Wealth Inequality and Labor Mobility: the Job Trap*

Elena Pellegrini†

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Abstract

This paper studies how wealth affects workers' ability to move to higher-paying jobs. Using microdata from the SIPP, I compare equally-skilled workers and find that those with higher liquid wealth are 35% more likely to change jobs than workers with no savings, on average. To explain these patterns, I develop a job ladder model with incomplete markets, risk-averse workers, and wage posting. If firms learn about workers' quality over time and fire those who turn out to be poor matches, on-the-job search becomes risky: wage increases come at the cost of restarting the learning process and facing a higher risk of job loss. To avoid this risk, workers with no liquidity prioritize job security over job mobility and remain trapped in low-paying jobs. This model explains approximately 60% of the wealth gap in job mobility observed in the data. However, higher replacement rates and extended unemployment benefits increase job mobility especially for poor workers at low-paying jobs, offering a potential pathway out of the job trap.

Keywords: Incomplete Markets, On-the-job Search, Unemployment Insurance
JEL Codes: E21, D31, J64, J65

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†Department of Economics, Boston College. Contact: pellegec@bc.edu

1 Introduction

Job mobility is a fundamental driver of life-cycle wage growth. A vast literature[1] has shown that workers who change jobs experience significant wage increases, which are estimated at 5-10% and outweigh those of workers who remain with the same employer. Workers are also aware of these potential benefits: they have accurate beliefs about the average wage they could potentially receive at different firms (Guo, 2025) and direct their search toward firms that pay them more (Caldwell et al., 2025).

The job ladder literature (Burdett and Mortensen, 1998) offers a theory for these income differences, suggesting that workers who receive more job offers have the ability to earn higher wages, even if equally skilled. Yet, in these search models, it is solely luck that determines who receives more job offers. Are wage disparities among similar workers truly a result of mere chance? Why are some able to climb the job ladder while others seem to remain trapped in low-paying jobs?

In this paper, I study how differences in wealth affect workers' ability to move to higher-paying jobs, within their job ladders[2]. In particular, I argue that job mobility is not only an opportunity for wage growth but also a source of unemployment risk. Because firms gradually learn about the quality of workers and fire those in bad matches, changing jobs resets their tenure and increases their risk of job loss. This risk is particularly costly for liquidity-constrained workers, who cannot easily smooth consumption during unemployment. As a result, poor workers are often forced to prioritize job security over mobility, remaining trapped in low-paying jobs and unable to climb their job ladder.

I begin by presenting evidence of a positive relationship between wealth and job-to-job flows using individual-level data from the Survey of Income and Program Participation (SIPP). For this exercise, I compare equally-skilled workers at similar jobs and stages of their careers to show that those with higher liquid wealth are significantly more likely to change jobs relative to workers with no savings. To this end, I compute workers' incentive to change jobs as the difference between predicted and actual wages, capturing how much of a wage increase they could expect from changing jobs. I use this wage gap measure to estimate the impact of liquid wealth on the probability of a job-to-job transition, focusing on the coefficient on the interaction of wage gap and wealth. As this wage gap increases, workers with higher savings have a significantly higher probability of changing jobs compared to liquidity-constrained workers. In particular, I find that having some positive savings increases job mobility by an average of 35% (0.3 percentage points) among workers with a

[1] See Bartel and Borjas (1981), Topel and Ward (1992), Fujita (2012), and Engbom (2022).

[2] This follows the idea of Borovičková and Macaluso (2024) that the job ladder varies significantly across different groups of workers, reflecting differences in job mobility and wage growth opportunities.

positive wage gap, and by up to 78% for workers earning 50% below the average wage or less. These results align with other patterns I document in the data: job-to-job flows are higher among white men with higher education levels, whereas women, minority groups, and noncitizens exhibit lower mobility rates.

Motivated by this suggestive evidence, I develop a continuous-time job ladder model with incomplete markets, risk-averse workers, and wage posting. The model introduces several novel features that capture both the risks and gains of job mobility. On the unemployment side, the model incorporates a detailed unemployment benefits policy with income-dependent replacement rates, a cap on payments, and benefit expiration. On the employment side, I microfound the declining relationship between job separations and tenure using a framework inspired by Jovanovic (1984) and Moscarini (2005), where firms have imperfect information about match quality[3]. When workers accept a new job, they draw a match quality with the firm that can be either *good* or *bad*. Workers and firms do not observe this quality initially, but over time they learn whether the match is bad, in which case the worker is fired. This simple mechanism generates a declining separation hazard over tenure, as bad matches are progressively screened out, while good matches persist. Importantly, this framework captures the unemployment risk faced by workers trying to climb the job ladder.

This trade-off yields a reservation wage for employed workers that, contrary to other search-and-matching models, depends on workers' current wealth and incorporates a new term: the "job security premium". This premium reflects the additional compensation required to offset the risk of losing the new job and becoming unemployed, and it inherently depends on wealth. Liquidity-constrained workers have a particularly high job security premium, as their inability to smooth consumption makes unemployment far more costly. In addition, the premium increases with tenure, as workers with longer tenure face a lower risk of job loss compared to those with little or no tenure. This dynamic enables wealthy workers to accept higher wages out of unemployment, as they can wait for better offers and climb the job ladder once employed.

To quantify the impact of wealth inequality on labor mobility, I estimate the model parameters to match key empirical moments, and especially the relationship between involuntary separations and job tenure. The model successfully captures the magnitude of job flows and the dispersion of earnings among workers with homogeneous skills. It endogenously generates job-to-job transitions that decline with both tenure and wages, consistent with the empirical pattern that most job changes occur among low-tenure, low-wage workers.

Crucially, the model replicates the relationship between wealth and job mobility doc-

[3] In this context, match quality represents the worker's suitability for the job, so that a poor match is costly to the firm and may generate substantial revenue losses.

umented in the data: while unemployment-to-employment transitions decline with wealth, job-to-job flows increase, particularly for workers with large wage gaps. Among workers with positive wage gaps, those with liquid assets are approximately 0.26 percentage points more likely to change jobs than their liquidity-constrained peers. On average, this accounts for 60% of the mobility gap between wealth groups observed in the data.

This difference arises because liquidity-constrained workers face higher reservation wages during employment, and in particular, a higher job security premium. They demand much larger wage gains to offset the added risk of job loss, whereas wealthier workers, who can better smooth income shocks, are willing to switch for smaller raises. In the model, the average job security premium exceeds 40% of monthly wages and declines sharply with wealth, from nearly 40% for workers with no liquid assets to about 32% for those with $10,000 in savings. The data show a similar pattern: after switching jobs, workers with no savings gain nearly 80%, compared to roughly 50% for those with $1,000 in savings. By prioritizing job security over mobility, liquidity-constrained workers remain disproportionately trapped in low-paying jobs.

To measure the importance of the tenure-dependent separation risk, I construct a counterfactual in which job loss rates are fixed at the average observed in the data, independent of tenure. This removes the added penalty for job switching and allows me to quantify the importance of this mechanism for the job trap. Without tenure-based separation risk, job-to-job mobility rises by 0.15 percentage points (a 22% increase), with especially large gains for liquidity-constrained workers, whose mobility increases by 0.26 percentage points. Greater mobility translates into lower inequality: the 90/10 income ratio falls by nearly 4 percent, while the wealth Gini declines by 0.7 points. These results indicate that tenure-driven job security significantly discourages mobility and amplifies both income and wealth inequality.

Unemployment insurance can help mitigate this amplification mechanism. To quantify its welfare effects, I plan to re-estimate the model under alternative values of the replacement rate, benefit cap, and benefit duration, varying each component separately while keeping the government budget balanced. Preliminary results indicate that higher replacement rates and longer benefit durations generate the largest welfare gains, with especially strong effects for liquidity-constrained workers. I also intend to examine how UI generosity influences the job security premium: by reducing the income risk of job loss, more generous UI should lower the premium and encourage greater job-to-job mobility.

1.1 Related Literature

This paper contributes to three main strands of the literature. First, this study relates to the literature on the role of wealth in determining labor market outcomes. Previous research, including Bloemen and Stancanelli (2001), Algan et al. (2003), Card et al. (2007), and Chetty (2008), as well as more recent contributions such as Basten et al. (2014), Krueger and Mueller (2016), Herkenhoff (2019), Huang and Qiu (2022), Clymo et al. (2022) and Herkenhoff et al. (2024), has shown that higher savings or access to credit allow workers to smooth consumption during periods of unemployment. This results in higher quits into nonemployment, longer unemployment durations, and higher accepted wages, as workers can afford to search for better job matches.

To the best of my knowledge, this paper is the first to suggest a positive correlation between wealth and job mobility for equally-skilled workers at similar stages in their careers. This new evidence highlights how liquidity constraints affect not only unemployment spells and accepted wages, but also mobility within employment—a dimension that has received less attention in the literature.

Second, this paper builds on the literature that studies labor markets in economies with incomplete markets, initiated by the foundational works of Bewley (1983), Huggett (1993), Imrohoroğlu (1989), and Aiyagari (1994). Subsequent papers (Lentz and Tranaes, 2005; Rendon, 2006; Chetty, 2008; Krusell et al., 2010; Clymo et al., 2022), study optimal savings, job search, and quit decisions of risk-averse workers who face unemployment risk. More recent work, such as Ferraro et al. (2022), Huang and Qiu (2022), Eeckhout and Sepahsalari (2024), and Herkenhoff et al. (2024), has shown how the interaction between wealth and worker-firm heterogeneity influences job search, matching, and sorting decisions, as well as equilibrium wages.

This paper extends this body of work by incorporating on-the-job search into a random search framework with incomplete markets, introducing a novel trade-off with important implications for job mobility. While directed search models with on-the-job search have been explored in recent work (Griffy, 2021; Chaumont and Shi, 2022; Baley et al., 2022), they typically predict a negative correlation between wealth and job mobility[4]. Although this negative relationship is plausible when comparing workers over the life-cycle or across different careers, I focus on the cross-section of workers at the same stage of their careers and try to understand the origins of these different mobility patterns.

The most closely related works are Lise (2013) and Hubmer (2018), who estimate a random search model of on-the-job search with precautionary savings[5], and Caratelli (2024), who studies cyclical differences in job-switching across the wealth distribution[6]. This paper

[4]This prediction is consistent with the established finding that job mobility decreases with age, tenure, and wages (see Mincer and Jovanovic (1981) and Molloy et al. (2016)). Since wealthier people tend to be older, more tenured, and higher-earning than poorer cohorts, it is not surprising to find that job mobility decreases with wealth when not controlling for one of these factors.

[5]They endogenize search effort, yielding a negative correlation between job-to-job flows and wealth.

[6]Caratelli develops a search and matching model with heterogeneous workers, incorporating a generalized

advances their contributions by developing a tractable random search model that incorporates two novel elements: heterogeneity in job separation risk and an unemployment benefits policy that accounts for benefit expiration, UI payments caps, and wage-dependent replacement rates. These features not only capture more realistic labor market dynamics, but also have new, important implications for the effects of wealth on job mobility, especially for the trade-offs between job security and mobility. In particular, this study aims to identify those workers earning lower wages than their similar peers, and asks whether differences in wealth constrain them from moving to a higher-paying job. This new approach allows me to quantify the effects of wealth on job mobility implied by the proposed mechanism and its policy implications.

Lastly, this study contributes to the rich literature on optimal unemployment insurance (UI). Seminal works such as Meyer (1990), Gruber (1997), and Acemoglu and Shimer (1999) analyze the effects of UI on unemployment duration, consumption, and accepted wages, respectively, while Chetty (2008) and Lentz (2009) study optimal UI in the presence of incomplete markets and moral hazard, particularly for liquidity-constrained workers. More recent contributions by Lalive et al. (2015), Landais (2015), Hagedorn et al. (2019), and Kuka (2020) explore the implications of UI policies for job finding rates and long-term unemployment, labor supply, vacancy creation, and health effects, respectively. Birinci and See (2023) study the implications of income and wealth heterogeneity for UI eligibility, take-up, and replacement, while Doniger and Toohey (2022) document the general equilibrium spillovers from UI replacement rates and benefit caps. This paper builds on this literature by studying the optimal unemployment policy, including the replacement rate, duration, and benefits cap, and its effect on welfare in a model where UI affects job mobility and reallocation across the job ladder. Incorporating job mobility broadens our understanding of how UI policies influence labor market dynamics and worker welfare.

The remainder of the paper is organized as follows. Section 2 describes the data and the methodology, and suggests a new set of empirical facts on wealth inequality and job mobility. Section 3 develops a tractable model and derives the main proposition of the paper. Section 4 introduces the full quantitative model and characterizes the equilibrium of the economy. Section 5 estimates the model and discusses the key quantitative results, while Section 6 analyzes the welfare implications. Finally, Section 7 concludes.

alternating offer bargaining protocol that accommodates risk-aversion, wealth accumulation, and on-the-job search.

2 Motivating Evidence

In this section, I show some suggestive evidence of a novel relationship between labor mobility and liquid wealth. First, I describe the data and my measure of job-to-job transitions, then I introduce the empirical strategy and the main results, and finally discuss possible threats to identification in the robustness. My reduced-form estimates provide a robust motivation for the model that I will develop in the next section.

2.1 Data and Sample Construction

For my analysis, I use data from the Survey of Income and Program Participation (SIPP). The SIPP is a longitudinal survey that provides monthly data on income, labor force participation, and general demographic characteristics. It is divided into panels that span over four years and include a sample size of 50,000 households. Each panel, in turn, is divided into "waves" which cover the four months preceding each interview. In 1996 the SIPP underwent a major redesign that changed the panel overlapping structure, extended the length of the panels, and introduced computer-assisted interviewing that checks for respondents' consistency. Given the strong dissimilarities with the pre-1996 panels, my analysis focuses on SIPP panels ranging from 1996 to 2004[7].

I choose this survey because it contains the most detailed data on demographic and job characteristics and, more importantly, on employment relationships. In fact, not only is employment observed at the weekly level, but workers are also assigned a unique numerical ID for each employer and are asked the reason for job ending. All these features are crucial to identify job-to-job flows correctly and to distinguish between voluntary and involuntary separations. Using this information, I then define a job-to-job transition as an indicator equal to one if the worker quits the current employer for work-related reason, reports a different employer within four weeks, and does not spend time looking for work in between jobs. I also allow for the possibility of three months of non-employment in between jobs only in the case in which the individual reported to be quitting his current job to take another job.

To measure workers' wealth, I use SIPP's detailed information on assets and liabilities, both at the individual and household levels. All assets are observed at yearly frequency, as usual in this type of data, and the values correspond to the last day of the reference period. For this reason, I interpolate all asset variables linearly, so that wealth can be thought of as "initial wealth" at the beginning of the period. Following Kaplan et al. (2014), I then define liquid wealth as the sum of checking and savings accounts, money markets, mutual funds,

[7] I only use data up to December 2006 and exclude the 2008 panel altogether because the topical modules on assets and liabilities were not released for the years 2006 to 2008, creating a 3-year gap in asset data.

stock, bonds, and equity; net liquid wealth is liquid wealth net of bills and credit card debt; while illiquid wealth includes all remaining assets[8].

Since I aim to analyze and model the U.S. workforce, I only keep individuals between the age of 18 and 60. Moreover, I drop all individuals who are serving in the military, unpaid family workers, full-time students, and self-employed at the time of the interview, and individuals that either have never worked 6 straight months or identify themselves as out of the labor force. I also exclude type-Z respondents, who have the majority of their responses imputed, individuals with imputed assets or no reported earnings, and the bottom 3% of the income distribution. These individuals are likely to be working in part-time or temporary jobs, and as will become clear in the estimation, it is important to exclude workers whose wage does not reflect their true productivity. However, including this group in the estimation does not change the quality of the results.

2.2 Evidence on Wealth and Labor Mobility

To isolate how wealth influences workers' incentives to switch jobs, I proceed in two steps. First, I residualize wages by estimating a Mincerian regression of income on a set of controls, using the high–dimensional fixed effects estimator of Correia (2016)Correia (2016)[9]:

$$w_{it} = \alpha_i + \gamma_t + \boldsymbol{\delta} D_{it} + \boldsymbol{\varphi} J_{it} + \epsilon_{it}$$

where w_{it} is log income, α_i are workers fixed effects, and γ_t are month fixed effects. The vector D_{it} includes demographic characteristics such as age and age squared, education, marital status, number of children, disability status, and state of residence. The vector J_{it} includes job characteristics such as tenure, industry, occupation, class of worker, and indicators for union membership and full-time employment.

The regression results, reported in Table 5 in Appendix A, show that the model explains nearly 88% of the variation in income, indicating an excellent fit. Much of this explanatory power comes, of course, from worker fixed effects, which capture unobserved, predetermined traits such as ability or social skills, and from time fixed effects, which account for macroeconomic trends such as inflation or unemployment. Consistent with the literature, higher age, education, tenure, full-time status, and union membership are associated with higher wages. By contrast, women, racial and ethnic minorities, and workers with disabilities tend to earn

[8]This includes IRA and 401K accounts, KEOGH, home equity, vehicles and business equity, real estate equity and other assets.

[9]This estimator controls for high–dimensional fixed effects without explicitly estimating them. Least squares estimates can be obtained by first regressing each variable on the fixed effects and then regressing the residuals, as proposed by Guimaraes and Portugal (2010).

lower wages, underscoring persistent labor market inequalities. Geographic differences, although not reported in the table, also play an important role: states in the Northeast offer significantly higher wages than those in the South.

The predicted wage from this regression, $\hat{w}_{it}$, represents the average wage for workers with given demographic characteristics and skills employed in a similar job, in the same state and month. Then, I define the wage gap as the difference between the predicted and actual wage:

$$wage\_gap_{it} = \hat{w}_{it} - w_{it}$$

which measures the potential wage gains from switching jobs within the same state, industry, and occupation, and represents workers' incentives to search for other jobs. Because this variable is essentially the residual from the wage regression, it should be centered around zero but positively correlated with job-to-job transitions. Figure 1 plots the distribution of the wage gap and the corresponding average probability of a job-to-job move. As shown, the distribution is centered near zero, and workers with larger expected wage gains are more likely to change jobs. For example, earning 50% below the predicted wage ($wage\_gap_{it} = 0.4$) increases the probability of a job-to-job move by about 1 percentage point. The positive correlation between the wage gap and job mobility suggests that the measure captures mismatch rather than unobserved worker quality. If low wages simply reflected lower ability, job mobility would decline with the wage gap, since such workers would be unable to move to better jobs. Instead, the evidence shows that workers earning below their predicted wage are more mismatched and, consequently, more likely to change employers.

After constructing this measure, I estimate the effect of wealth (a_{it}) on job-to-job transitions ($J2J_{it}$), conditional on the worker's position on the job ladder ($wage\_gap_{it}$):

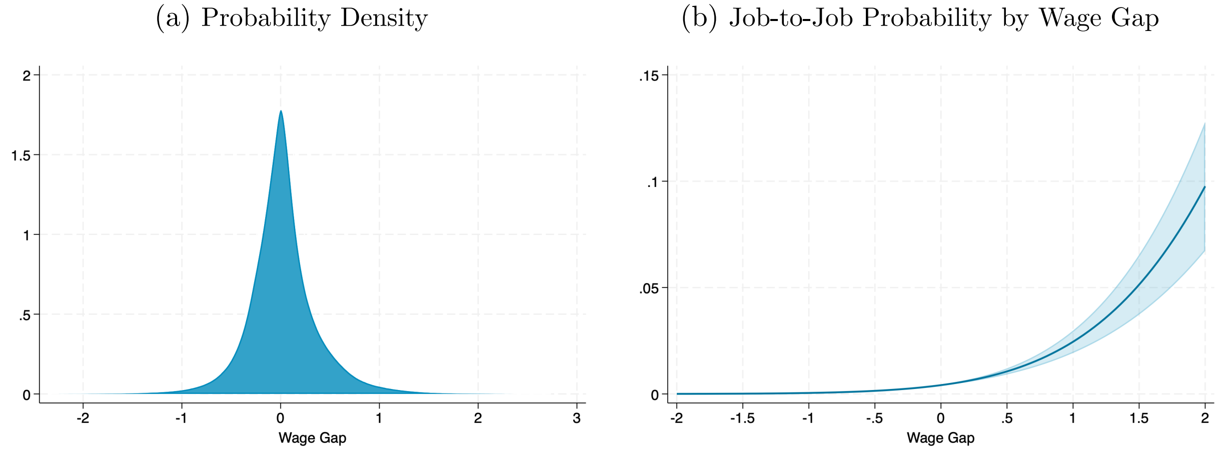
$$J2J_{it} = \Phi\left(\gamma_t + \beta_1 gap_{it} + \beta_2 gap_{it} * a_{it} + \beta_3 a_{it} + \boldsymbol{\delta} D_{it} + \boldsymbol{\varphi} J_{it}\right)$$

where α_t are month fixed effects, D_{it} and J_{it} are the same set of controls used in the wage regression, including both the demographic and job characteristics[10], and a_{it} is the wealth variable. The main coefficient of interest in this specification is that on the interaction of the wage gap and wealth (β_2). This coefficient captures whether low wealth prevents workers from changing jobs in the case in which they have large gains from doing so. Hence, I expect this coefficient to be positive: as the wage gap increases, workers with higher wealth will be more likely to change jobs.

The results of the probit regression, the linear probability model (LPM), and the LPM with worker fixed effects are presented in Table 1. Each model is estimated with two defi-

[10]For the purpose of this estimation, I use aggregated occupation and industry measures.

Figure 1. Wage Gap and Job Mobility



Note: Panel (a): Probability density function of the wage gap fitted to a normal distribution. Panel (b): Average predicted probability of job-to-job transitions evaluated at 100 grid points of the wage gap, which is defined as the difference between the workers' predicted income and their actual income. Confidence interval level is 5%. *Source*: SIPP, 1996-2004 panel.

nitions of wealth: a dummy for positive liquid wealth and the inverse hyperbolic sine transformation (IHS). Across all specifications, the coefficient on $wage\_gap_{it}$ remains consistently positive and strongly significant, confirming that job mobility is increasing in the expected wage gain. Importantly, while liquid wealth alone has no effect on mobility, its interaction with $wage\_gap_{it}$ is positive and highly significant in every regression. This pattern suggests that wealth does not affect job mobility when workers have no incentive to move, but as expected income gains increase, workers with higher savings have a significantly higher probability of changing jobs[11].

Quantitatively, the effect of wealth is sizable. In the LPM and fixed effects specifications (columns 4 and 6 of Table 1), when workers are 10% below the average wage ($wage\_gap = 0.1$) and liquid wealth increases by \$500, job-to-job flows increase by an additional:

$$[(0.09\%) \cdot \ln(500 + \sqrt{1 + 500^2}) * 10\%] \approx 0.06$$

percentage points with respect to workers without savings. Hence, being 10% below the average job-ladder income increases job-to-job moves by about 0.093 percentage points for workers with no wealth, and by over 0.15 percentage points for those with \$500 in savings. This effect is much stronger at the bottom of the job ladder ($wage\_gap \geq 1$): here, an

[11] Coefficients for net-liquid wealth and other asset types are reported in Table 4 in Appendix A. Although the coefficient on net-liquid wealth is also significant, liquid wealth is the preferred measure because access to credit allows workers to smooth consumption and has been linked to better labor market outcomes (see Herkenhoff et al. (2024)).

Table 1. Regressions of Job-to-Job Transitions on Liquid Wealth

	Job-to-job transition					
	Probit		**LPM**		**LPM + FE**	
Specification:	Dummy	IHS	Dummy (%)	IHS (%)	Dummy (%)	IHS (%)
wage_gap	0.332***	0.377***	0.750***	0.927***	0.691***	0.854***
	(0.079)	(0.085)	(0.238)	(0.229)	(0.224)	(0.212)
Liquid_wealth	−0.007	−0.005**	0.028	0.000	0.061	0.009
	(0.023)	(0.002)	(0.035)	(0.003)	(0.059)	(0.007)
$Liquid\_wealth \cdot wage\_gap$	0.373***	0.047***	0.883***	0.087***	0.964***	0.099***
	(0.087)	(0.011)	(0.256)	(0.029)	(0.242)	(0.028)
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Worker Fixed Effects	-	-	-	-	Yes	Yes
N	824,452	824,452	824,452	824,452	824,452	824,452

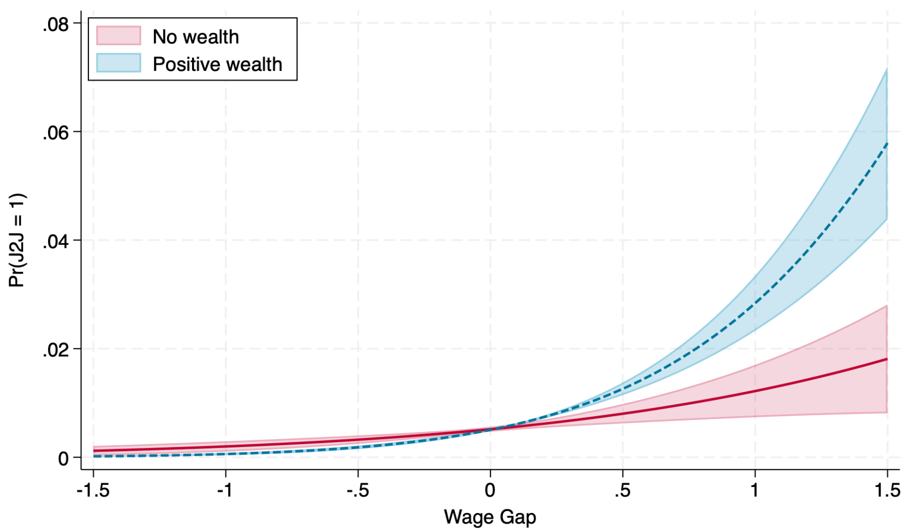
Note: The table shows the coefficients for a dummy (liquid wealth greater than zero) and IHS ($\ln(a + \sqrt{1 + a^2})$) specifications for liquid wealth using a probit regression (columns 1-2), a linear probability model (columns 3-4), and the LPM with worker fixed effects using the Correia (2016) estimator (columns 5-6). The coefficients for both LPMs are reported in percentage. $wage\_gap_{it}$ represents the expected wage gains from switching jobs, defined as the difference between the workers' predicted income and their actual income. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

additional \$500 in liquid wealth increases job-to-job transitions by about 0.6 percentage points, roughly double the sample's average mobility rate. The dummy specification tells a similar story: for workers at the bottom, having any liquidity increases job mobility by an additional 0.88–0.96 percentage points compared to those with no savings, and by as much as 2.5 percentage points for the lowest earners.

Finally, to interpret the magnitude of the coefficients in the probit regression, Figure 2 plots the average predicted probabilities of the liquid wealth dummy on job-to-job flows across different levels of the wage gap. As evident from the graph, job-to-job flows increase in the wage gap, but the increase is much steeper for wealthier workers. In particular, having some savings increases job mobility by an average of 35% for workers with some wage gaps, and by nearly 0.8 percentage points (78%) for workers who are at least 50% below the average wage ($wage\_gap > 0.4$).

What other factors influence job-to-job flows? Table 6 in Appendix A reports the coefficients for the additional controls included in regression 2.2. Consistent with prior research,

Figure 2. Average Predicted Probabilities of Wealth Dummy on J2J



Note: The figure shows the average predicted probability of a job-to-job move for a dummy of liquid wealth, evaluated at 100 grid points of the wage gap, which are defined as the difference between the workers' predicted income and their actual income. Positive wealth is defined as liquid wealth greater than zero. Standard errors are first clustered at the state level and then bootstrapped using a two-step estimator. Confidence interval level is 5%. *Source*: SIPP, 1996-2004 panel.

job-to-job transitions decline with age and tenure. Even after controlling for job-switching incentives, industry, and occupation, I find that these flows are higher among white men and workers with higher education. By contrast, women, racial and ethnic minorities, and noncitizens exhibit lower mobility. For instance, the probability of switching jobs is 0.13 percentage points higher for college graduates compared to workers without a high school diploma, but 0.11 percentage points lower for people of color relative to white workers. Unsurprisingly, mobility is also lower among unionized workers and those with disabilities, while having children does not significantly affect job-to-job transitions. These disparities in mobility likely contribute to persistent gender and racial pay gaps, an issue I will explore further in future research.

A related pattern emerges among unemployed workers. Consistent with the idea that wealth relaxes liquidity constraints and enables workers to take greater risks, I find that higher liquid wealth is associated with longer unemployment spells and higher re-employment wages (see Appendix A.2). Following the approach of Huang and Qiu (2022), I estimate that workers with $1,000$ in savings accept re-employment wages that are, on average, 8.4% higher than those accepted by workers with no savings. This evidence reinforces the mechanism that liquidity enables workers to search for better matches rather than accepting the first available offer.

2.3 Robustness

In this section, I test the robustness of the model under a different set of specifications. First, I address the potential endogeneity of liquid wealth by instrumenting it with parents' liquid wealth. Second, I broaden the definition of job ladder to include job-to-job moves across different states, industries, and occupations. Third, I test the correlation between income and job amenities, showing that workers who move to higher-paying jobs tend to also gain access to better non-wage benefits. Lastly, I test different model specifications by allowing for different functional forms of the wage gap measure and incorporating multiple interaction terms.

Additional robustness checks are reported in Appendix A.5. I show that the results are consistent across different age groups (Table 11), and when restricting the sample to workers who move to higher paying jobs (Table 12) or have positive wage gaps (Table 13). I also explore the role of unobserved heterogeneity by excluding worker fixed effects from the first-stage wage regression (Table 14). Across all these specifications, the main findings remain robust.

Wealth Endogeneity An important concern in the main estimation is that liquid wealth is potentially endogenous, as it may reflect unobserved characteristics that also influence job mobility, such as risk preferences. To address this, I follow Holmberg et al. (2024) and use parents' liquid wealth as an instrument. Intuitively, this can serve as a form of informal insurance, relaxing liquidity constraints for the children. As a result, I restrict the sample to young workers (aged 18–35) who live with their parents and are not full-time students, and assign to each of them the sum of their parents' reported liquid wealth. This yields a sample of approximately 4,000 individuals, for which I re-estimate the main specification. Table 7 presents the results. The interaction between the wage gap and parents' wealth is positive and statistically significant, particularly in the IHS specifications, reflecting the patterns found in the baseline regressions. While standard errors are larger due to the smaller sample size, the magnitudes of the coefficients remain very similar. Figure 9 further supports this result: the predicted probabilities of j2j transitions conditional on wage gap and parental wealth follow the same upward-sloping pattern as in the main analysis, with nearly identical coefficients but much larger standard errors.

Different Job Ladders The estimation faces a major trade-off between accurately predicting income and allowing workers to search across a wide range of jobs. The current specification assumes that when workers change jobs, they primarily search within the same industry, occupation, and state. While this assumption holds for the vast majority of workers, particularly those climbing the wage ladder, it might underestimate potential wages for workers who consider jobs outside of their current industry, state, or occupation. To address this concern, I estimate four alternative wage regressions: three excluding industry, occupation, or state one at a time, and a fourth excluding all three simultaneously. Although these specifications yield lower R^2 and a larger income variance, they allow for a richer distribution of the wage gap measure. I then re-estimate the probit regression 2.2 using the liquid wealth dummy with these four alternative wage gap variables. The results of each exclusion are presented in Table 8 in Appendix A, where Column I excludes industry, Column II excludes occupation, Column III excludes state, and Column IV excludes all three[12]. As shown in the table, the coefficients on the wage gap measure and the interaction term remain positive and strongly significant across all four specifications.

Job Amenities A potential concern is that when changing jobs, workers care not only about their wages, but also about other job amenities, such as flexible schedules, employer-provided health insurance, tuition assistance, and retirement savings plans. Recent studies (Lamadon et al., 2022; Sockin, 2022) have shown that higher-paying and more productive firms tend to offer better non-wage amenities and report higher job satisfaction. As a result, workers who change jobs for better wages often also gain better job amenities (Sockin, 2022). Conversely, those who move to lower-satisfaction firms are more likely to face pay cuts. To ensure these findings are consistent in my data, I validate them and present the results in Table 10 in Appendix A. The table shows that, within the same industry and occupation, workers who have access to remote work, do not work on weekends, and receive employer-sponsored benefits — such as health insurance, tuition assistance, or retirement savings plans — tend to earn higher wages[13]. Furthermore, Figures 10 show that, within similar jobs, workers whose employers offer these amenities earn, on average, \$250–450 more per month than those who do not.

Functional Forms Finally, I address potential misspecifications in the functional forms of the model. One concern is that the observed differences in job mobility by wealth could be driven by the negative tail of the wage gap measure (i.e., workers with a negative wage gap).

[12] While these controls are removed in the wage regression, they remain included as controls in the second-stage probit regression.

[13] This information is provided in two separate topical modules with non-overlapping time periods. As a result, I run three separate regressions: one for each topical module, and a third to preserve a larger sample size.

To tackle this issue, I redefine the measure to include only positive values:

$$wage\_gap_{ist} = -min(w_{ist} - \hat{w}_{ist}, 0)$$

This new measure compares workers with a positive wage gap and does not distinguish those with zero or negative gaps. The estimated coefficients, which are reported in Column I of Table 9 in Appendix A, are still significant and even larger than the original ones, suggesting that the results are robust to this alternative measure. A similar concern arises in the specification of Equation 2.2, where the effect of expected wage gains may vary with characteristics besides wealth. To address this, I interact the wage gap measure with additional controls (Z_{it}):

$$J2J_{it} = \alpha_t + \beta_1 wage\_gap_{it} + \beta_2 wage\_gap_{it} * a_{it} + \beta_3 wage\_gap_{it} * Z_{it} + \beta_4 a_{it} + \beta_5 X_{it} + \epsilon_{it}$$

Table 9 in Appendix A reports the coefficients for the interaction with education (Column II), marital status (Column III), and both education and marital status (Column IV). All coefficients on the wage gap measure and the interaction with liquid wealth remain positive and strongly significant. In contrast, although not reported in the table, the coefficients on the interactions between wage gap and education, as well as wage gap and marital status, are not statistically significant in any of the regressions.

Overall, these results suggest that both wages and wealth matter for workers' decisions to change jobs. Workers with no savings may refrain from changing jobs despite having incentives to do so, hinting at liquidity constraints and the role of consumption smoothing in job mobility decisions.

3 Simple Model

To study the mechanisms through which wealth affects job mobility, I develop a tractable job-ladder model with incomplete markets, risk-averse workers, and wage posting. A novel feature of this model is that the risk of job loss declines with job tenure[14], introducing a new trade-off for on-the-job search: higher-paying jobs come at the cost of a higher separation risk. Consequently, in this framework, job-to-job transitions depend on both tenure and wealth. In the next section, I extend this framework into a quantitative model that microfounds this mechanism.

[14] See Section 4 for a possible microfoundation of this relationship.

3.1 Environment

Time is continuous and infinite, agents discount the future at rate ρ, and there is no aggregate uncertainty. Workers are *ex-ante* heterogeneous in assets a and risk-averse, with preferences represented by a concave utility function $u(\cdot)$. They choose consumption and savings at the risk-free rate r to insure against income loss. Firms post wages w from a common exogenous distribution $F(w)$, which governs the wage offers available to workers.

Workers, who may be employed or unemployed, are always searching for jobs and receive offers at an exogenous Poisson arrival rate λ_s, where $s \in \{u, e\}$ denotes the employment status. After finding a job, workers accumulate job tenure over time, which resets to zero following a job change or a layoff. Job loss occurs at an exogenous rate $\delta(\tau)$ that decreases with tenure ($\delta'(\tau) < 0$). Thus, while higher tenure improves job security, switching jobs resets tenure and exposes workers to the high separation risk of new hires.

3.2 Value Functions

Workers choose consumption to maximize expected lifetime utility, subject to the budget constraint and the liquidity constraint. When unemployed, workers receive unemployment benefits b, they encounter offers at a Poisson arrival rate λ_u, and draw a wage from the exogenous distribution $F(w)$. They accept the job if the offered wage exceeds their reservation wage, which occurs whenever the value of being unemployed, $U(a)$, is lower than the value of being employed at that wage, $V(a, w, 0)$[15].

Upon accepting an offer, workers begin their job with a wage w and no job tenure ($\tau = 0$). Over time, as they accumulate tenure, they face a lower job loss risk at rate $\delta(\tau)$. While employed, workers also receive job offers from new employers at rate λ_e. The Bellman equation of an employed worker with assets a, wage w, and tenure τ is given by:

$$
\begin{aligned}
\rho V(a, w, \tau) = \max_c \quad & u(c) + (ra + w - c)\frac{\partial V}{\partial a} + \frac{\partial V}{\partial \tau} + \delta(\tau)[U(a) - V(a, w, \tau)] \\
& + \lambda_e \left(\int \max\{V(a, w, \tau), V(a, \tilde{w}, 0)\} dF(\tilde{w}) - V(a, w, \tau) \right) \\
\text{s.t.} \quad & a \geq \underline{a}
\end{aligned}
$$

Since all new jobs start off with no tenure, changing job is risky: a wage increase comes at the expense of a higher chance of layoff. As a result, high-tenure workers are more reluctant to switch, unless the wage gain compensates for the loss of job security. Wealth amplifies this trade-off, as workers value job loss differently based on their assets: while

[15] Where $\rho U(a) = \max_c \;\; u(c) + (ra + b - c)\frac{\partial U}{\partial a} + \lambda_u \left(\int \max\{V(a, \tilde{w}, 0) - U(a), 0\} \;\; dF(\tilde{w}) \right)$

wealthy unemployed workers can afford to be selective, holding out for better offers, liquidity-constrained workers accept early offers to escape unemployment, often resulting in worse long-term outcomes.

3.3 Reservation Wages

The unemployed reservation wage $R_u(a)$ is the wage that equates the value of accepting a job offer and remaining unemployed, and solves:

$$V(a, R_u(a), 0) = U(a)$$

If search is more effective when unemployed ($\lambda_u > \lambda_e$), as more time is devoted to job search, wealthier workers may decline low-wage offers and wait for better opportunities. In this scenario, the reservation wage is increasing in wealth, consistent with the empirical findings of Krueger and Mueller (2016) and Bloemen and Stancanelli (2001).

The employed reservation wage $R_e(a, w, \tau)$ is the minimum wage at which workers are willing to switch to a new employer, starting with no job tenure:

$$V(a, R_e(a, w, \tau), 0) = V(a, w, \tau)$$

While in standard search models this reservation wage equals the current wage, in this framework it includes an additional term which I denote the *job security premium*.

Proposition 1. *The employed reservation wage $R_e(a, w, \tau)$ depends on assets and tenure, and it is given by:*

$$R_e(a, w, \tau) = w + \underbrace{\frac{[\delta(0) - \delta(\tau)] * [V(a, w, \tau) - U(a))]}{u'(c(a, w, \tau))}}_{\text{job security premium}} \tag{1}$$

In particular:

- $\delta(0) < \delta(\tau) \implies R_e < w$: *lower reservation wage than under constant separations;*
- $\delta(0) = \delta(\tau) \implies R_e = w$: *reservation wage under constant separations;*
- $\delta(0) > \delta(\tau) \implies R_e > w$: *higher reservation wage than under constant separations.*

Proof. See Appendix B. □

Intuitively, the job security premium represents the additional compensation needed to offset the risk of losing the new job and becoming unemployed. Its size is proportional to the gap in separation rates between new hires $\delta(0)$ and tenured workers $\delta(\tau)$, as well as the difference between the value of being employed and unemployed. When separation rates are constant ($\delta(0) = \delta(\tau)$), there is no security premium and the reservation wage simply equals the current wage. However, when the separation rate decreases with tenure ($\delta(0) > \delta(\tau)$) and workers value employment more than unemployment, the reservation wage always exceeds the current wage, reflecting the worker's trade-off for job security.

Workers with higher tenure demand a larger job security premium, and therefore a higher reservation wage, because their risk of separation is lower ($\delta(\tau) > \delta(\tau'),\ \forall \tau < \tau'$). Conversely, the reservation wage tends to decrease with assets, as wealthier workers are better able to bear the financial risks of unemployment $\left(\frac{\partial U(a)}{\partial a} > \frac{\partial V(a,w,\tau)}{\partial a} \text{ if } c^U < c^E\right)$[16].

4 Quantitative Model

I now extend the tractable model into a richer quantitative framework. While the basic structure remains the same—workers are risk-averse, face incomplete markets, and engage in on-the-job search—the quantitative model incorporates more realistic labor market dynamics. In particular, it microfounds the declining relationship between tenure and separation risk, allows for exogenous labor market entry and exit, and introduces a detailed unemployment insurance policy financed by income taxes, with income-dependent replacement rates and benefit expiration.

4.1 Environment

The setup builds on the previous framework with several key extensions. First, I model labor market entry and exit following the perpetual youth framework of Yaari (1965) and Blanchard (1985). Each period, a measure of new workers enters the labor market as unemployed with zero assets, while existing workers retire or die at exogenous rate σ.

Second, to capture differences in the value of employment relative to unemployment, unemployed workers receive benefits $b(w, d)$ that depend on their previous wage w and current unemployment duration d. Benefits replace a fraction of past income but are subject to a cap $\bar{b}$. Unemployment duration evolves according to a Markov process $\Pi(d'|d)$, and once it reaches a threshold d^*, benefits expire and are replaced by the subsistence transfer $\underline{b}$. This mechanism aligns with U.S. labor market policy, where unemployment insurance typically lasts up to six months, whereas standard search-and-matching models often assume that

[16] However, this condition depends in part on the parametrization of the model and the concavity of the value function. Importantly, this condition does not hold if the value of being unemployed is greater than that of being employed ($V(a, w, \tau) < U(a)$)

benefits persist indefinitely.

After finding a job, workers accumulate tenure stochastically according to a similar Markov process $\Pi(\tau'|\tau)$. However, tenure resets to zero if the worker moves to a new job, quits into unemployment, or is fired by the firm. Wages also grow deterministically with tenure as a fixed fraction of the initial wage[17].

4.2 The Tenure Channel

To offer a possible microfoundation for the negative relationship between job separations and tenure, I adopt a framework inspired by Jovanovic (1984) and Moscarini (2005). In this framework, job separations arise from imperfect information about match quality, which, in this context, represents the worker's suitability for the job. When a worker accepts a new job, neither the employer nor the worker observes the match quality at the beginning. Over time, however, they learn if the match turns out to be bad, in which case the firm terminates the worker immediately. Intuitively, this represents a case in which a poor match is costly to the firm, for instance by generating substantial revenue losses. This mechanism naturally generates a declining separation hazard over tenure, as bad matches are progressively screened out.

Match Quality and Learning Process Upon job entry, workers draw the match quality ω with the firm, which can either be *good* ($\omega = 1$) with probability p or *bad* ($\omega = 0$) with probability $1 - p$:

$$\Pr(\omega = 1) = p, \qquad \Pr(\omega = 0) = 1 - p,$$

Initially, neither workers nor firms observe ω, but if the match is bad, they receive a perfectly informative signal at an exogenous Poisson rate μ. Hence, the time until a bad match is discovered, denoted T, is exponentially distributed: $T \sim \text{Exp}(\mu)$. The probability that the match has been identified as bad by time t is therefore:

$$\Pr(T \leq t) = 1 - e^{-\mu t}$$

Separation Rate Firms fire workers only after learning that a match is bad, while good matches are never terminated. Let $\Gamma(t)$ denote the cumulative probability of separation by time t, and let $S(t)$ be the corresponding survival probability, i.e., the probability that the

[17] Wage growth is proportional to the initial wage, so higher-paid workers see larger absolute gains. Allowing for heterogeneity in wage-tenure profiles (e.g., intercept and slope) would increase flexibility but also expand the state space significantly. Empirically, higher-wage workers tend to experience steeper wage growth (see Borovičková and Macaluso (2024)).

worker is still employed at time t. Then:

$$
\begin{aligned}
\Gamma(t) &= \Pr(\omega = 0) \cdot \Pr(T \leq t) = (1-p) \cdot \left(1 - e^{-\mu t}\right) \\
S(t) &= 1 - \Gamma(t) = p + (1-p)\, e^{-\mu t}
\end{aligned}
$$

The hazard rate, then, is the instantaneous rate of separation at time t conditional on survival until t:

$$
\delta(t) = \frac{\gamma(t)}{S(t)} = \frac{(1-p)\,\mu\, e^{-\mu t}}{p + (1-p)\, e^{-\mu t}}
$$

where $\gamma(t)$ is the separation density. This function is strictly decreasing in t, reflecting the fact that as tenure increases, the pool of workers becomes increasingly composed of good matches. In the limit:

$$
\lim_{t \to \infty} \delta(t) = 0,
$$

because, eventually, all bad matches are identified and terminated, and only good matches survive. Appendix B.2 derives the hazard rate endogenously from the firm's problem in general equilibrium.

4.3 Value Functions

The problem of an unemployed worker with assets a, previous wage w, and unemployment duration d is summarized by the continuous-time Bellman equation:

$$
\begin{aligned}
(\sigma + \rho) U(a, b(w,d)) = \max_c \quad & u(c) + \dot{a}\frac{\partial U}{\partial a} + \frac{\partial U}{\partial d} \\
& + \lambda_u \left(\int \max\{U(a, b(w,d)), V(a, \tilde{w}(0), 0)\} \;\; dF(\tilde{w}) - U(a, b(w,d)) \right) \\
\text{s.t.} \quad & \dot{a} = ra + b(w,d) - c \\
& a \geq \underline{a}
\end{aligned}
\tag{2}
$$

Unemployed workers receive benefits $b(w,d)$ that depend on their unemployment duration and previous wage[18]. When unemployment duration exceeds a threshold d^*, benefits expire, forcing workers to dissave their assets in order to consume. All unemployed actively search for jobs and accept any offer that exceeds their reservation wage, which depends on their assets. The Bellman equation of an employed worker with assets a, wage w, and tenure τ is

[18] For tractability, instead of tracking past wages, I assume benefits are a fixed fraction of the wage the worker would have earned had they been employed.

given by:

$$
\begin{aligned}
(\sigma+\rho)V(a,w(\tau),\tau) = \max_{c} \quad & u(c) + \underbrace{\max\{V(a,w(\tau),\tau),U(a,b(0,0))\} - V(a,w(\tau),\tau)}_{\text{voluntary quits}} \quad (3)\\
& + \underbrace{\lambda_e \left(\int \max\{V(a,w(\tau),\tau),V(a,\tilde{w}(0),0)\}dF(\tilde{w}) - V(a,w(\tau),\tau)\right)}_{\text{on-the-job search}}\\
& + \underbrace{\frac{(1-p)\,\mu\, e^{-\mu\tau}}{p+(1-p)\,e^{-\mu\tau}}[U(a,b(w,0)) - V(a,w(\tau),\tau)]}_{\text{involuntary separations}} + \frac{\partial V}{\partial \tau} + \dot{a}\frac{\partial V}{\partial a}\\
\text{s.t.} \quad & \dot{a} = ra + (1-\theta)w(\tau) - c\\
& a \geq \underline{a}
\end{aligned}
$$

Upon accepting an offer, workers begin their job with no job tenure ($\tau = 0$) and draw the quality of their match with the firm. Over time, they accumulate tenure stochastically, which gains them both a higher wage and a lower separation risk. In particular, job loss risk decreases with tenure at rate $\frac{(1-p)\,\mu\, e^{-\mu\tau}}{p+(1-p)\,e^{-\mu\tau}}$, where p is the probability that the match is *good* and μ is the Poisson learning rate. Workers also receive job offers from new employers at rate λ_e and may voluntarily quit into unemployment at any time, but receive no benefits upon doing so. Finally, workers pay a fraction θ of their income in taxes to the government.

4.4 Government

The government finances unemployment benefits through a proportional tax on labor income. There is no government consumption or debt, and the budget must balance in every period. Let θ denote the labor income tax rate, and let $e(a,w,\tau)$ denote the employed stationary distribution over individual assets, wages, and tenure, and let $u(a,b(w,d))$ be the steady-state distribution of the unemployed over assets and unemployment benefits. The government's budget constraint requires that revenues equal government costs and is given by:

$$
\theta \int w(\tau)\, e(a,w,\tau)\; da\, dw\, d\tau = \int b(w,d)\, u(a,b(w,d))\, da\, dw\, dd, \tag{4}
$$

where $w(\tau)$ denotes labor income for a worker with tenure τ, and $b(w,d)$ is the unemployment benefit received by an unemployed individual with unemployment duration d and previous wage w.

4.5 Equilibrium

In a stationary equilibrium, all the flows are constant over time. Consequently, the mass of workers leaving employment must equal the mass of workers entering unemployment, and vice versa. This allows me to derive the Kolmogorov Forward Equations (KFE), which summarize the dynamics of the distributions in the long-run steady state. The mass of unemployed $\mathbf{u} = u(a, b(w, d))$ over assets and unemployment benefits $b(w, d)$ satisfies:

$$
\begin{aligned}
0 = &-\frac{\partial \mathbf{u}}{\partial a}[ra + b(w,d) - c(a, b(w,d))] - \frac{\partial \mathbf{u}}{\partial d} - \sigma \mathbf{u} \\
&- \lambda_u [1 - F(R_u(a, b(w,d)))]\mathbf{u} \ + \sigma(\mathbf{u} + \mathbf{e})\mathbf{1}_{\{a=0\}} \\
&+ \mathbf{1}_{d=0} \int \frac{(1-p)\,\mu\, e^{-\mu\tau}}{p + (1-p)\, e^{-\mu\tau}} \mathbf{e}\, \mathrm{d}\tau + \mathbf{1}_{\{U>V\}} \mathbf{1}_{\{d=0, w=0\}}
\end{aligned}
\tag{5}
$$

where $\mathbf{e} = e(a, w, \tau)$ is the distribution of workers over assets, wages, and tenure, and solves:

$$
\begin{aligned}
0 = &-[ra + (1-\theta)w(\tau) - c(a, w, \tau)]\frac{\partial \mathbf{e}}{\partial a} - \frac{(1-p)\,\mu\, e^{-\mu\tau}}{p + (1-p)\, e^{-\mu\tau}} \mathbf{e} \\
&+ f(w)\lambda_u [1 - F(R_u(a, b(w,d)))]\mathbf{u} - \frac{\partial \mathbf{e}}{\partial \tau} - \sigma \mathbf{e} \\
&- \lambda_e [1 - F(R_e(a, w, \tau))]\mathbf{e} - \mathbf{1}_{\{U>V\}} \mathbf{1}_{\{d=0, w=0\}} \\
&+ \lambda_e f(w) \mathbf{1}_{\{\tau=0\}} \iint_{\underline{w}}^{w} \mathbf{e}\, \mathrm{d}\tilde{w} \mathrm{d}\tilde{\tau}
\end{aligned}
\tag{6}
$$

and the total population mass is normalized to one:

$$
\int \mathbf{u}(a, b(w,d))\, da\, dw\, dd + \int \mathbf{e}(a, w, \tau)\, da\, dw\, d\tau = 1.
$$

At each instant, the densities evolve due to asset accumulation, pinned down by the budget constraint, as well as increases in tenure ($\frac{\partial \mathbf{e}}{\partial \tau}$) or unemployment duration ($\frac{\partial \mathbf{u}}{\partial d}$). Retirement or death occurs at exogenous rate σ and is offset by an inflow of newborn unemployed at zero assets. With probability $\lambda_u[1 - F(R_u(a, d))]$, an unemployed worker receives a wage offer above their reservation wage and flows into employment, while workers lose their jobs and flow into unemployment at rate $\frac{(1-p)\,\mu\, e^{-\mu\tau}}{p+(1-p)\, e^{-\mu\tau}}$. Finally, workers search for jobs while employed and move up the job ladder if they receive an offer above their employed reservation wage, which occurs at rate $\lambda_e[1 - F(R_e(a, w, \tau))]$.

Definition 1. *A stationary recursive equilibrium consists of:*

- *Two value functions $\{U(a, b(w, d)), V(a, w, \tau)\}$ satisfying the Bellman equations (2)* *and (3);*

- *A set of policy functions $\{c(a, w, \tau), \dot{a}\}$ that solve the optimization problem;*
- *Two distributions $u(a, b(w, d))$ and $e(a, w, \tau)$ satisfying the Kolmogorov forward equations (5) and (6);*
- *A tax policy θ that balances the government budget constraint (4).*

This equilibrium characterizes the joint behavior of employed and unemployed workers and the government in the steady state.

5 Quantitative Analysis

In this section, I describe the details of the numerical implementation, the parameterization, and calibration of the model, which is set to match key features of the U.S. labor market. The model is calibrated in steady state.

5.1 Numerical Implementation

The model is set to monthly frequency and discretizes the state space over uniform grids of assets (100 points), wages (50 points), as well as tenure and unemployment duration (5 points). Both tenure and unemployment duration evolve stochastically, with transition probabilities π_τ and π_d, respectively, and are divided into 5 bins, each representing 6 months.

The model is solved using the finite difference method, following the solution algorithm of Achdou et al. (2022). This method is particularly well-suited for solving continuous-time heterogeneous agent models, as it ensures monotonicity, consistency, and numerical stability regardless of the step size Δ, which can be arbitrarily large. The algorithm follows these key steps until convergence[19]:

1. **Initial Guess**: Guess the value function and tax rate: $V_0(a, w, \tau) = \frac{u(w+ra)}{\rho}$; $\theta = \theta_0$.
2. **Solve the HJB equations**:
   - **Savings Policies**: Consumption satisfies the Euler equation:

$$u'(c) = \rho \mathbf{V_a}$$

[19] See Appendix C for a detailed explanation of the algorithm and construction of the transition matrix.

- **Update the Value Function:** Solve using sparse matrix inversion:

$$\left(\left(\frac{1}{\Delta}+\rho\right)\mathbf{I}-\mathbf{A^n}\right)\mathbf{V^{n+1}}=\mathbf{u^n}+\frac{1}{\Delta}\mathbf{V^n}.$$

  where A^n is a Poisson transition matrix that encodes the evolution of the stochastic processes as well as labor market flows. It is a sparse matrix derived from the Kolmogorov Forward Equations and it is updated at each iteration because it depends on the value function.

- **Check Convergence**: If $||\mathbf{V}_{\text{new}}-\mathbf{V}_{\text{old}}||<\epsilon$ stop. Otherwise go back to step 2.

3. **Steady State Distributions**: Solve the stationary distribution of workers using:

$$\mathbf{A^T g}=0, \quad \sum \mathbf{g}=1$$

4. **Government Budget Constraint**: Revenues must equal costs:

$$\theta\int \mathbf{w}\cdot\mathbf{e} \;=\int \mathbf{b}\cdot\mathbf{u}$$

   If this condition is satisfied, stop. Otherwise, update the tax rate to: $\theta=\frac{\int b\cdot\mathbf{u}}{\int w\cdot\mathbf{e}}$ and go back to step 2.

5.2 Parametrization

I assume that the utility function exhibits constant relative risk aversion (CRRA) with parameter γ:

$$u(c)=\frac{c^{1-\gamma}}{1-\gamma}, \quad \gamma>0;\ \gamma\neq 1,$$

The wage offer distribution $F(w)$ is assumed to be log-normal with parameters μ_w and σ_w. The probability of drawing each wage w is given by:

$$f(w)=\frac{1}{w\sigma_w\sqrt{2\pi}}\exp\left(-\frac{(\ln w-\mu_w)^2}{2\sigma_w^2}\right), \quad w>0.$$

Unemployment benefits are parametrized as a piecewise function that depends on both the previous wage w and unemployment duration d:

$$b(w,d) = \begin{cases} \min\{\chi w, \bar{b}\}, & \text{if} \quad d < d^* \\ \underline{b}, & \text{if} \quad d \geq d^* \end{cases}$$

where χ is the fraction of previous income replaced (the replacement rate) and $\bar{b}$ is the maximum benefit cap[20]. Once unemployment duration reaches the threshold d^*, benefits expire and workers receive the subsistence level of benefits $\underline{b}$.

5.3 Calibration

Table 2 provides an overview of the model parameters, which are expressed at monthly frequency, and the corresponding moment conditions used to inform them. The parameters are either set externally following the literature, directly estimated from the data, or estimated internally by moment matching.

Externally Set The first group of parameters are set externally. I assume that the utility function has parameter $\gamma = 1.5$[21], that workers retire, on average, after 35 years, and that they cannot borrow against unemployment risk: $\underline{a} = 0$. Following Birinci and See (2023), I set the income replacement rate χ to 50%[22], while the benefits cap is set to 50% of average wages ($1,450). Although benefits caps vary widely by state, Doniger and Toohey (2022) suggest that they are typically near 50 percent of state average weekly wages. This yields unemployment benefits in the range [$250,$1450], which are in line with the data as well as previous estimates.

Directly Estimated The risk-free rate r is fixed and matches a 2% annual interest rate. The Markov transition probabilities $\pi_\tau = \pi_d$ are set such that, each month, one-sixth of workers gain an additional six months of either job tenure or unemployment duration. Wage growth profiles target the average wage growth observed in the data for 6-month tenure bins, defined as {[0-5], [6-11], [12-17], [18-23], [24-29]}.

To map the model's hazard rate to the data, I estimate the parameters of the function by minimizing the distance to the empirical EU rate using non-linear least squares. In particular,

[20]This functional form follows Doniger and Toohey (2022), although they do not account for benefits expiration.

[21]This value is in line with that of Lise (2013), who estimates a relative risk aversion parameter of 1.455.

[22]Using SIPP data, Birinci and See (2023) estimate an average replacement rate of 52% among UI recipients, while Doniger and Toohey (2022) estimate an average replacement of 75% for UI recipients *below* the cap.

Table 2. Model Parameters

	Parameter	Value	Targeted Moment	Model	Data
Externally Set					
γ	CRRA parameter	1.50	Externally set	-	-
$\underline{a}$	Borrowing constraint	0.00	Externally set	-	-
σ	Death/Retirement rate	0.0024	35 years working life	-	-
χ	Replacement rate	0.5	Birinci and See (2023)	50%	50%
$\bar{b}$	Benefits cap	1.45	0.5∗(average wage)	$1,450	$1,450
$\underline{b}$	Subsistence level	0.073	1996 SNAP benefits	$73	$73
Directly Targeted					
r	Risk free rate	0.02/12	Annual interest rate	2%	2%
π_τ	Markov probability	1/6	Size of tenure bins	6 months	6 months
π_d	Markov probability	1/6	Size of duration bins	6 months	6 months
δ_τ	Separation rate by tenure	Fig3a	Monthly EU by tenure	2.94-0.71%	2.7-0.91%
w_τ	Wage growth by tenure	Fig3b	Income growth by tenure	0-0.3%	0-0.3%
Internally Estimated					
μ_w	Wage offer parameter	0.002	Income distribution	Fig4a	Fig4a
σ_w	Wage offer parameter	0.713	Income distribution	Fig4a	Fig4a
ρ	Discount rate	0.079	Wealth Distribution	Fig4b	Fig4b
λ_u	Job finding rate (unemp)	0.047	Monthly UE rate	20.42%	21.3%
λ_e	Job finding rate (emp)	0.006	Monthly J2J rate	0.66%	0.66%

Note: All parameters are expressed at monthly frequency

I estimate the involuntary separation rate by tenure using SIPP data, following the approach of Menzio et al. (2016). To do so, I compute the monthly separation rate for workers with tenure τ as the share of individuals who experience an involuntary separation in a given month, divided by the number of employed workers with tenure τ in the previous month. Unlike Menzio et al. (2016), who consider all employer-to-unemployment (EU) transitions, I focus exclusively on employer-initiated separations.[23]

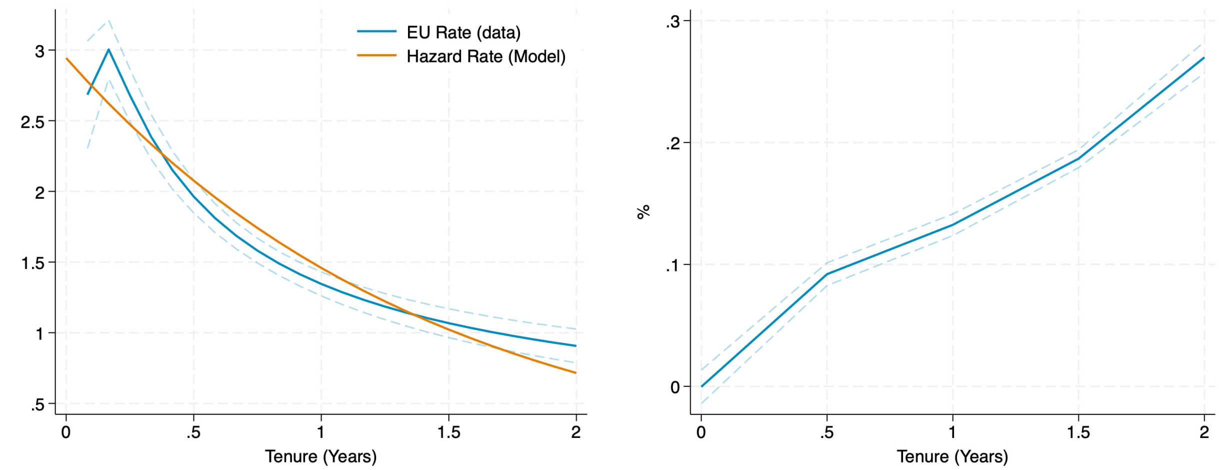
The best-fit parameters are $\hat{p} = 0.9593$ and $\hat{\theta} = 0.7232$. As shown in Figure 3a, the empirical hazard rate falls sharply over the first year of tenure, from 2.7% down to 1.5% monthly before flattening out. The model captures the broad shape of this decline, although it slightly understates the steepness of the initial drop. This pattern aligns with the well-documented decline in separation risk over job tenure, as established by Topel and Ward

[23]This includes temporary layoffs that may result in recall. In the SIPP, it is not possible to distinguish workers on temporary layoff who are actively searching from those passively waiting to be recalled, so all such cases are grouped together.

Figure 3. Directly Targeted Moments

(a) Job Separation Rate by Tenure

(b) Income Growth by Tenure



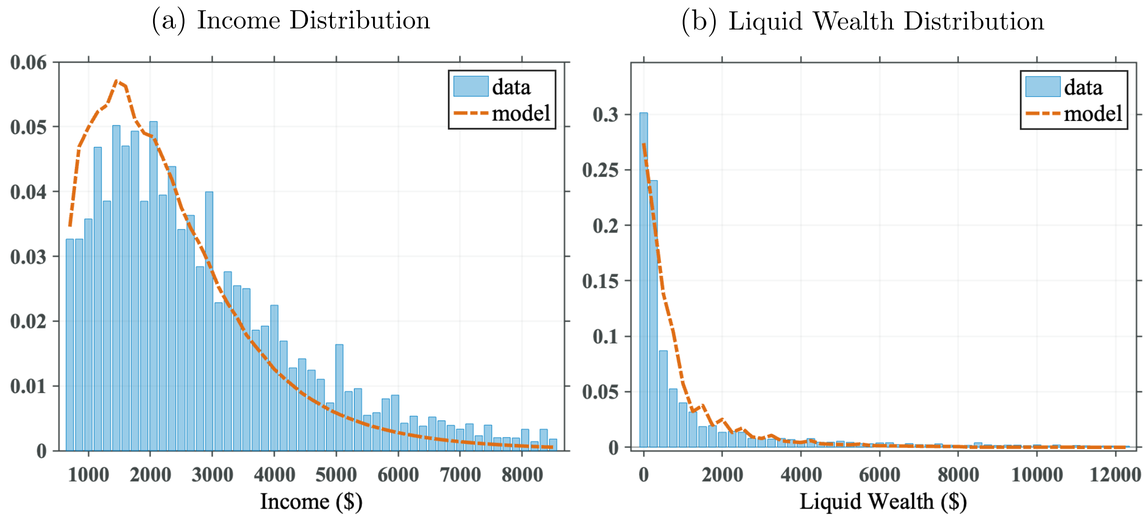
Note: Panel (a) plots the monthly job separation rate by tenure in the data, computed as the number of workers with a given tenure who experience an involuntary separation in a month, divided by the total number of employed workers with that tenure in the previous month. The series is compared to the model hazard rate, with parameters chosen to minimize the distance between the curves. Panel (b) plots average income growth by 6-month tenure bins, defined as {[0-5], [6-11], [12-17], [18-23], [24-29] *Source*: SIPP, 1996-2004 panel.

(1992) and Farber (1994).

While my model focuses on average separation rates declining in tenure, Jarosch (2023) shows that job loss rates vary systematically by job type, with higher-paying jobs exhibiting lower separation rates. Although this pattern is supported by German data, other studies, such as Cahuc et al. (2002) and Sockin (2022), suggest that firms with higher separation rates may compensate workers with higher wages. My model abstracts from such heterogeneity by assuming that all workers are homogeneous in skills, and that wage differences arise solely from wealth and job search dynamics. As a result, I assume constant separation rates within each job ladder, abstracting from variations across different jobs.

In reality, workers with differing skills, education levels, or employment histories likely sort into distinct job ladders, each characterized by unique separation rates and wage-tenure profiles. To examine whether separation rates meaningfully vary across these dimensions, Appendix D presents empirical evidence on EU rates by tenure, disaggregated by education and employment status. Figure 12a shows that higher-educated workers experience lower separation rates, although the EU rate declines with tenure across all education groups. Similarly, Figure 12b confirms that separation rates decline with tenure even when restricting the sample to workers who recently made job-to-job transitions. To explore the quantitative

Figure 4. Internally Matched Moments



Note: Panel (a) compares the income distribution in the data (blue) to the steady-state income distribution generated by the model (orange). Panel (b) presents the liquid wealth distribution in both the data (blue) and the model (orange). The model successfully captures the overall shape and dispersion of both distributions. *Data Source*: SIPP, 1996-2004 panel.

implications of this heterogeneity, I conduct an alternative model calibration in Appendix D, contrasting outcomes for college-educated and high-school-educated workers.

Internally Estimated These assumptions leave five parameters to be estimated internally by SMM:

$$\mathbf{p} = \{\mu_w, \sigma_w, \lambda_u, \lambda_e, \rho\}$$

The wage offer distribution parameters μ_w and σ_w are directly informed by the distribution of accepted wages in the data. In particular, the two parameters are estimated to match average accepted wages (\$2,900), the first and third quartiles of the income distribution, as well as the 10th and 90th percentile. The job-finding rate in unemployment (λ_u) is calibrated to match the average monthly unemployment-to-employment (UE) transition rate of 21.32%, while the employed job-finding rate (λ_e) targets the monthly job-to-job (J2J) transitions rate of 0.66%. This latter estimate is lower than those in previous studies, as I focus exclusively on voluntary quits associated with finding a better job. Finally, I estimate the discount rate to match the first and third quartiles of the liquid wealth distribution. Since workers are risk-averse and aim to smooth consumption, the model typically generates substantial asset accumulation as workers save to insure themselves against income loss. Hence, a high discount rate is required to ensure that some households hold no liquid assets.

5.4 Model Fit

Targeted Moments The model successfully matches key moments observed in the data. It slightly underestimates the UE rate while closely matching the J2J rate. The estimated parameters imply that job search intensity is much higher for the unemployed than for the employed ($\lambda_u > \lambda_e$). This relative intensity is somewhat lower than in previous estimates but remains broadly consistent with the literature[24].

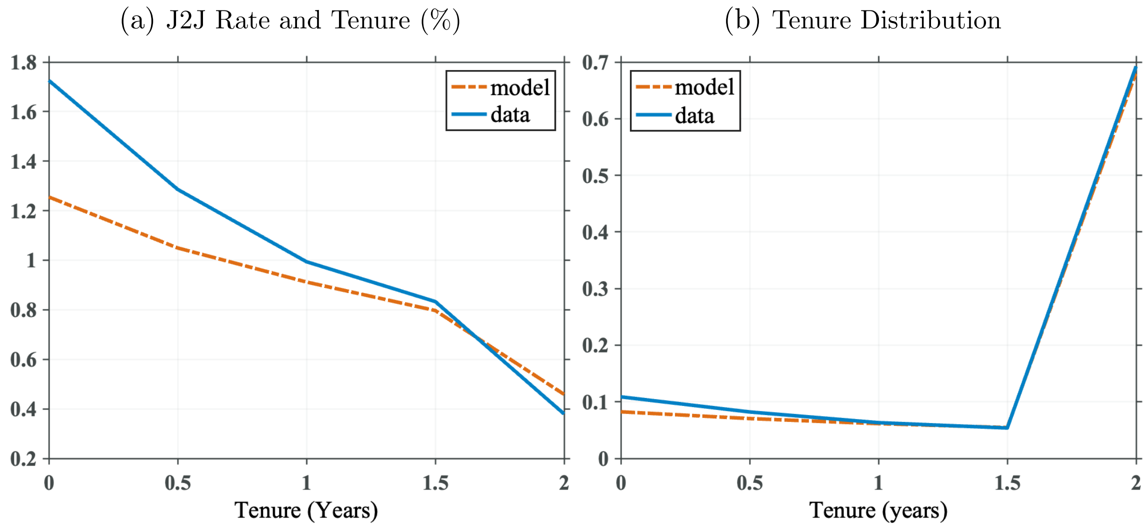
As shown in Figure 4, the steady-state distributions generated by the model align closely with the observed income and wealth distributions from the data. In particular, the model successfully reproduces the fraction of workers at the borrowing constraint, albeit at the cost of a high discount rate. The difficulty in matching certain moments of the wealth distribution, especially the fraction of households at the borrowing constraint, is a well-documented limitation of one-asset incomplete markets models. A potential solution is to introduce an illiquid asset that can be converted into liquid wealth after paying a transaction cost. However, this approach is computationally expensive, as it adds another state variable and policy function. To address the high discount rate, Appendix D presents an alternative calibration that fixes the discount rate at a more reasonable level. Naturally, this adjustment comes at the expense of a poorer match with the wealth distribution.

Untargeted Moments The model captures other aspects of the labor market that were not directly targeted in the calibration exercise. The steady-state unemployment rate is 4.85%, which aligns closely with empirical estimates for the time period. Additionally, as shown in Figure 5, the model endogenously replicates major tenure patterns: it closely matches the overall tenure distribution and reproduces the well-known decline in J2J transitions with tenure. However, the model tends to underestimate the overall number of J2J transitions, especially at low tenure levels. On average, gaining one year of tenure reduces J2J transitions by 0.3 percentage points, both in the model and in the data. This occurs because a higher tenure increases the opportunity cost of switching jobs, as workers face a greater risk of job loss when moving to a new employer.

The model also successfully replicates the spike in U2E transitions around the expiration of unemployment benefits, a pattern first documented by Moffitt (1985), Meyer (1990), and Katz and Meyer (1990). Specifically, the model predicts that U2E transitions increase by 1.59 percentage points when benefits expire. This arises because liquidity-constrained workers lower their reservation wages as benefits run out, accepting lower-paying jobs to avoid prolonged unemployment.

[24] Engbom (2022) estimates the relative search efficiency to be 39.4%.

Figure 5. Untargeted Moments



Note: Panel (a): Monthly job-to-job transition rate, averaged across wages and assets, for workers with different tenure in the model (orange) and data (blue). J2J rates in the data are computed as the share of employed workers with a given tenure who quit their job in a given month. Panel (b): Tenure distribution in the data (blue) compared to the steady-state tenure distribution generated by the model (orange). *Data Source*: SIPP, 1996-2004 panel.

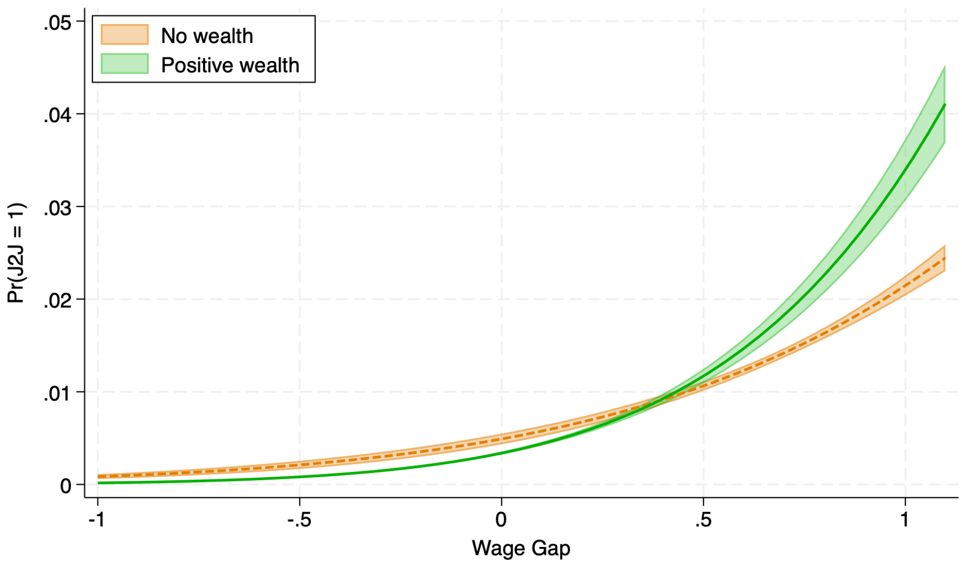
Indeed, the model suggests that wealth influences both U2E transitions and the reservation wages of unemployed workers. In particular, U2E transitions decline with wealth by nearly 0.9 percentage points, from 20.94% for workers with no liquid wealth to 20.05% for workers with some savings, suggesting that wealthier unemployed workers remain jobless longer. However, this effect varies significantly across UI recipients, with the difference exceeding 6 percentage points near the benefits cap. The rationale behind this result lies in the option value of searching: since the job-finding rate is higher while unemployed, wealthier individuals can dissave their assets and remain unemployed longer while waiting for higher-paying job offers. In fact, on average, the reservation wage is about $150 per month higher for workers with savings, allowing them to hold out for better job opportunities rather than immediately accepting lower-wage positions.

5.5 Quantifying the Effect of Wealth on Labor Mobility

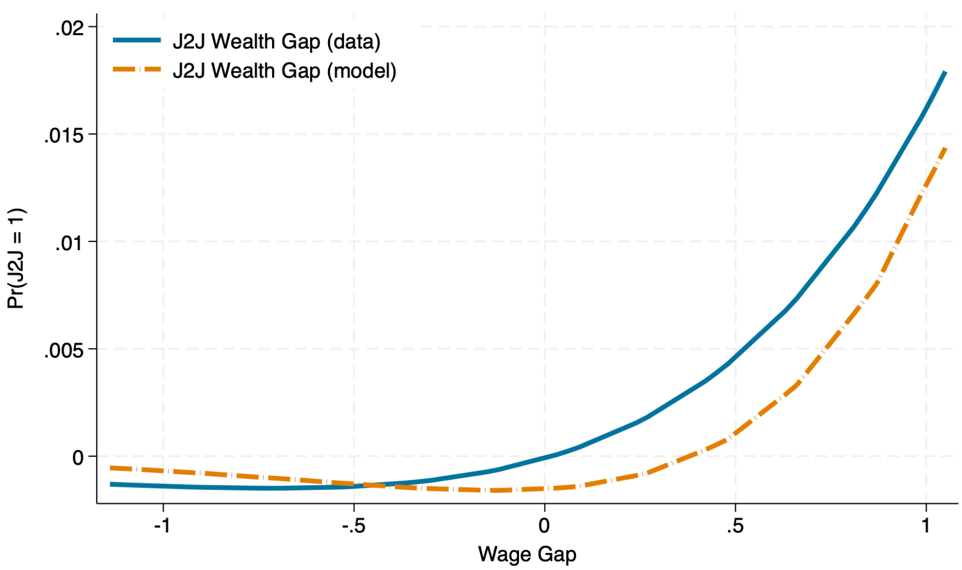
To compare the model's predictions to the data, I simulate a panel of 30,000 workers over a four-year horizon. In line with the data, I define the wage gap as the difference between predicted log wages and each individual's log wage. I then estimate a probit regression of J2J transitions as a function of incentives, liquid wealth, their interaction, and job tenure.

Figure 6. Wealth and Labor Mobility: Model vs Data

(a) Average Predicted Probabilities of Wealth Dummy on J2J (Model vs Data)



(b) Gap in J2J Predicted Probabilities by Wealth (Model vs Data)



Note: Panel (a): Average predicted probability of a job-to-job move for an indicator for positive liquid wealth in the model and the data, evaluated at 100 grid points of the wage gap. Panel (b): Difference in the predicted probability of a job-to-job move by wealth ($J2J_{\{a>0\}} - J2J_{\{a=0\}}$) in the model and the data, evaluated at 100 grid points of the wage gap. In the model and the data, the wage gap is defined as the log-difference between predicted and actual income. *Data Source*: SIPP, 1996-2004 panel.

Figure 6a plots the average predicted probability of J2J transitions across levels of the wage gap, by wealth group, in the simulated data.

The model is able to replicate the patterns observed in the data: workers at the lower end of the job ladder, who have higher expected wage gains, change jobs far more frequently than those in high-paying jobs. Importantly, the model captures the heterogeneous response to wealth across the wage gap distribution: job mobility increases more rapidly with the wage gap for wealthier workers than for liquidity-constrained workers. Quantitatively, among workers with a positive wage gap, the average transition rate is approximately 0.26 percentage points higher for high-wealth individuals relative to the liquidity-constrained.

Both patterns arise endogenously in the model, as the calibration targets only the average J2J transition rate and the quartiles of the wealth distribution separately, without explicitly matching how mobility changes with wealth or the wage gap. As expected, workers in the top income quartile, who have lower wage gaps, rarely change jobs regardless of their wealth status.

To assess the model fit, Figure 6b plots the gap in J2J transitions by wealth (defined as $J2J_{\{a>0\}} - J2J_{\{a=0\}}$) at each level of the wage gap in the model and the data. I then compute the ratio of the areas under the wealth gap curves, conditional on a positive wage gap, in the model and in the data. This ratio suggests that, on average, the model accounts for approximately 60% of the wealth gap observed in the data. In particular, the model explains over 75% of the gap at the bottom of the income distribution, where incentives are strongest, but struggles to match the gap at lower levels of the wage gap.

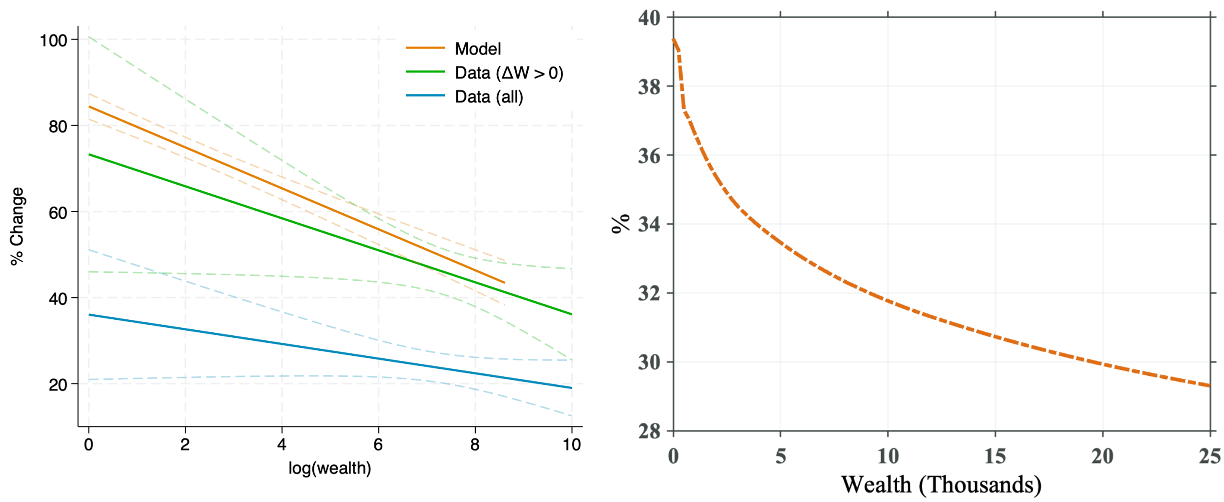
5.6 Reservation Wages

The mechanism behind the relationship between wealth and job mobility can be understood through reservation wages. Recall that the employed reservation wage is the minimum wage offer a worker is willing to accept in order to change jobs. The model predicts that the employed reservation wage declines with liquid assets: wealthier workers are willing to switch jobs for lower offers than liquidity-constrained workers because they can better bear the income risk associated with job mobility. On average, the reservation wage for a high-wealth worker is about \$500 lower than that of an otherwise identical liquidity-constrained worker.

Since reservation wages are not directly observable in the data, I approximate them using the distribution of accepted wage changes after job-to-job (J2J) transitions across the wealth distribution. Figure 7a compares the average percentage change in accepted wages in the model and the data, as well as in the data restricted to J2J movers who transition to higher-paying jobs. This restriction is needed because some job switches in the data reflect career changes or non-pecuniary motives, and therefore involve pay cuts. The figure shows a sharp decline in wage gains as wealth increases. Workers with no liquid wealth accept jobs paying 70–80% more than their previous job, while wealthier workers experience gains that are roughly half as large. This pattern reflects the higher option value of job security for constrained workers: they only switch when the wage gain is sufficiently large to compensate for the higher risk of separation.

Figure 7. Reservation Wage and Job Security Premium

(a) % Change in Accepted Wages after J2J (b) Job Security Premium for Median Worker (%)



Note: Panel (a): Predicted wage change after a job-to-job transition as a function of workers' IHS-transformed liquid wealth, model vs data. $\Delta W > 0$, in green, restricts the sample to J2J movers who transition to higher-paying jobs. Shaded area represents the 95% confidence interval. Panel (b): Job security premium for workers with median income and tenure as a percentage of current wage. *Data Source*: SIPP, 1996-2004 panel.

These dynamics can be summarized in terms of the job security premium, which measures the trade-off workers face between higher wages and higher separation risk when switching jobs. Following Proposition 1, I compute the premium as the difference between the values of employment and unemployment, scaled by the tenure-dependent difference in separation risk, and normalized by current wages. In the model, the average premium is approximately \$1,218, or 42.5% of average monthly wages. This magnitude is substantially higher than the empirical range of switching costs estimated by Caldwell et al. (2025), who report values between 7% and 18% of annual pay. Importantly, the model predicts a steep wealth decline in the premium. For the median worker, the premium declines from nearly 40% of wages for those with no liquidity to 32% for those with \$10,000 in savings. However, the slope is much steeper at low wealth levels, where an additional \$500 decreases the job security premium by over 2 percentage points. This highlights how liquidity-constrained workers prioritize job security over job mobility, and why they tend to remain stuck in lower-paying jobs.

5.7 Quantifying the Job Trap

I now quantify the contribution of the model's main mechanism to inequality and mobility, and explain why I refer to it as a job trap. Recall that in the baseline model, separation rates decline with tenure, so new hires face higher separation risk than tenured workers. This discourages mobility, especially for workers with few assets who cannot easily smooth income fluctuations. To isolate the importance of this channel, I construct a counterfactual in which separation risk is fixed at the average layoff rate observed in the data (0.94%), independent of tenure. This restriction removes the added penalty for job switching, allowing me to quantify how much of the observed inequality is attributable to the tenure-dependent separation risk. I then re-estimate the model under this assumption and compare the resulting outcomes to those of the baseline model.

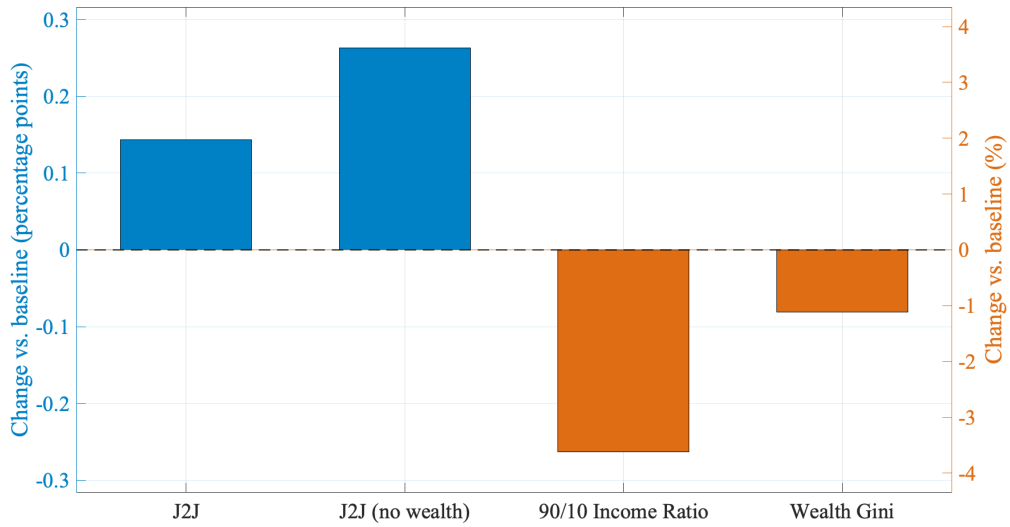
The results of this exercise are presented in Figure 8, which plots the point differences in key mobility and inequality indicators across the two models. Without the tenure-dependent separation risk, job-to-job transitions are nearly 0.15 percentage points higher, a 22.1% increase from 0.65% to 0.79%. Higher job mobility translates directly into lower inequality: the 90/10 income ratio falls by 3.8%, with disproportionate gains for workers at the bottom of the distribution. For instance, among workers with no liquid wealth, job mobility increases by 0.26 percentage points (from 1.49% to 1.76%), suggesting that the removal of additional layoff risk disproportionately benefits the liquidity-constrained.

The counterfactual also yields substantial effects on wealth inequality. The share of workers with no liquid wealth falls by more than 2 percentage points, while average liquid wealth increases by 20%. In turn, the wealth Gini coefficient declines from 63.93 to 63.22, a reduction of 0.7 points. Although this change might sound modest, it is quantitatively meaningful: it exceeds the wealth Gini gap between France and China in 2020[25], and is comparable in magnitude to the entire rise in the U.S. income Gini over the past two decades.

Taken together, these results suggest that favoring job security over mobility is not simply a marginal friction but a quantitatively important source of inequality. Workers do not fully internalize the potential benefits of mobility and remain trapped in low-wage jobs by switching less than they should. Removing this mechanism not only increases job mobility but also reduces both income and wealth inequality in meaningful ways.

[25] Credit Suisse Global Wealth Report 2021, Table 3.

Figure 8. Effects of Removing Tenure-Dependent Layoff Risk on Mobility and Inequality



Note: The figure shows differences between the counterfactual model with constant separation risk and the baseline model. Bars on the left (blue) report changes in job-to-job transition rates, expressed in percentage points. Bars on the right (orange) report changes in inequality indicators (90/10 income ratio and wealth Gini coefficient), expressed in percentages. Positive values indicate increases in the counterfactual relative to the baseline.

6 Welfare Implications

To quantify the welfare effects of different unemployment insurance (UI) policies, I re-estimate the model under alternative parameterizations of the replacement rate, the benefit cap, and the duration of benefits. Each component is varied separately to measure its individual contribution to aggregate welfare. In all cases, the government budget remains balanced through adjustments in the labor income tax rate.

The results highlight distinct roles for each policy parameter. Higher replacement rates provide stronger income smoothing during unemployment spells and deliver the largest direct welfare gains, particularly for liquidity-constrained households. Raising the benefit cap primarily benefits higher earners, while extending benefit duration disproportionately helps lower-wealth workers by reducing their need to dissave during long unemployment spells. Together, these components shape both the average welfare level and its distribution across the population.

Finally, I intend to evaluate how UI generosity interacts with labor mobility by computing the job security premium under more generous policies. In the baseline, liquidity-constrained workers require very high wage gains to offset the risk of job loss. More generous UI should reduce this risk, lowering the premium and encouraging greater job-to-job mobility.

7 Conclusion

This paper studies the role of wealth in shaping job mobility and labor market outcomes. I propose and quantify a new mechanism through which household liquidity affects job mobility, thereby shaping wage dynamics and labor market outcomes. Using survey data from the SIPP, I document that workers with higher liquid wealth exhibit substantially greater job-to-job mobility than their liquidity-constrained counterparts, especially at the bottom of the job ladder. These patterns persist even after controlling for tenure, income, and demographic characteristics, suggesting a critical role for wealth in facilitating labor reallocation.

To interpret these findings, I construct a job ladder model model with on-the-job search, risk-averse workers, and incomplete markets. The model incorporates heterogeneous workers facing idiosyncratic income risk, borrowing constraints, and a precautionary savings motive. Calibrated to match key features of the U.S. labor market and the wealth distribution, the model replicates both the overall level of job mobility and its heterogeneity across the wealth distribution. In particular, it generates a quantitatively significant gap in mobility between high- and low-wealth workers in response to wage incentives, explaining nearly 60% of the pattern observed in the data.

A central mechanism underlying this result is the endogenous decline in reservation wages with wealth: workers with greater liquidity are more willing to accept riskier transitions, leading to more frequent mobility and higher lifetime income. This channel explains why job mobility increases with wealth despite similar incentives and why liquidity-constrained workers require a higher job security premium to switch employers. The model also accounts for roughly half of the observed wealth gradient in mobility and matches empirical estimates of switching costs and wage gains upon transition.

Counterfactual simulations reveal that tenure-dependent separation risk is a major driver of inequality: removing it raises mobility by over 20%, reduces the 90/10 income ratio by nearly 4%, and lowers the wealth Gini by 0.7 points. These findings have important implications for labor market dynamics and policy. They suggest that liquidity constraints may prevent low-wealth workers from accessing better job opportunities, slowing wage growth and deepening earnings inequality. Policies aimed at easing short-term liquidity, such as expanded unemployment insurance or emergency cash transfers, may provide a pathway out of this job trap for low-wealth workers.

Future work will extend this framework into a full HANK environment to examine how the expansion of unemployment insurance during the COVID-19 recession affected job-to-job transitions among low-income workers and contributed to inflationary pressures.

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Appendix

A Empirics

This appendix describes the construction of the dataset used in the empirical analysis, based on the 1996–2004 panels of the Survey of Income and Program Participation (SIPP). It outlines the data sources, variable definitions, sample selection criteria, and harmonization procedures. In addition, this section presents supplementary empirical results and a series of robustness checks not included in the main text.

A.1 Data

The SIPP is a longitudinal survey in which respondents are interviewed every four months and asked retrospective questions covering the previous four-month period. Each panel spans multiple years and is structured into a core set of monthly labor market and demographic variables, as well as a series of topical modules that collect more detailed information at specific intervals. The following topical modules provide the key information used in the analysis:

- *Employment Experience:* Topical Module 1;
- *Education Background and Citizenship:* Topical Module 2;
- *Assets and Liabilities:* Topical Modules 3, 6, 9, 12;
- *Work schedule:* Topical Modules 4 and 10;
- *Amenities:* Topical Module 5.

The available waves vary by panel year: the 1996 and 2004 panels contain up to 12 waves, while the 2004 panel contains only 8. All modules are harmonized across panels and merged at the individual-wave level, or at the person level, for example, in the case of static characteristics such as education or work history.

Job Transitions: Using information on separation reasons, employer identifiers, and job search behavior, I construct monthly labor market transitions. A job-to-job (J2J) transition is defined as a voluntary separation: specifically, when a worker reports quitting for work-related reasons—followed by re-employment with a different employer within four weeks and no intervening job search activity. In cases where the worker explicitly states quitting to take another job, I allow for up to three months of non-employment between jobs.

Employment-to-unemployment (E2U) transitions are identified when the separation is initiated by the employer. This includes cases where the respondent reports being laid off (temporarily or permanently), dismissed, or ending a fixed-term contract. Unemployment-to-employment (U2E) transitions are coded when an unemployment spell ends in re-employment, or when an individual not actively searching reports starting a new job.

Wealth Variables: Wealth variables are constructed using detailed asset and liability information from the topical modules. To compute liquid wealth, I include individual and jointly held balances in checking and savings accounts, stocks, bonds, mutual funds, and money market accounts. Joint account balances are split evenly across spouses. Net liquid wealth subtracts credit card and short-term liabilities. Illiquid wealth includes defined-contribution retirement accounts (IRAs, 401(k)s, KEOGH), home equity, vehicle value, business equity, and other real estate holdings. Observations with hot-deck imputed values for core asset or debt variables are excluded. Because wealth is only measured annually in SIPP, I linearly interpolate all asset variables at the monthly level. Forward interpolation is used in the last year of the panel when necessary.

Job Characteristics: Job-level variables (including union coverage and disability, industry, and occupation) are harmonized across SIPP panels to ensure consistency over time. In particular, industry classifications differ across panels: the 1996 and 2001 panels follow the 1990 Census industry codes, while the 2004 and later panels follow the 2000 Census scheme. I harmonize these into 50 consistent industry groupings, following a modified version of the recoding scheme used by Pollard et al. (2019), which aggregates detailed industries into broader sectors. Occupation codes are similarly harmonized using the classification scheme proposed by Meyer and Osborne (2005), which maps various Census occupation codes into consistent categories across time. I additionally aggregate occupations into 14 major groups, which are used in Regression 2.2.

Demographics and Harmonization: Demographic variables are harmonized across panels with particular attention to changes in coding schemes in the 2004 panel. Race and ethnicity are recoded to produce consistent four-category classifications (White, Black, Hispanic, Other). Citizenship is coded consistently across survey years by adjusting for differences in the recording of naturalized status. Education is collapsed into five categories: less than high school, high school, some college, college degree, and graduate degree. State identifiers and birth state codes are recoded to account for inconsistencies across waves and to aggregate low-frequency observations.

Sample Selection: I restrict the analytic sample to individuals aged 18 to 60 who are part of the civilian labor force. I exclude military personnel, full-time students, unpaid family workers, and individuals who have never worked for six consecutive months. Respondents with zero reported income, fully imputed wealth data, or in the bottom 3% of the income distribution are also excluded. These restrictions ensure that the analysis focuses on working-age individuals with observable and meaningful attachment to the labor market and valid asset information. Including these cases does not significantly change the core estimation results.

A.2 Wealth and Unemployment

I now turn to provide additional evidence of how wealth affects the job search behavior of unemployed workers. Several studies (Bloemen and Stancanelli, 2001; Algan et al., 2003; Card et al., 2007; Basten et al., 2014; Huang and Qiu, 2022) have shown that higher liquidity increases unemployment duration and leads to higher accepted wages upon re-employment. In this section, I validate these findings in my data, following the methodology of Huang and Qiu (2022). First, I estimate the elasticity of net-liquid wealth on the probability of finding a job out of unemployment:

$$Pr(U2E_{it} = 1) = F(\alpha_t + \beta_1 a_{it} + \beta_2 X_{it} + \epsilon_{it}) \quad \text{if} \quad U = 1$$

where α_t represents month fixed effects, a_{it} is the inverse hyperbolic sine (IHS) transformation of net-liquid wealth, $\ln(a + \sqrt{1 + a^2})$, and X_{it} is a set of demographic controls, including a quadratic function of both age and experience, race, gender, education, marital status, disability, and current state[26]. The sample consists of unemployed individuals actively searching for work. In this specification, a negative coefficient on wealth implies that, conditional on being unemployed, wealthier individuals tend to remain unemployed longer.

Next, I estimate the impact of wealth on accepted wages upon re-employment:

$$ln(w_{it}) = \alpha + \beta_1 a_{it} + \beta_2 X_{it} + \epsilon_{it} \quad \text{if} \quad U2E = 1$$

where w_{it} is the first month's income after unemployment, X_{it} includes the same demographic controls as in the previous estimation, and a_{it} is the IHS transformation of net-liquid wealth. The estimates for both regressions are reported in Table 3. The results confirm that unemployed workers with higher savings experience longer unemployment durations and accept

[26] Unlike Huang and Qiu (2022), I am unable to control for observed workers skills.

Table 3. Regressions of Liquid Wealth on U2E and Accepted Wages

	U2E	**ln(w)**
Liquid Wealth	-0.007^{**}	0.011^{***}
	(0.003)	(0.002)
Full Controls	Yes	Yes
Month Fixed Effects	Yes	Yes
N	36,741	5,324

Note: All regressions are estimated for unemployed workers only, controlling for both demographic characteristics and time fixed-effects. Elasticities are w.r.t $\ln(a+\sqrt{1+a^2})$. Net-liquid wealth is defined as the sum of checking and savings accounts, money markets, mutual funds, stock, bonds, and equity net of bills and credit card debt. *** statistically significant at 1%. *Source* SIPP, 1996 panel.

higher wages upon finding a job. Specifically, workers with $1,000 in savings accept wages that are 8.4% higher than those with no savings.

A.3 Additional Results

Table 4 presents the coefficients from the probit regressions in Equation 2.2 for four different wealth measures: net liquid wealth, illiquid wealth, net-illiquid wealth, and household liquid wealth. Although the results are only reported for the dummy specification, they remain qualitatively similar if using the IHS specification of wealth.

Across all three regressions, the coefficient on the incentive measure (ΔW) remains consistently positive and strongly significant. Notably, while the coefficient on the dummy for net liquid wealth is initially insignificant, it becomes positive and highly significant when interacted with the incentive measure. This suggests that as incentives increase, workers with some positive liquid assets, net of any debt, are significantly more likely to change jobs than those with no wealth. In contrast, none of the regressions for illiquid wealth or net illiquid wealth yield significant coefficients. One possible explanation is that illiquid wealth, such as home equity or retirement accounts, cannot be readily accessed to smooth consumption, making it less relevant for short-term job search decisions. Additionally, younger workers, who make up the majority of job movers, tend to hold little illiquid wealth, further reducing its influence on job-to-job transitions.

In addition, I report additional coefficients estimates from the main two regressions. First, Table 5 reports the results of earnings regressions that relate log monthly income to demographic and job characteristics. The estimates align with standard findings: earnings increase with age and tenure but at a decreasing rate, are significantly higher for more educated workers, and are lower for women, racial minorities, part-time workers, and those

Table 4. Probit Regression of Job-to-Job Transitions on Different Wealth Variables

	Job-to-job transition			
Asset Type:	Net-liquid	Illiquid	Net-illiquid	HH Liquid
ΔW	0.537***	0.570***	0.658***	0.377***
	(0.071)	(0.179)	(0.052)	(0.116)
Wealth	−0.015	0.022	−0.007	0.006
	(0.022)	(0.039)	(0.018)	(0.029)
Wealth$*\Delta W$	0.155**	0.058	0.062	0.379***
	(0.074)	(0.203)	(0.074)	(0.127)
Full Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes

Note: The table reports the coefficients from a probit regression on a wealth dummy and transition incentives (Δw), defined as the difference between a worker's predicted income and actual income. The three columns correspond to different wealth measures: Column I includes net-liquid wealth, Column II includes illiquid wealth, Column III includes net-illiquid wealth, and Column IV includes household liquid wealth. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

with disabilities. Union membership and full-time status are associated with substantial earnings premiums. The inclusion of worker fixed effects in the LPM model explains a large share of the variation in earnings ($R^2 = 88\%$).

Second, Table 6 presents the coefficients estimates of the controls in the job-to-job transitions regression as a function of liquid wealth. J2J transitions are significantly less likely for older workers, those with longer job tenure, and union members, while higher education, citizenship, and good health are positively associated with mobility. Importantly, Black and Hispanic workers face lower J2J transition probabilities, even after controlling for a rich set of job and demographic factors.

Table 5. Regressions of Earnings on Demographic and Job Characteristics

	Log(Monthly Earnings)	
	OLS + FE	OLS
age	0.053***	0.016***
	(0.004)	(0.002)
age^2	−0.0007***	−0.0002***
	(0.000)	(0.000)
log(tenure)	0.030***	0.097***
	(0.003)	(0.002)
experience	-	0.009***
		(0.001)
education		
high school degree	0.065*	0.064***
	(0.038)	(0.008)
some college	0.034	0.135***
	(0.037)	(009)
college degree	0.160***	0.333***
	(0.045)	(0.014)
graduate degree	0.224***	0.506***
	(0.051)	(0.014)
race		
black	-	−0.060***
		(0.008)
hispanic	-	−0.070***
		(0.023)
other	-	−0.029**
		(0.013)
female		−0.207***
		(0.006)
citizens	-	0.086***
		(0.018)
disability	−0.031***	−0.161***
	(0.006)	(0.010)
union	0.052***	0.151***
	(0.006)	(0.009)
Month Fixed Effects	Yes	Yes
Worker Fixed Effects	Yes	-
R^2	87.78%	57.15%
N	863,942	863,942

Note: The table show the coefficients for some of the controls used in wage regression. Other controls include month and state fixed effects, occupation and industry fixed effects, experience square, marital status, class of workers, full time worker and number of kids. The OLS regression also includes the type of high school attended, and birth state or country. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

Table 6. Regressions of Job-to-Job Flows on Liquid Wealth and Controls

	Job-to-job transition	
	Probit	**LMP** (%)
log(age)	−0.425***	−0.409***
	(0.045)	(0.080)
log(tenure)	−0.211***	−0.254***
	(0.009)	(0.013)
log(experience)	0.044**	0.042
	(0.021)	(0.037)
education		
high school degree	−0.004	0.002
	(0.027)	(0.036)
some college	0.087***	0.118***
	(0.025)	(0.041)
college degree	0.117***	0.129***
	(0.035)	(0.046)
graduate degree	0.131***	0.143***
	(0.038)	(0.052)
female	−0.035**	−0.049**
	(0.016)	(0.022)
kids	0.013	−0.027
	(0.016)	(0.021)
race		
black	−0.098***	−0.114***
	(0.027)	(0.034)
hispanic	−0.085***	−0.113***
	(0.024)	(0.035)
other	−0.066***	−0.089***
	(0.024)	(0.032)
citizenship	0.071***	0.147***
	(0.027)	(0.040)
disability	−0.142***	−0.147***
	(0.0391)	(0.037)
union	−0.188***	−0.065***
	(0.032)	(0.019)
Month Fixed Effects	Yes	Yes
N	823,817	823,817

Note: The table show the coefficients for some of the controls used in the probit regression (column 2) and the linear probability model (column 3). The results are reported for the IHS specification of wealth, but the coefficients are nearly identical in the dummy specification. Other controls include month and state fixed effects, occupation and industry fixed effects (aggregated), marital status, class of workers, and the type of high school attended. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. * statistically significant at 10%; ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

A.4 Robustness

This section presents the main robustness checks discussed in the main text. Specifically, I examine the sensitivity of the results to concerns about wealth endogeneity (Table 7), alternative definitions of the job ladder (Table 8), different functional forms for the baseline specification (Table 9), and the role of job amenities (Table 10). Each exercise confirms the main findings: liquidity constraints tend to lower job-to-job mobility. In particular, the estimates remain robust when instrumenting liquid wealth with parents' wealth among young workers, when relaxing assumptions on the definition of job ladders, and when considering job amenities.

In addition, I report several robustness checks not discussed in the main text. First, I explore heterogeneity in the relationship between wealth, incentives, and job mobility across age groups (Table 11). This test is motivated by the idea that older workers may face different mobility constraints and that their accumulated wealth may reflect long-run earnings histories. As expected, the strength of the wealth-incentive interaction is somewhat attenuated among older cohorts, but it remains positive and significant across all age groups.

Second, I restrict the sample to workers who experience positive wage gains following a job-to-job transition. This ensure that the estimated effect of liquid wealth is driven by workers climbing the job ladder towards higher-paying jobs, rather than by wage cuts. As shown in Table 12, the coefficient on the interaction between liquid wealth and transition incentives remains positive and statistically significant across all specifications. The magnitude of the coefficients is even larger than those in the main specification, suggesting that the effect is particularly pronounced among workers who move to better-paying jobs.

Third, I limit the sample to workers with strictly positive incentives (those whose predicted wage exceeds their current wage), thus excluding individuals for whom switching jobs may not be beneficial because they are already well-matched. The results, reported in Table 13, show that the effect of incentives increases in magnitude compared to the main specification, and the wealth-incentive interaction remains positive and statistically significant in the dummy specification.

Lastly, I test whether the use of worker fixed effects in the wage regression may overcorrect for unobserved traits that are correlated with wealth and mobility, such as job switching behavior or individual ambition. To address this, I re-estimate the main specification excluding worker fixed effects from the first-stage wage regression (Table 14). The coefficient on the interaction between wealth and incentives remains positive and statistically significant across all specifications, indicating that the results are not sensitive to this modeling choice.

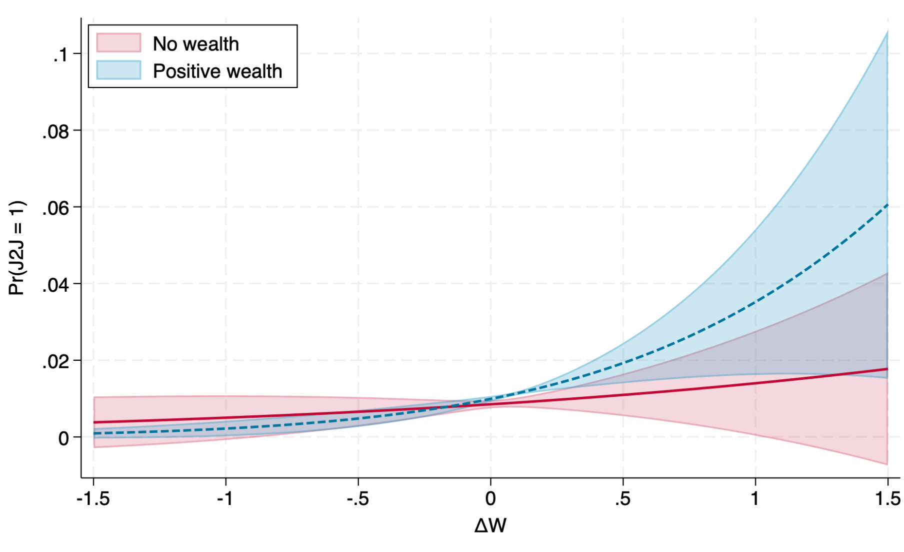
Taken together, these robustness show that the main results are consistent across a wide variety of specifications, reinforcing the role of liquid wealth in shaping job mobility.

Table 7. Regressions of Job-to-Job Transitions on Parents' Liquid Wealth

	Job-to-job transition			
	Probit		LPM	
Specification:	Dummy	IHS	Dummy (%)	IHS (%)
Δw	0.195	0.144	0.80*	0.340
	(0.205)	(0.137)	(0.105)	(0.473)
Liquid wealth	0.059*	0.0005	0.245**	0.015
	(0.036)	(0.005)	(0.105)	(0.013)
Liquid wealth$*\Delta w$	0.343	0.053**	1.640*	0.308**
	(0.294)	(0.027)	(0.938)	(0.130)
Full Controls	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
N	42,381	42,381	42,381	42,381

Note: The table shows the coefficients for a dummy and IHS ($\ln(a+\sqrt{1+a^2})$) specifications for *parents* liquid wealth using a probit regression (columns 1-2), and a linear probability model (columns 3-4). The coefficients for the LPMs are reported in percentage. Δw_{it} represents transitions incentives, defined as the difference between the workers' predicted income and their actual income. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

Figure 9. Average Predicted Probabilities of Parents Wealth Dummy on J2J



Note: The figure shows the average predicted probability of a job-to-job move for a dummy of parents' liquid wealth, evaluated at 100 grid points of incentives (Δw), which are defined as the difference between the workers' predicted income and their actual income. Standard errors are first clustered at the state level and then bootstrapped using a two-step estimator. Confidence interval level is 5%. *Source*: SIPP, 1996-2004 panel.

Table 8. Probit Regressions of Job-to-Job Flows on Liquid Wealth - Different Job Ladders

	Job-to-job transition			
Specification:	**(I)**	**(II)**	**(III)**	**(IV)**
Δw	0.380***	0.381***	0.357***	0.169***
	(0.084)	(0.084)	(0.084)	(0.030)
Liquid wealth	−0.014	−0.007	−0.006	0.018
	(0.023)	(0.022)	(0.023)	(0.022)
Liquid wealth$*\Delta w$	0.348***	0.349***	0.366***	0.077**
	(0.091)	(0.090)	(0.092)	(0.030)
Full Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
N	823,817	823,817	823,817	823,817

Note: The table reports the coefficients from a probit regression on a dummy for liquid wealth and transition incentives (Δw), defined as the difference between a worker's predicted income and actual income. The four columns correspond to different incentive measures, each estimated with a distinct set of controls: Column I excludes industry, Column II excludes occupation, Column III excludes state, and Column IV excludes all three. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

Table 9. Probit Regressions of Job-to-Job Flows on Liquid Wealth - Functional Forms

	Job-to-job transition			
Specification:	**(I)**	**(II)**	**(III)**	**(IV)**
Δw	0.933***	0.341**	0.396***	0.399***
	(0.072)	(0.144)	(0.109)	(0.157)
Liquid wealth	−0.016	−0.009	−0.011	−0.007
	(0.023)	(0.023)	(0.023)	(0.023)
Liquid wealth$*\Delta w$	0.205***	0.348***	0.358***	0.321***
	(0.069)	(0.108)	(0.105)	(0.113)
Full Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
N	823,817	823,817	823,817	823,817

Note: The table reports the coefficients from a probit regression on a dummy for liquid wealth and transition incentives (Δw), defined as the difference between a worker's predicted income and actual income. The four columns correspond to different specifications: in Column I, incentives are defined as $\Delta w = -min(w_{ist} - \tilde{w}_{ist}, 0)$; Column II includes an interaction between incentives and education; Column III includes an interaction between incentives and marital status; and Column IV includes both interactions simultaneously. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

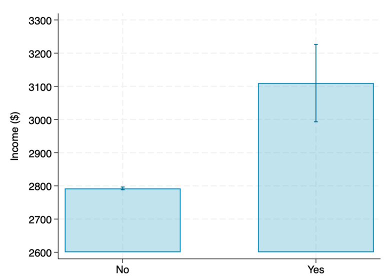
Table 10. Regressions of Income on Job Amenities

	Income ($)		
Specification:	**(I)**	**(II)**	**(III)**
Work from Home	309.5***	-	-
	(54.1)		
Work on Weekends	−85.6***	-	-
	(22.2)		
Saving Plan	401.5***	-	-
	(27.8)		
Health Insurance	-	232.8***	-
		(28.4)	
Tuition Assistance	-	-	468.5***
			(58.2)
Full Controls	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
N	72,556	53,907	6,461

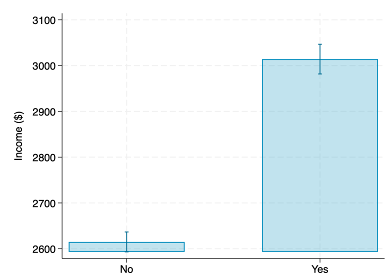
Note: The table shows the coefficients from an income regression on various job amenities, controlling for both demographic and job characteristics. The three columns correspond to different model specifications: Column I includes work-from-home, weekend work, and employer-sponsored savings plans, all sourced from SIPP Topical Module 4. Column II and Column III include solely employer-provided health insurance and tuition assistance, respectively, which are obtained from SIPP Topical Module 5. Since tuition assistance is only reported for currently enrolled students, creating a sample restriction and selection issue, it is analyzed separately from health insurance. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator.*** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

Figure 10. Income and Job Amenities

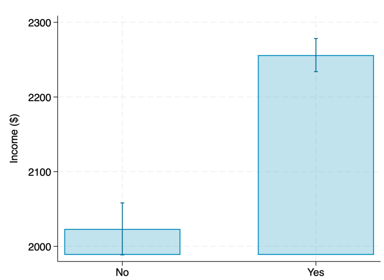
(a) Work from Home



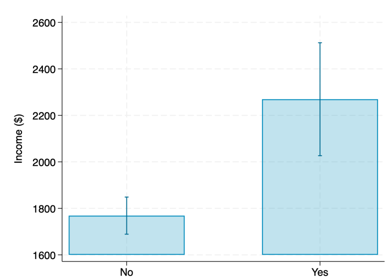
(b) Saving Plan



(c) Health Insurance



(d) Tuition Reimbursement



A.5 Additional Robustness

Table 11. Robustness: Regressions by Age Group

	Job-to-job transition			
Age Group:	**(18-35)**	**(18-40)**	**(36-60)**	**(41-60)**
Δw	0.350***	0.322**	0.335***	0.418***
	(0.115)	(0.113)	(0.101)	(0.127)
Liquid wealth	−0.022	−0.021	−0.005	0.004
	(0.030)	(0.026)	(0.031)	(0.032)
Liquid wealth$*\Delta w$	0.423***	0.443***	0.354***	0.236*
	(0.128)	(0.121)	(0.106)	(0.135)
Full Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes

Note: The table shows the coefficients for a dummy specifications for liquid wealth using a probit regression. The four columns correspond to regressions across different age groups. Δw_{it} represents transitions incentives, defined as the difference between the workers' predicted income and their actual income. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

Table 12. Robustness: Regressions on Positive Wage Gains after J2J

	Job-to-job transition			
	Probit		**LPM**	
Specification:	Dummy	IHS	Dummy (%)	IHS (%)
Δw	0.336***	0.381***	0.741***	0.925***
	(0.092)	(0.083)	(0.234)	(0.227)
Liquid wealth	−0.009	−0.005**	0.033	0.000
	(0.023)	(0.002)	(0.034)	(0.003)
Liquid wealth$*\Delta w$	0.393***	0.046***	0.886***	0.085***
	(0.099)	(0.011)	(0.253)	(0.029)
Full Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes

Note: The table shows the coefficients for a dummy and IHS ($\ln(a + \sqrt{1+a^2})$) specifications for liquid wealth using a probit regression (columns 1-2), and a linear probability model (columns 3-4). The sample is restricted to workers that experience a positive wage increase after a j2j transition. The coefficients for the LPMs are reported in percentage. Δw_{it} represents transitions incentives, defined as the difference between the workers' predicted income and their actual income. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

Table 13. Robustness: Regression over Positive Incentives

	Job-to-job transition			
	Probit		**LPM**	
Specification:	Dummy	IHS	Dummy (%)	IHS (%)
Δw	1.075***	1.143***	3.613***	4.165***
	(0.065)	(0.056)	(0.525)	(0.487)
Liquid wealth	0.032	0.004	−0.043	0.004
	(0.028)	(0.035)	(0.046)	(0.006)
Liquid wealth$*\Delta w$	0.106*	0.003	1.242**	0.068
	(0.062)	(0.007)	(0.506)	(0.061)
Full Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes

Note: The table shows the coefficients for a dummy and IHS ($\ln(a + \sqrt{1 + a^2})$) specifications for liquid wealth using a probit regression (columns 1-2), and a linear probability model (columns 3-4). The sample is restricted to workers who have positive incentives. The coefficients for the LPMs are reported in percentage. Δw_{it} represents transitions incentives, defined as the difference between the workers' predicted income and their actual income. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

Table 14. Robustness: Allowing for Unobserved Worker Heterogeneity

	Job-to-job transition			
	Probit		**LPM**	
Specification:	Dummy	IHS	Dummy (%)	IHS (%)
Δw	0.098**	0.125***	0.163*	0.245***
	(0.048)	(0.045)	(0.088)	(0.085)
Liquid wealth	0.017	0.003	0.029	0.007
	(0.024)	(0.035)	(0.034)	(0.004)
Liquid wealth$*\Delta w$	0.190***	0.021***	0.271***	0.021**
	(0.056)	(0.006)	(0.093)	(0.010)
Full Controls	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes

Note: The table shows the coefficients for a dummy and IHS ($\ln(a + \sqrt{1 + a^2})$) specifications for liquid wealth using a probit regression (columns 1-2) and a linear probability model (columns 3-4). The coefficients for the LPMs are reported in percentage. Δw_{it} represents transitions incentives, defined as the difference between the workers' predicted income and their actual income. In this case, predicted income *does not* include workers fixed effects. Standard errors, shown in parentheses, are first clustered at the state level and then bootstrapped using a two-step estimator. ** statistically significant at 5%; *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

B Model

B.1 Proofs

Proof of Proposition 1. Let $u(\cdot)$ be a continuous and twice differentiable function. By definition of reservation wage, we have: $V(a, R(a, w, \tau), 0) = V(a, w, \tau)$. Expanding the equation, this becomes:[27]:

$$\begin{aligned}\rho V(a, R, 0) - \rho V(a, w, \tau) = {} & u(c(a, R, 0)) + \frac{\partial V}{\partial a}(ra + R - c(a, R, 0)) + \frac{\partial V}{\partial \tau}\pi_\tau \\ & + \lambda_e \left(\int \max\{V(a, R, 0), V(a, \tilde{w}, 0)\} dF(\tilde{w}) - V(a, R, 0) \right) \\ & + \delta(0)[U(a) - V(a, R, 0)] \\ & - \left(u(c(a, w, \tau)) + \frac{\partial V}{\partial a}(ra + w - c(a, w, \tau)) + \frac{\partial V}{\partial \tau}\pi_\tau \right. \\ & + \lambda_e \left(\int \max\{V(a, w, \tau), V(a, \tilde{w}, 0)\} dF(\tilde{w}) - V(a, w, \tau) \right) \\ & \left. + \delta(\tau)[U(a) - V(a, w, \tau)] \right) = 0\end{aligned}$$

Substituting the definition of reservation wage $V(a, R, 0) = V(a, w, \tau)$ and the first order condition for consumption $u'(c) = \frac{\partial V(a,R,0)}{\partial a} = \frac{\partial V(a,w,\tau)}{\partial a}$, this simplifies to:

$$\begin{aligned}0 = {} & u'(c)[(R - w) + (c(a, R, 0) - c(a, w, \tau))] \\ & + [u(c(a, R, 0)) - u(c(a, w, \tau))] \\ & + [\delta(0) - \delta(\tau)][U(a) - V(a, w, \tau)]\end{aligned}$$

Solving for the reservation wage we have:

$$\begin{aligned}R = w + {} & \frac{[\delta(0) - \delta(\tau)][V(a, w, \tau) - U(a)]}{u'(c)} \\ & + \underbrace{[(c(a, R, 0) - c(a, w, \tau))]}_{=0} + \underbrace{\frac{[u(c(a, R, 0)) - u(c(a, w, \tau))]}{u'(c)}}_{=0}\end{aligned}$$

Note, however, that from the first order conditions we have that $c(a, R, 0) = u'(\frac{\partial V}{\partial a})^{-1} = c(a, w)$. This implies that the last two terms cancel out and we can rewrite the reservation

[27] For simplicity, in the proof I abbreviate $R(a, w, \tau) = R$

wage as

$$R = w + \frac{[\delta(0) - \delta(\tau)][V(a, w, \tau) - U(a)]}{u'(c)}.$$

Finally, we can see that $R > w$ since $\delta(0) > \delta(\tau)$ (as separations are downward-sloping in tenure) and $V(a, w, \tau) > U(a)$, as workers prefer working to being unemployed.

□

B.2 General Equilibrium Derivation of the Hazard Rate

This section derives the separation hazard rate endogenously from the firm's problem. Firms post vacancies at flow cost k and meet workers according to a standard Cobb–Douglas matching function[28]. Upon meeting, the worker and the firm first draw the quality of their match ω, which is unknown to both and is either good with probability p or bad with probability $1 - p$. In addition, the pair draws an output level y from a known distribution $G(y)$, representing the productivity of a good match.

Firms commit to pay workers *at least* an exogenous fraction $\beta \in (0, 1)$ of expected output for the duration of the match: $w(y) = \beta \mathbb{E}[y]$. This wage rule can be interpreted as arising from union contracts or rigid bargaining, with the additional assumption of firm commitment, so that wages cannot be reduced once agreed upon. Initially, firms cannot observe match quality. They therefore earn expected revenues $\mathbb{E}[y] = py$ based on their beliefs and pay the pre-learning wage $w(y) = \beta py$. Over time, as the match survives, the firm updates its belief that the match is good and adjusts revenues and wages accordingly. In particular, expected profits for a filled match at time t depend on the posterior probability that the match is good (p), conditional on survival until time t:

$$P(t) = \frac{p}{p + (1 - p)e^{-\mu t}},$$

so expected revenues evolve according to $\mathbb{E}[y] = P(t)y$. If the match is revealed to be bad, revenues drop to zero (or, alternatively, the firm can be interpreted as incurring a large cost for the worker mistake), but the firm must still pay the pre-committed wage: $w_{\text{post}} = \beta P(t)y$. Thus, wages and revenues increase with the duration of the match unless learning reveals that the match is bad, in which case the worker is fired.

The firm's problem is summarized by the following value functions:

[28] Meetings are governed by $M(U, V) = U^{\alpha} V^{1-\alpha}$, $\alpha \in (0, 1)$, with labor-market tightness $q = V/U$.

- $J(y,t)$: value of a filled job with output y and match duration t before learning if the match quality is bad.
- J_v: value of a vacancy. By free entry, $J_v = 0$ in equilibrium.
- $J_b(y,t)$: value of a filled match known to be bad ($\omega = b$).

Value of a Filled Job. The firm's Bellman equation $J(y,t)$ for a match producing output y with duration t is:

$$\rho J(y,t) = \underbrace{(1-\beta)P(t)y}_{\text{flow expected profit}} + \frac{\partial J(y,t)}{\partial t} + \underbrace{\mu(1-p)\left(J_b(y,t) - J(y,t)\right)}_{\text{Poisson learning}} + \underbrace{\left(J_v - J(y,t)\right)\mathbb{1}_{\{U > V(w(r))\}}}_{\text{worker quits}} + \underbrace{\lambda\left(J_v - J(y,t)\right)\mathbb{1}_{\{V(w(r')) > V(w(r))\}}}_{\text{worker poached}} \tag{7}$$

where the first term captures expected flow profits when match duration is t; $\partial_t J$ captures the deterministic change in the continuation value as the posterior probability $P(t)$ evolves with match duration, the second accounts for Poisson learning at rate μ, while the last two terms capture worker separations due to quitting or poaching.

Value of a Bad Match. If the firm learns the match is bad ($\omega = b$), it earns flow profit $y = 0$ but, due to its wage commitment, must still pay workers the pre-committed wage $w(y) = \beta P(t)y$. Since firing is costless, the firm compares the value of continuation with the vacancy option:

$$\rho J_b(y,t) = -w(y,t) + (J_v - J_b(y,t))\,\mathbb{1}_{\{J_v > J_b(r)\}} + (J_v - J_b(y,t))\left(\mathbb{1}_{\{U > V(w(r))\}} + \lambda \mathbb{1}_{\{V(w(y')) > V(w(y))\}}\right)$$

Since $J_b < J_v = 0$, it is strictly optimal to fire bad matches immediately and retain good matches indefinitely.

Value of a Vacancy and Free Entry. Posting a vacancy costs k until it fills at rate $q(\theta)$, yielding expected match value $\mathbb{E}_y[J(y,t)]$. Free entry requires

$$J_v = -k + q(\theta) \int J(y,t)\, dF_r(y) \;=\; 0$$

which pins down labor-market tightness $\theta = V/U$.

Hazard Rate. At any time t, separation occurs only if (i) the match is bad ($\omega = 0$), and (ii) the firm receives the bad signal at that instant. Since learning arrives at Poisson rate μ, the unconditional separation intensity is:

$$\mu(1-p)$$

However, conditional on a match surviving until time t, some other bad matches have already been screened out. The probability that a bad match remains undiscovered at tenure t is $(1-p)e^{-\mu t}$, while the probability of a surviving good match is p. Thus, the instantaneous hazard rate from the worker's perspective is given by:

$$\delta(t) = \frac{(1-p)\,\mu\, e^{-\mu t}}{p + (1-p)\, e^{-\mu t}}\,,$$

which is strictly decreasing in tenure. As $t \to \infty$, only good matches remain and $\delta(t) \to 0$.

C Computational Appendix

C.1 HJB Equations

Substituting the first order conditions $u'(c) = \rho V_a(a, w, \tau)$ and $u'(c) = \rho U_a(a, b(w, d))$, we can rewrite the HJB equations as:

$$\begin{aligned}
\rho U(a, b(w,d)) &= \max_c \;\; u(c) + (ra + b(w,d) - c)\frac{\partial U}{\partial a} + \pi_d \frac{\partial U}{\partial d} \\
&+ \lambda_u \left(\int \max\{U(a, b(w,d)), V(a, \tilde{w}, 0)\} \;\; dF(\tilde{w}) - U(a, b(w,d)) \right) \\
\rho V(a, w(\tau), \tau) &= \max_c \;\; u(c) + (ra + w(\tau) - c)\frac{\partial V}{\partial a} + \pi_\tau \frac{\partial V}{\partial \tau} \\
&+ \lambda_e \left(\int \max\{V(a, w(\tau), \tau), V(a, \tilde{w}, 0)\} dF(\tilde{w}) - V(a, w(\tau), \tau) \right) \\
&+ \max\{V(a, w(\tau), \tau), U(a, b(0,0))\} - V(a, w(\tau), \tau) \\
&+ \delta(\tau)[U(a, b(w, 0)) - V(a, w(\tau), \tau)]
\end{aligned}$$

Next, I parallelize the HJB equations by stacking them into a column vector $v = \begin{bmatrix} U \\ V \end{bmatrix}$. Let α denote the grid point on assets, ω the grid points of wages, and θ the grid points on either tenure or duration. This allows me to rewrite the HJB equation in the following form:

$$\begin{aligned}
\frac{v^{n+1}_{\alpha,\omega,\theta} - v^{n}_{\alpha,\omega,\theta}}{\Delta} + \rho v^{n+1}_{\alpha,\omega,\theta} &= u(c^n_{\alpha,\omega,\theta}) + (v^{n+1}_{\alpha,\omega,\theta})'(w_\omega(T_\theta) + ra_\alpha - c_{\alpha,\omega,\theta}) + A_w(v^{n+1}_{\alpha,-\omega,\theta} - v^{n+1}_{\alpha,\omega,\theta}) \\
&+ A_\tau(v^{n+1}_{\alpha,\omega,-\theta} - v^{n+1}_{\alpha,\omega,\theta}).
\end{aligned}$$

where $T = [d, \tau]$, $A_w = [\lambda_u, [\lambda_e \; \delta(\theta)]]$, $A_\theta = [\pi_d, \pi_\tau]$ for each respective employment state.

C.2 Upwind Scheme

To ensure the numerical stability of the algorithm, it is important to use the upwind scheme. This scheme consists in using a forward difference approximation whenever the drift of the state variable (in this case, savings) is positive and to use a backwards difference whenever it is negative. First, I compute the forward and backwards difference approximations:

$$v'_{a,F} = \frac{v_{\alpha+1} - v_\alpha}{\Delta a}, \quad v'_{a,B} = \frac{v_\alpha - v_{\alpha-1}}{\Delta a}.$$

and next, I define the derivative with respect to assets as:

$$v_a' = v_{a,F}' \mathbf{1}_{\{s_{\alpha,\omega,\theta,F}>0\}} + v_{a,B}' \mathbf{1}_{\{s_{\alpha,\omega,\theta,B}<0\}} + \bar{v}_a' \mathbf{1}_{\{s_{\alpha,\omega,\theta,F}\le 0\le s_{\alpha,\omega,\theta,B}\}}.$$

where $s_{a,F} = w_{\omega,\theta} + ra_\alpha - u'(v_{a,F}')$ and $s_{a,B} = w_{\omega,\theta+ra_\alpha-u'(v_{a,B}')}$. This allows me to rewrite the HJB equation in terms of $v_{a,F}'$, $s_{a,F}$ and $v_{a,B}'$, $s_{a,B}$:

$$\frac{v_{\alpha,\omega,t}^{n+1} - v_{\alpha,\omega,\theta}^{n}}{\Delta} + \rho v_{\alpha,\omega,\theta}^{n+1} = u(c_{\alpha,\omega,\theta}^{n}) + \frac{v_{\alpha+1,\omega,\theta}^{n+1} - v_{\alpha,\omega,\theta}^{n+1}}{\Delta a}(s_{\alpha,\omega,\theta,F}^{n})^{+} + \frac{v_{\alpha,\omega,\theta}^{n+1} - v_{\alpha-1,\omega,\theta}^{n+1}}{\Delta a}(s_{\alpha,\omega,\theta,B}^{n})^{-}$$
$$+ \alpha_w(v_{\alpha,-\omega,\theta}^{n+1} - v_{\alpha,\omega,\theta}^{n+1}) + \alpha_\theta(v_{\alpha,\omega,-\theta}^{n+1} - v_{\alpha,\omega,\theta}^{n+1}).$$

where $(s_{\alpha,\omega,\theta,F}^{n})^{+} = \max\{s^n, 0\}$ and $(s_{\alpha,\omega,\theta,B}^{n})^{-} = \min\{s^n, 0\}$.

C.3 Implicit Method

In matrix notation, I can rewrite the system as:

$$\frac{1}{\Delta}(v^{n+1} - v^{n}) + \rho v^{n+1} = u^n + \mathbf{A}^n v^{n+1}.$$

where $\mathbf{A}^n$ is the Poisson transition matrix containing all movements across and within the asset, wage, and tenure-duration grids.

1. **Asset Update:** Changes in assets are discretized using the upwind scheme, which uses either backward, central, or forward difference approximation. The asset transition matrix is given by:

$$A_a = \begin{bmatrix} a_{1,1} & a_{1,2} & 0 & \cdots & 0 \\ a_{2,1} & a_{2,2} & a_{2,3} & \cdots & 0 \\ 0 & a_{3,2} & a_{3,3} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & a_{N,N} \end{bmatrix}$$

   where the diagonal entries are given by:

$$a_{i,i} = \min\left\{\frac{s_{\alpha,\omega,\theta,B}^{n}}{\Delta a}, 0\right\} - \max\left\{\frac{s_{\alpha,\omega,\theta,F}^{n}}{\Delta a}, 0\right\}, \quad \Longrightarrow \text{ central difference } (v_{\alpha,\omega,\theta})$$
$$a_{i,i+1} = \max\left\{\frac{s_{\alpha,\omega,\theta,F}^{n}}{\Delta a}, 0\right\}, \quad \Longrightarrow \text{ forward difference } (v_{\alpha+1,\omega,\theta})$$
$$a_{i,i-1} = -\min\left\{\frac{s_{\alpha,\omega,\theta,B}^{n}}{\Delta a}, 0\right\} \quad \Longrightarrow \text{ backward difference } (v_{\alpha-1,\omega,\theta})$$

2. **Tenure/Duration Update:** Tenure and unemployment duration update stochastically with probability π to the next tenure bin. Since they both increase over time for workers at the same job, only forward difference is needed. For this reason, the diagonal entry is given by $-\frac{\pi}{\Delta\tau}$, and the right diagonal entries, which correspond to the forward difference, are given by $\frac{\pi}{\Delta\tau}$. The probability π of tenure updating is zero when the worker reaches the maximum tenure. Thus, the transition matrix is given by

$$A_\tau = \begin{bmatrix} -\frac{\pi}{\Delta\tau} & \frac{\pi}{\Delta\tau} & 0 & 0 & \cdots & 0 \\ 0 & -\frac{\pi}{\Delta\tau} & \frac{\pi}{\Delta\tau} & 0 & \cdots & 0 \\ 0 & 0 & -\frac{\pi}{\Delta\tau} & \frac{\pi}{\Delta\tau} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

3. **Labor Market Transitions** Workers face two type of separations: they can either quit into unemployment, which happens whenever $\mathbf{1}_{U(a,b(0,d))>V(a,w,\tau)}$, or they involuntarily lose their job at rate $\delta(\tau)$. In both cases, workers end up unemployed, but for the involuntary separations, workers move to the corresponding wage-grid point and receive a fraction χ of their previous income. Workers find jobs at rate λ, which differs from unemployment and employment. The rate at which workers move out of unemployment to a job w_j is given by: $P_{u_j} = \lambda_o * f(w_j) * \mathbf{1}\{V(a,w,0) > U(a,b(w,d))\}$, while employed worker move to a different job w_j at rate: $P_{w_j} = \lambda * f(w_j) * \mathbf{1}\{V(a,w,\tau) > V(a,w_j,0)\}$. The transition matrix across different jobs is given by:

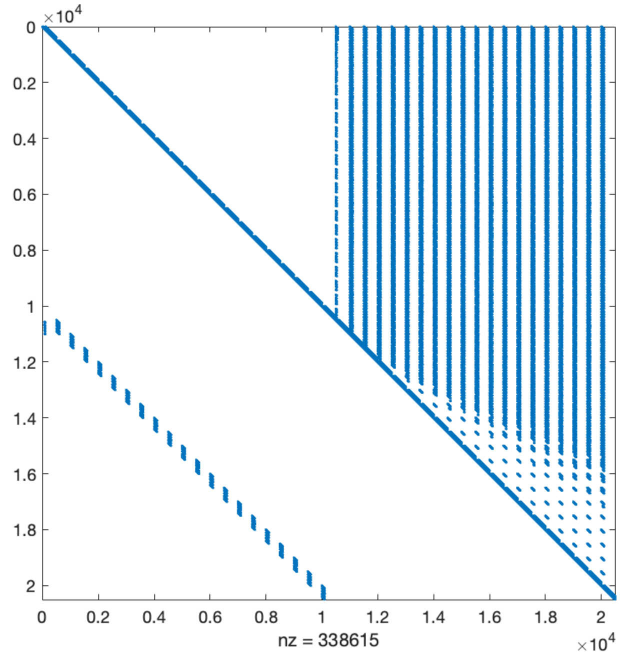
$$A_w = \begin{bmatrix} -\sum\limits_j P_{u_j} & 0 & \cdots & P_{u_1} & P_{u_2} & \cdots & P_{u_J} \\ 0 & -\sum\limits_j P_{u_j} & \cdots & P_{u_1} & P_{u_2} & \cdots & P_{u_J} \\ \vdots & \vdots & \ddots & \vdots & \vdots & & \vdots \\ \delta(\tau) + \mathbf{1}_{U>V} & 0 & \cdots & -\sum\limits_{j>1} P_{w_j} - \delta(\tau) - \mathbf{1}_{U>V} & P_{w_2} & \cdots & P_{w_J} \\ 0 & \delta(\tau) + \mathbf{1}_{U>V} & \cdots & 0 & -\sum\limits_{j>2} P_{w_j} - \delta(\tau) - \mathbf{1}_{U>V} & \cdots & P_{w_J} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \\ 0 & 0 & \cdots & 0 & 0 & & \end{bmatrix}$$

$$\underbrace{\qquad\qquad\qquad\qquad}_{\text{Unemployed}} \quad \underbrace{\qquad\qquad\qquad\qquad\qquad\qquad\qquad}_{\text{Employed}}$$

Fig. 11 plots this sparse matrix. Finally, I can invert this system of equation and solve for v^{n+1}:

$$\left(\left(\frac{1}{\Delta}+\rho\right)\mathbf{I}-\mathbf{A}^n\right)v^{n+1} = u^n + \frac{1}{\Delta}v^n$$
$$v^{n+1} = \left(\left(\frac{1}{\Delta}+\rho\right)I-\mathbf{A}^n\right)^{-1}\left(u^n+\frac{1}{\Delta}v^n\right)$$

Figure 11. Poisson Transition Matrix



D Numerical Appendix

D.1 Calibration Strategy

To estimate the model parameters, I employ a global search strategy with multiple restarts to minimize the loss function, which measures the discrepancy between model-implied and empirical moments. First, I solve the model 10,000 times using starting parameters from a Sobol sequences. From these runs, I select the 100 parameter sets that yield the lowest values of the loss function. Next, I apply a local optimization routine using fminsearchbnd, which implements the Nelder-Mead simplex method with bound constraints, to each of the 100 selected parameter sets. This step refines the parameter estimates by searching for a local minimum within a constrained region, further reducing the loss function. The final parameter set corresponds to the run that achieves the lowest loss function across all iterations. This two-step procedure—a broad global search followed by a focused local refinement—helps mitigate the risk of getting stuck in local minima and ensures that the calibrated parameters align closely with the empirical data.

D.2 Alternative Calibration

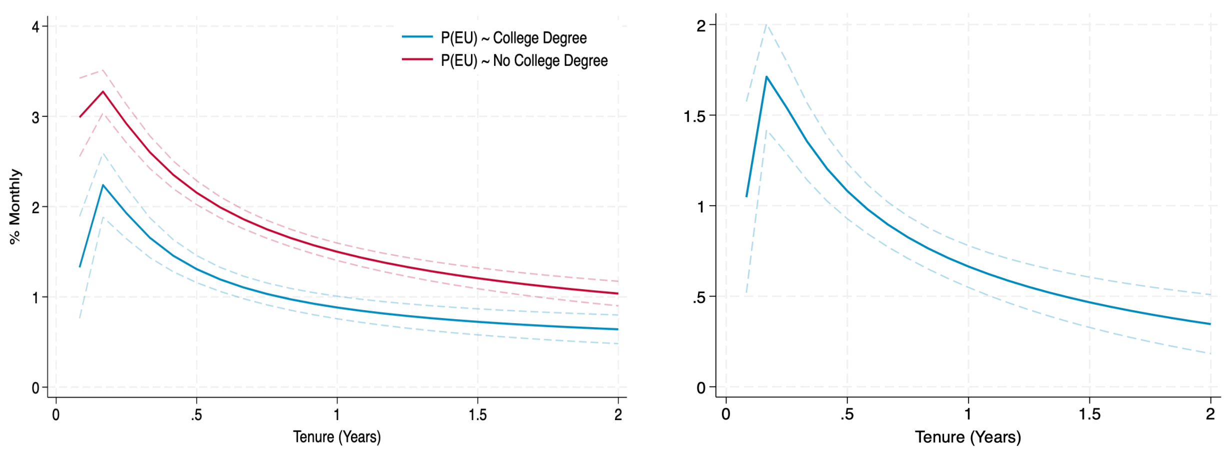
In this section, I explore heterogeneity in the EU rate across multiple dimensions. Specifically, Figure 12a and Figure 12b show how separation rates over tenure vary by education level and employment history. Importantly, while separation levels differ substantially across groups, the hazard rate consistently declines with tenure.

As an alternative calibration exercise, I re-estimate the model separately for high-skill (college-educated) and low-skill (non-college) workers, allowing for group-specific separation rates and wage-tenure dynamics. This exercise underscores how worker heterogeneity influences labor market transitions and wage growth within different job ladders.

Figure 12. Heterogeneity in EU Rate

(a) EU Rate by Tenure and Education

(b) EU Rate by Tenure Following an EE move



Note: Panel (a) plots the monthly job separation rate by tenure and education level, defined as the number of workers with a given tenure and education who experience an involuntary separation in a given month, divided by the total number of employed workers with the same tenure and education in the previous month. Panel (b) shows the monthly separation rate by tenure for workers who previously experience a job-to-job transition, using the same calculation method. *Source*: SIPP, 1996–2004 panel.