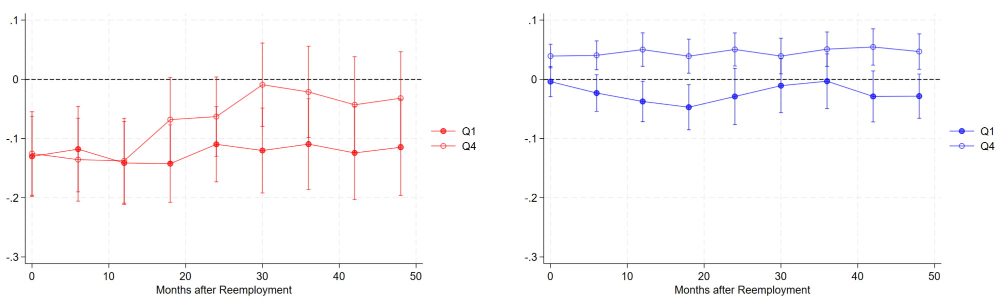
Figure C.7: Robustness Check: Different Definitions of Liquid Wealth



(a) *L1*: "Total market value of stocks/bonds/mutual funds" + "Total amount of money assets like savings accounts of r/spouse"

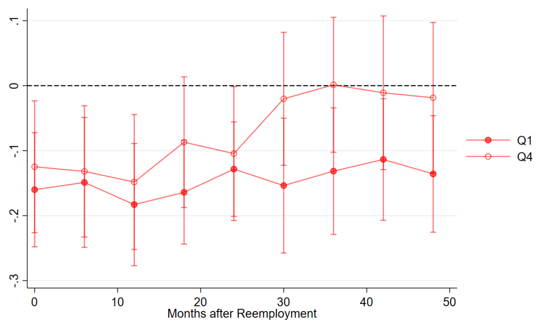


(b) *L2* = *L1* + "Total market value of vehicles inc. autos r/spouse own"- "Total amount of money r/spouse owe on vehicles inc. autos"

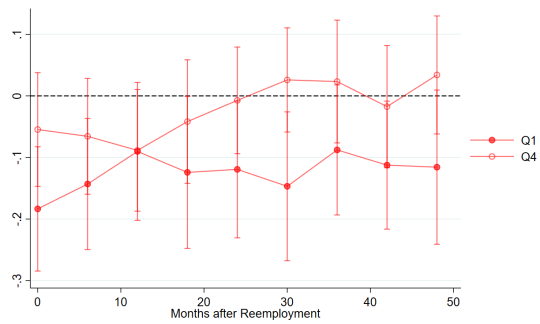


(c) *L3* = *L2* + "Total amount of money in assets like IRAs or Keogh" + "Total amount of money in assets like CDs or loans"

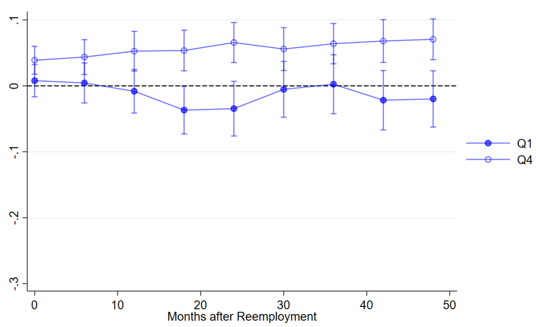
Figure C.8: Wages after Job Loss by Wealth and Tier Mobility



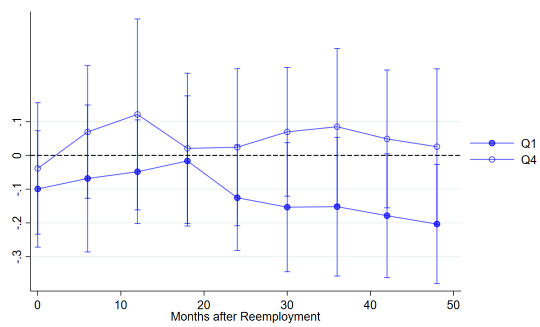
(a) Turbulent: Within Tier



(b) Turbulent: Across Tiers



(c) Tranquil: Within Tier



(d) Tranquil: Across Tiers

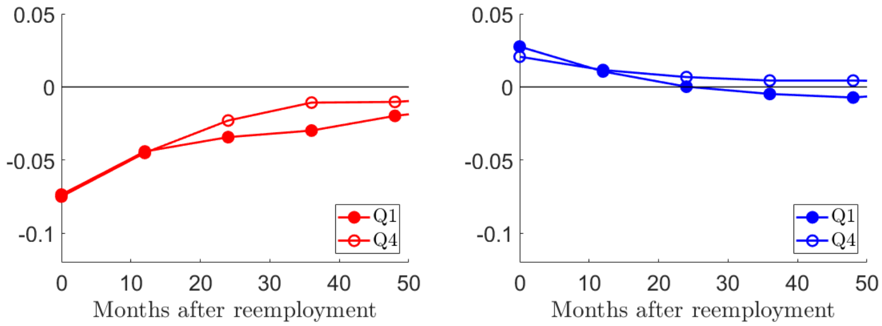
D Additional model outcomes

D.1 Counterfactuals

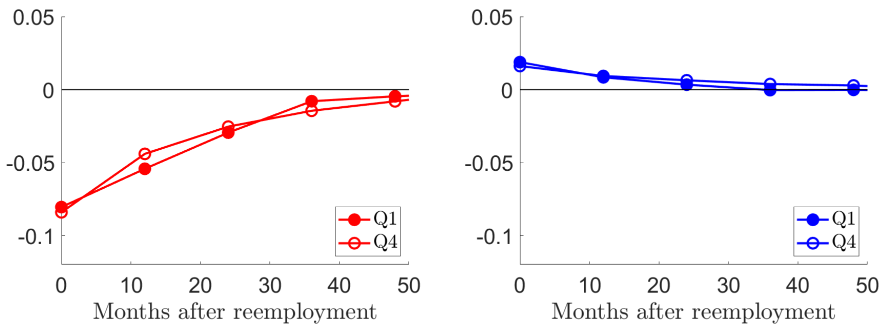
Figure D.1 reports average residual wage growth at reemployment and at 12-month intervals thereafter under alternative calibrations that weaken precautionary tier mobility. In each panel, the left plot shows turbulent transitions and the right plot shows tranquil transitions. Q1 and Q4 denote the first and fourth quartiles of the liquid-wealth distribution at the beginning of the unemployment spell. Panel (a) sets $\nu \to \infty$, making tier choices increasingly insensitive to differences in continuation values across wealth levels.[31] As a result, wealth no longer meaningfully affects the probability of searching across tiers. Panel (b) sets all Tier-B parameters equal to their Tier-A counterparts, eliminating the technological and search differences between tiers. In both exercises, the wealth gradient in post-displacement wage losses becomes substantially weaker. This confirms that the baseline gradient operates through the interaction of liquidity constraints with economically meaningful differences across tiers.

[31] In practice, we set $\nu = 10$, which is roughly 8.3 times its value in the estimated model.

Figure D.1: Effects of Removing Precautionary Tier Mobility



(a) No role for wealth in tier choice ($\nu \to \infty$)



(b) One-tier model

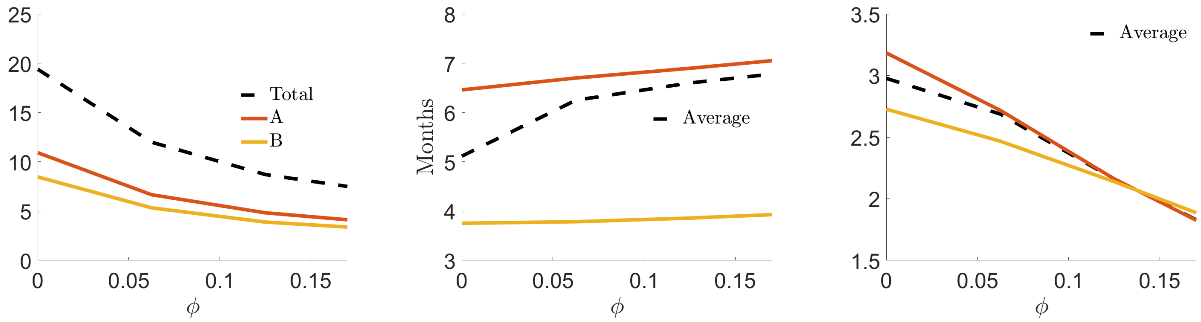
Note: The figure reports average residual wage growth at reemployment and at twelve-month intervals thereafter under alternative calibrations. The left plots show turbulent transitions, and the right plot shows tranquil transitions. Q1 and Q4 denote the first and fourth quartiles of liquid wealth at the beginning of the unemployment spell.

D.2 Precautionary Channels Across Tiers

Figures D.2 and D.3 show how the model's main precautionary channels respond to unemployment insurance generosity ϕ and the Tier-A vacancy subsidy ω. In each figure, Panel (a) shows total tier mobility and mobility by destination tier. The line labeled A denotes transitions into Tier A, while the line labeled B denotes transitions into Tier B. Panel (b) reports average unemployment duration, both in the aggregate and by tier. Panel (c) reports average liquid assets.

More generous unemployment insurance reduces precautionary tier mobility by relaxing liquidity constraints, allowing workers to remain selective longer, but it also lengthens unemployment spells and crowds out private savings. The vacancy subsidy instead expands Tier A job opportunities, altering mobility and search duration while affecting savings more heterogeneously.

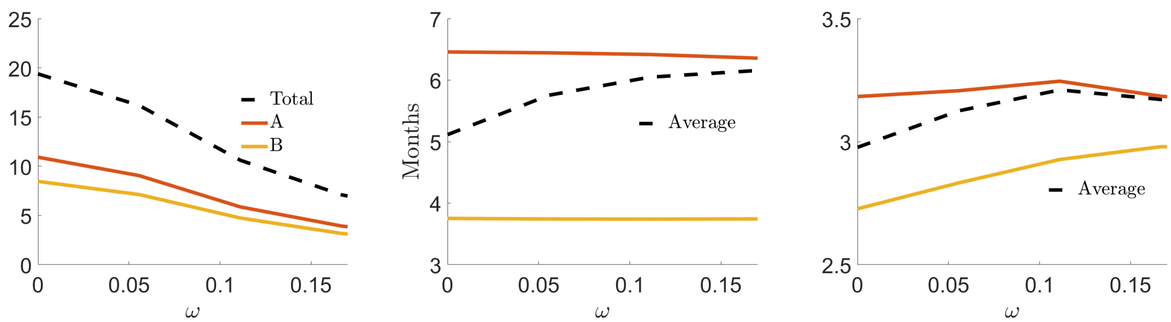
Figure D.2: Precautionary channels for different unemployment benefits ϕ



(a) Tier Mobility Rates (b) Unempl. duration (c) Average assets

Note: Panel (a) shows tier mobility rates (aggregate and by tier; 'A' line denotes switchers to A, and 'B' line shows switchers to B); Panel (b) shows unemployment duration in months, on average, and by tier; and Panel (c) shows assets, on average, and by tier. All outcomes are equilibrium values under varying UI generosity ϕ.

Figure D.3: Precautionary channels by tier for Tier-A vacancy subsidy ω



(a) Tier Mobility Rates (b) Unempl. duration (c) Average assets

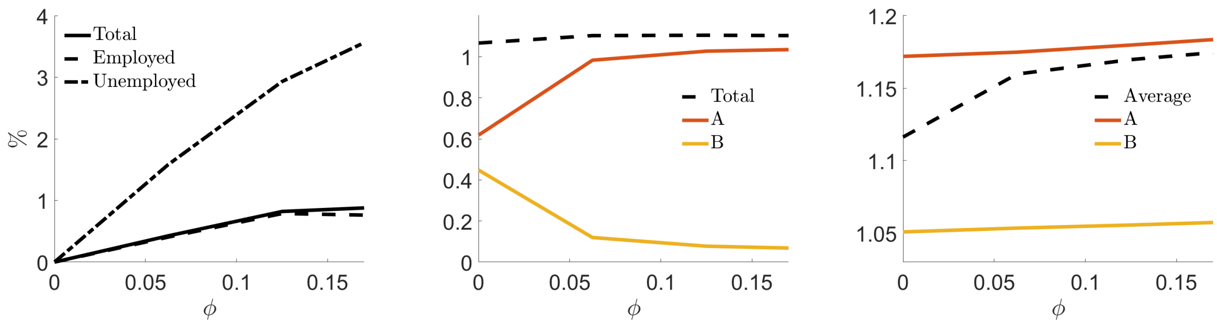
Note: Panel (a) shows tier mobility rates (aggregate and by tier; 'A' line denotes switchers to A, and 'B' line shows switchers to B); Panel (b) shows unemployment duration in months, on average and by tier; and Panel (c) shows assets, on average and by tier. All outcomes are equilibrium values under varying job creation subsidy ω.

D.3 Macro Outcomes Across Tiers

Figures D.4 and D.5 report the aggregate effects of unemployment insurance and vacancy subsidies. Panel (a) shows welfare, both economy-wide and separately by employment status. Panel (b) reports output in the aggregate and by tier. Panel (c) reports average wages overall and within each tier.

The two policies operate through distinct mechanisms. Unemployment insurance primarily affects workers' liquidity, savings, and search selectivity. The Tier-A vacancy subsidy instead changes firms' vacancy-posting incentives and the composition of employment across tiers. The figures therefore complement the main policy analysis by showing how the welfare and output effects are connected to changes in wages, employment allocation, and self-insurance behavior.

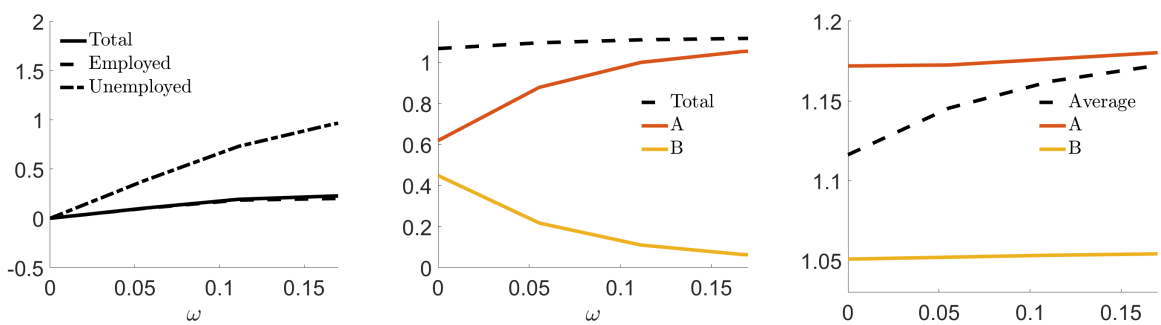
Figure D.4: Macro Outcomes for different unemployment benefits ϕ



(a) Welfare (b) Output (c) Wages

Note: Panel (a) shows welfare, aggregate and by employment status; Panel (b) shows output, total and by tier; and Panel (c) shows wages, average and by tier. All outcomes are equilibrium values under varying UI generosity ϕ.

Figure D.5: Macro outcomes for Tier A vacancy subsidy ω



(a) Welfare (b) Output (c) Wages

Note: Panel (a) shows welfare, aggregate and by employment status; Panel (b) shows output, total and by tier; and Panel (c) shows wages, average and by tier. All outcomes are equilibrium values under varying vacancy subsidy ω.