Wealth Inequality and Labor Mobility: The Job Trap

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March 21, 2025

PRELIMINARY AND INCOMPLETE

Abstract

In this paper, I study how wealth affects workers' ability to move to higher-paying jobs. Using microdata from the SIPP, I compare equally skilled workers in similar careers and find that those with higher liquid wealth are 1.24 percentage points more likely to change jobs than workers with no savings, particularly at the bottom of the job ladder. To explain these patterns, I develop a job ladder model with incomplete markets, risk-averse workers, and wage posting. Allowing for separations to decrease in job tenure introduces a novel trade-off for on-the-job search: wage increases come at the cost of a higher risk of separation. To avoid this risk, workers with no liquidity prioritize job security over job mobility and remain trapped in low-paying jobs. This mechanism explains about 60% of the observed gap in job mobility by wealth in the data. However, extending unemployment benefits increases 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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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 generally aware of these potential benefits, as wages are the primary driver of job changing decisions among young workers (Topel and Ward, 1992). 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 random search models, it is purely 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 respective job ladders[2]. While job changes may lead to substantial wage gains, I argue that they also come with potential risks. Among these, I focus on the risk of giving up job tenure and facing a higher probability of losing the new job, as I document in the data. In this scenario, workers with no savings cannot afford the risk of changing jobs and ending up unemployed. Forced to prioritize job security over job mobility, liquidity-constrained workers may find themselves trapped in low-paying jobs and unable to climb their job ladder.

I begin by documenting 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 empirical exercise, I compare equally-skilled workers at similar jobs and stages of their career 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 job as the difference between their predicted wage – given their skills and observable characteristics – and their actual wage, capturing how much of a wage increase the worker could expect from changing jobs. I use this incentive 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 incentive and wealth. As these incentives increase, 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 1.24 percentage point among workers with incentives, and by up to 3.5 percentage points for workers at the bottom of the job ladder. These results are corroborated by the coefficients

[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), who suggest that the job ladder varies significantly across different groups of workers, reflecting differences in job mobility and wage growth opportunities.

on the demographic controls, which show that 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, I develop a detailed unemployment benefits policy that incorporates benefit expiration, a cap on payments, and replacement rates that depend on prior wages. On the employment side, I assume that the risk of job loss is exogenous and declines with tenure, introducing a novel trade-off for on-the-job search: a wage increase comes at the cost of a higher probability of losing the job, rendering job-to-job transitions inherently risky[3]. These features help me capture the risk of unemployment faced by workers trying to climb the job ladder.

This novel 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 that I denote 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 to climb the job ladder once employed.

To quantify the impact of wealth inequality on labor mobility, I estimate the model parameters to match key moments observed in the data, and particularly the relationship between involuntary separations and tenure. The model successfully captures both the magnitude of job flows and the dispersion of income among workers with similar skills. It endogenously generates job-to-job transitions that decline with both tenure and wages, effectively capturing that the vast majority of such transitions occur among low-wage workers with low tenure. More importantly, the model is able to endogenously replicate the relationship between labor market flows and wealth documented earlier in the paper: while transitions from unemployment decrease with wealth, job-to-job flows tend to increase with wealth, especially at the bottom of the job ladder. In particular, among workers with positive incentives, those with high wealth change jobs at a rate approximately 0.45 percentage points higher than liquidity-constrained workers. On average, this difference explains about 60% of

[3]The downward-sloping relationship can easily be microfounded by assuming that match quality is unobserved and agents must learn it over time (Jovanovic, 1984; Moscarini, 2005).

the observed gap in job mobility by wealth in the data, over the same range of incentives. The dynamics of the reservation wage suggest that this occurs because liquidity-constrained workers prioritize job security over mobility, leaving them trapped in low-paying jobs.

These frictions suggest a potential role for labor market policies to increase labor market mobility and reduce inequality. To this end, I compare the impact of a $200/month increase in Unemployment Insurance (UI) to a six-month extension in UI benefits. Interestingly, while the increase in UI has little to no effect on job-to-job flows, the six-month extension significantly boosts job mobility for poor workers in low-paying jobs. The intuition is as follows: since unemployment benefits expire after six months, unemployed, liquidity-constrained workers are forced to accept the first job offer they receive to escape unemployment. While a $200 increase in UI allows these workers to maintain higher consumption during those six months, it does not reduce their pressure to find a job before the benefits expire. In contrast, an extension of UI benefits enables workers to remain unemployed longer, giving them time to wait for higher wage offers. Meanwhile, employed workers are less impacted by an eventual job loss and can take more risks by lowering their reservation wage and, consequently, switching jobs more often. Ultimately, an extension in UI offers a potential pathway out of the job trap for liquidity-constrained workers, allowing them to move to higher-paying jobs and reducing the overall income inequality.

1.1 Related Literature

This paper contributes to three main strands of the literature. First, it 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) study optimal savings and job search 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 predict a negative correlation between wealth and job mobility[4]. Although this negative

[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

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 advances their contributions by developing a tractable random search model that incorporates several 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 low wages, given their observable characteristics, 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.

Second, this study contributes to the empirical literature on the role of wealth in determining labor market outcomes. Previous research, including Bloemen and Stancanelli (2001), Algan et al. (2003), and Card et al. (2007), and more recently Basten et al. (2014), Krueger and Mueller (2016), Herkenhoff (2019), Huang and Qiu (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 empirically document a positive correlation between wealth and job mobility within specific career tracks. By focusing on equally-skilled workers at similar stages in their careers, I show how wealth directly impacts their ability to move to higher-paying jobs. This suggestive 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.

Lastly, this study contributes to the rich literature on unemployment insurance (UI).

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

Seminal works such as Meyer (1990) and Gruber (1997) explore the effects of UI on unemployment duration, while Acemoglu and Shimer (1999) link UI to higher-wage (but also riskier) jobs. Chetty (2008) and Lentz (2009) show that UI provides consumption smoothing during periods of unemployment, particularly for liquidity-constrained workers. More recent contributions by Landais (2015), Hagedorn et al. (2019), and Kuka (2020) explore the implications of UI policies for labor supply, vacancy creation, and the health effects of job loss, respectively. Birinci and See (2023) study the implications of income and wealth heterogeneity for UI eligibility, take-up, and replacement. This paper builds on this literature by examining the effects of both an increase in UI benefits and an extension of UI durations on job mobility. This novel focus on 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 establishes a new set of empirical facts on wealth inequality and job mobility. Section 3 proposes the model and characterizes the equilibrium of the economy. Section 4 takes the model to the data and shows the key results, while Section 5 concludes.

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].

[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.

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, 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 the effect of wealth holdings on workers' job switching incentives, I proceed in two steps. First, I estimate a simple wage regression in which income is regressed on several

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

control variables using the estimator developed by 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. D_{it} includes a set of demographic characteristics, such as age and age square, gender, race, education, marital status, number of kids, disability, and current state; while J_{it} is a set of job characteristics, including log months of tenure, years of experience and experience squared, industry, occupation, working class, and indicators for union membership and full-time employment.

The main coefficients of this regression, alongside the OLS estimates, are reported in Table 5 in Appendix A. The model explains 87% of the variation in income, indicating a really strong fit. A significant share of this explanatory power comes, of course, from worker fixed effects, which capture unobserved traits like ability or social skills, as well as time fixed effects, which account for macroeconomic trends like inflation or unemployment. As in the literature, higher age, education levels, longer tenure, full-time employment, and union membership are associated with higher wages. In contrast, women, people of color, and workers with disabilities tend to earn lower wages, highlighting persistent labor market inequalities. In addition, although not directly reported in the table, geographic differences play an important role, with states in the New England region offering significantly higher wages than southern states.

I then define the predicted wage ($\tilde{w}$) as the linear projection from this estimation, $\tilde{w}_{it} = \boldsymbol{\delta} D_{it} + \boldsymbol{\varphi} J_{it} + \alpha_i + \gamma_t$, which reflects the average wage for a population group with specific demographic characteristics and skills who works at similar jobs, in the same state and month. I compute workers' incentive to change job (Δw_{it}) as the difference between the average (predicted) wage given their characteristics and their actual wage:

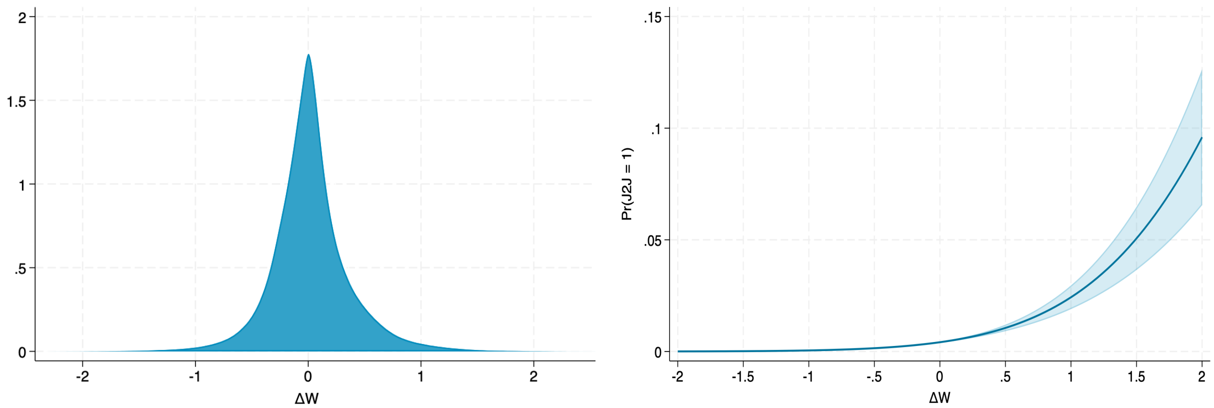
$$\Delta w_{it} = \tilde{w}_{it} - w_{it}$$

This term captures the wage increase a worker could expect from searching for another job within the same state, industry and occupation, serving as an "incentive" measure for changing jobs. Intuitively, we expect this incentive measure to be centered around zero, as most workers are well-matched and have no reason to move, while also being positively correlated with job-to-job flows. To check these properties, I plot its density and the average predicted

[9] This estimator allows to control for high–dimensional fixed effects without estimating the fixed effects coefficients. The least squares estimates can be recovered by first regressing each variable against all the fixed effects, and then regressing the residuals of these variables, as proposed by Guimaraes and Portugal (2010).

Figure 1. Incentives to Change Jobs

(a) Probability Density (b) Job-to-Job Probability by Incentives



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

probability of job-to-job transitions for different incentives values. Figure 1 confirms that the distribution is centered around zero, with most of its mass below one, and that workers with higher incentives are more likely to change jobs. Specifically, earning 50% below the average wage ($\Delta w = 0.4$) increases the probability of a job-to-job move by approximately 1 percentage point. These findings confirm that on average workers have no incentives to switch jobs ($\mathbb{E}[\Delta w] = 0$) but those earning below their job's average wage are indeed more likely to move.

After constructing this measure, I can assess the impact of wealth (a) on the likelihood of changing job ($J2J$), while taking into account the incentive (Δw) to move:

$$J2J_{it} = \alpha_t + \beta_1 \Delta w_{it} + \beta_2 \Delta w_{it} * a_{it} + \beta_3 a_{it} + \boldsymbol{\delta} D_{it} + \boldsymbol{\varphi} J_{it} + \epsilon_{it} \tag{1}$$

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 incentive and wealth. This coefficient captures whether low wealth prevents workers from changing jobs in the case in which they have incentives to do so. Hence, I expect this coefficient to be positive: given a fixed incentive, workers with higher wealth will be more likely to change jobs.

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

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 (%)
Δw	0.340***	0.377***	0.754***	0.929***	0.668***	0.845***
	(0.092)	(0.084)	(0.236)	(0.228)	(0.246)	(0.234)
Liquid wealth	−0.013	−0.002	0.029	0.000	0.060	0.009
	(0.023)	(0.002)	(0.034)	(0.003)	(0.059)	(0.007)
Liquid wealth$*\Delta w$	0.385***	0.046***	0.862***	0.084***	0.911***	0.090***
	(0.099)	(0.011)	(0.254)	(0.022)	(0.267)	(0.031)
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Worker Fixed Effects	-	-	-	-	Yes	Yes
N	823,817	823,817	823,817	823,817	823,817	823,817

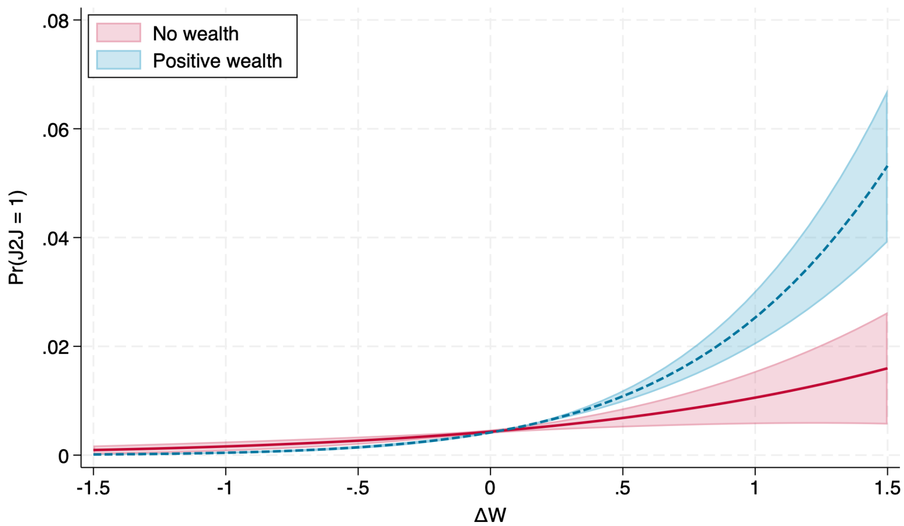
Note: The table shows the coefficients for a dummy (liquid wealth greater than zero) and IHS ($\ln(a + \sqrt{1+a^2})$) specifications for liquid wealth using a probit regression (columns 1-2), a linear probability model (columns 3-4), and the LPM with worker fixed effects using the Correia (2016) estimator (columns 5-6). The coefficients for both LPMs are reported in percentage. 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.

The results of the probit regression, along with the linear probability model (LPM) and the LPM with worker fixed effects, are presented in Table 1. The table includes the regression coefficients for both a liquid wealth dummy and the inverse hyperbolic sine transformation of liquid wealth ($\ln(a + \sqrt{1+a^2})$). Across all six regressions, the coefficient on the incentive measure (Δw) remains consistently positive and strongly significant. Importantly, while coefficients on liquid wealth alone are initially insignificant, they become positive and highly significant when interacted with the incentive measure. This suggests that wealth has no impact on job mobility for workers with no incentives, but as incentives increase, workers with higher savings have a significantly higher probability of changing jobs[11].

Specifically, the LPM and the fixed effects regressions show that, when workers are 10% below the average wage ($\Delta w = 0.1$) and liquid wealth increases by \$500, job-to-job flows increase by an additional $[(0.09\%) * \ln(500 + \sqrt{1+500^2}) * 10\%] \approx 0.06$ percentage points

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

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 incentives (Δw), 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.

with respect to workers without savings. Hence, on average, being 10% below the average job ladder income would increase job-to-job moves by about 0.085 percentage points for workers with no wealth, and by approximately 0.15 percentage points for workers with \$500 in savings. This effect is much stronger for workers at the very bottom of the job ladder ($\Delta w \geq 1$), where an increase in liquid wealth by \$500 increases job-to-job transitions by an additional 0.63 percentage points (i.e., double the average job mobility in the sample). Similarly, the dummy specification suggests that, for workers at the bottom of the job ladder, having some liquid wealth increases job mobility by approximately $0.86 - 0.91$ percentage points compared to workers with no savings, and by up to 2.5 percentage points for the lowest income earners.

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 incentives. As evident from the graph, job-to-job flows increase in incentive, but the increase is much steeper for wealthier workers. In particular, having some savings increases job mobility by an average of 1.24 percentage points for workers with some incentives, and up to 3.73 percentage points for workers with the highest incentives.

What other factors influence job-to-job flows? Table 6 in Appendix A reports the coefficients for several controls included in regression 1. As established in previous research, the

Table 2. Regressions of Liquid Wealth on U2E and Accepted Wages

	U2E	**ln(w)**
Liquid Wealth	-0.006^{**}	0.011^{***}
	(0.003)	(0.003)
Full Controls	Yes	Yes
Month Fixed Effects	Yes	Yes
N	42,267	5,238

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.

results show that job-to-job transitions tend to decline with age and tenure. However, after controlling for incentives to change jobs, industry, and occupation, I find that these flows are higher for white men with higher education levels. Conversely, job-to-job flows are lower for women, minority groups, and noncitizens. For example, the probability of switching jobs is 0.13 percentage points higher for college graduates compared to workers without a high school diploma, and 0.11 percentage points lower for people of color relative to white workers. Unsurprisingly, job mobility is also lower among unionized workers and those with disabilities. However, having children does not appear to significantly affect job-to-job transitions. These differences in mobility patterns likely contribute to persistent gender and racial pay gaps, which will be explored further in future research.

2.3 Wealth and Unemployment

I now turn to studying 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[12]. 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 2. The results confirm that unemployed workers with higher savings experience longer unemployment durations and accept 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.

2.4 Robustness

In this section, I test the robustness of the model under a different set of specifications. First, I broaden the definition of job ladder to include job-to-job moves across different states, industries, and occupations. Second, I show that workers' income is positively correlated with job amenities, implying that when workers move to higher-paying jobs, they gain better amenities on average. Lastly, I test different model specifications by allowing for different functional forms of the incentive measure and incorporating multiple interaction terms. Further robustness are reported in Appendix A.

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 three alternative wage regressions, each excluding one variable: three excluding one variable at a time (industry, occupation, or state) 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 incentive measure. I then re-estimate the probit regression 1 on a dummy of liquid wealth with these four alternative incentive vari-

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

ables. The results of each exclusion are presented in Table 7 in Appendix A, where Column I excludes industry, Column II excludes occupation, Column III excludes state, and Column IV excludes all three[13]. As shown in the table, the coefficients on the incentive 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 take into account not only their wages, but also 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 experience improvements in job amenities as well (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 9 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[14]. Furthermore, Figures 9 suggest 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 incentive measure (i.e., workers with negative incentives). To tackle this issue, I redefine the incentive measure to include only positive values:

$$\Delta w_{ist} = -min(w_{ist} - \tilde{w}_{ist}, 0)$$

This new measure compares workers with positive incentives to those with zero or negative incentives. The estimated coefficients, which are reported in Column I of Table 8 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 1, where the effect of incentives may vary with other characteristics other than wealth. To

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

[14] 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.

address this, I interact the incentive measure with additional controls (Z_{it}):

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

Table 8 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 incentive 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 incentives and education, as well as incentives 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 a potential consumption-smoothing mechanism.

3 Model

To understand how wealth affects job mobility, I develop a continuous-time job ladder model with incomplete markets, risk averse workers, and wage posting. The novel ingredient in this environment is the involuntary job separation, which is exogenous and decreasing in job tenure. The interaction between tenure and separation introduces a novel trade-off for workers searching on the job: while they can earn a higher wage, they also face an increased risk of job loss. Hence, in this new framework, job-to-job transitions become a function of tenure and wealth.

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. They face a concave utility $u(\cdot)$ and decide how much to save at the risk-free rate r to ensure themselves against income loss. Firms post initial wages from the same exogenous distribution $F(w_0)$, which governs the wage offers available to workers. After hiring, all wages grow with tenure at the same rate[15].

[15] Since wages grow as a percentage of the initial wage, higher initial wages result in greater absolute wage growth. Alternatively, one could model wage growth by allowing workers to draw both an intercept and a slope for the wage-tenure profile, enabling lower initial wages to grow at a steeper rate. However, this approach would significantly expand the state space and reduce the efficiency of the solution algorithm. Furthermore, the assumption that workers in higher-paying jobs experience greater wage growth is strongly supported by the data (see, for example, Borovičková and Macaluso (2024)).

Workers, who may be either employed or unemployed, are always searching for jobs and take flow unemployment benefits $b(w, d)$ and flow wage-tenure profiles $w(\tau)$ as given. They encounter job offers at an exogenous Poisson arrival rate λ_s, where s denotes the employment status ($s = u, e$), and search efficiency could depend on wealth. This latter assumption represents the idea that wealthy workers have access to better social networks, potentially receiving more job offers. For the remaining part of the paper, job search efficiency will not depend on wealth, although I will relax this assumption in future work.

Unemployed workers receive unemployment benefits $b(w, d)$ as a fraction of their previous income, subject to a maximum cap $\bar{b}$. Their unemployment duration d evolves according to the Markov process $\Pi(d'|d)$, increasing with probability π_d. Once duration reaches the threshold d^*, unemployment benefits expire[16]. This mechanism aligns with U.S. labor market data, where unemployment benefits are typically available for up to six months. However, most search-and-matching models assume that benefits persist indefinitely.

After finding a job, workers accumulate tenure stochastically according to a similar Markov process $\Pi(\tau'|\tau)$. In each period, tenure increases to the next bin with probability π_τ, thus increasing their wage $w(\tau)$, but it resets to zero if the worker moves to a new job, quits into unemployment, or experiences an involuntary separation. In particular, workers face involuntary separations at an exogenous rate $\delta(\tau)$ that decreases with job tenure, meaning workers with tenure who switch jobs face a higher risk of job loss.

3.2 The Tenure Channel

Although exogenous in the model, the downward-sloping relationship between separations and tenure can be microfounded using the frameworks of Jovanovic (1984) and Moscarini (2005). Intuitively, firms may incur substantial productivity costs from a "bad hire", i.e. a worker who is unsuited for the job. For example, the U.S. Small Business Administration (SBA) estimates that the cost of a bad hire can range from 1.25 to 1.4 times the worker's salary[17]. Initially, firms cannot observe whether a worker is a good match, but they learn over time through a signal that follows a Brownian motion. When the signal deviates sufficiently from expectations, the firm learns that the match is likely bad and optimally fires the worker to avoid further costs. Conversely, if no bad signal is observed, the firm implicitly assumes that the worker is a good fit, and as $t \to \infty$, only good matches survive.

This process implies that job separations decline with tenure, as bad matches are progressively terminated. Meanwhile, wages tend to be initially lower due to firms' uncertainty about worker quality, but they increase over time for matches that survive the initial screen-

[16]Benefits cannot expire entirely, otherwise the value function would tend toward $-\infty$.
[17]See the article: https://www.sba.gov/blog/how-much-does-employee-cost-you

ing period[18].

3.3 Value Functions

Workers take wages as given and choose consumption to maximize expected lifetime utility, subject to the budget constraint and the Markov processes for unemployment duration and tenure. The problem of an unemployed worker with assets a, previous wage w, and unemployment duration d can be summarized by the continuous time Bellman equation:

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

When unemployed, workers receive unemployment benefits $b(w,d)$, which depend on their unemployment duration and their previous wage. Although all unemployed start receiving unemployment benefits $b(0,w)$ as a fraction of their previous wage, when their unemployment duration increases, benefits expire and require workers to dissave their assets to consume. During their job search, workers 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 is higher than their reservation wage and, in that event, receive the employed worker value $V(a,w,0)$.

Upon accepting an offer, workers begin their job with a wage $w(0)$ and no job tenure ($\tau = 0$). Over time, they accumulate tenure stochastically, which gains them both a higher wage and a lower separation risk. While employed, workers receive job offers from new employers at rate λ_e, may voluntarily quit into unemployment at any time, in which case do not receive unemployment benefits, and face job loss at an exogenous separation rate $\delta(\tau)$. If any of these separations occur, they lose both their job and their accumulated tenure. Finally, workers decide how much to save to ensure themselves against job loss. The

[18] See Appendix B for a formal microfoundation of this mechanism.

Bellman equation of an employed worker with assets a, wage w, and tenure τ is given by:

$$
\begin{aligned}
\rho V(a, w(\tau), \tau) = \max_{c} \quad & u(c) + \dot{a}\frac{\partial V}{\partial a} + \frac{\partial V}{\partial \tau} + \underbrace{\delta(\tau)[U(a, b(w, 0)) - V(a, w(\tau), \tau)]}_{\text{Involuntary Separations}} \\
& + \underbrace{\lambda_e \left(\int \max\{V(a, w(\tau), \tau), V(a, \tilde{w}(0), 0)\} dF(\tilde{w}) - V(a, w(\tau), \tau) \right)}_{\text{On the Job Search}} \\
& + \underbrace{\max\{V(a, w(\tau), \tau), U(a, b(0, 0))\} - V(a, w(\tau), \tau)}_{\text{Voluntary Quits into Unemployment}} \\
\text{s.t.} \quad & \dot{a} = ra + w(\tau) - c \\
& a \geq \underline{a}
\end{aligned}
\tag{3}
$$

Since all new jobs start off with no tenure, changing job carries inherent risks: a wage increase comes at the expense of a higher risk of separation. As a result, workers with substantial job tenure may find that a marginal wage increase is not worth the increased probability of job loss. Moreover, individuals value job loss differently based on their assets. During unemployment, wealthier workers can maintain a high consumption level by dissaving and take advantage of a higher job-finding rate to secure better-paying jobs. For this reason, some wealthy workers in low-paying jobs may choose to voluntarily quit into unemployment to search for better opportunities. In contrast, liquidity-constrained workers tend to prioritize job security, often accepting the first available offer to escape unemployment and ending up worse off.

3.4 Reservation Wages

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

$$
V(a, R_u(a, d), 0) = U(a, b(w, d))
$$

If search is more effective when unemployed ($\lambda_u > \lambda_e$), as more time is dedicated 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, which is consistent with the empirical findings of Krueger and Mueller (2016). This higher reservation wage, however, results in longer unemployment durations, aligning with established evidence on duration dependence[19], as well as lower job-finding rates, as in Huang and Qiu (2022)[20].

The employed reservation wage $R_e(a, w, \tau)$ is the wage that equates the value of accepting a job offer from a new employer and remaining employed at the current job, and solves:

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

Intuitively, the reservation wage consists of two components: the current wage for the given tenure $w(\tau)$ and a job security premium. This premium represents the additional compensation needed to offset the risk of losing the new job and becoming unemployed. The size of this premium 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 separations rate 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.

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

$$R_e(a, w, \tau) = w(\tau) + \underbrace{\frac{[\delta(0) - \delta(\tau)] * [V(a, w, \tau) - U(a, b(w, 0))]}{u'(c(a, w, \tau))}}_{\text{job security premium}} \tag{4}$$

In particular:

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

Proof. See Appendix B. □

Workers with higher tenure demand a larger job security premium, and consequently 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 ($\frac{\partial U(a,b(w,0))}{\partial a} > \frac{\partial V(a,w(\tau),\tau)}{\partial a}$.)[21].

[19]See, for example, Card et al. (2007), Chetty (2008) and Basten et al. (2014).

[20]They show that the job finding rate out of unemployment is decreasing in wealth in a model with skill heterogeneity and Nash bargaining.

[21]However, this condition depends in part on the parametrization of the model and the concavity of the

3.5 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 over assets and unemployment benefits $b(w, d)$ satisfies:

$$
\begin{aligned}
0 = & -\frac{\partial u(a, b(w,d))}{\partial a}[ra + b(w,d) - c(a,d)] - \pi_d \frac{\partial u(a, b(w,d))}{\partial d} \\
& - \lambda_u[1 - F(R_u(a, b(w,d)))]u(a, b(w,d)) \\
& + \mathcal{I}_{d=0} \int_0^T \int_0^{\bar{w}} \delta(\tau) g(a, w, \tau) d\tau dw
\end{aligned} \tag{5}
$$

where $g(a, w, \tau)$ is the distribution of workers over assets, wages, and tenure, and solves:

$$
\begin{aligned}
0 = & f(w)\lambda_u[1 - F(R_u(a,d))]u(a,d) - \delta(\tau)g(a,w,\tau) \\
& - [ra + w(\tau) - c(a,w,\tau)]\frac{\partial g(a,w,\tau)}{\partial a} - \pi_\tau \frac{\partial g(a,w,\tau)}{\partial \tau} \\
& - \lambda_e[1 - F(R_e(a,w,\tau))]g(a,w,\tau) \\
& + \lambda_e f(w) \mathbb{1}_{\{\tau=0\}} \int_0^T \int_{R_e}^{\bar{w}} g(a, \tilde{w}, \tilde{\tau}) d\tilde{w} d\tilde{\tau}
\end{aligned} \tag{6}
$$

and the total number of employed workers is given by $e = 1 - \int u(a,d)\ da\ dd$. At each instant, the densities change due to asset accumulation, which is pinned down by the budget constraint, and due to increases in tenure ($\frac{\partial g(a,w,\tau)}{\partial \tau}$) or unemployment duration ($\frac{\partial u(a,d)}{\partial d}$), which are summarized by the corresponding Markov processes π_τ and π_d. With probability $\lambda_u[1 - F(R_u(a,d))]$ an unemployed is offered a wage above the reservation wage and flows into employment, while workers lose their jobs and flow into unemployment at exogenous separation rate $\delta(\tau)$. Finally, workers search on the job and move up the job ladder if they receive an offer above their employed reservation wage, which occurs at rate $\lambda_e[1 - F(R_e(a,w,\tau))]$.

Proposition 2. *A stationary recursive equilibrium consists of:*

- *Two values functions $\{U(a, b(w,d)), W(a,w,\tau)\}$ satisfying (2) and (3);*

value function. Importantly, this condition does not hold if the value of being unemployed is greater than that of being employed ($V(a,w,\tau) < U(a, b(w,0))$)

- *A set of policy functions $\{c(a, w, \tau), \dot{a}\}$ that solve the optimization problem;*

- *Two distributions $u(a, b(w, d))$ and $g(a, w, \tau)$ that satisfy the Kolmogorov forward equations (5) and (6).*

4 Quantitative Analysis

In this section, I describe the details of the numerical implementation, the parametrization, 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.

4.1 Numerical Implementation

The model is set to monthly frequency and discretizes the state space over uniform grids of assets (100 points), wages (20 points), as well as tenure and unemployment duration (5 points). Both tenure and unemployment duration evolve stochastically with 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 the value function converges[22]:

1. **Initial Guess**: Guess the value function: $V_0(a, w, \tau) = \frac{u(w+ra)}{\rho}$.

2. **Solve the HJB equations**:

   - **Upwind Scheme**: To approximate the marginal value of assets, use the the upwind scheme, which consists in using a forward difference approximation whenever the drift of the state variable is positive ($s_{a,F} > 0$) and to use a backwards difference whenever it is negative ($s_{a,B} < 0$):

$$V'_a = V'_{a,F}\mathbb{1}\{s_{a,F} > 0\} + V'_{a,B}\mathbb{1}\{s_{a,B} < 0\} + \bar{V}'_a\mathbb{1}\{s_{a,F} \leq 0 \leq s_{a,B}\}.$$

   - **Savings Policies**: Consumption satisfies the Euler equation:

$$u'(c) = \rho V_a(a, w, \tau)$$

[22]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:

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

  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, since it depends on the value function.

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

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

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

4.2 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:

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

where χ is the fraction of previous income replaced (the replacement rate) and $\bar{b}$ is the maximum benefit cap[23]. Once duration reaches the threshold d^*, unemployment benefits expire and workers receive the subsistence level of benefits $\underline{b}$.

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

Table 3. Model Parameters

Parameter		Value	Targeted Moment	Model	Data
Externally Set					
γ	Relative risk aversion	2.00	Externally set	-	
$\underline{a}$	Borrowing constraint	0.00	Externally set	-	
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 Estimated					
r	Risk free rate	0.02*100	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	2.8-0.5%	2.8-0.5%
w_τ	Wage growth by tenure	Fig3b	Income growth by tenure	0-0.3%	0-0.3%
Internally Estimated					
ρ	Discount rate	0.069	Wealth Distribution	$\mu = 3.6$k	$\mu = 4.4$k
μ_w	Wage offer parameter	0.001	Income distribution	$\mu = \$2.9$k	$\mu = \$2.9$k
σ_w	Wage offer parameter	0.65	Income distribution	$\sigma = 0.43$	$\sigma = 0.42$
λ_u	Job finding rate (unemp)	0.075	Monthly UE rate	20.04%	21.3%
λ_e	Job finding rate (emp)	0.019	Monthly EE rate	0.6%	0.49%

Note: All parameters are expressed at monthly frequency

4.3 Calibration

Table 3 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 in the data, or estimated internally by moment matching.

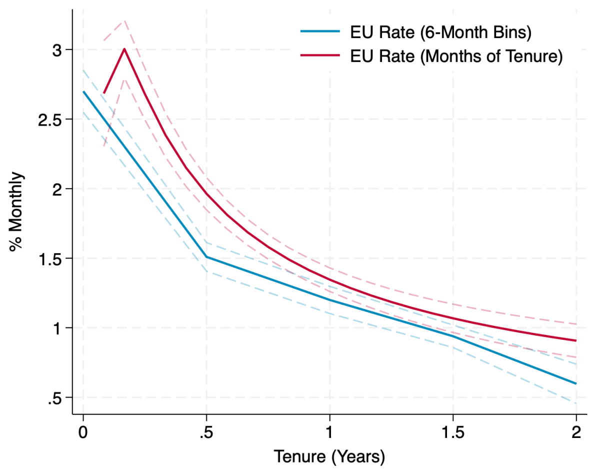
Externally Set The first group of parameters are set externally. I assume that the utility function has parameter $\gamma = 2$ and that workers cannot borrow against unemployment risk: $\underline{a} = 0$. Following Birinci and See (2023), I set the income replacement rate χ to 50%[24], while the benefits cap are 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

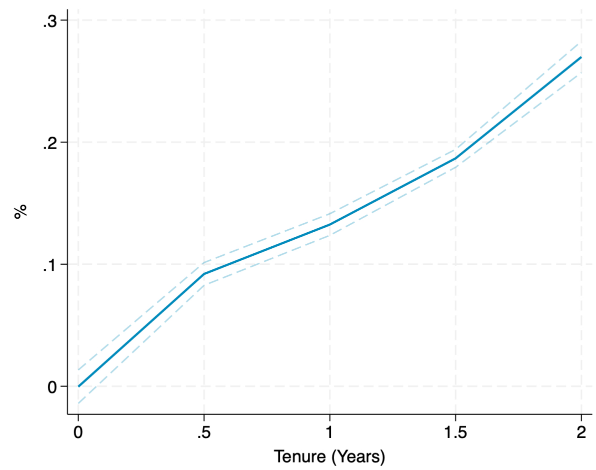
[24] Using SIPP data, Birinci and See (2023) estimate an average replacement rate of 52% among UI recipients, while Doniger and Toohey (2022) estimate an average replacement of 75% for UI recipients *below* the cap.

Figure 3. Empirical Targeted Moments

(a) Job Separation Rate by Tenure

(b) Income Growth by Tenure





Note: Panel (a) plots the monthly job separation rate by tenure, 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 displayed both by exact months of tenure (red) and by 6-month bins (blue), where monthly tenure is grouped into {[0-5], [6-11], [12-17], [18-23], [24-29]}. Panel (b) plots average income growth by 6-month tenure bins, using the same intervals as in Panel (a). *Source*: SIPP, 1996-2004 panel.

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]}. The separation rate parameters $\delta(\tau)$ over the same tenure bins are estimated directly from the SIPP following Menzio et al. (2016). Specifically, the monthly separation rate for workers with tenure τ is computed as the share of workers who experience an involuntary separation in a given month, relative to the number of employed workers with tenure τ in the previous month. Unlike Menzio et al. (2016), who focus on all types of EU transitions, I focus strictly on employer-initiated separations[25]. As evident from Figure 3a, separations decline sharply in the first six months, falling from 2.7%

[25]This includes temporary layoffs that could potentially lead to a recall. The reason is that, in the SIPP, it is not possible to distinguish workers on temporary layoff who are actively searching for work from those who are only waiting to be recalled by their employer.

down to 1.5% monthly, and then flatten out thereafter. This relationship is consistent with the established decline in job separation risk over job tenure, already documented by Topel and Ward (1992) and Farber (1994).

While my model focuses on average separation rates declining in tenure, Jarosch (2023) suggests that job loss rates vary systematically by job type, with higher-paying jobs exhibiting lower separation rates. While this holds in German data, other studies such as Cahuc et al. (2002) and Sockin (2022) suggest that firms with higher separation rates compensate workers with higher wages. Additionally, my model assumes that workers are homogeneous in skills, meaning that wage differences arise purely from wealth and job search behavior. Because my model does not incorporate skill heterogeneity, I assume that separation rates are constant within each job ladder, abstracting from variation across different jobs.

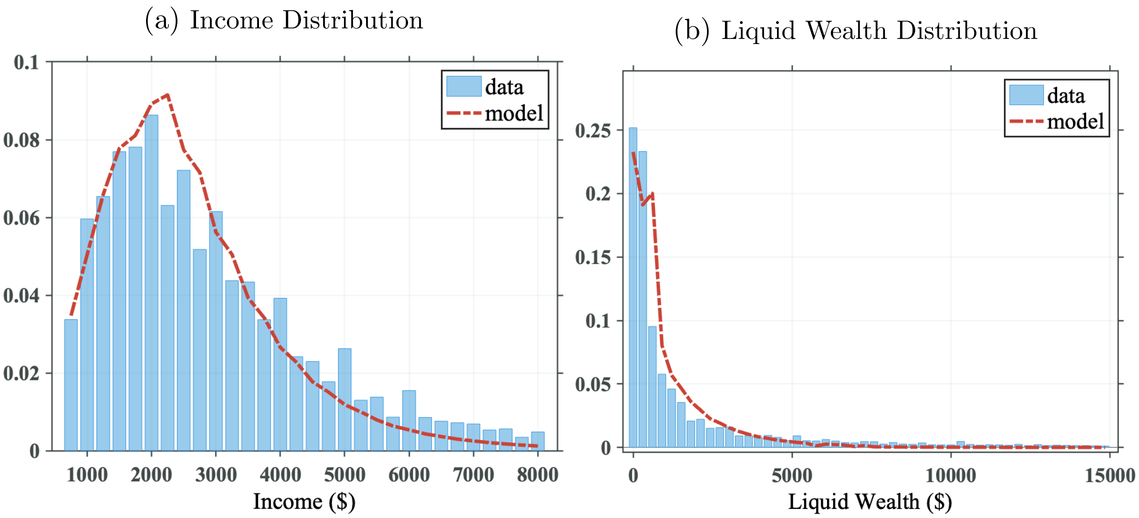
In reality, workers with different skills and education levels are likely to sort into different job ladders, each with its own separation rates and wage-tenure profiles. To assess whether separation rates vary meaningfully by skill level, Figure 11 in Appendix D plots the EU rate by college degree. The graph confirms that higher-educated workers experience lower separation rates, though the EU rate still declines with tenure across all education levels. To examine the importance of this heterogeneity in greater details, I propose an alternative model calibration for workers with a college degree versus those with a high school degree in Appendix D.

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 from unemployment (λ_0) is calibrated to match the average monthly unemployment-to-employment (UE) transition rate of 21.32%, while the the employed job finding rate (λ_1) targets the monthly job-to-job (J2J) transitions rate of 0.5%. 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 quartile of the liquid wealth distribution. Since workers are risk-averse and aim to smooth consumption, the model typically generate substantial asset accumulation as workers save to insure themselves against income loss. Thus, a high discount rate is required to ensure that some households hold no liquid assets.

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 (red). Panel (b) presents the liquid wealth distribution in both the data (blue) and the model (red). The model successfully captures the overall shape and dispersion of both distributions. *Data Source*: SIPP, 1996-2004 panel.

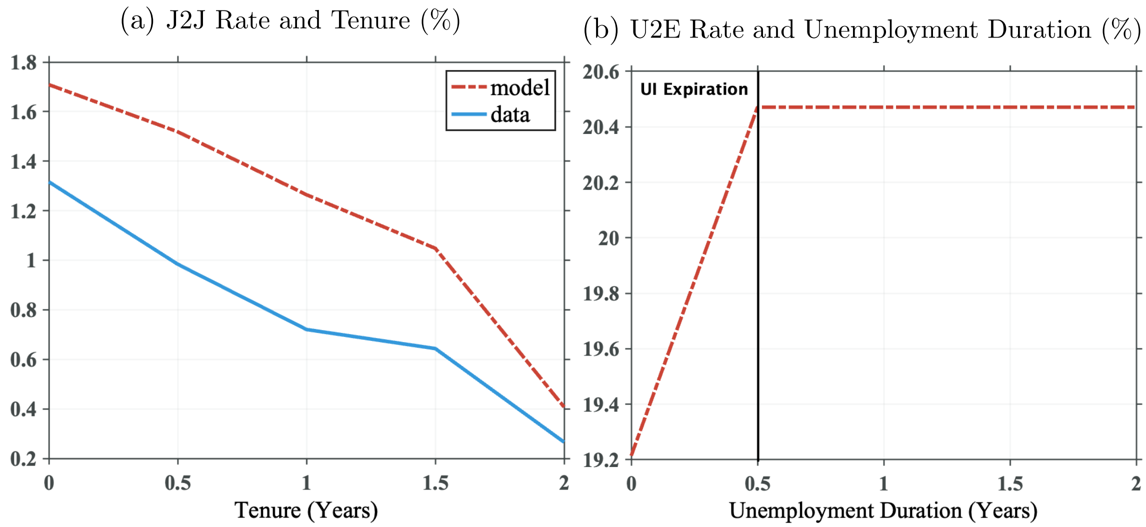
4.4 Model Fit

Targeted Moments The model successfully matches key moments observed in the data, with a total loss function value of about 8%. It slightly underestimates the UE rate while closely matching the EE rate. The estimated parameters suggest that the job search intensity of the employed is 25% of that of the unemployed ($\lambda_u > \lambda_e$), which is somewhat lower than previous estimates but remains broadly consistent with the literature[26].

As shown in Figure 4, the steady-state distributions in the model closely align with the observed income and wealth distributions. 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 where the discount rate is fixed at a more reasonable level. Naturally, this adjustment comes at the expense of a poorer match with the wealth distribution.

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

Figure 5. Untargeted Moments



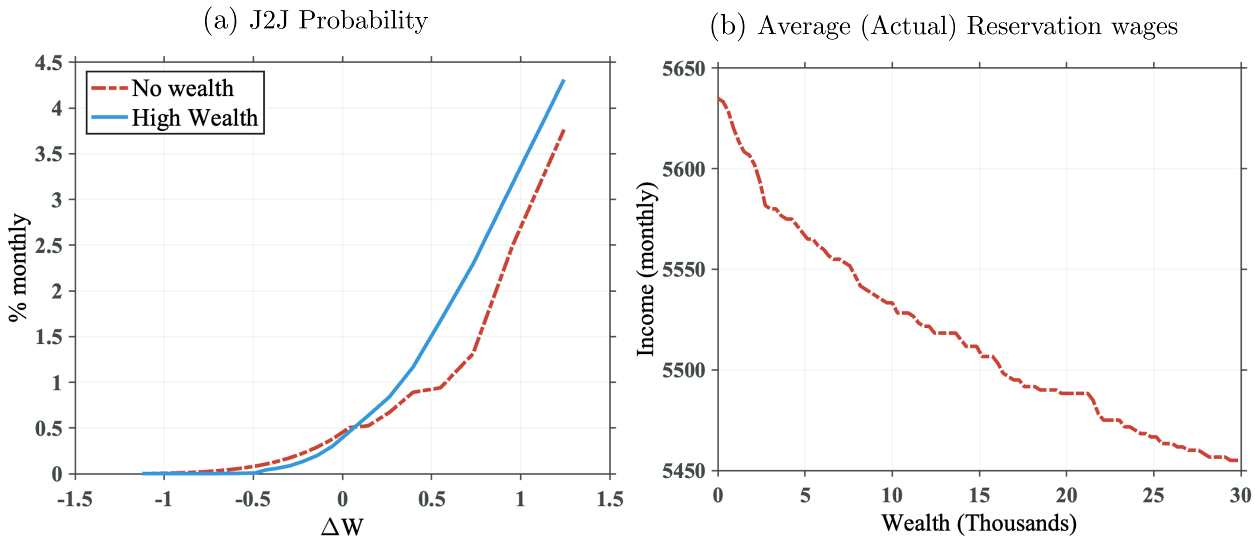
Note: Panel (a): Monthly job-to-job transition rate, averaged across wages and assets, for workers with different tenure in the model (red) and data (blue). J2J rates in the data are computed as the share of employed workers with a given tenure who quits their job in a given month. Panel (b): Average monthly unemployment-to-employment transition rate, averaged across unemployment benefits and assets, for workers with different unemployment duration. *Data Source*: SIPP, 1996-2004 panel.

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 3.7%, which aligns closely with empirical estimates for the time period. Additionally, as shown in Figure 5a, the model endogenously generates J2J transitions that decline with tenure, a well-established pattern in the data. The model closely matches the slope of this decline, though it slightly overestimates the overall number of J2J transitions. On average, gaining one additional year of tenure reduces J2J transitions by 0.5 percentage points, both in the model and in the data. This occurs because 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 (1988), and Katz and Meyer (1990). As shown in Figure 5b, the model predicts that U2E transitions increase by 2.2 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.

Indeed, I find that wealth influences both U2E transitions and the reservation wages of unemployed workers. Specifically, U2E transitions decline from 20.47% for workers with no liquid wealth to 19.62% for workers with some savings, suggesting that wealthier unemployed

Figure 6. Job-to-job Transitions and Wealth



Note: Panel (a): Monthly job-to-job transition rate, averaged across tenure, for workers of different incentives and wealth. As in the data, incentives are calculated as the log difference between the steady-state average wage and actual wages. High wealth is defined as average wealth of workers in the third quartile of the wealth distribution. Panel (b): Average monthly employed reservation wage, in thousands of dollars, for workers of different asset holding. Assets represent liquid wealth in thousands of dollars. Rates are averaged probabilities.

workers remain jobless longer. However, this effect varies significantly across UI recipients, with the difference exceeding 2 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 increases by about $125 per month for workers with savings, allowing them to hold out for better job opportunities rather than immediately accepting lower-wage positions.

4.5 Quantifying the Effect of Wealth on Labor Mobility

The main results of the model are summarized in Figure 6, which plots the untargeted monthly J2J transition rates across different levels of incentives, as well as the model-implied reservation wages by wealth. As shown in the figure, workers at the lower end of the job ladder, who have higher incentives, change jobs far more frequently than those in high-paying jobs. More importantly, J2J transitions increase more rapidly for workers with savings compared to liquidity-constrained workers. In particular, among workers with positive incentives, those with high wealth change jobs at a rate approximately 0.45 percentage points higher than their liquidity-constrained counterparts. This difference arises endogenously in the model, as the calibration exercise targets only the average J2J transition rate and the quartiles of the wealth distribution separately, without explicitly matching the wealth gap in mobility. Not surprisingly, workers in the top wage quartile have low incentives and rarely change jobs, regardless of their wealth.

To assess the goodness of fit, I compare the model's predicted wealth gap in J2J transitions to the data across different incentive levels. On average, the model underestimates the wealth gap by 0.005 percentage points, while the weighted difference (accounting for the steady-state distribution) is 0.019 percentage points. Given that the average J2J transition rate is 0.5%, these errors are relatively small.

However, J2J transitions vary substantially across different incentive levels. In particular, workers in high-paying jobs with low incentives rarely switch jobs at all, and the model tends to overestimate the wealth gap in J2J transitions for these workers. As a result, the model's explanatory power may be inflated. To adjust for this overprediction, I compute the mean absolute error (MAE) between the model and the data. The model's MAE is 0.18 percentage points, while the weighted MAE (accounting for income distribution) is 0.21 percentage points. These errors correspond to 36% and 42% of the average J2J transition rate, respectively. This suggests that, on average, the model explains approximately 60% of the observed wealth gap in J2J transitions in the data.

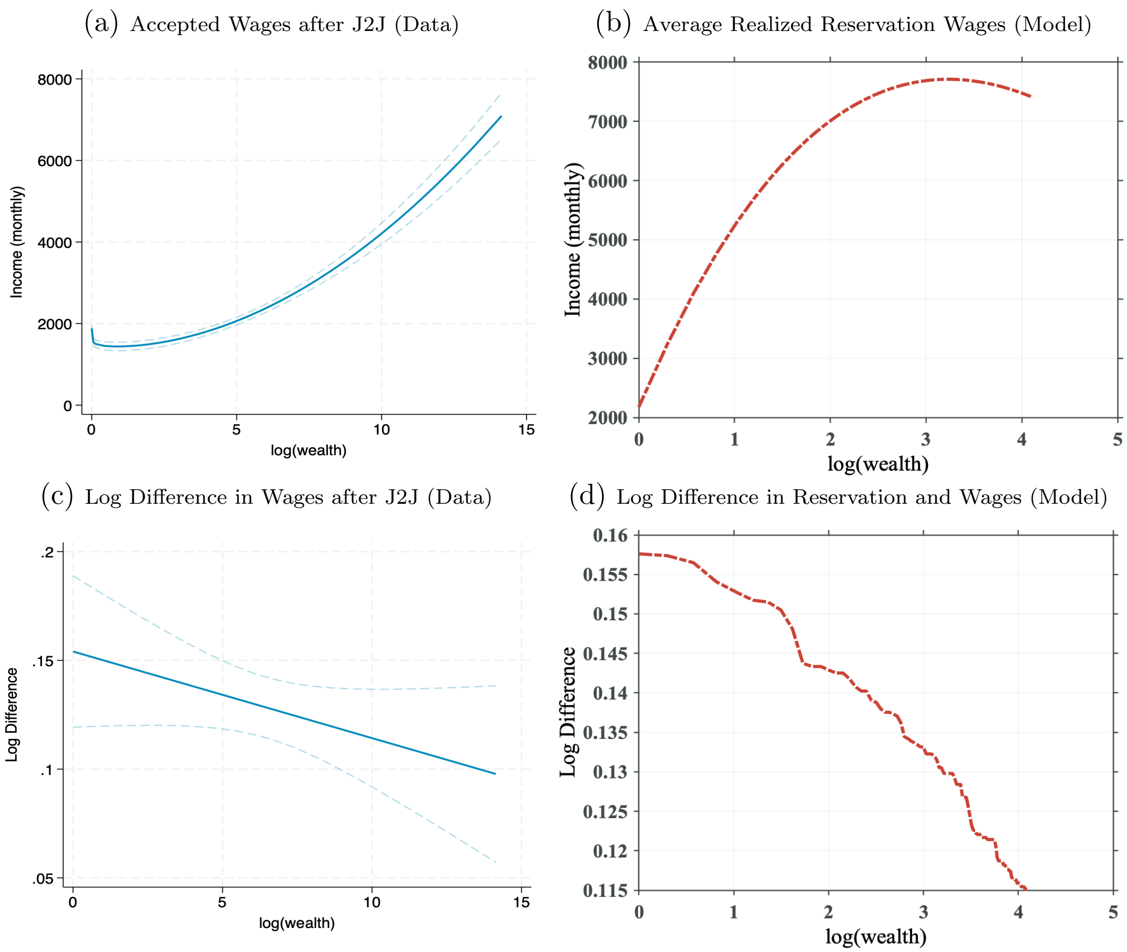
4.6 Reservation Wages

The mechanism driving these findings can be understood through the reservation wage, as shown in Figure 6b. The reservation wage for employed workers decreases with assets, reflecting that wealthier workers can afford the greater risk of job loss associated with job changes. On average, the reservation wage of high-wealth workers is approximately $200 per month lower than that of liquidity-constrained workers. This decline is particularly pronounced among low-wealth workers, where the reservation wage falls at a steeper rate.

However, in the data, only the realized reservation wages are observable. The difference between actual and realized reservation wages arises from the steady-state distribution, which suggests that wealthier workers are more successful in climbing the job ladder. As a result, in steady-state, very wealthy workers are unlikely to hold low-paying jobs, though we can compute their hypothetical reservation wage at such positions. To approximate realized reservation wages in the data, I compute accepted wages after job-to-job transitions and compare them to the average realized reservation wages in the model. As shown in Figure 7, panels (a) and (b), accepted wages following a J2J move increase from approximately $2,000 per month for liquidity-constrained workers to nearly $8,000 per month for the wealthiest. The model captures this upward trend, though the slope differs significantly between the data and the model.

As an additional validation, Figure 7, panels (c) and (d), show the log difference in wages before and after a job-to-job move in the data and the log difference between reservation wages and actual wages in the model, respectively. The figure shows that after changing jobs, low-wealth workers experience an average wage increase of 16%, while wealthier workers see a 10% gain. The model successfully captures this pattern, showing that the gap between reservation wages and actual wages decreases from 16.7% to 12.2% as wealth increases.

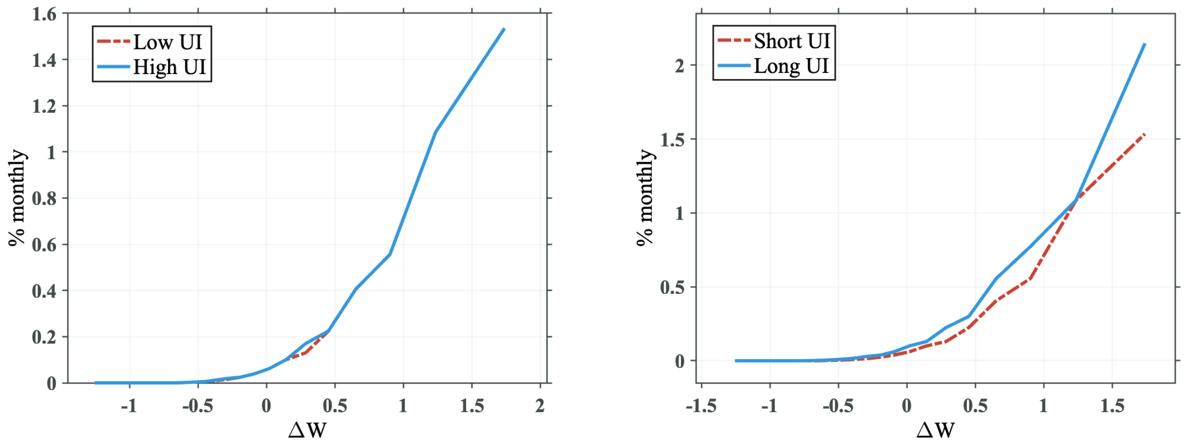
Figure 7. Reservation Wages and Wealth



Note: Fractional-polynomial prediction of accepted wages after job-to-job transitions as a function of workers' IHS-transformed liquid wealth (data). Shaded area represents the 95% confidence interval. Panel (b): Average realized reservation wages in the model, plotted against workers' IHS-transformed liquid wealth. Wages are smoothed using a third-degree polynomial. Panel (c): Fractional-polynomial prediction of the log difference in wages before and after a job-to-job transition as a function of workers' IHS-transformed liquid wealth (data). Shaded area represents the 95% confidence interval. Panel (d): Log difference between reservation wages and actual wages in the model across workers' IHS-transformed liquid wealth (unsmoothed). *Data Source*: SIPP, 1996-2004 panel.

Figure 8. Change in Unemployment Insurance

(a) $200/month Increase in UI (b) 6 Months Extension in UI



Note: Panel (a): Monthly job-to-job transition rate for two different levels of unemployment benefits, averaged across tenure, for workers with different wages and no savings. Panel (b): Monthly job-to-job transition rate for two different levels of unemployment benefits, averaged across tenure, for workers with different wages and no savings. Assets represent liquid wealth in thousands of dollars. Rates are averaged probabilities.

4.7 Counterfactual Analysis

As a first policy experiment, I compare two changes in unemployment insurance (UI): a $200 increase in UI benefits for all workers and a six-month extension of UI duration. While the first policy has little impact on job-to-job (J2J) transitions, the UI extension significantly boosts job mobility, particularly for liquidity-constrained workers at low-paying jobs.

Figure 8 presents the results of this experiment. The response to the UI extension is highly heterogeneous across the job ladder and the wealth distribution. As shown in the graph, J2J transitions increase by over 0.5 percentage point for liquidity-constrained workers in low-paying jobs, narrowing the gap with the transition rates of wealthier individuals. The intuition is that the extended benefits allow unemployed workers to wait longer for better wage offers, while employed individuals, less concerned about potential job loss, lower their reservation wages and switch jobs more frequently. In contrast, the $200 increase in UI provides only a marginal improvement in consumption smoothing and does not significantly alter job-to-job transition rates, as Figure 8b illustrates. Wealthy workers and those in high-paying jobs remain unaffected under both policies, as they either already transition optimally or have no incentive to change jobs.

5 Conclusion

This paper examines the role of wealth in shaping job mobility and labor market outcomes. Using a structural job ladder model with incomplete markets, I show that liquidity constraints significantly impact workers' ability to change jobs, ultimately affecting wage growth and labor market inequality. The model successfully matches key labor market moments, including observed job-to-job and unemployment-to-employment transition rates, as well as the income and wealth distributions. Importantly, it replicates the well-documented decline in J2J transitions with tenure and the spike in U2E transitions at the expiration of unemployment benefits.

The main mechanism driving these results is the separation rate decreasing in tenure. Workers with higher savings can afford to take more risks and switch jobs more often, leading them to set lower reservation wages while employed and search more aggressively for higher-paying jobs. Conversely, liquidity-constrained workers exhibit higher reservation wages, limiting their job mobility and making it harder for them to climb the job ladder. The model captures approximately 60% of the observed gap in job mobility between low- and high-wealth workers in the data, providing strong evidence of the importance of this mechanism.

These findings have important policy implications. Policies that improve access to liquidity, such as more generous unemployment insurance or portable benefits, could reduce the frictions preventing job transitions and enhance overall wage growth, particularly for low-income workers. Moreover, the results suggest that wealth inequality can perpetuate labor market inequality, as constrained workers remain trapped in low-paying jobs while wealthier workers are better able to leverage job mobility for higher wages. However, an extension in UI offers a potential path out of this job trap.

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Appendix

A Data

Table 4 presents the coefficients from the probit regressions in Equation 1 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.

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.

Table 5. Regressions of Earnings on Demographic and Job Characteristics

	Log(Monthly Earnings)	
	LPM (Correia)	OLS
age	0.029***	0.016***
	(0.005)	(0.003)
age^2	−0.001***	−0.0002***
	(0.000)	(0.000)
log(tenure)	0.029***	0.096***
	(0.003)	(0.002)
experience	-	0.009***
		(0.037)
education		
high school degree	0.061	0.066***
	(0.038)	(0.008)
some college	0.029	0.139***
	(0.038)	(009)
college degree	0.154***	0.336***
	(0.046)	(0.014)
graduate degree	0.218***	0.511***
	(0.051)	(0.014)
race		
black	−0.212***	−0.064***
	(0.063)	(0.008)
hispanic	−0.016	−0.087***
	(0.051)	(0.018)
other	0.043	−0.038***
	(0.067)	(0.014)
female	−0.366*	−0.206***
	(0.216)	(0.007)
full time	0.197***	0.532***
	(0.009)	(0.021)
disability	−0.031***	−0.161***
	(0.006)	(0.010)
union	0.051***	0.152***
	(0.006)	(0.009)
Month Fixed Effects	Yes	Yes
Worker Fixed Effects	Yes	-
R^2	87.77%	57.15%
N	863,263	863,263

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, and number of kids. The OLS regression also includes the type of high school attended, citizenship status, 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.

Table 7. 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 8. 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.

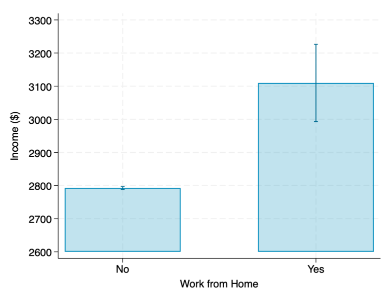
Table 9. Regressions of Income on Job Amenities

	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

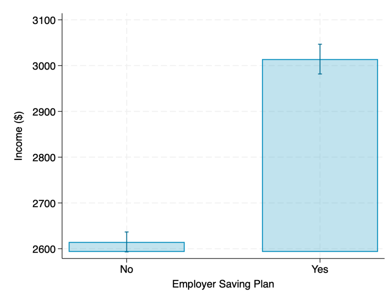
Note: The table shows the coefficients from an income regression on various job amenities, controlling for both demographic and job characteristics. The three columns correspond to different model specifications: Column I includes work-from-home, weekend work, and employer-sponsored savings plans, all 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 9. Income and Job Amenities

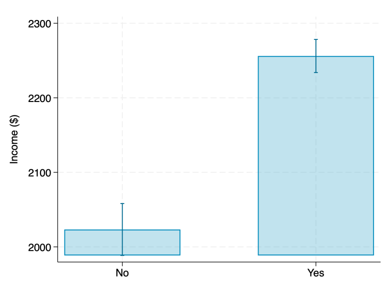
(a) Work from Home



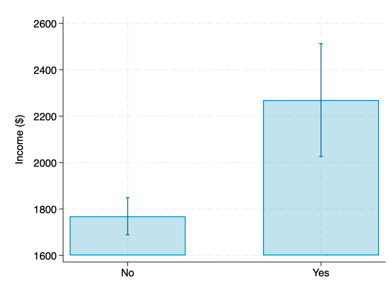
(b) Saving Plan



(c) Health Insurance



(d) Tuition Reimbursement



A.1 Additional Robustness

Table 10. 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: Standard errors are bootstrapped with a 2-step estimator. *** statistically significant at 5%. *** statistically significant at 1%. *Source*: SIPP, 1996-2004 panel.

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 four columns correspond to regressions across different age groups. *** 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: $V(a, R(a, w, \tau), 0) = V(a, w(\tau), \tau)$. Expanding the equation, this becomes:[27]:

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

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

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

Solving for the reservation wage we have:

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

Note, however, that from the first order conditions we have that $c(a, R, 0) = u'(\frac{\partial V}{\partial a})^{-1} = c(a, w(\tau)$. 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

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

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

$\square$

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:

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

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:

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

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:

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

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 $v'_{a,B}, s_{a,B}$:

$$\frac{v^{n+1}_{\alpha,\omega,t} - v^n_{\alpha,\omega,\theta}}{\Delta} + \rho v^{n+1}_{\alpha,\omega,\theta} = u(c^n_{\alpha,\omega,\theta}) + \frac{v^{n+1}_{\alpha+1,\omega,\theta} - v^{n+1}_{\alpha,\omega,\theta}}{\Delta a}(s^n_{\alpha,\omega,\theta,F})^+ + \frac{v^{n+1}_{\alpha,\omega,\theta} - v^{n+1}_{\alpha-1,\omega,\theta}}{\Delta a}(s^n_{\alpha,\omega,\theta,B})^-$$
$$+ \alpha_w(v^{n+1}_{\alpha,-\omega,\theta} - v^{n+1}_{\alpha,\omega,\theta}) + \alpha_\theta(v^{n+1}_{\alpha,\omega,-\theta} - v^{n+1}_{\alpha,\omega,\theta}).$$

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

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:

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

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 to a different job w_j or out of unemployment is given by: $P_{w_j} = \lambda * f(w_j) * \mathbf{1}\{V(a,w,\tau) > V(a,w_j,0)\}$. The transition matrix across different jobs is given by:

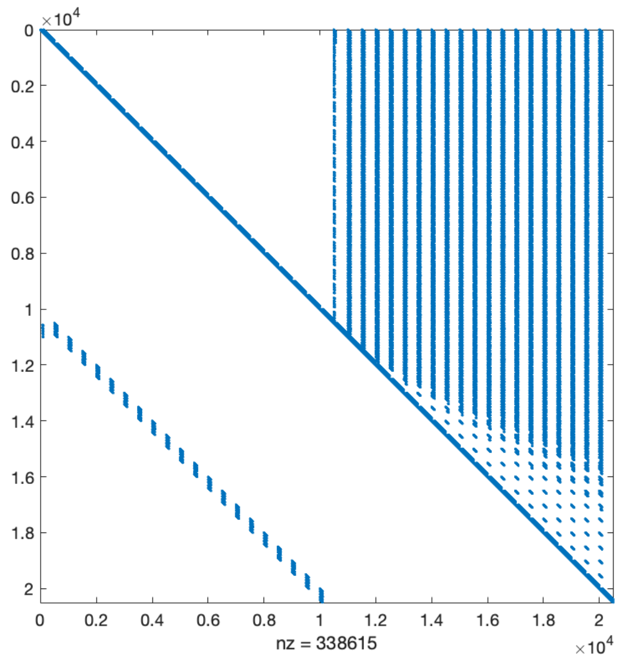
$$A_w = \begin{bmatrix} -(\sum_j P_{w_j}) & 0 & \cdots & P_{w_1} & P_{w_2} & \cdots & P_{w_J} \\ \delta(\tau) + \mathbf{1}_{U>V} & 0 & \cdots & -\sum_{j>1} P_{w_j} - \delta(\tau) - \mathbf{1}_{U>V} & P_{w_2} & \cdots & P_{w_J} \\ 0 & \delta(\tau) + \mathbf{1}_{U>V} & \cdots & 0 & -\sum_{j>2} P_{w_j} - \delta(\tau) - \mathbf{1}_{U>V} & \cdots & P_{w_J} \\ \vdots & \vdots & \vdots & \ddots & & & \\ 0 & 0 & 0 & \cdots & -(\delta + P_{w_J}) & & \end{bmatrix}$$

Fig. 10 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 10. 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

As an alternative calibration, I calibrate the model for both low skills (no college degree) and high skill workers.

Figure 11. Poisson Transition Matrix