Unemployment Insurance and Worker Reallocation: The Experimentation Channel in Job-to-Job Mobility

[Preliminary and Incomplete. Do not cite.]

Yusuf Mercan[*] Benjamin Schoefer[†]
U Melbourne UC Berkeley

February 2019

Abstract

The risk of job loss is concentrated in the early months of the job; after the initially high levels of unemployment risk, jobs become stable. We argue that this initial excess exposure to unemployment risk renders job-to-job transitions risky. We formalize this mechanism in a search and matching model in which job offers are "lotteries", placing probabilities on job qualities, which are revealed early on in the new job. Workers know the probability weights, and lotteries are heterogeneous in those weights. A set of job quality realizations lead workers to prefer quitting into unemployment. In this model, job mobility is affected by the value of unemployment, which represents the downside risk of accepting a job lottery. This consideration constitutes a mobility friction for employed workers. We explore all these properties and predictions in a calibrated version of the model. We also highlight a new role of unemployment insurance (UI): In our model, UI insures the downside risk of job-to-job transitions, and thereby subsidizes job mobility of workers already employed, and tilts the job composition to ex-ante riskier jobs. We close by discussing potential implications of this new view of unemployment insurance. Our study therefore sheds light on how labor market policies affect the behavior of employed job seekers through a novel "experimentation subsidy" channel.

[*]yusuf.mercan@unimelb.edu.au
[†]schoefer@berkeley.edu

1 Introduction

Labor markets are characterized by large degrees of wage dispersion between otherwise similar workers and jobs.[1] Through the lens of frictionless labor market models, such wage dispersion is puzzling because workers should sort into firms offering the highest wage.[2] *Mobility frictions* may rationalize workers' decision to stay put in underpaid positions. An open question is which particular frictions support wage dispersion observed in the data.

We propose, formalize and explore a mobility friction that is motivated by the empirical fact that job transitions expose the worker to excess unemployment risk: The risk of job loss is concentrated in the early months of the job; after the initially high levels of unemployment risk, jobs become stable. This initial excess exposure to unemployment risk renders job-to-job transitions risky. Since job loss into unemployment is costly to workers, workers stay put in worse, yet safer, jobs, passing on better job offers, all to avoid the downside of unemployment. We also highlight a new role of unemployment insurance (UI): In our model, UI insures the downside risk of job-to-job transitions, and thereby subsidizes job mobility of workers already employed. In future work, we plan to provide a direct test of this mechanism exploiting quasi-experimental variation in UI.

Our main motivation is empirical: Employed workers moving into a new job are exposed to considerably higher unemployment risk early on in that job, compared to their previous job or to later stages of the new employment relationship. We document this pattern in a large U.S. household survey, the Survey of Income and Program Participation. While stably employed workers with a median amount of tenure, around 50 months, have on average a 4% probability of separation into unemployment in a given year, workers that just started a job face a 17% probability of job loss into unemployment. These patterns are consistent with theories of imperfect information in the labor market, by which neither workers nor firms can assess job quality perfectly at the recruitment stage, and additional information is revealed gradually after the match has been formed, and potentially production has begun. As a result, ex-post, inferior matches are dissolved and workers are pushed into unemployment. Alternative mechanisms for the excess unemployment risk right after job-to-job transitions are institutional, formal or informal, such as seniority rules shielding higher tenured workers from separation risk. For example, in many OECD countries, formal firing restrictions are lax in the early tenure weeks and months, but sharply increase with tenure in the given now-permanent job contract, i.e. "Last in, first out".

Our paper explores the consequences of this robust empirical fact of tenure dependence of unemployment risk for job-to-job transitions: Due to excess unemployment risk, job-to-job transitions are risky lotteries, and their expected value is sensitive to unemployment. The

[1]See e.g. Hornstein et al. (2011); Card et al. (2013); Sorkin (2018).

[2]Alternative explanations appeal to amenity differences or compensation differentials.

value of the job offer inherits the shape of the payoff function of this lottery, except that it is horizontal at the value at which the job value equals unemployment, which is the outside option of the worker. Unemployment therefore bounds the downside value of an accepted job offer, generating limited liability.

We formalize this lottery view of job mobility in a search model, featuring uncertainty about job offers, heterogeneity in match quality and on-the-job search. These features of the model generate a job ladder that employed workers seek to climb. However, job transitions are risky: Job offers are not deterministic but come in terms of *lotteries*, that is in probability weights on actual match qualities. Realization of the lottery outcome occurs after the worker has quit her old job, therefore the worker chooses between unemployment and the realized job. We propose a model that is nonparametric in terms of the distributions of these lotteries over match types. Our model collapses to a standard McCall search model when job lotteries are deterministic, i.e. when prospective match productivities are perfectly observed ex-ante. On the firm side, we feature endogenous job creation with random search.

To assess the potential quantitative role of this mechanism in shaping job mobility, we calibrate the model. Our most important empirical target is the excess unemployment risk following transitions into new jobs in the first year, compared to the unemployment risk faced by longer-tenured workers.

In our calibrated model, the effects of unemployment risk on job mobility are potentially large. We reach this conclusion by exploring how job mobility responds to a well-defined policy experiment: We increase the generosity of unemployment insurance benefits.

Substantively, this experiment reflects a new role for unemployment insurance: With risky jobs observed in real-world labor markets, UI subsidizes risky job offers by insuring the downside. We explore this intuition for two regimes of UI generosity, which shifts the value of unemployment. The value of the risky job offer is increasing in the value of unemployment. We call this new effect the *experimentation channel of unemployment insurance*, subsidizing job-to-job transitions.

In particular, this experimentation channel of UI subsidizes job mobility into ex-ante *risky* jobs. A "safe" job offer, which puts no weight on unemployment, is invariant in the value of unemployment and thus to unemployment insurance.[3] The intuition is simple: Only those job-to-job transitions that expose the workers to excess unemployment risk depend on the value of unemployment. Models that do not feature this real-world risk of job mobility would preclude UI's role in job mobility. Rather than only increasing job-to-job transitions overall, UI affects the *composition* of jobs, tilting it towards ex-ante risky jobs.

In future research, we plan to test the role of UI in insuring risk associated with job mobility directly, exploiting quasi-experimental variations in UI. Specifically, we will use Austrian ad-

[3]Except for equilibrium adjustments.

ministrative data and take advantage of variations in UI introduced by the 1988 Austrian labor market reforms. In this paper, we present the theoretical and quantitative framework we will use to complement this future empirical work.

The rest of our paper is organized as follows. Section 2 provides motivating facts on job mobility and unemployment risk. Section 3 presents our model, and Section 4 discusses the calibration strategy, Section 5 presents a quantitative analysis of the model, and Section 6 provides quantitative exercises. Section 7 concludes.

2 Motivating Facts: Job Mobility Entails Unemployment Risk

This section presents our key facts on the riskiness of job-to-job transitions using U.S. household level panel data. The argument takes three steps. First, the probability of an employed worker entering unemployment is sharply larger in the first year of employment, around 20%, and then quickly stabilizes to around 4% per year. Second, we show that this pattern holds even for jobs formed as a result of a direct job-to-job transition, where the associated numbers are 16% and 4%. Third, we show that these results are robust to composition adjustment and sample restrictions.

Data Our primary dataset is constructed from the Survey of Income and Program Participation (SIPP). SIPP covers a representative sample of households interviewed every four months (called a "wave"), where survey questions cover the previous four calendar months ("reference period"). The maximum panel length is four years. A new set of households are sampled every two to four years ("panels"). Each panel is named after the year it starts and tracks households for the duration of the survey period. Therefore, SIPP's design makes it possible to follow individuals up to four years.[4]

We construct a monthly panel, covering the period between 1992 and 2013. To this end, we use the 1993, 1996, 2001 and 2008 SIPP panels. We restrict our sample to workers between ages 20 and 65. We use the reported status of workers in the last week of each month to determine their labor market status. To calculate our measures of labor-market transitions, we first follow Nagypál (2008) in order to make indicators of labor market status consistent with the CPS: employed, unemployed and out of the labor force. In the current analysis, we however consider nonemployment and employment only, except for a slight narrowing of the nonemployment definition.[5] Using the monthly employment status and job identifier variables, we then define an employer-to-employer transition as an event where a worker is employed in two consecutive

[4]This duration is much shorter in the Current Population Survey (CPS), where households are surveyed for two four-month periods with an eight month break in between. Furthermore, the CPS is address-based, so movers are dropped out of the sample. SIPP makes an effort to track households in case of an address change.

[5]We exclude spells of individuals enrolled in school or in the army, and of the self-employed.

months with a change in employer-employee match ID.[6]

Constructing monthly separation rates in the SIPP We start by constructing monthly separation probabilities for employed workers using our monthly panel. For each cross-section of workers with a given tenure on current job, we calculate the share that separate into nonemployment and to another job in the subsequent month. These two fractions represent our monthly transition probabilities by job tenure, ρ_τ^{EU} and ρ_τ^{EE}. These separation rates are our first variables of interest that highlight the riskiness of taking a new job overall.[7]

ρ_τ^{EU} and ρ_τ^{EE} are the weighted average of two components based on the labor market status prior to the current job: job matches formed out of unemployment, and those formed as a result of job-to-job transitions – the two margins by which tenure gets reset to zero. Our paper is particularly interested in the excess unemployment risk that job-to-job switchers incur early on in the new job. We therefore additionally construct *conditional* separation rates by origin: E-EU and U-EU transition probabilities $\rho_t^{(E)EU}$ and $\rho_t^{(U)EU}$. We do so by simply splitting up the panel into two parts: those jobs for which we recorded previous labor market status as nonemployment, and those jobs formed directly after a preceding spell of employment. We present the results below.

Tenure-specific separation rates Figure 1 presents the evolution of the separation rate of an employed worker at a given tenure. Our separation margin is from employment into nonemployment. The separation rate is defined at the monthly frequency, i.e. the share of employed workers that separate in the subsequent month given the tenure level. This granular specification allows us to zoom into the early months of the job and highlight a striking pattern: The separation rate is far from constant but is tenure-dependent. Specifically, the separation rate is above 2% for workers in their first four months on the job, implying that 2% of lowest-tenure workers separate into unemployment *in a given month*. By contrast, workers with a more typical amount of tenure, around three years, exhibit a separation rate of only 0.6%, i.e. less than a *third* of workers that are newly employed. Figure 1 shows that starting a new job exposes newly hired workers to excess nonemployment risk, compared to their higher-tenure colleagues.

Companion Figure 2 casts these monthly transition rates into *annually-cumulated* separation rates. It preserves the monthly tenure bins and summarizes the probability of separation into

[6]SIPP assigns a unique ID for each employer-employee pair, together with the start and possible end date of the match in each four-month reference period. Job IDs in the 1993 panel are subject to miscoding as identified in Stinson (2003) and pointed out in Fujita and Moscarini (2017). We correct for miscoding by using the revised job IDs. In case of multiple jobs, we define a worker's main job to be the one where she has worked the most hours. If hours worked are equal then we choose the job that was held the longest.

[7]The tenure gradient of the separation rate has previously be documented by Farber (1994) using the National Longitudinal Survey of Youth. See Menzio et al. (2016), Jung and Kuhn (2016) and Nagypál (2007), which also document the negative relationship between hazard rate of job separations and tenure, among many other papers.

unemployment during the upcoming 12 months rather than the single month.[8] A worker that just started a job (i.e. tenure at most one month) has a 17% probability of separating into unemployment in the next year. By contrast, workers with a median amount of tenure, around 50 months, have unemployment risk of around 4% per year. Unemployment risk is therefore four times as likely in the early years of a job than in jobs with typical durations, implying that job-to-job transitions, which pull workers out of the "safe" portion of the gradient in which they are insulated from unemployment risk, back to the maximal unemployment risk.

The tenure gradient of separations by the origin of the current job: jobs formed out of unemployment vs. from job-to-job transitions We so far have examined the average separation rate for any newly formed job as a function of tenure. Jobs can be formed out of nonemployment or as a result of job-to-job transitions. Perhaps among the low-tenure jobs, most jobs were formed out of unemployment, and perhaps it is no surprise that recently unemployed workers are more exposed to unemployment risk. Instead, our paper focuses on the excess unemployment risk employed job seekers are exposed to when engaging in job-to-job transitions. Next, we show that the excess unemployment risk is also pronounced for jobs formed as a result of job-to-job transitions. We take the sample of jobs that are formed during the SIPP panel. For those jobs, we also observe the household's previous labor market status: unemployment vs. employment. We separate the sample into those two sets, and compute annually-cumulated EU transition probabilities separately for each sample as a function of tenure.

Figure 3 presents the tenure profile of EU separations for each sample separately for the monthly transition probability; Figure 4 does so for the annually-cumulated versions. Indeed, jobs formed out of unemployment exhibit a large EU risk early on and overall, almost 3% at the monthly frequency, which stabilizes very quickly; annualized rates are 22% in the first month (dropping to and below 10% after a year). The jobs formed as result of job-to-job transitions exhibit a qualitatively similarly pattern: Unemployment risk is concentrated in the early months of the newly formed job, and declines steeply with tenure. The year-one risk of unemployment is 13% at the beginning of the job, sharply dropping below 5% within a year. This evidence demonstrates the excess unemployment risk entailed by job mobility. While the typical employed worker with tenure above three years is unlikely to undergo unemployment, a job-to-job transition dramatically increases this risk.

Robustness: (E)EE transitions The picture is amplified if we consider EE transitions early on in a given job. Note that we count a worker only as undergoing unemployment if the worker happens to be nonemployed in the last month of the year. However, job finding rates are high in

[8] We compute this *annually-cumulated* rate for each tenure level by i) calculating the probability of a worker, who just started her job, to separate into nonemployment within that given tenure duration ii) taking a 12 month ahead difference to arrive at separation probability within the following year, conditional on having that certain tenure duration.

the United States, such that between 30% and 50% of workers find a job within a given month. We may therefore miss a considerable amount of separators into unemployment that quickly find a job before the end of the subsequent month, when we record the labor market status. To address this question, we provide an additional analysis that investigates EE transitions, in our data set those workers who are employed at different firms between a given last week of a month and the last week of the subsequent month. Figure 5 presents these results for $\rho_\tau^{(E)EE}$ and $\rho_\tau^{(U)EE}$. Indeed, the separation rate at the EE margin is 25% in the first month for both jobs that originate from unemployment and nonemployment. This result suggests that the total separation rate in month one is close to 40% for jobs resulting from job to job transitions. For 13ppt of this fraction we account with nonemployment observations, whereas the remaining 25% are likely a mixture of short nonemployment spells and direct job-to-job transitions.

Robustness: composition adjustment The tenure gradients of the separation rate are simple averages of jobs spells. The explanation for the declining pattern is either due to the selection over the job spell, such that jobs further into the tenure distribution carry larger surplus, or may be compositional, surplus-unrelated factors that may explain the declining pattern. For example, perhaps older workers are less effective in job search and thus have a lower arrival rate of job offers, but also have a lower probability of receiving idiosyncratic shocks leading to unemployment. This would then lead to the right side of the tenure distribution to exhibit a lower separation rate not because of job quality selection but because of the pure age effect. Similarly, perhaps young workers are in a segmented labor market and look for temporary jobs; as a result, they make up a low fraction of low-tenure jobs and exhibit a large turnover, compared to older workers that dominate the higher-tenure bins. In both situations, the tenure gradient of EU transitions would not capture the experiment of moving a worker from the unemployment-insulated middle of the distribution to the front of the line with high unemployment risk.

To start tackling these compositional effects, we DFL-reweight our observations. We illustrate this nonparametric and transparent procedure along the age dimension, an important determinant of job mobility. We sort workers into five age bins, and then sort observations into these give groups. We then compute simple means within each age-tenure cell. We then take weighted averages of the separation rate in each tenure bin, where the weight is held constant across all observations. We choose the sample weights given by the lowest tenure bin.

Figure 6 plots the separation rates, $\rho_\tau^{(E)EU}$, from the outcome of this reweighting procedure along with the unweighted graph. The reweighted graph, which accounts for dynamic selection by age, is very close to the original graph that includes the age-specific compositional effects. We therefore conclude that the excess EU transitions in the early tenure bins are still high even compared to reweighted means beyond tenure year one. By weighting by year-one age composition, the graph traces out the tenure gradient representative of the cohort initially hired into new jobs under the assumption of homogeneous separation rates. This perspective is most useful to trace out the decline in the unemployment risk the newly hired cohort should expect to have conditional on surviving until a given tenure level.

A complementary approach is to reweight observations based on the age composition of a higher-tenure reference group. The resulting gradient, in particular the lowest-tenure separation rate, now captures the risk perceived by a higher-tenure group considering a job-to-job transition. That is, we compute the age shares prevailing in the sample with 50 months of tenure, and apply those weights across all other tenure bins. Figure 6 presents the resulting reweighted tenure gradient. The gradient is very close to the unweighted graph and to the graph that uses the low-tenure reference group. Therefore, even when considering the sample that typically ends up having high tenure, the observations exhibit an excess separation rate of 13%.

Robustness: voluntary job changes One concern with interpreting the steep downward sloping tenure profile of $\rho_\tau^{(E)EU}$ as excess unemployment risk associated with job mobility is that observed job-to-job transitions might not be voluntary. To address this concern, we split the workers into those who make wage gains and losses upon job switch.[9] We plot $\rho_\tau^{(E)EU}$ for these two groups of workers separately in Figure 7. Figure 7 shows that the nonemployment risk for these two groups are very similar, indicating that even voluntary job-to-job transitions come with substantial nonemployment risk.[10]

3 A Model of Risky Job Mobility

This section formalizes the link between risky job mobility, unemployment value and unemployment insurance benefits. Specifically, we write down a tractable model of the labor market characterized by search frictions, on-the-job search, match heterogeneity and ex-ante uncertainty about the fundamental match productivity. Firms and workers do not observe the quality of their match at the time of contact, but instead they base their decisions on a job lottery they receive. This lottery provides a probability distribution over match productivities, and only after taking the lottery the agents observe the outcome. The key insight from the model is: An increase in the level of unemployment benefits, by insuring the “downside risk” of a job offer lottery, shifts the composition of job switchers to risky lottery takers, and encourages experimentation and worker mobility.

[9]Wage loss upon job change is an important feature of the data as documented by Tjaden and Wellschmied (2014).

[10]This conclusion depends on the extent that we can interpret wage gains pointing to a voluntary job switch.

3.1 Environment

Time is discrete. Firms and workers in the economy are risk neutral, and live forever. Agents discount the future with a common factor $\beta \in (0,1)$. In each period, matches are destroyed with exogenous separation rate δ.

Matching The labor market is characterized by search frictions. We allow for on-the-job search. Employed workers search with intensity λ relative to unemployed workers. Firms post vacancies by paying a flow cost κ. Meetings are determined randomly according to a constant returns to scale matching function given by $M(S,V)$. Labor market tightness is the ratio of vacancies to job seekers in the economy and denoted by $\theta \equiv V/S$, where S is the aggregate search effort (including both employed and unemployed workers), and V is the mass of vacancies posted. The contact rate for an unemployed worker is given by $f(\theta) \equiv \frac{M(S,V)}{S} = M(1,\theta)$. It follows that the contact rate for an employed worker is $\lambda f(\theta)$. Similarly, firms contact workers at a rate $q(\theta) \equiv \frac{M(S,V)}{V} = M(1/\theta,1)$ each period.

Job Lotteries and Match Quality Matches are heterogeneous and differ by their fundamental productivity $\mu \in \{\mu_1,\ldots,\mu_m\}$ with $\mu_1 < \cdots < \mu_m$, where m is the number of possible match types. When a firm and a worker meet for the first time, they do not observe what their underlying match productivity is going to be, instead they randomly draw a job lottery. There are n lotteries, and probability of drawing a particular lottery $\vec{q}_i \in \{\vec{q}_1,\ldots,\vec{q}_n\}$ is given by $Pr(\vec{q}_i)$, where $\sum_{i=1}^{n} Pr(\vec{q}_i) = 1$. Job lottery $\vec{q}_i = \begin{pmatrix} q_{i1} \\ \vdots \\ q_{im} \end{pmatrix}$ describes a probability distribution over fundamental match productivities. That is, q_{ij} denotes the probability of getting a match with productivity μ_j under lottery $\vec{q}_i$, and thus satisfies $\sum_{j=1}^{m} q_{ij} = 1 \ \forall i \in \{1,\ldots,n\}$. We note that the outcome of this lottery is revealed only after the firm and worker decide to take it.

Timing The timing of the model is as follows. First production takes place and workers consume their labor or unemployment income. Then, some matches are exogenously destroyed. Afterwards, workers search for jobs with differing intensities depending on their employment status. Workers and firms upon contact draw a job offer lottery. They decide whether to consummate the match or not by comparing their current value to their expected joint value from forming a match under the lottery. Then, the fundamental match quality is realized under the accepted job lottery. If the productivity turns out to be too low, the firm and the worker jointly decide to end the match, otherwise they continue to the next period with the newly realized match productivity. Figure 8 depicts the timing of the model from the worker's point of view.

3.2 Value Functions

In this section, we outline the worker and firm problems. Since contact rates are exogenous to the worker and the firm, we suppress the dependence of $f(\theta)$ and $q(\theta)$ on market tightness θ for notational brevity.

Worker's Value Functions A worker has unemployment value defined by the following Bellman Equation

$$U = b + \beta\Bigg[(1-f)U + f\sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{U, \vec{q}_i \max\{W(\mu'), U\}\Big\}\Bigg]. \tag{1}$$

An unemployed worker consumes unemployment benefit b. She contacts a firm with probability f, in which case she draws an employment lottery $\vec{q}_i$ with probability $Pr(\vec{q}_i)$. She then decides whether to take the lottery or not. If she rejects the lottery, she continues unemployed to the next period. If the worker decides to take the lottery, she observes the realization of match productivity, after which she can start next period employment with a new match productivity or decide to quit into unemployment. For an unemployed worker there is no loss in option value from taking a lottery, therefore unemployed workers always take job lotteries.

A worker has employment value defined by the following Bellman Equation

$$\begin{aligned} W(\mu) = w(\mu) + \beta\Bigg[&\delta U \\ &+ (1-\delta)\Bigg((1-\lambda f)W(\mu) + \lambda f\sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{W(\mu), \vec{q}_i \max\{\vec{W(\mu')}, U\}\Big\}\Bigg)\Bigg]. \end{aligned} \tag{2}$$

An employed worker in a type-μ job consumes bargained wage $w(\mu)$. Her match is destroyed with exogenous probability δ. With probability λf she contacts an outside firm and draws a job offer lottery $\vec{q}_i$. Based on the expected value of the lottery, she decides whether to stay in her current job or switch to the new firm to observe the new match productivity. After the lottery outcome is realized, she can stay at her current job or decide to quit into unemployment.

Firm's Value Function The value of a filled job to the firm is given by

$$\begin{aligned} J(\mu) = \mu - w(\mu) \\ + \beta(1-\delta)\Bigg((1-\lambda f)J(\mu) + \lambda f\sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\Big\{W(\mu) \geq \vec{q}_i \max\{\vec{W(\mu')}, U\}\Big\}J(\mu)\Bigg). \end{aligned} \tag{3}$$

The firm collects flow profit $\mu - w(\mu)$ from the match. If the match is not destroyed exogenously, or the worker either does not receive or rejects an outside offer, it continues into the next period with the same productivity. Otherwise the firm's value drops to 0.[11]

Surplus We assume that the outside option of a worker is always unemployment, that is an employed worker cannot use her current match as her outside option while bargaining with a potential employer.

Match surplus from a job with productivity μ is denoted by $S(\mu)$ and defined as

$$S(\mu) \equiv J(\mu) + W(\mu) - U. \tag{4}$$

We assume wages are determined according to Nash Bargaining with worker share $\phi \in (0, 1)$. This implies linear surplus sharing rules given by

$$W(\mu) - U = \phi S(\mu) \tag{5}$$
$$J(\mu) = (1 - \phi)S(\mu). \tag{6}$$

That is, the worker captures a constant share ϕ of the match surplus, whereas the firm receives the remaining share $1 - \phi$.

Rather than solving the individual Bellman equations, we work with the value of match surplus directly. Using Bellman Equations 1, 2, 3, definition of surplus in Equation 4, and the linear sharing rules in Equations 5 and 6, we arrive at the surplus value given by the following Bellman equation

$$\begin{aligned} S(\mu) =& \mu - b + \beta(1-\delta)\Bigg[(1-\lambda f)S(\mu) + \phi\lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\max\left\{S(\mu), \vec{q}_i \max\{S(\vec{\mu}'), 0\}\right\} \\ & + (1-\phi)\lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\left\{S(\mu) \geq \vec{q}_i \max\{S(\vec{\mu}'), 0\}\right\}S(\mu)\Bigg] \\ & - \beta\phi f \sum_{i=1}^{n} Pr(\vec{q}_i)\vec{q}_i \max\{S(\vec{\mu}'), 0\}. \end{aligned} \tag{7}$$

We note that Equation 7 does not depend on the level of wages and its value, given a market tightness value, is sufficient to determine worker decisions. We provide details of the derivation of $S(\mu)$ in Appendix A.1.

Free Entry We assume workers and firms meet randomly, and there is free entry. The mass of job seekers comprises both employed and unemployed workers, and is given by $S = u + \lambda(1 -$

[11] We assume that there is free entry, therefore the outside value of a firm is 0.

$\delta)(1-u)$, where u denotes the share of unemployed workers. Firms post vacancies until the value of a vacancy becomes zero. The free-entry condition implies

$$\begin{aligned}\kappa &= \beta q(\theta)\mathbb{E}[J(\mu)]\\ &= \beta q(\theta)(1-\phi)\mathbb{E}[S(\mu)]\\ &= \beta q(\theta)\frac{(1-\phi)}{u+\lambda(1-\delta)(1-u)}\Bigg(u\sum_{i=1}^{n}Pr(\vec{q}_i)\sum_{j=1}^{m}q_{ij}\mathbb{I}\{S(\mu_j)>0\}\\ &+\lambda(1-\delta)\sum_{k=1}^{m}e(\mu_k)\sum_{i=1}^{n}Pr(\vec{q}_i)\mathbb{I}\{S(\mu_k)<\vec{q}_i\max\{S(\vec{\mu}),0\}\}\sum_{j=1}^{m}q_{ij}\mathbb{I}\{S(\mu_j)>0\}\Bigg)\end{aligned} \tag{8}$$

where $e(\mu_j)$ denotes the share of workers employed in productivity-μ_j matches, and $u+\sum_j e(\mu_j)=1$. In the second line we make use of the linear surplus sharing rule for the firm given in Equation 6. The third line in the free-entry condition captures unemployed job searchers, who fill posted vacancies. The last line captures employed searchers, who take outside job-offer lotteries and form a new match. We describe the laws of motion that characterize the worker distribution, u and $e(\mu_j)$, in Appendix A.2.

3.3 Equilibrium

We solve the model in steady state.[12] The stationary equilibrium of the model is a value function $S(\mu)$ for match surplus, and market tightness θ such that:

- Value of surplus $S(\mu)$ solves Equation 7.
- Distribution of workers over employment states, $(u, \{e(\mu_j)\}_{j=1}^{m})$, evolves according to the laws of motion in Equations A.1 and A.2, and is time-invariant.
- Market tightness θ satisfies the free-entry condition in Equation 8.

4 Calibration

In this section we discuss the choice of parameters and the calibration strategy. In the subsequent sections, we use our calibrated model to evaluate the role of unemployment risk in shaping job mobility, as well as the effect of unemployment insurance, b, shifts on job mobility. In our framework, this variable not only changes the unemployed job seeker's selectivity and thus prolongs the unemployment spell duration, but also it subsidizes job-to-job transitions by insuring the downside of job-offer lotteries, i.e. unemployment risk.

[12]For most of our quantitative exercises, we compare steady states of the model under different unemployment insurance regimes. In Section B.3 we outline an algorithm used to study the transition behavior of our model to one time unanticipated shocks to the unemployment insurance level.

Functional Forms To solve and ultimately calibrate the model, we need to make a number of parametric and functional form assumptions.

First, we choose a functional form for $M(S,V)$. We assume a constant elasticity of substitution matching function as proposed by Haan et al. (2000):

$$M(S,V) = \frac{SV}{(S^\eta + V^\eta)^{1/\eta}}$$

This matching function yields contact rates for unemployed job seekers and firms given by

$$f(\theta) = \frac{\theta}{(1+\theta^\eta)^{1/\eta}} \text{ and } q(\theta) = \frac{1}{(1+\theta^\eta)^{1/\eta}}$$

where η is the elasticity parameter.[13]

Second, we make parametric choices about the job lottery offer distribution $Pr(\vec{q}_i)$. We assume that workers are equally likely to receive each lottery, i.e. $Pr(\vec{q}_i) = \frac{1}{n}\ \forall i \in \{1, \ldots, n\}$.

Third, we assume a probability distribution to determine "placement probabilities", q_{ij}. Specifically, we start from base probabilities, q_{0j}, whose values are normalized (to add up to 1) probability density values from a normal distribution with mean $\tilde{\mu}$ and standard deviation σ evaluated at m equally-spaced μ_j values between μ_L and μ_H. Once we determine q_{0j}, we randomly assign its values for each of the n different lotteries. This gives us a probability matrix $\begin{bmatrix} q_{11} & \ldots & q_{1m} \\ \vdots & & \vdots \\ q_{n1} & \ldots & q_{nm} \end{bmatrix}$, whose ith row is a random permutation of q_{0j}.

Calibration Strategy There are 13 parameters in the model. We choose 7 parameters without solving the model, and jointly estimate the remaining 6 parameters to be consistent with a number empirical labor market moments. We set a model period to one year.

Parameters Set Outside the Model We set the discount factor $\beta = 0.9615$ to reflect a 4% annual interest rate. We set the exogenous separation rate δ to 0.03 to match the medium-run UE transition probability of employed workers, around 3%.

We assume an equal bargaining share for the worker and firm, and set $\phi = 0.5$. We set the minimum and maximum match productivities, μ_L and μ_H, to 0 and 10 respectively. We further assume that $n = 50$, and the match-productivity grid is equally spaced between μ_L and μ_H. Finally, we assume that the number of job-offer lotteries is $m = 250$. We fix our baseline UI level to $b = 0$.

[13] An advantage of the CES matching function is that contact rates f and q always lie between zero and one. The more standard Cobb-Douglas form requires ensuring contact probabilities do not exceed one.

Table 1 summarizes the choice of parameters set without solving the model, together with their values.

Parameters Set via Solving the Model We calibrate the remaining 5 parameters to match steady state model moments to their empirical counterparts. Below we discuss the estimated parameters together with the target moments, although the parameters are estimated jointly.

The model features free entry and the cost of posting a vacancy κ determines market tightness θ given the surplus values, matching function parameter and stationary distribution of workers. Market tightness in turn determines contact rate of firms and workers, which determines the equilibrium unemployment rate in the model. The unemployment rate is determined by two sources: the inflow rate into unemployment and the outflow rate. The inflow into unemployment from employment is given by the exogenous separation rate δ, as well as endogenous separations from attempted job mobility. The outflow from unemployment into employment is given by the job finding rate of the given unemployed job seeker, times the probability of the worker accepting the given job. The unemployment rate follows the standard expression:

$$u = \frac{\rho_{eu}}{\rho_{eu} + \rho_{ue}}$$

where the transition rates are are now functions of our augmented model of job lotteries:

$$\begin{aligned}
\rho_{eu} &= \delta + (1-\delta)\lambda f(\theta)\times \\
&\left\{ \sum_{k=1}^{m} \left[\sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\left\{ S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'), 0\} \right\} \sum_j q_{ij}\mathbb{I}\{S(\mu_j) < 0\} \right] \frac{e(\mu_k)}{1-u} \right\} \\
\rho_{ue} &= f(\theta) \sum_{i=1}^{n} Pr(\vec{q}_i)\vec{q}_i \mathbb{I}\{S(\vec{\mu}') \geq 0\}
\end{aligned}$$

Thus, our first empirical target to match is an average yearly unemployment rate of 5% percent.

Second, we target the average job-to-job transition probability of the average employed worker, which in our SIPP sample is around 2% per month. Its theoretical counterpart is given by:

$$\begin{aligned}
\rho_{ee} &= \frac{e(\mu_k)}{1-u} \times \\
&\left\{ \sum_{k=1}^{m} \underbrace{\left[(1-\delta)\lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\left\{ S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'), 0\} \right\} \sum_j q_{ij}\mathbb{I}\{S(\mu_j) \geq 0\} \right]}_{\rho_{ee}(\mu_k)} \right\}
\end{aligned}$$

Third, we target moments of the tenure gradient of job-to-job transitions for jobs that have been created as a result of direct job transitions. Specifically, we target the job-to-job transition rates for workers with tenure equal to one, two and three years. In our model, the job mobility probability is independent of tenure and only depends on the decision rules for the given job level μ_j that with the job offer distribution generate a μ_j-specific EE probability $\rho_{ee}(\mu_j)$. In the model, the average EE rate is therefore the weighted average of μ_j-specific rates weighted by employment:

$$\rho_{ee}^{\tau} = \sum_{j=1}^{m} \frac{e^{\tau}(\mu_j)}{\sum_{k=1}^{m} e^{\tau}(\mu_k)} \rho_{ee}(\mu_j)$$

The aggregate tenure-gradient of EE transitions therefore only reflect composition shifts in the employment stock – which are all due to heterogeneous job mobility decisions in the background of homogeneous exogenous separation rates δ and lottery offer arrival rates λf. For each tenure bin $\tau \geq 1$, we have a law of motion:

$$e^{\tau\geq 1}(\mu_j) = (1-\delta)\left[1 - \lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\left\{S(\mu_j) < \vec{q}_i \max\{S(\vec{\mu}'), 0\}\right\}\right] e^{\tau-1}(\mu_j)$$

Since all workers face the same lottery arrival rate λf, the EE gradient will be declining due to advantageous selection: low-μ jobs have lower surplus, therefore increasing the share of job offers that make the cut for a transition. In reality, other moments besides selection may contribute to this pattern, although empirical evidence suggests the wage gradient to be driven by precisely the job offer-driven selection in our model, as in the mechanism emphasized by Hagedorn and Manovskii (2013). The initial stock distribution reflects merely the composition of accepted lotteries that yield viable jobs, formed out of existing jobs:

$$e^{\tau=0}(\mu_j) = \sum_{k=1}^{m} \sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\left\{S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'), 0\}\right\} q_{ij}\mathbb{I}\{S(\mu_j) \geq 0\}(1-\delta)\lambda f e(\mu_k)$$

Fourth and most importantly, we target the excess unemployment risk in period 1 for jobs created as a result of direct job to job transitions. This moment is our key motivation. In the data, we count all separations in period 1 as sampling of job lotteries that resulted in unemployment. This definition differs from our model setup, which for analytical tractability has unsuccessful sampling of jobs result in unemployment even before production begins, which we consider a stand-in for a richer experience good mechanism. In our model, this moment is given by:

$$\rho^{``\tau=0"}_{(E)EU} = \frac{\sum_{k=1}^{m}\sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\left\{S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'),0\}\right\}\sum_{j=1}^{m} q_{ij}\mathbb{I}\{S(\mu_j)<0\}e(\mu_k)}{\sum_{k=1}^{m}\sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\left\{S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'),0\}\right\}e(\mu_k)}$$

This effect captures the riskiness of job-to-job transitions in our model, which arises as an equilibrium outcome given the job lottery offer distribution. We discuss the associated considerations in detail in Section 5.

Our estimation procedure minimizes the equally weighted sum of squared percent deviations of model moments from their empirical counterparts. We elaborate on computational details regarding the solution and calibration of the model in Appendix B.1 and B.2. Table 2 reports the parameters estimated by solving the model. Table 3 presents the empirical moments used in the estimation, together with the fit of the model. The current calibration matches the tenure gradients well, which is the focus of our paper. We note that the average job-mobility rate is difficult to match even when estimating λ flexibly. We conjecture that this is related to our assumption of homogenous $F(\vec{q}_i)$. Faberman et al. (2017) shows that the employed receive higher quality offers than the unemployed. We conjecture that this will help us match average EE, and we plan this in future work.

5 Quantitative Analysis: Job Riskiness and Job Mobility

In this Section we assess the quantitative properties of the calibrated model in steady state. Our particular focus is the novel *unemployment-risk* view of job mobility that our model formalizes.

A worker's job-to-job transition decision is driven by the expected value from taking a lottery. Here we dissect this expected lottery value and explore the implications for equilibrium job mobility its dispersion creates. Ex-ante, job lottery values are characterized by upside and downside risk, where we define downside risk of a lottery as the probability it yields match productivities over which the worker prefers unemployment. Unemployment therefore limits the downside of risky job transitions. For that reason, job offers – and thus job mobility decisions – are sensitive to the value of unemployment U and thus all factors that affect U. In the next Section, we build on these insights to examine unemployment insurance as a shifter in U and then trace its effects on job mobility and the resulting equilibrium job quality distribution.

The expected value of a job Formally, the expected value of a job offer is the probability-weighted average of eventual job values $W(\mu)$. A lottery is characterized by a probability vector

$\vec{q}_i$, and the expected value of taking that lottery is given by

$$\Omega_i \equiv \vec{q}_i \max\{\vec{W(\mu)}, U\}$$

An example job lottery Figure 9 plots the base probability values, q_{0j}, against the support of discrete productivity values μ. The figure also includes the underlying payoff structure of the lottery outcomes. Similarly, Figure 10 plots the value of q_{ij}, a random permutation of q_{0j}, against the support of discrete productivity values μ for an example lottery $\vec{q}_i$. Lotteries differ only in their distribution of probabilities over the support of productivity values. In the same Figure, we superimpose the value of the max operator in Ω_i against match-productivity μ. This kinked line applies to all job lotteries. Ω_i is then simply the weighted average of this value with weights given by "placement probabilities", q_{ij}.

Downside vs. upside risk of job lotteries We decompose expected job lottery value into downside risk – low realizations of job values in which the worker prefers unemployment – and upside risk – high realizations that yield jobs better than unemployment:[14]

$$\Omega_i = \underbrace{\sum_{j \in \{j:S(\mu_j)<0\}} q_{ij} U}_{\text{Downside}} + \underbrace{\sum_{j \in \{j:S(\mu_j)\geq 0\}} q_{ij} W(\mu_j)}_{\text{Upside}}$$

where the first term captures the expected value of states that result in unemployment, and the second term captures the expected value of employment states following job transition. The reservation μ is identified by the kink in the schedule; all job realizations below this value would, if formed, yield job values below U: $W(\bar{\mu}) = U$.

The quit-into-unemployment option therefore limits the downside of the job offer. Figure 10 thus makes it clear that the downside value of the lottery is simply U (that portion of Ω is flat in the realized μ) times the cumulative probability of the downside. Downside-risk-preserving perturbations of the precise risk allocation *within* the downside leave the total job lottery value Ω_i unchanged.

[14] Our notion of downside risk differs from an alternative useful definition that defines downside risk with respect to the *previous* job's value: Any realized job value that falls short of the worker's previous job value is therefore also downside risk. We note this alternative view to clarify that our notion of downside specifically refers to the unemployment risk:

$$\Omega_i = \boxed{\underbrace{\sum_{j \in \{j:S(\mu_j)<0\}} q_{ij} U}_{\text{Unemployment Downside}}} + \underbrace{\sum_{j \in \{j:0\leq S(\mu_j)<S(\mu_{j_{old}})\}} q_{ij} W(\mu_j)}_{\text{"Regret but Stay"}} + \underbrace{\sum_{j \in \{j:0\leq S(\mu_{j_{old}})<S(\mu_j)\}} q_{ij} W(\mu_j)}_{\text{"Happy and Stay"}}$$

We define a downside risk that we next show to sufficiently characterize the jobs with respect to the channel we explore: the probability of a lottery resulting in a match quality, which leads to a quit into unemployment. More formally, downside risk for each lottery $\vec{q}_i$ is defined as

$$r_i \equiv \sum_{j \in \{j : S(\mu_j) < 0\}} q_{ij} \tag{9}$$

This probability is simply the sum of probabilities in the flat part of Figure 10, and captures the downside of a job offer: Riskier lotteries are more likely to lead to unemployment. The complement of downside risk is upside risk $r_i^u \equiv \sum_{j \in \{j : S(\mu_j) \geq 0\}} q_{ij} = 1 - r_i$.

This definition allows us to reformulate the job lottery value:

$$\Omega_i = r_i U + (1 - r_i) \sum_{j \in \{j : S(\mu_j) \geq 0\}} \frac{q_{ij}}{1 - r_i} W(\mu_j)$$

The upside value is the weighted sum of the upward sloping part of Figure 10. Importantly, unlike in the downside, perturbations of placement probabilities q_{ij} within the upside portion of the job space do affect job lottery value Ω_i. However, we next clarify that our specification of job lotteries features a particular notion of conditional independence of the upside in the downside risk, which allows us to cleanly study the downside risk channel. Specifically, we will frequently characterize jobs solely by their downside risk and study the effect of U (e.g. through unemployment insurance) on job mobility and in particular the shift of the economy into jobs that are "risky" as precisely and succinctly captured by their downside risk r_i.

Conditional independence of the upside from the downside In Figure 11 we explore the relationship between job values and downside risk in the cross section of jobs that our calibrated model features. Our sample is the full menu of job lotteries q_i. We plot the relationship between downside risk r_i and two job values: the total job lottery value Ω_i, and the conditional value of the upside. While the expected lottery value Ω_i is decreasing in the downside risk, the conditional upside is invariant in downside risk. That is, the only channel by which downside risk, r_i affects a lottery's value Ω_i is by putting weight on unemployment, but not by affecting the conditional distribution of q_{ij} within the upside. This independence allows us to characterize job lotteries q_i cleanly and solely by their downside risk r_i when examining the role unemployment risk plays in job mobility; this sorting will not indirectly select jobs by other characteristics unrelated to the downside (i.e. the distribution of placement probabilities within the upside). The *only* channel through which U and thus unemployment insurance can differentially affect particular job lotteries is through the size of the downside risk. This feature is not trivial; we achieve this conditional independence by drawing placement probabilities q_{ij} *independently*.

Job mobility, downside risk, and the value of unemployment Next we discuss the interaction between the value of unemployment and a job lottery's downside risk in job mobility. Job transitions occur when, conditional on a lottery, the lottery value Ω_i exceeds the worker value from the current match. This implies that for each job lottery Ω_i, there is a lottery acceptance vector with μ_j-specific binary (zero or one) elements that describe whether the worker currently employed in job μ_k accepts ("samples") the job lottery: $\mathbb{I}\left\{W(\mu_k) < \overbrace{\vec{q}_i \max\{W(\vec{\mu'}), U\}}^{\Omega_i}\right\}$. This directly implies that there is a reservation $\bar{\mu}(\Omega)$ for any job lottery value Ω, which is simply defined by $W(\bar{\mu}(\Omega)) = \Omega$. All jobs with $\mu < \bar{\mu}(\Omega)$ reject a lottery of value Ω; all jobs with $\mu \geq \bar{\mu}(\Omega)$ accept and sample the lottery, leaving their old job, onward into employment or into unemployment.

The worker-level probability of job mobility Panel (a) Figure 12 plots, as a function of current job's productivity μ_j, the probability of departing one's current job in an attempted job to job transition (which may or may not lead to a viable job):

$$\sigma(\mu_j) = \sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\{W(\mu_j) < \Omega_i\} \tag{10}$$

Panel (b) plots $\rho_{ee}(\mu_j)$, i.e. the probability of a job to job transition into an ultimately viable job in which production occurs.

All lines are decreasing in μ_j. The transition probabilities illustrate that higher quality jobs are more stable. The conditional average downside risk of accepted jobs shows that when workers in higher μ_j do accept jobs, these jobs carry less downside risk, which is a consequence of the negative relationship between Ω_i and r_i.

The relationship between job mobility, job quality and tenure In the model, existing jobs only differ in their productivity μ, which allows us to trace out binary decision rules conditional on job offers. In the data μ is not measured. However, we have indirectly exploited the link between μ and job mobility by estimating the free model parameters to have the model's EE–tenure gradient match the empirical one at three tenure points.

Figure 13 plots the tenure gradient (out of jobs formed from EE transitions) of three variables: the probability of EE transitions for the model and the data, as well as the average productivity μ – which we do not observe in the data. Our model captures this critical moment qualitatively.

Figure 14 plots three complementary model moments: the employment distribution of jobs, formed after a job-to-job transition, by match productivity μ for tenures $\tau = 1$, $\tau = 3$, $\tau = 5$, and the steady state. All figures convey a similar message, as tenure increases, jobs become more stable, workers make fewer transitions and average match productivity increases.

The job ladder: the relationship between job mobility, job quality and tenure Our model features a job ladder by which workers accept outside offers that in expectation allow them to move up the job ladder as defined by job quality μ. Figure 15 plots the average gain in μ for job switchers as a function of their original μ. The relationship is negative simply because well-matched workers are closer to having maxed out their match quality.

Unemployment risk while switching jobs Our labor market features two types of separations that throw the worker off the job ladder: first, standard exogenous separation rate δ forces even the stayers to move into unemployment. Second, job switchers may find themselves ex post in unsatisfactory matches to which they prefer unemployment, and thus quit. In our calibrated model, 13.2% of EU transitions are due to such endogenous separations. 19% of EE transitions end in unemployment due to negative surprises.

The composition of accepted job lotteries From the perspective of a lottery valued at Ω, the probability of being accepted depends on fraction of jobs above the reservation value $\bar{\mu}(\Omega)$: $\sum_j \frac{e(\mu_j)}{1-u}\mathbb{I}\{W(\mu_j) < \Omega\}$. A given cross-section of newly formed jobs takes this lottery/$\vec{q}_i$-specific sampling probability and takes a weighted average using the McCall job lottery distribution:

$$\sum_{i=1}^{n} Pr(\vec{q}_i) \sum_j \frac{e(\mu_j)}{1-u}\mathbb{I}\{W(\mu_j) < \Omega_i\} \tag{11}$$

Since Figure 11 has shown that Ω_i decreases in downside r_i, jobs with high downside make up a smaller share of accepted jobs because fewer employed workers decide to sample them.

Figure 16 plots the distribution of accepted lotteries by unemployment risk. We rank the lotteries according to our risk measure, r_i and calculate the share of job switches resulting from each lottery. More formally, we calculate:

$$\frac{\sum_j e(\mu_j) Pr(\vec{q}_i)\mathbb{I}\{W(\mu_j) < \Omega_i\}}{\sum_i \sum_j e(\mu_j) Pr(\vec{q}_i)\mathbb{I}\{W(\mu_j) < \Omega_i\}}$$

Since jobs in our calibration are assumed to be equally likely such that $Pr(\vec{q}_i) = \frac{1}{n}$, the composition of accepted job lotteries reflects solely differentials in the probability of acceptance.

The plot yields a negative slope: low-risk job offer lotteries have a higher probability of being sampled. As a result, the job matches actually formed in the economy are ex-ante low in downside risk. For completeness, we reiterate the downward slope of a lottery's ex ante value Ω_i in r_i, as well as the conditional independence of the upside, presented in Figure 11.

6 Application: The Experimentation Channel of Unemployment Insurance

In this section we undertake a number of quantitative exercises to shed further light on the role of unemployment risk in shaping employed workers' job mobility decisions, and in turn the distribution of job quality and labor market performance overall. We do so by studying shifts in the value to unemployment U. Our U shifter is the generosity of unemployment insurance as captured by UI benefit level b.

Our experiment has also substantive and empirical predictions: We trace out a mechanism through which UI promotes job-to-job transitions by lowering the downside risk of jobs, and thereby leads to more experimentation.

We compare two UI regimes: our original level of "low" UI ($b_L = 0$) and a counterfactual "high" UI level ($b_H = 1$). We first compare steady states, essentially comparing long-run or cross-country implications of UI generosity. Second, we study the transition between steady states. The transition dynamics are particularly interesting because they map into empirical work we plan to conduct in future work. We plan to empirically study quasi-experimental variation in b brought about by replacement rate reforms in Austria, to examine whether job mobility and the risk composition of jobs is affected by UIB.[15] We will use the estimate as an additional empirical target for our calibrated model.

6.1 Steady State Comparison

The effect on job offer values We start by studying how lottery values respond differentially to changes in b, which is the channel through which we argue UI will affect job mobility of employed workers. Figure 17 plots a histogram of Ω_i under the two UI regimes, for $b_L = 1$ and $b_H = 5$. Not surprisingly, the distribution shifts to the right when b increases, as more generous unemployment insurance benefits increase both the value of unemployment U and value of employment $W(\mu)$. (Due to separation risk δ any job should put some weight on U even absent risky job mobility.) This implies that lotteries across the board become more attractive with more generous UI, which insures against outcomes that lead to unemployment.

The role of downside risk in the effect of UI on job offer values Figure 18 plots the lottery-specific changes in value. There is considerable *dispersion* in the change of lottery values induced by b shifts. Our model clarifies that this dispersion should be related to downside risk r_i, the lottery's probability that the worker ends up placed in a job μ that generates job value lower than U. Precisely, an *increase* in UI generosity raises the value of lotteries with larger

[15] This planned extension of our work will be coauthored work with Simon Jäger, Damian Osterwalder and Josef Zweimüller.

downside risk i.e. put more weight on U to begin with. To see this, recall that lottery value is $\Omega_i = \vec{q}_i \max\{\vec{W(\mu)}, U\}$. From this expression, one can see that an increase in b, which increases U, will increase lottery values by more the more they put weight on unemployment, i.e. r_i. To see this more clearly, consider:

$$d\Omega_i = dU\left(r_i + (1-r_i)\sum_{j\in\{j:S(\mu_j)\geq 0\}}\frac{q_{ij}}{1-r_i}\frac{dW(\mu_j)}{dU}\right)$$

Figure 19 plots our risk measure in Equation 9 against expected lottery value. Along with the originally calibrated value of b, we now also include the high b regime. The figure points to a negative relationship between risk and lottery value in both regimes. Clearly, lotteries that put more weight on bad states of the world, i.e. U, have a lower expected value.[16]

Figure 20 plots the *difference* between lottery values under high and low UI levels against risk. This figure confirms that an increase in b improves lottery value by more for riskier lotteries. Therefore, b, by increasing U, subsidizes risky job offers. The differential effect of U on the job value is the key mechanism we propose and explore in this paper. Consequently, b will affect not only the overall level of job-to-job transitions but also the composition.

The composition of accepted job offers Next, we show how UI levels, lottery risk and job-mobility are related. We again rank the lotteries according to our risk measure, r_i, under the low UI regime, b_L. We then calculate the share of job switches resulting from each lottery. More formally, we calculate

$$\frac{\sum_j e(\mu_j)Pr(\vec{q}_i)\mathbb{I}\{S(\mu_j) < \vec{q}_i \max\{\vec{S(\mu)}, 0\}\}}{\sum_i \sum_j e(\mu_j)Pr(\vec{q}_i)\mathbb{I}\{S(\mu_j) < \vec{q}_i \max\{\vec{S(\mu)}, 0\}\}}.$$

To facilitate comparison between the high and low UI regimes we keep the distribution of workers over match types, $e(\mu_j)$, constant. This allows us to abstract away from compositional effects of b on employment.[17] Figure 16 plots this share as a function of lottery risk for b_H and b_L. Not surprisingly, both plots yield a negative slope: A larger share of job transitions are made when facing low-risk job offer lotteries. But importantly, this job-mobility risk profile exhibits a different slope for low and high UI states of the world. When UI becomes more generous, the

[16]Recall that this negative slope captures only the differences in the downside risks associated with each lottery, as the upside value is independent of the lottery once conditioned on employment. Figure 11 plots the expected lottery value conditional on it resulting in employment. As the figure shows, this expected value is independent of lottery risk.

[17]One caveat here is that under b_H some match productivities become unviable, that is the marginal matches yield a negative surplus. These matches mechanically cause more job-mobility-decisions, therefore when we calculate this share under b_H, we use the same worker distribution as in b_L only for those matches that are feasible, we fix the worker share to zero for all negative surplus matches.

share of job transitions shifts from low-risk lotteries to higher-risk lotteries. In this sense, UI encourages job-mobility by insuring workers against downside risk and lets them experiment more with uncertain job prospects.

Job mobility and unemployment insurance generosity Next we explore the differences in steady state decisions in workers' job mobility. Figure **??** plots two job mobility outcomes by job quality μ, separately for the two UI regimes: the rate at which workers sample job offers and the rate at which they move into stable jobs. The higher b regime increases sampling and transitions across the board, showing that b subsidizes job mobility by insuring the downside.

The figure also includes a clean measure of experimentation and the outcome of the subsidy: we also plot $\rho^{(E)EU}(\mu)$, i.e. the probability that the worker moves into a job that ex post turns out to yield unemployment. Overall, this risk declines in μ. However, the figure also clarifies that higher b leads to an expansion of unemployment risk across the board.

This "moral hazard" effect is not just due to more job transitions across the board. Figure 22 plots the ratio of $\frac{\rho^{(E)EU}(\mu)}{\sigma(\mu)}$, i.e. the fraction of sampling decisions that ultimately lead to unemployment, and the average r_i of accepted lotteries, by μ. Both are decreasing in μ. However higher b raises the level of this gradient. In other words, UI encourages workers to take riskier lotteries in the hope of climbing up the job ladder. Therefore, b increases experimentation.

Aggregate job mobility and ex-ante selection Figure 23 plots the employment shares by μ for each b regime. Thanks to the subsidy of unemployment, the reservation job qualities increase when b is high, leading workers to reject worse offers and giving workers opportunities to move up the job ladder. However, this implies that on *average* in the new steady state there are fewer job-to-job transitions despite the subsidy. The reason is that the economy, in the new steady state, switches to better matched workers, who are the workers that are least likely to run into jobs that make it worth sampling. In fact, we find that in the high b regime, the average EE rate declines.

6.2 Transitional Dynamics: Low to High b Steady State

In this section we explore the transition dynamics of the model. We do so because the experimentation subsidy channel of UI is testable in quasi-experimental empirical designs that allow the researcher to track the transition. Moreover, we have previously found that because of the equilibrium shift in job qualities, average job mobility may in fact decline despite μ-specific increases in experimentation. We outline the algorithm we use to solve for the transition path in Appendix B.3.

Figure 24 plots the transition from the low to the high UI steady state within 50 periods for job mobility variables. The dot on the y-axis describe the initial steady state level; the lines trace out transitional dynamics. The solution method imposes that after 50 periods the transition to the next steady state is complete.

The first transitional time series denotes EE transition rates. EE transitions spike at the onset of the reform that makes b more generous. The reason is simple: The employment distribution is still characterized by the old b regime that features lower matches than the high b would generate. Job sampling increases because job offer values have increased at the onset of the reform, and therefore workers stuck in bad matches accept a larger fraction of the job offers (i.e. the barely unviable job offer now becomes sampled), and for each given job offer, a larger fraction of workers samples the lottery. However, the EE time-series then declines and settles in at a lower level than the initial steady state.

The Figure also plots average $(E)EU$ rates and average downside risk r_i for sampled lotteries oer the transition period; both proxies for job risk taking initially spike but ultimately settle as lower steady states.

The intuition is simply selection. Figure 25 plots the average μ during the adjustment period. This value is gradually increasing and ultimately settles in on a level that is higher than the original one. UI therefore raises the productivity level, as Figure 23 already described for the steady states in a histogram of μ levels in employment.

7 Conclusion

We proposed, formalized and analyzed a model of *risky job-to-job transitions*. Employed workers receive noisy job offers that may ultimately place them into a variety of different match qualities. That is, in our model, job offers arrive in the form of lotteries. The upside of job offers are harvested by lucky job seekers whose eventual realization places them into matches they prefer to unemployment. The downside risk of job offers manifest themselves as matches that are inferior to unemployment: The job seeker then separates into unemployment.

The downside risk of job mobility is a robust empirical feature, which we documented in the U.S. labor market, using the Survey of Income and Program Participation. We documented the tenure gradient of employment-to-unemployment transitions for cross-sections of employed workers. The typical employed job seeker of tenure above two years is largely isolated from unemployment risk, facing an annual risk of only 4%. By contrast, the recently employed worker that transitioned from another job faces an excess 13% probability of unemployment in the first year, three times the value that employed worker would have had had she stayed in her old job.

We argue that this consideration should pose a friction to job mobility in real-world labor markets. Moreover, our model implies that the downside risk is the more severe, the lower the value of the unemployment state. This insight suggests natural implications that we find empirically reasonable: Recessions are times when the value of unemployment decreases; they are also times when job-to-job transitions collapse.

A particularly interesting implication we explore and plan to empirically test in follow-up work concerns policy: Specifically, we argue that the generosity of unemployment insurance benefits is predicted to subsidize job mobility of employed workers by insuring the downside risk of unemployment. We explore this implication in our model and confirm that UI generosity triggers job-to-job transitions, in particular towards high-unemployment-risk jobs.

We close by reflecting on an implicit yet crucial assumption of our model as well as real-world labor markets: the absence of a return option into one's old job after disappointing realizations of the job lottery. Our sampling mechanism is a short hand for e.g. jobs as experience goods that require workers to actually leave one's old job and start production in the new job. We have taken this realistic fact for granted and naturally presented the job switcher with a choice between unemployment and formation of the match with the realized job quality. However, it is not obvious whether this feature should be thought of as a friction or a technological feature of labor markets. In our model, the job seeker returns to unemployment yet would have preferred to return to the old job (which yielded a higher value than unemployment by revealed preference). Standard search and matching frictions are not a plausible foundation for this inability to return to a previous employer in a job that yielded positive surplus; moreover in the data, recalls after temporary employment are frequent, suggesting that those return transitions should be possible in principle.

In a counterfactual economy with return options, the worker would never forgo opportunities to move up the job ladder; she would in fact accept and sample all jobs that have positive probability over better jobs. (A transaction cost of job switching would attenuate this extreme implication.) Perhaps the absence of such a return option captures a friction (arising from strategic, behavioral or cultural causes). If so, then the amount of job mobility is not efficient (or constrained efficient, taking the matching frictions as given). In future extensions, we will explore the welfare properties of the model from this perspective.

References

Card, David, Heining, Jörg, and Kline, Patrick (2013). "Workplace Heterogeneity and the Rise of West German Wage Inequality". *The Quarterly Journal of Economics* 128.3, pp. 967–1015.

Faberman, R. Jason, Mueller, Andreas I., Şahin, Ayşegül, and Topa, Giorgio (2017). *Job Search Behavior among the Employed and Non-Employed*. Working Paper 23731. National Bureau of Economic Research.

Farber, Henry S. (1994). "The Analysis of Interfirm Worker Mobility". *Journal of Labor Economics* 12.4, p. 554.

Fujita, Shigeru and Moscarini, Giuseppe (2017). "Recall and Unemployment". *American Economic Review*.

Haan, Wouter J den, Ramey, Garey, and Watson, Joel (2000). "Job Destruction and Propagation of Shocks". *American Economic Review* 90.3, pp. 482–498.

Hagedorn, Marcus and Manovskii, Iourii (2013). "Job Selection and Wages over the Business Cycle". *American Economic Review* 103.2, pp. 771–803.

Hornstein, Andreas, Krusell, Per, and Violante, Giovanni L (2011). "Frictional Wage Dispersion in Search Models: A Quantitative Assessment". *American Economic Review* 101.7, pp. 2873–2898.

Jung, Philip and Kuhn, Moritz (2016). "Earnings Losses and Labor Mobility over the Lifecycle".

Menzio, Guido, Telyukova, Irina A., and Visschers, Ludo (2016). "Directed search over the life cycle". *Review of Economic Dynamics* 19, pp. 38–62.

Nagypál, Éva (2007). "Learning by Doing vs. Learning About Match Quality: Can We Tell Them Apart?" *Review of Economic Studies* 74.2, pp. 537–566.

— (2008). "Worker Reallocation over the Business Cycle: The Importance of Employer-to-Employer Transitions".

Sorkin, Isaac (2018). "Ranking Firms Using Revealed Preference". *The Quarterly Journal of Economics*.

Stinson, Martha (2003). "Technical Description of SIPP Job Identification Number Editing in the 1990-1993 SIPP Panels".

Tjaden, Volker and Wellschmied, Felix (2014). "Quantifying the Contribution of Search to Wage Inequality". *American Economic Journal: Macroeconomics* 6.1, pp. 134–161.

8 Tables

Table 1: Externally Set Parameters

Parameter	Description	Value	Source
β	Discount factor	0.9615	4% annual interest rate
δ	Exogenous separation rate	0.03	Annual E-U rate at $\tau = 50$ months
b	Unemployment insurance	0	-
ϕ	Worker bargaining share	0.5	Equal worker and firm share
$\mu_{\min}$	Minimum match productivity	0	-
$\mu_{\max}$	Maximum match productivity	10	-
m	Number of μ's	50	-
n	Number of lotteries	250	-

Notes: This table reports parameters chosen without solving the model.

Table 2: Internally Set Parameters

Parameter	Description	Value
η	Matching function parameter	9.7
κ	Vacancy creation cost	0.001
λ	On-the-job search intensity	0.9
$\tilde{\mu}$	Mean of the distribution for base q_{0j}	15
σ	Std. of the distribution for base q_{0j}	1.5

Notes: This table reports parameters chosen by solving the model.

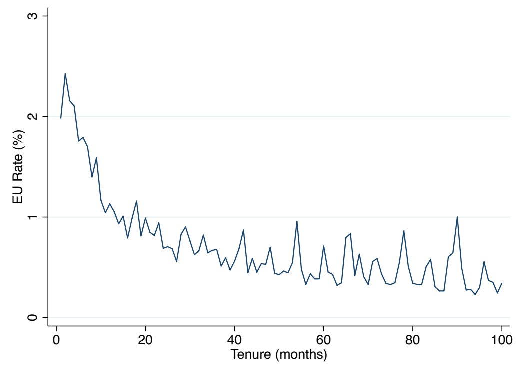
Table 3: Targets and Model Fit

Moment	Target	Model
Average unemployment rate	5%	6%
$\rho^{\tau=0}_{(E)EU}$	13.5%	12.9%
$\rho^{\tau=1}_{(E)EE}$	11%	7%
$\rho^{\tau=1}_{(E)EE}$	7.7%	5.8%
$\rho^{\tau=1}_{(E)EE}$	7.5%	4.9%

Notes: This table reports target moments and model fit in the baseline calibration.

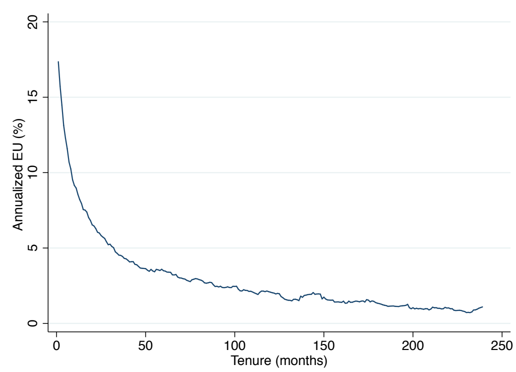
9 Figures

Figure 1: Monthly EU Rate by Tenure



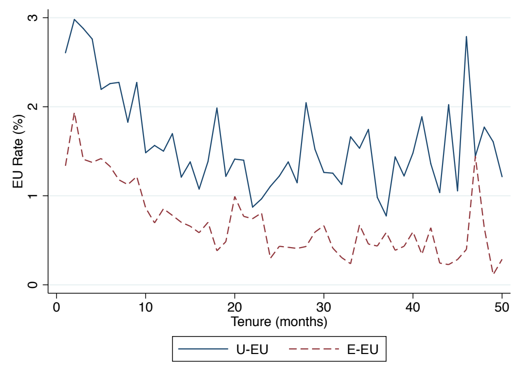
Notes: This figure plots the monthly share of employed workers that separate into nonemployment by tenure, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 2: Annualized EU Rate by Tenure



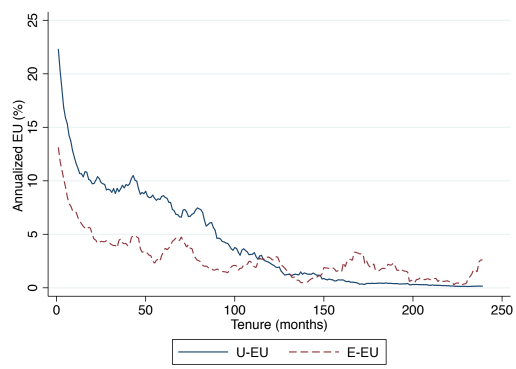
Notes: This figure plots the probability of making an employment-to-nonemployment transition within the next 12 months by tenure, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 3: Monthly EU Rate by Tenure and Origin



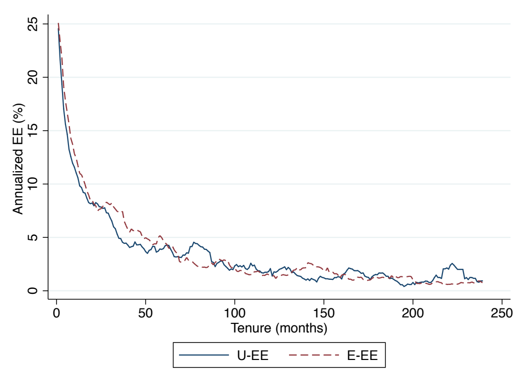
Notes: This figure plots the monthly share of employed workers that separate into nonemployment by tenure and labor market status prior to finding current job, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 4: Annualized EU Rate by Tenure



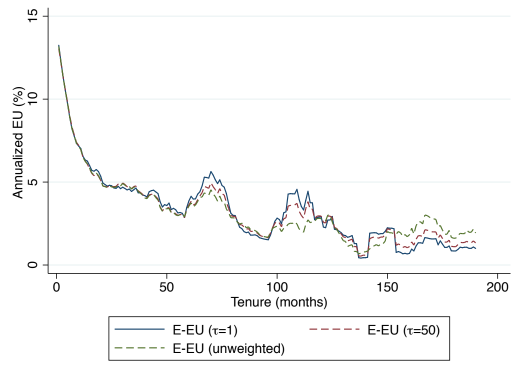
Notes: This figure plots the probability of making an employment-to-nonemployment transition within the next 12 months by tenure and labor market status prior to finding current job, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 5: Annualized EE by Tenure



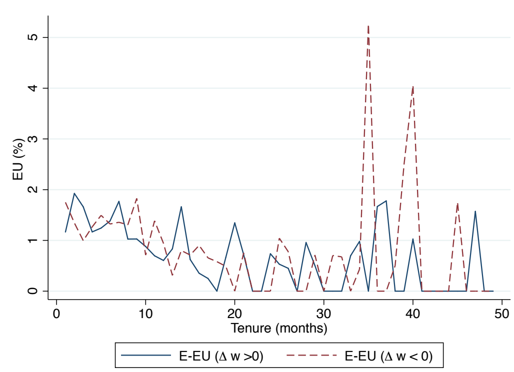
Notes: This figure plots the probability of making an employment-to-employment transition within 12 months by tenure and labor market status in previous employment spell using data from the SIPP.

Figure 6: Reweighted Annualized EU Rate by Tenure



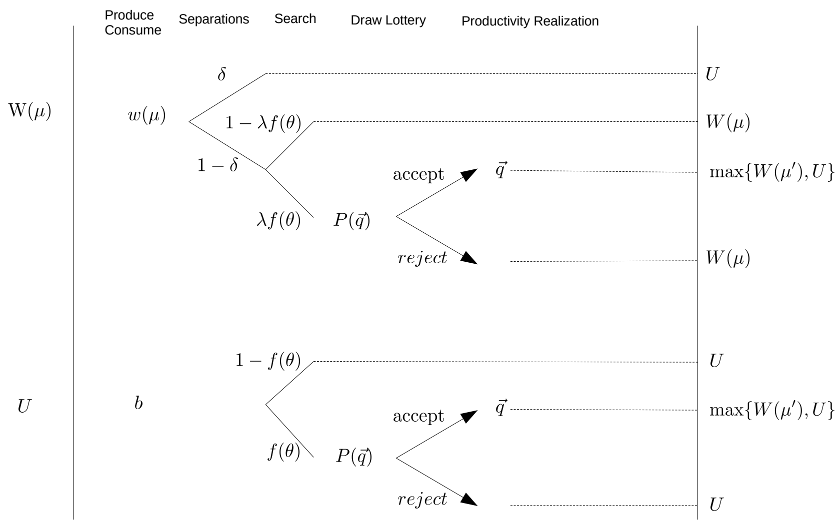
Notes: Notes: This figure plots the probability of making an employment-to-nonemployment transition within the next 12 months by tenure for workers who found their current job through a job-to-job transition, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels. The solid blue line fixes the age-composition to that of workers who have only one month of tenure. The red dashed line does the same by fixing the age composition to workers with 50 months of tenure.

Figure 7: Monthly EU Rate by Tenure for Jobs Originating from Direct EE-Transition With Wage Increases and Decreases



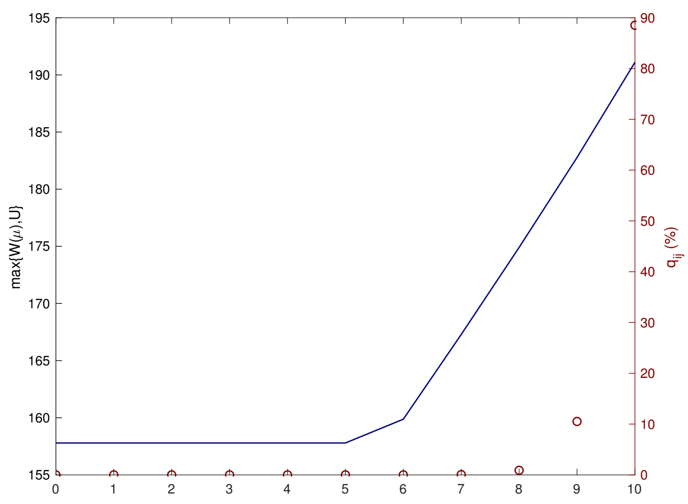
Notes: This figure plots the monthly share of employed workers that separate into nonemployment for workers that started their current through a job-to-job transition by tenure and sign of wage growth at job transition, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 8: Model Timing



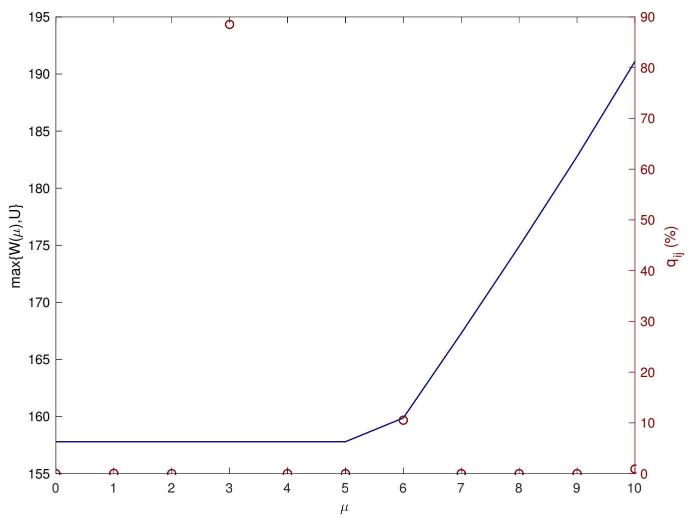
Notes: This figure summarizes the timing of the model from the worker's point of view.

Figure 9: Base Lottery Profile vs Payoffs



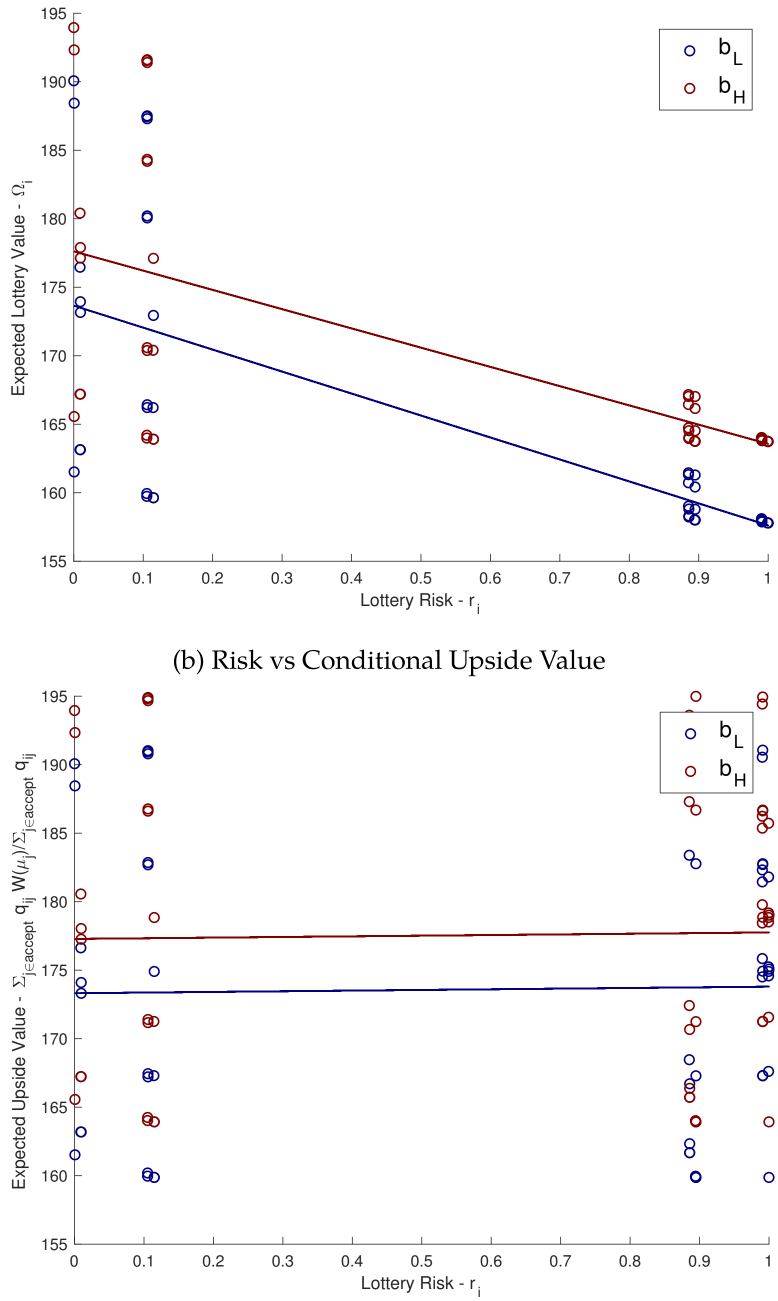
Notes: This figure plots the base "placement probabilities", q_{0j}, superimposed on the lottery payoff structure.

Figure 10: Lottery Profile vs Payoffs



Notes: This figure plots a typical lottery, a random permutation of q_{0j}, superimposed on the lottery payoff structure.

Figure 11: Lottery Values by Risk



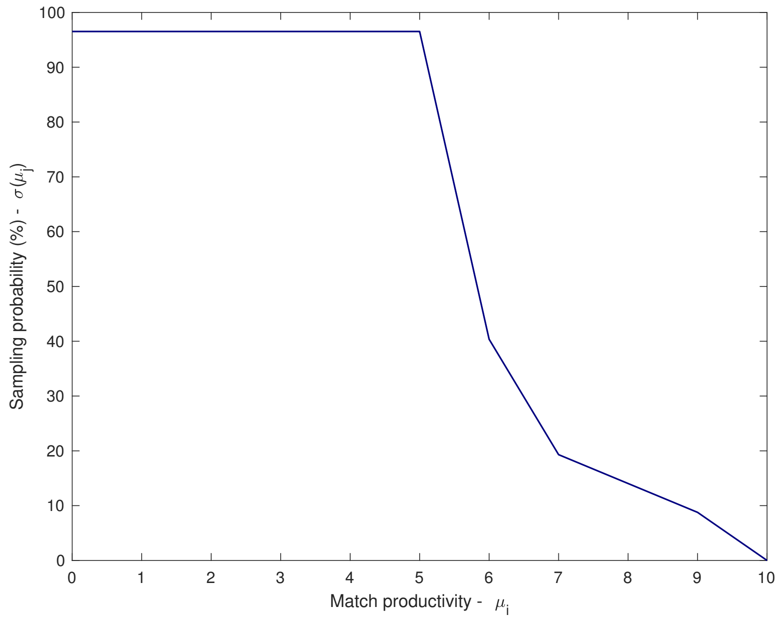
(a) Risk vs Expected Lottery Value

(b) Risk vs Conditional Upside Value

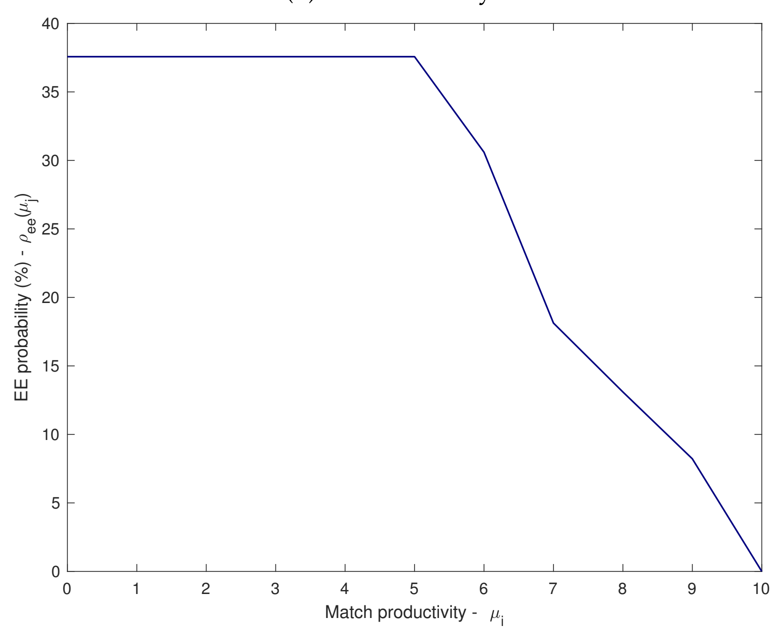
Notes: Panel (a) plots the relationship between expected lottery value, Ω_i, and lottery risk r_i. Panel (b) plots the expected value of the lottery conditional on the worker preferring to employed over quitting unemployed, i.e. the conditional upside value.

Figure 12: EE and Lottery Sampling Probabilities by μ

(a) Sampling Probability



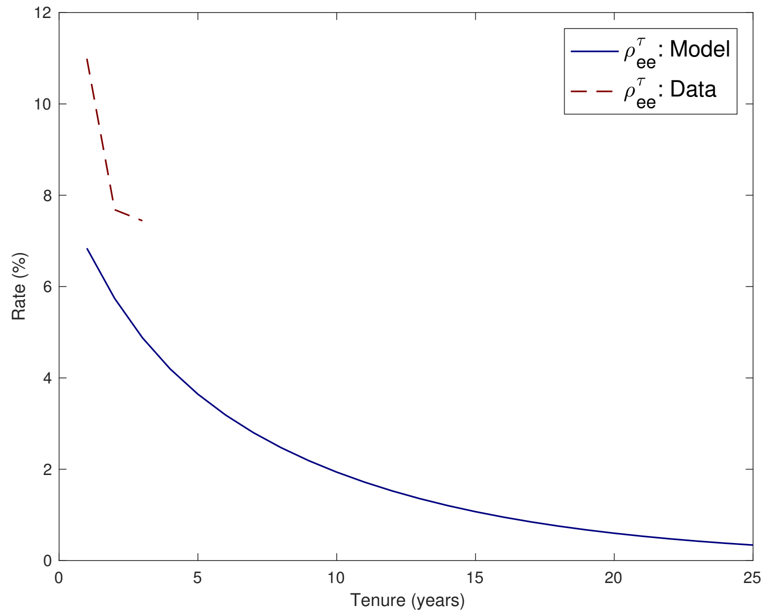
(b) EE Probability



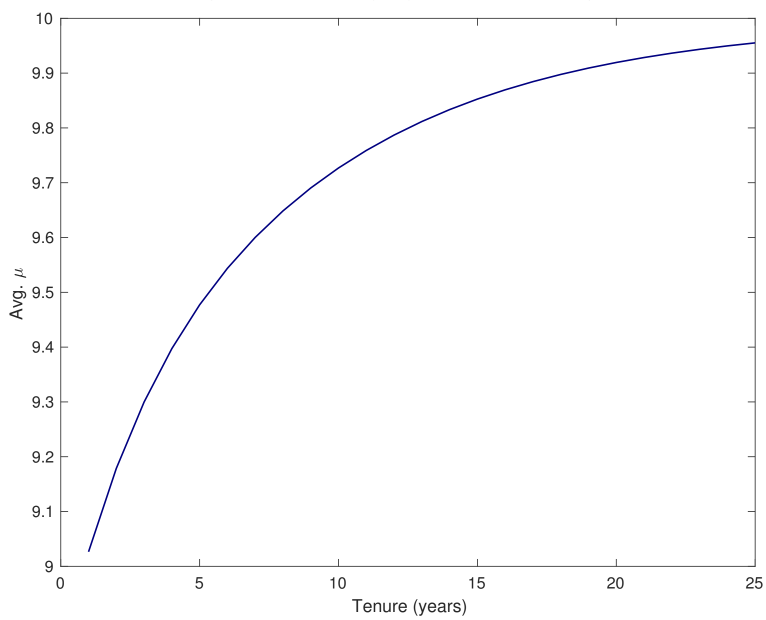
Notes: Panel (a) plots the probability of sampling a lottery conditional on contact against match quality μ. Panel(b) plots the probability of making a successful job-to-job transition, conditional on haveing sampled the lottery agains match quality.

Figure 13: Tenure Profiles

(a) (E)EE by Tenure

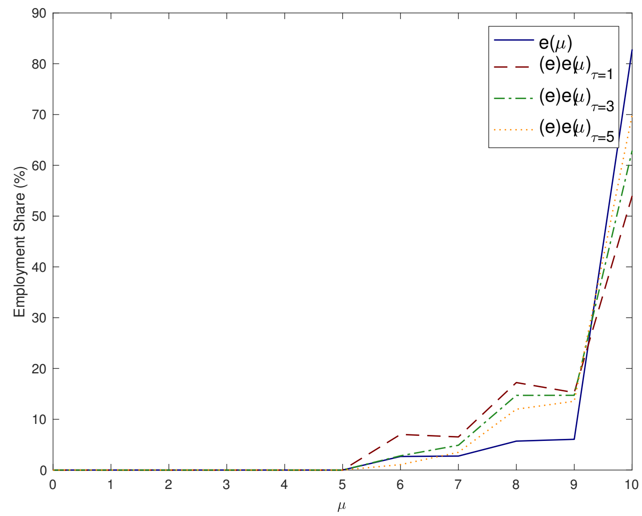


(b) Average Productivity by Tenure among (E)EE



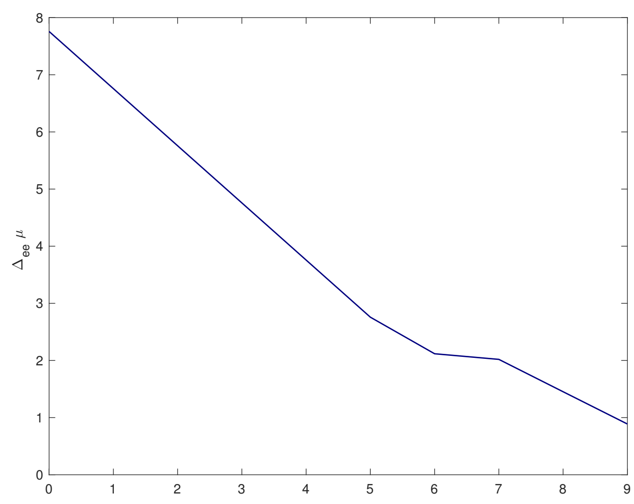
Notes: Panel (a) plots the job-mobility rate of a worker by tenure in a job, together with its data counterparts for the first 3 tenure years. Panel(b) plots the evolution of average match productivity by tenure.

Figure 14: Employment Distribution



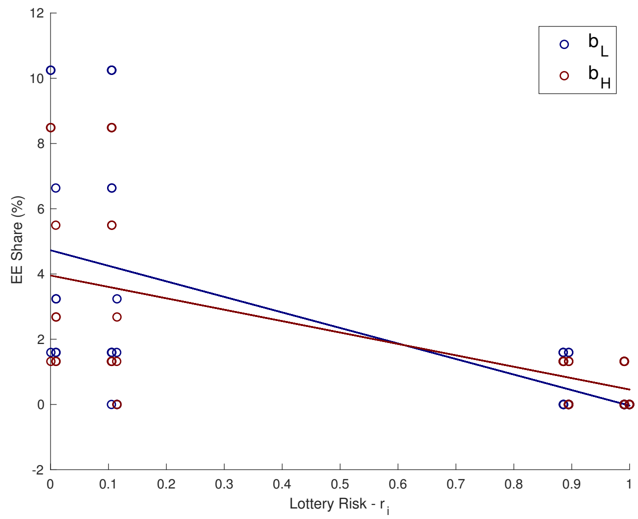
Notes: This figure plots the share of employed workers by match productivity in the steady state, and for workers who started their current job through a job-to-job transition at tenures 1, 3 and 5 years.

Figure 15: Average Change in μ upon Job Switch



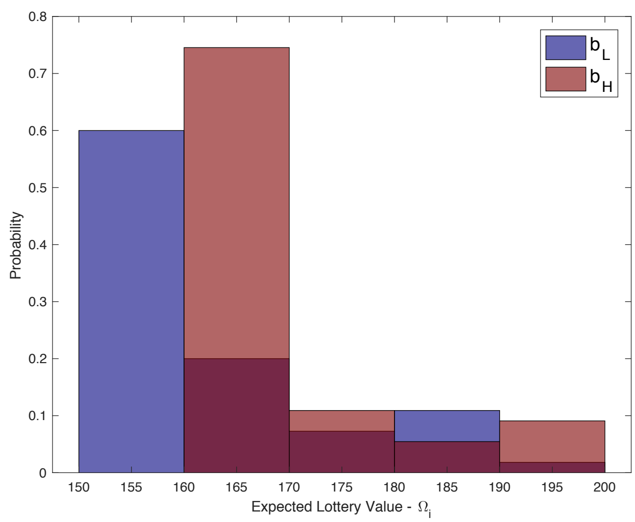
Notes: This figure plots the average change in match productivity upon job switch for different against match productivity of the current job.

Figure 16: Risk - Experimentation



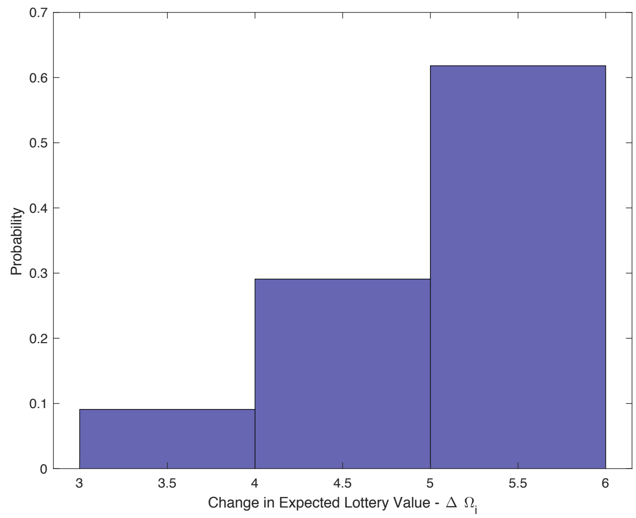
Notes: This figure plots lottery take-up rates vs lotteries' probability of yielding a match productivity over which worker prefers unemployment.

Figure 17: Histogram of Lottery Values



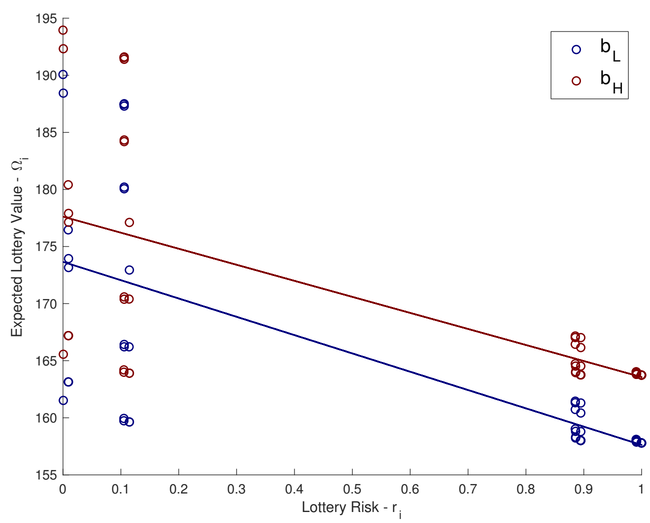
Notes: This figure plots the distribution of expected lottery values given by $\sum_j q_{ij} \max\{W(\mu_j), U\}$ under high and low unemployment benefit level regimes.

Figure 18: Histogram of Lottery Value Changes



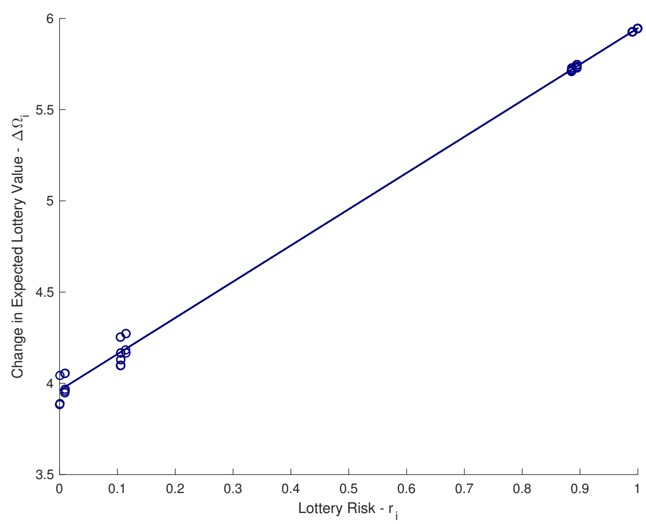
Notes: This figure plots the distribution of the change in expected lottery values moving from a low to high unemployment insurance benefit regime.

Figure 19: Risk vs Expected Lottery Value



Notes: This figure plots the expected value of lotteries against their ex-ante downside risk under low and high unemployment benefit regimes. Risk is calculated under the low unemployment benefit regime. Market tightness is kept fixed across regimes.

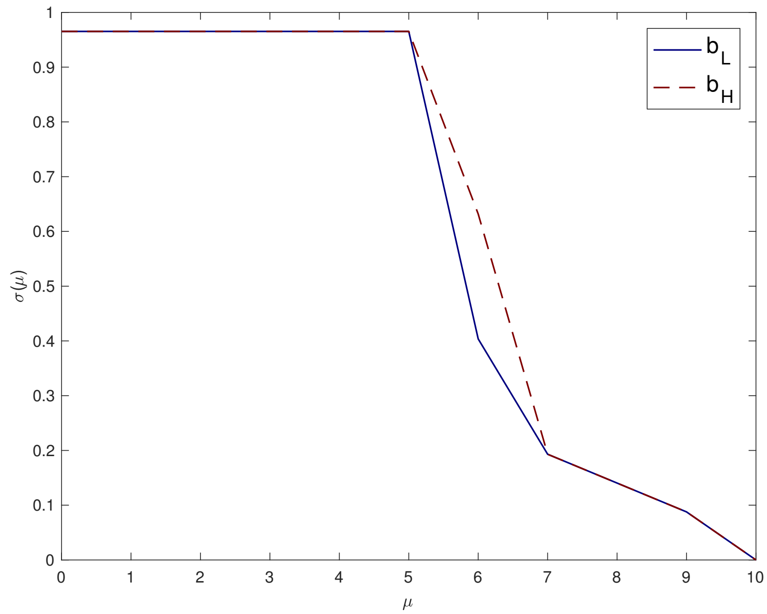
Figure 20: Risk vs Change in Value



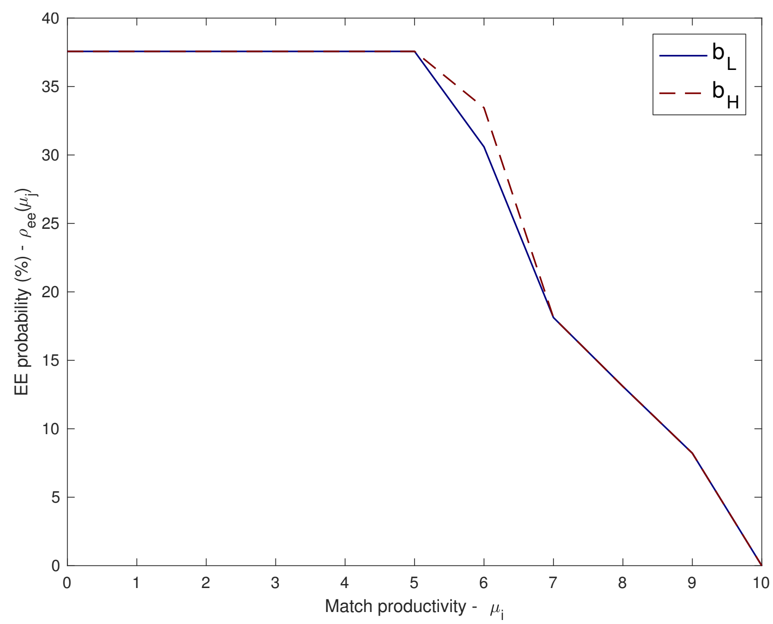
Notes: This figure plots the change in expected lottery value from the low to the high UI regime against lottery risk.

Figure 21: Sampling and Job Mobility Probabilities by Productivity

(a) Sampling by μ

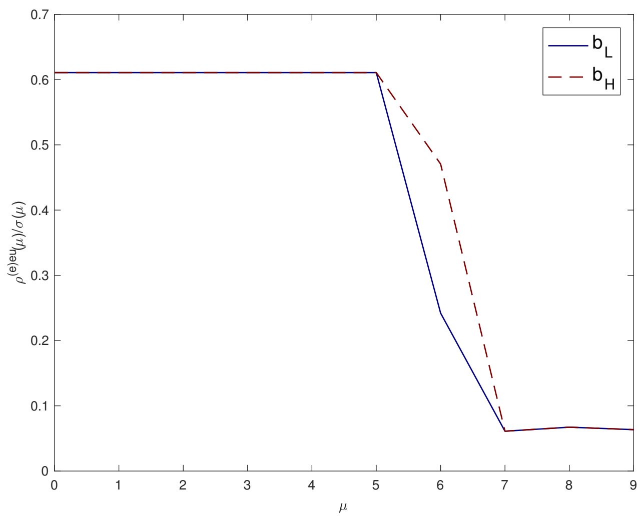


(b) EE by μ



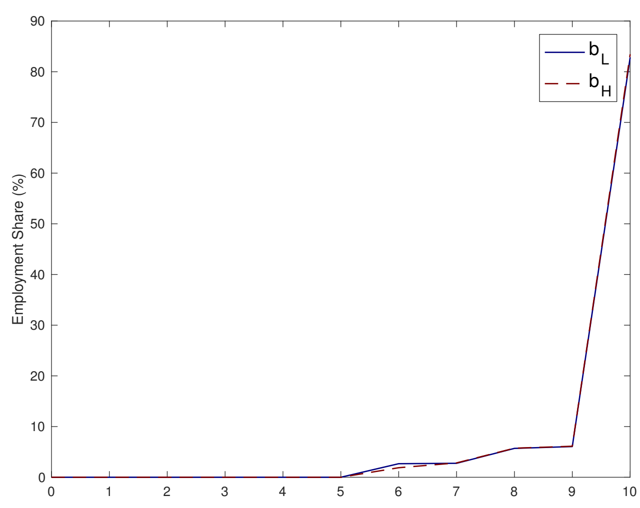
Notes: Panel (a) plots the sampling rate of a worker by μ. Panel(b) plots the job mobility rate by μ.

Figure 22: Share of Quits in Sampled Lotteries



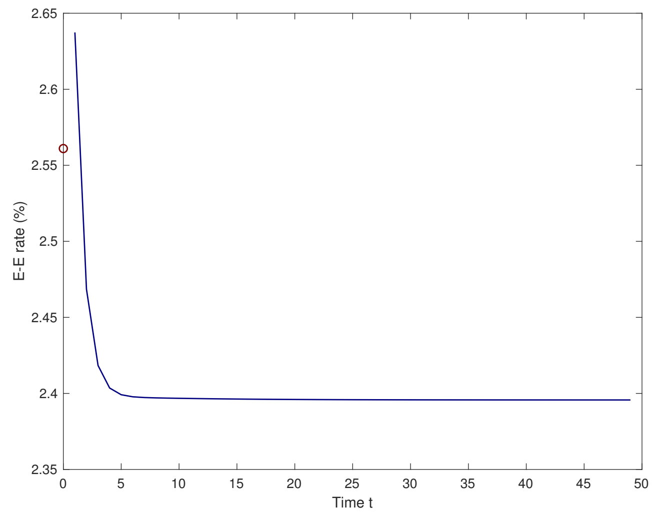
Notes: This figure plots the share of sampled lotteries that result in a quit to unemployment by match productivity.

Figure 23: Employment Distribution



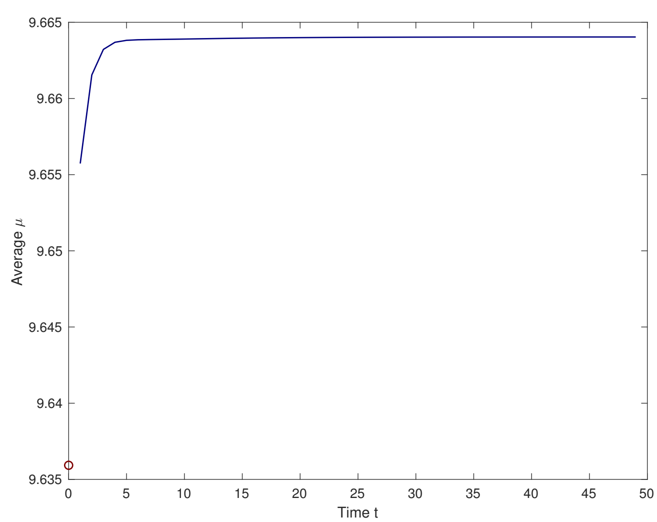
Notes: This figure plots the employment share by match productivity under the low and high UI regimes.

Figure 24: EE Rate Transition



Notes: This figure plots the transition path of successful job-to-job transitions from the low UI steady state to the high UI regime.

Figure 25: Average μ



Notes: This figure plots the evolution of average match productivity from the initial steady state to the high UI steady state.

A Appendix: Model

In this section we elaborate on some of the derivations omitted in the main text and provide computational details.

A.1 Derivation of Surplus

We use worker value functions in Equations 1 and 2 to calculate worker surplus, $W(\mu) - U$. Simple algebraic manipulation yields the following

$$\begin{aligned} W(\mu) - U =& w(\mu) - b + \beta\Bigg[(1-\delta)\Bigg((1-\lambda f)(W(\mu)-U) \\ &+ \lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{W(\mu)-U, \vec{q}_i \max\{W(\vec{\mu}') - U, 0\}\Big\}\Bigg)\Bigg] \\ &- \beta\Bigg[f \sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{0, \vec{q}_i \max\{W(\vec{\mu}') - U, 0\}\Big\}\Bigg]. \end{aligned}$$

We add firm's value, $J(\mu)$ to the expression above, and use the definition of match surplus in 7 to arrive at

$$\begin{aligned} \underbrace{J(\mu) + W(\mu) - U}_{S(\mu)} =& \mu - b + \beta\Bigg[(1-\delta)\Bigg((1-\lambda f)\underbrace{(W(\mu) - U + J(\mu))}_{S(\mu)} \\ &+ \lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{W(\mu)-U, \vec{q}_i \max\{W(\vec{\mu}') - U, 0\}\Big\}\Bigg) \\ &+ \lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\Big\{W(\mu) - U \geq \vec{q}_i \max\{W(\vec{\mu'}) - U, 0\}\Big\}J(\mu)\Bigg] \\ &- \beta\Bigg[f \sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{0, \vec{q}_i \max\{W(\vec{\mu}') - U, 0\}\Big\}\Bigg]. \end{aligned}$$

Finally using the linear surplus sharing rules in Equations 5 and 6, we cast everything in terms of total match surplus

$$
\begin{aligned}
S(\mu) =& \mu - b + \beta\big(1-\delta\big)\Bigg[(1-\lambda f)S(\mu) + \phi\lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{S(\mu), \vec{q}_i \max\{S(\vec{\mu}'), 0\}\Big\} \\
&+ (1-\phi)\lambda f \sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\Big\{S(\mu) \geq \vec{q}_i \max\{S(\vec{\mu}'), 0\}\Big\}S(\mu)\Bigg] \\
&- \beta f \sum_{i=1}^{n} Pr(\vec{q}_i)\max\Big\{0, \vec{q}_i \max\{\phi S(\vec{\mu}'), 0\}\Big\}.
\end{aligned}
$$

Eliminating the redundant max operator in the final term, we arrive at the desired expression in Equation 7.

A.2 Worker Flows

In this section, we describe the equations that characterize the steady state worker distribution induced by worker and firm problems. We note that in steady state the worker distribution over the state space is time invariant, and thus inflows and outflows are equalized for each employment state.

The steady state unemployment rate satisfies the following equation.

$$
\begin{aligned}
u =& \Bigg[(1-f) + f \sum_{i=1}^{n} Pr(\vec{q}_i)\vec{q}_i\mathbb{I}\{S(\vec{\mu}') < 0\}\Bigg]u \\
&+ \delta(1-u) \\
&+ (1-\delta)\lambda f \times \\
&\sum_{k=1}^{m}\Bigg[\sum_{i=1}^{n} Pr(\vec{q}_i)\mathbb{I}\Big\{S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'), 0\}\Big\}\sum_{j} q_{ij}\mathbb{I}\{S(\mu_j) < 0\}\Bigg]e(\mu_k)
\end{aligned}
\tag{A.1}
$$

The first line captures unemployed workers, who do not contact a firm or contact a firm but turn down the job offer lottery. The second line captures exogenous separations from employment into unemployment. The third line captures employed workers, who receive an offer and consummate the match, but end up in a very low quality match so they decide to quit.

Workers employed with productivity μ_j as a share of the worker population satisfies the following equation

$$
\begin{aligned}
e(\mu_j) =&(1-\delta)\left[(1-\lambda f)+\lambda f\sum_{i=1}^{n}Pr(\vec{q}_i)\mathbb{I}\left\{S(\mu_j)>\vec{q}_i\max\{S(\vec{\mu}'),0\}\right\}\right]e(\mu_j) \qquad \text{(A.2)}\\
&+(1-\delta)\lambda f\times\\
&\sum_{k=1}^{m}\left[\sum_{i=1}^{n}Pr(\vec{q}_i)\mathbb{I}\left\{S(\mu_k)<\vec{q}_i\max\{S(\vec{\mu}'),0\}\right\}q_{ij}\mathbb{I}\{S(\mu_j)>0\}\right]e(\mu_k)\\
&+f\left[\sum_{i=1}^{n}Pr(\vec{q}_i)q_{ij}\mathbb{I}\{S(\mu_j)>0\}\right]u.
\end{aligned}
$$

The first line captures employed workers in type-μ_j jobs, who do note receive offers or those that turn down their offers. The second line captures employed workers flowing into type-μ_j matches. The last line captures workers flowing in from unemployment.

B Appendix: Computational Details

This section provides details on how we solve and calibrate the model.

B.1 Solution

Rather than solving the individual worker and firm value functions, we directly work with the value of joint surplus from a match. Therefore, we do not have to determine the level of wages at the solution phase. We use value function iteration over the discrete state space of μ to solve the model. We outline the algorithm below.

1. For a given parameterization of the model, start with an initial guess of market tightness θ_0.

2. For each guess of θ_n in iteration n:

   (a) Iterate on Equation 7 to solve $S(\mu)$.

   (b) Iterate on the laws of motion in equations A.1 and A.2 to compute the steady-state values of employment and unemployment shares by match-specific productivity, μ.

   (c) Solve the market tightness level $\tilde{\theta}_{n+1}$ that satisfies the free-entry condition in equation 8. Calculate its percent deviation from θ_n.

   (d) If the percent deviation is less than the tolerance level, stop. Otherwise update the guess for market tightness to $\theta_{n+1}=\omega\theta_n+(1-\omega)\tilde{\theta}_{n+1}$ with a dampening parameter $\omega=0.85$.

B.2 Calibration

For the baseline calibration of the model, we first create a coarse grid over the parameter space (κ, λ, η). Then for each parameter combination in this space, we solve the model according to the algorithm outlined above, and compute model moments. Afterward, we calculate the sum of squared percent differences between the model moments and their empirical counterparts. We determine a number of candidate solutions among the parameter combinations that yield the smallest percent deviation. Finally, using these points as initial values, we use a derivative free optimization method to find the parameter combination that yields the best fit.

B.3 Transition Dynamics

In this section we outline the algorithm used to solve for the transition path from a low unemployment insurance benefit regime to a high one.

1. Fix the number of time periods it takes to reach a new steady, T.
2. Compute the steady state equilibrium for low and high unemployment insurance regimes, $b = b_0$ and $b = b_T$.
3. Guess a sequence of market tightness, $\{\theta_t^0\}_{t=1}^{T-1}$.
4. Solve for the sequence of match surplus, $\{S_t\}_{t=1}^{T-1}$, backwards given $\{\theta_t^0\}_{t=1}^{T-1}$.
5. Using $\{\theta_t^0\}_{t=1}^{T-1}$ and $\{S_t\}_{t=1}^{T-1}$, calculate the evolution of worker distribution, $\{u_t, e(\mu_j)_t\}_{t=1}^{T}$.
6. Compute the sequence of market tightness $\{\theta_t^1\}_{t=1}^{T-1}$ consistent with the evolution of the worker distribution and match surplus using the free-entry condition.
7. Check if $\max\limits_{1\leq t<T}|\theta_t^1 - \theta_t^0| < \epsilon$. If yes continue, if no go adjust $\{\theta_t^0\}_{t=1}^{T-1}$ and go back to step 3.
8. Check if $\max|\theta_T^1 - \theta_T^0| < \epsilon$. If yes stop, if no increase T and go back to step 1.