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Publication Date

2018

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Essays on Macroeconomics and Labor Markets

by

Ahmet Yusuf Mercan

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Economics

in the

Graduate Division

of the

University of California, Berkeley

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Spring 2018

Essays on Macroeconomics and Labor Markets

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Abstract

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University of California, Berkeley

Professor Yuriy Gorodnichenko, Chair

Job mobility – the rate at which employed workers change their jobs without experiencing unemployment in between – plays a significant role in shaping individual level economic outcomes as well aggregate labor market dynamics. At the micro level, workers climb up the job ladder and receive wage increases by changing employers. Experimentation by way of switching jobs leads young workers into their right career paths. At the aggregate level, job mobility might improve the allocative efficiency of the labor market by facilitating the match of productive workers and firms. This dissertation sheds light on two issues pertaining to job mobility in the U.S. Chapter 1 studies the observed decline in employer-to-employer transitions in the U.S. during the last two decades, and proposes an explanation for this downward trend. Chapter 2 proposes a framework for analyzing the excess unemployment risk following a job-to-job transition and lays the groundwork for a broader future research agenda.

Chapter 1 starts from the observation that employer-to-employer (E-E) transitions have declined in the United States during the last 20 years from a monthly rate of 2.7 percent in 1996 to 1.7 percent in 2016. In this chapter, I study the factors behind this observed decline. I document that most of the decrease in E-E transitions is accounted for by declines in matches with less than 12 months of job tenure. I attribute this decline to an increase in information about the quality of job opportunities. I then develop a search model with heterogenous matches and on-the-job search with learning about match quality. I show that the information channel can be identified from the change in the wage growth of job switchers. I estimate my model and find that workers in recent years have substantially more information about matches before they are formed, turning jobs into inspection goods rather than experience goods. I find that this increase in information explains 50 to 60 percent of the decline in job mobility over the last two decades.

Chapter 2 starts from the empirical finding that 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 chapter argues that this initial excess exposure to unemployment risk renders job-to-job transitions risky. It formalizes 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. It explores all these properties and predictions in a calibrated version of the model. The chapter also highlights a new role of unemployment insurance (UI): In the 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. Chapter 2 closes by discussing potential implications of this new view of unemployment insurance. The study therefore sheds light on how labor market policies affect the behavior of employed job seekers through a novel “experimentation subsidy” channel.

To my parents, İnci and Murat, and to my sister Simin

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Acknowledgments

I am especially indebted to my advisor Yuriy Gorodnichenko for his continuous guidance and encouragement during my time in Berkeley as a graduate student. Yuriy's enthusiasm for macroeconomics, calming demeanor, constant intellectual and emotional support contributed tremendously to my training as a scholar. I am also indebted to Benjamin Schoefer, who joined Berkeley not too long before my graduation. His kindness, support and friendship have made graduate school a very pleasant experience. I also owe a great debt to Andrés Rodríguez-Clare, who encouraged and supported me through many years, and helped me look at macroeconomic issues with a different perspective. His great relationship with his students, dedication to research and scientific rigor have set a standard for me as a scholar.

I would especially like to thank Fatih Karahan, who first sparked my interest in macro-labor issues. Fatih has been a role model, both as a person and a researcher. His friendship, guidance and advice have been priceless, and without his generosity and patience in my technical training, writing this dissertation would not have been possible.

I benefited tremendously from my discussions with other faculty members at Berkeley. In particular, I thank Pierre-Olivier Gourinchas, Thibault Fally and Reed Walker. I also benefited from many seminar participants both at Berkeley and elsewhere. They are too many to acknowledge by name, nevertheless their comments are no less valuable.

I would also like to thank my friends, with whom my time in Berkeley overlapped. I am grateful to Eser Ateş, Türker Beyazoğlu, Ekrem Karpuzcu, Melih Aksan, Yegan Erdem, Yusuf Buğra Erol, Emre Kuşakçı, Barlas-Yasemin-Erdem Oğuz, Mehmet Bentürk, Yusuf Akça, Halil Karsatar, Kemal Güler, Hacı Mustafa Toraman, Sandile Hlatshwayo, Maria Coelho, Pablo Muñoz, Maxime Sauzet, Ganesh Viswanath Natraj, Yury Yatsynovich, Slavik Sheremirov, Seongjoo Min and Chris Jauregui.

Finally, I thank my family, who took the time from their busy schedules to visit me in Berkeley over the years. I am grateful for their patience and understanding. Without them none of this would have been possible.

Introduction

This dissertation is motivated by two related questions. First, why have the observed job-to-job transitions been falling since 1996? Second, does job mobility, by exposing workers to excess unemployment risk following the move, result in a form of labor market friction, and if so, can policy tools such as unemployment insurance benefits mitigate inefficiencies associated with such a friction?

Chapter 1 is related to the first question. Specifically, I first document the decline in the U.S. job mobility rate and show that it is common to many subsets of the worker population. I also find evidence supporting the view that, contrary to the conventional wisdom that lower job mobility is inherently a negative labor market outcome, the observed decline can be partly attributed to technological improvements that render worker-firm matches better, thus resulting in less need for job changes. In Chapter 2, I document broad facts showing that job mobility decisions are succeeded by high unemployment risk. I propose an economic model that features these observed features of the data. In this chapter, I emphasize that unemployment benefits can also insure against the downside associated with job-to-job transitions and can be a useful to reduce labor market frictions.

Fewer but Better: The Decline in Job Mobility and the Information Channel

There has been a growing concern about the decline in labor market fluidity in the United States. Many indicators, such as new business formation, hiring and separation rates, and workers' geographic mobility are on a steady downward trend. In this chapter, I focus on another important measure of labor market dynamism, which has shown a similar pattern: Employer-to-employer (E-E) transitions in the U.S. have declined in the last 20 years. 2.7 percent of workers in January of 1996 ended up working at a different employer a month later. As of July 2017, eight years after the Great Recession was officially over, this rate has dropped to 1.7 percent per month.

Any systematic change in the job mobility of workers has important consequences due to its significant role in shaping individual outcomes as well aggregate labor market dynamics. At the micro level, workers climb up the job ladder and receive wage increases by changing employers. Experimentation by way of switching jobs leads young workers into their right career paths. At the aggregate level, E-E transitions improve the allocative efficiency of the labor market by facilitating the match of productive workers and firms.

The concern over the decline in E-E transitions is based on the premise that the U.S. labor market has become less flexible. This conventional wisdom views employer transitions as an important indicator of the flexibility of the labor market and the decline as a symptom of an underlying pathology. Thus, understanding the reason behind the decline in job mobility is of crucial importance due to its direct implications for welfare and policy design. On the one hand, if the decline is a result of changes in frictions preventing workers from switching employers, this may warrant a policy intervention. If, on the other hand, the decline in transitions is an optimal response to some structural change in the economy, then there is little scope for active policies targeting the labor market. In fact, the trend could even be an indicator of enhanced worker welfare.

The pattern in the aggregate decline of job mobility can be observed in many subsets of the worker population. I document that the downward trend is common among many worker demographic groups, states, occupational categories and firm characteristics. This broad-based trend points to a common cause behind the decline in E-E transitions.

I propose and evaluate a particular channel for the decline in the E-E rate based on improvements in access to information about prospective matches. My hypothesis is that many factors used in job search that have gained popularity in the last 20 years contributed to workers and firms having better information about one another. The increase in access to information about potential jobs reduces the necessity for experimentation by facilitating better assessment of a match's quality before forming an employment relationship. This implies that there is less need for the worker to switch employers in search of a better match.

To evaluate this theory quantitatively, I develop an equilibrium search model with match heterogeneity and employer competition. Match quality is determined randomly upon a meeting and is not observable. Firms and workers receive an initial signal about this potential job and base their decision whether to start an employment relationship on the signal's information content. Over time, firms and workers learn about the true quality of their match by observing their stochastic output. Workers improve their match quality by searching on the job. Learning generates a negative relationship between tenure and E-E transitions. The model

predicts that as the precision of signals about potential jobs increases, job mobility decreases. In other words, when workers are better informed about a prospective job, they are ex-ante more likely to turn down low quality offers, and they are ex-post subject to fewer negative surprises, because average uncertainty about match quality is smaller.

I jointly estimate the parameters that capture information and OJS efficiency by targeting the flatter late period E-E tenure profile and the change in wage growth of job switchers. While doing so, I keep all other parameters at their baseline values. This exercise implies that increase in information about potential matches can explain between 50 and 60 percent of the decline in the aggregate E-E rate.

In contrast to the conventional view of the decline in E-E transitions as an indicator of an unhealthy labor market, this chapter arrives at the opposite conclusion. In my model, the decline is an optimal outcome of a structural change in the economy, namely the availability of new hiring tools that provide better information for workers and firms about their potential matches. This would call into question interpretations of the decline in job mobility being a sign of a less flexible labor market, which has potentially adverse consequences for workers individually and the economy as a whole.

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

Labor markets are characterized by large degrees of wage dispersion between otherwise similar workers and jobs. Through the lens of frictionless labor market models, such wage dispersion is puzzling because workers should sort into firms offering the highest wage. *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.

In this chapter, I and Benjamin Schoefer 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 after their first year of tenure in a given job have on average a 4% probability of separation into unemployment in a given year, workers within their first year of a new 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 the 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”.

This chapter 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 value of the job offer lottery 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. We feature endogenous job creation with random search.

To assess the potential quantitative role of this mechanism in shaping job mo-

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

Chapter 1

Fewer but Better: The Decline in Job Mobility and the Information Channel

. . . labor market flows tend to reflect not only cyclical but also structural changes in the economy. Indeed, these flows may provide evidence of reduced labor market dynamism, which could prove quite persistent.

Janet Yellen, Jackson Hole,
2014

1.1 Introduction

There has been a growing concern about the decline in labor market fluidity in the United States. Many indicators, such as new business formation, hiring and separation rates, and workers' geographic mobility are on a steady downward trend.¹

¹ Hyatt and Spletzer 2013 documents a decline in hires, separations, job creation and destruction, and job-to-job flows. Molloy et al. 2016 also documents some of these declines and surveys possible causes that might explain decreasing labor market fluidity. For the decline in interstate migration, see Kaplan and Schulhofer-Wohl 2015 and Karahan and Rhee 2017. For the decline in firm start-up rates see Decker et al. 2014.

In this paper, I focus on another important measure of labor market dynamism, which has shown a similar pattern: Employer-to-employer (E-E) transitions in the U.S. have declined in the last 20 years.² 2.7 percent of workers in January of 1996 ended up working at a different employer a month later. As of July 2017, eight years after the Great Recession was officially over, this rate has dropped to 1.7 percent per month.

Any systematic change in the job mobility of workers has important consequences due to its significant role in shaping individual outcomes as well aggregate labor market dynamics. At the micro level, workers climb up the job ladder and receive wage increases by changing employers.³ Experimentation by way of switching jobs leads young workers into their right career paths. At the aggregate level, E-E transitions improve the allocative efficiency of the labor market by facilitating the match of productive workers and firms.⁴

The concern over the decline in E-E transitions is based on the premise that the U.S. labor market has become less flexible. This conventional wisdom views employer transitions as an important indicator of the flexibility of the labor market and the decline as a symptom of an underlying pathology. Thus, understanding the reason behind the decline in job mobility is of crucial importance due to its direct implications for welfare and policy design. On the one hand, if the decline is a result of changes in frictions preventing workers from switching employers, this may warrant a policy intervention. If, on the other hand, the decline in transitions is an optimal response to some structural change in the economy, then there is little scope for active policies targeting the labor market. In fact, the trend could even be an indicator of enhanced worker welfare.

The pattern in the aggregate decline of job mobility can be observed in many subsets of the worker population. I document that the downward trend is common among many worker demographic groups, states, occupational categories and firm characteristics. This broad-based trend points to a common cause behind the decline in E-E transitions.

² Molloy et al. 2016 dates the beginning of the downward trend in employment to *non-employment* separations, interstate migration, job destruction and creation to the 1980s. In the empirical section, I argue that the decline in E-E transitions started around late 1990s.

³ For instance, Topel and Ward 1992 document that one third of early career wage growth is due to job changes.

⁴ For instance, Foster, Haltiwanger, and Krizan 2001 studies how reallocation of production factors at the establishment level contributes to aggregate productivity. Directly related to worker transitions, there is a large literature on assortative matching. For example, Hagedorn, Law, and Manovskii 2017 provides evidence for positive assortative matching in Germany, Mendes, Berg, and Lindeboom 2010 in Portugal.

A prominent view of labor turnover emphasizes the role of information and learning about match quality in explaining the negative relationship between job tenure and worker separations, including E-E transitions.⁵ One implication of this theory is that as uncertainty about jobs is resolved, and the quality of surviving matches improves, there is less need for firms and workers to end their employment relationships. The empirical literature establishes that early periods of the life-cycle of a worker and a job are periods, where most of these transitions are observed.⁶ Based on these insights from the literature, I study if and how the tenure profile of job mobility changed over time, and uncover a new fact: The tenure profile of E-E transitions has become flatter, meaning that E-E rates have declined disproportionately more for recently formed jobs between the 1996-2000 and 2010-2016 periods. More specifically, the decline during the first 12 months of a job accounts for around 40 percent of the decline in the overall E-E rate. Closely related to this observation, I also document that during the same period, job mobility has declined more significantly for young workers between ages 20 and 30 compared to older workers. I corroborate these findings using data from two household surveys: the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP). What emerges from these data sources is that the experimentation phase of a job has become less important. In other words, jobs have become more “inspection” than “experience goods.”

I propose and evaluate a particular channel for the decline in the E-E rate based on improvements in access to information about prospective matches. My hypothesis is that many factors used in job search that have gained popularity in the last 20 years contributed to workers and firms having better information about one another.⁷ The increase in access to information about potential jobs reduces the necessity for experimentation by facilitating better assessment of a match’s quality before forming an employment relationship. This implies that there is less need for the worker to switch employers in search of a better match.

⁵ The seminal paper in this literature is Jovanovic 1979, which builds a model where there is no prior information about potential jobs. The paper shows that learning about job quality induces a strong negative relationship between tenure and separations. The role of information about match quality in shaping worker outcomes is also empirically relevant. Nagypál 2007, by studying firm level responses of separation-tenure profiles in France, finds that learning about match quality is a more dominant force than learning on the job.

⁶ See Topel and Ward 1992.

⁷ These factors include the increasing use of internet for posting and searching vacancies, online job platforms that provide insider reviews on the work environment of employers, background checks and employee referrals during recruitment, and professional hiring services. Figure A.1 presents some measures of resources allocated to hiring and job search, and shows a stark increase in the use of these resources during the last two decades.

To evaluate this theory quantitatively, I develop an equilibrium search model with match heterogeneity and employer competition. Match quality is determined randomly upon a meeting and is not observable. Firms and workers receive an initial signal about this potential job and base their decision whether to start an employment relationship on the signal's information content. Over time, firms and workers learn about the true quality of their match by observing their stochastic output. Workers improve their match quality by searching on the job. As in Jovanovic 1979, learning generates a negative relationship between tenure and E-E transitions. The model predicts that as the precision of signals about potential jobs increases, job mobility decreases. In other words, when workers are better informed about a prospective job, they are ex-ante more likely to turn down low quality offers, and they are ex-post subject to fewer negative surprises, because average uncertainty about match quality is smaller.

The main goal of my exercise is to quantify the role of information in declining job mobility. To this end, I first calibrate a version of the model by targeting several labor market related moments during the early period of 1996 – 2000. In particular, the baseline calibration targets the E-E tenure profile. In matching the early-period moments, I assume that the initial priors about potential jobs are formed based on signals that contain information equivalent to observing output for one month. I then allow two competing forces in the model to change that have observationally similar implications for worker flows: The precision of the initial signal and the efficiency of on-the-job search (OJS). I interpret the increase in signal precision as improvements in hiring and job search technologies that facilitate better matching of workers and firms, and the decline in OJS efficiency as a reduced form way of capturing any friction that might inhibit job switching.

The main challenge with this exercise is that both forces are unobservable, and they predict a similar change in E-E transitions. My strategy to distinguish their explanatory powers relies on their opposing wage implications. In particular, more information results in larger wage growths for job switchers. In contrast, the decline in OJS efficiency implies smaller wage gains.

To discipline the contributions of these two forces, I first measure how conditional wage growth changed over the last two decades. I find corroborating evidence for a positive trend in conditional wage gains using two distinct data sources. Specifically, I show that the wage growth of job switchers in the late period is nearly eight percentage points higher than in the early period. With an indirect inference approach, I use this new empirical moment to decompose the contribution of OJS efficiency and information to the aggregate decline in job mobility.

I jointly estimate the parameters that capture information and OJS efficiency by targeting the flatter late period E-E tenure profile and the change in wage growth

of job switchers. While doing so, I keep all other parameters at their baseline values. This exercise implies that increase in information about potential matches can explain between 50 and 60 percent of the decline in the aggregate E-E rate.

In contrast to the conventional view of the decline in E-E transitions as an indicator of an unhealthy labor market, this paper arrives at the opposite conclusion. In my model, the decline is an optimal outcome of a structural change in the economy, namely the availability of new hiring tools that provide better information for workers and firms about their potential matches. This would call into question interpretations of the decline in job mobility being a sign of a less flexible labor market, which has potentially adverse consequences for workers individually and the economy as a whole.

Related Literature This paper is related to three strands of the literature. First, it is related to the literature measuring job mobility. I am not the first to measure employer-to-employer transitions or document its recent decline. Fallick and Fleischman 2004 uses the 1994 redesign of the CPS to measure job mobility between 1994 and 2003. Hyatt and Spletzer 2013 complements this paper by measuring job-to-job flows using administrative data from the Longitudinal Employer-Household Dynamics (LEHD) between 2001 and 2012, and documents a decline in job mobility similar to the one I investigate in this paper. Hyatt and Spletzer 2013 points to several possible explanations for this decline, but does not test or quantify their relevance. Using data from the CPS, Bosler and Petrosky-Nadeau 2016 studies the decline in job mobility by age and shows that the decline is most pronounced for young workers between ages 16 and 24.

In the CPS and LEHD, E-E rates can be measured starting in 1994 and 2001, respectively. My paper contributes to this literature by providing measures of job mobility going back to 1988 using data from the SIPP and the Panel Study of Income Dynamics (PSID).⁸ This allows me to draw a more complete picture of the downward trend observed in the last two decades. Another contribution of my paper to this literature is to investigate changes in job switching patterns by tenure. In particular, I document that the E-E tenure profile has flattened since 1996. I also connect this finding to another new fact pertaining to the wage growth of job switchers. On this front, I establish that this group's wage growth has increased over the same period. To the best of my knowledge, I am the first to document these two facts.

⁸ Nagypál 2008 uses the SIPP to measure E-E transitions between 1996 and 2003, and focuses on the importance of job mobility in understanding worker turnover over the business cycle. I extend the time series to cover years between 1993 and 2013, and study the secular change over this longer horizon.

Second, my paper is related to a large literature on learning models of the labor market, building on Jovanovic 1979. The learning structure in my model is closely related to Moscarini 2005, which embeds learning into a search model in continuous time. Gorry 2016 uses the learning structure in Moscarini 2005 adapted to discrete time, and studies the role of learning in the life-cycle profile of job finding rates and wage volatility. On the theoretical front, I embed learning, on-the-job search and employer competition together with a realistic worker life-cycle into an otherwise standard search model. To this end, I combine the wage determination in Cahuc, Postel-Vinay, and Robin 2006 and Bagger et al. 2014 with learning about match quality in Jovanovic 1979 and Moscarini 2005. My paper differs from Gorry 2016 along a couple of important dimensions. Specifically, wages are set via sequential auctions (compared to competitive wages) and there is free entry of firms in my model. The latter allows me to take into account the response of firms to structural changes.

Third, this paper is broadly related to the growing literature on measuring the changes in labor market fluidity. The E-E transition rate is not the only measure of labor market fluidity that is exhibiting a downward trend. Hyatt and Spletzer 2013 documents a decline in hires, separations, job creation and destruction, in addition to job-to-job flows. Molloy et al. 2016 similarly documents some of these declines and surveys possible causes that might explain decreasing labor market fluidity. Decker et al. 2014 and Karahan, Pugsley, and Sahin. 2017 document the decline in firm start-up rates. Many of these papers identify the dimensions in which the decline is observed, but do not aim to explain the causes behind this decline.

The conventional wisdom in the measurement literature points to increased frictions as a possible driver of these declines. Contrary to this bleak view, I show that the decline in E-E transitions might not be an indicator of frictions preventing job switching, but could be an optimal response to changing fundamentals.

There are some notable exceptions to the literature that focuses on measurement. For instance, Karahan and Rhee 2017 studies the decline in inter-state migration, and attributes part of the decline to the general equilibrium effects of population aging. A related paper to mine is Kaplan and Schulhofer-Wohl 2015, which similarly studies the decline in inter-state migration in the United States. This paper attributes some of the decline in geographic mobility to better information about locations, and argues that better information is due to falling traveling costs and improvements in information technology. The paper uses the change in “repeat” and “return migration” rates to identify this channel. My paper has a similar insight, but I study employer-to-employer transitions, and use the change in the wage growth of job switchers to identify the contribution of the information channel. Another related paper is Ates and Saffie 2016, which studies firm entry and productivity costs of sudden stops. In

this paper, financial selection induces a tradeoff between the quantity and quality of entering firms, resulting in *fewer, but better* entrants during episodes of financial crises. My result is analogous, that is, fewer workers make an E-E transition, but they do so when they are sure of ending up in a good match. However, my mechanism emphasizes the information channel rather than financial frictions.

The rest of the paper is organized as follows. Section 1.2 documents the decline in E-E transition rate in the last two decades and establishes a number of stylized facts. Section 1.3 presents my model, and section 1.4 discusses the calibration strategy and presents quantitative results. Section 1.5 concludes.

1.2 Empirical Analysis

I start by documenting the decline in the aggregate E-E rate observed in the last two decades. I then show that the decline is common across many subsets of the worker population, which suggests that a common force reduces job mobility for all groups of workers. Third, I establish a new fact: The decline in transitions is concentrated in early periods of a job's life-cycle. Relatedly, I also document that the E-E age profile has flattened. I interpret these findings as suggestive of better initial matches that reduce the need for subsequent experimentation in an effort to find better career options. This motivates my choice of information as the explanation behind the aggregate decline in job mobility.

Data

This section provides a brief discussion of the various data sources I use in my analysis. To measure job mobility, I record a worker as making an employer-to-employer transition when the worker is employed in two consecutive months, but the reported employer changes in the second month. I utilize four different data sources, which have different designs and time spans, to construct measures of job mobility over time. This broad set of sources allows me to have the most comprehensive measure of job mobility possible covering the period between 1980 and 2016. Namely, I use three household surveys: the Current Population Survey (CPS), the Survey of Income and Program Participation (SIPP) and the Panel Study of Income Dynamics (PSID). I restrict my analysis to workers between ages 20 and 65 who are not enrolled in school, in the military or self-employed. To complement my use of surveys, I turn to the Longitudinal Employer-Household Dynamics (LEHD) database to present measures of E-E transitions based on administrative data.⁹ Appendix A.1 elaborates

⁹ LEHD links state-level unemployment insurance records with establishment-level data.

on sources and sample construction.

Aggregate Decline in Employer-to-Employer Transitions

This section presents various measures of employer-to-employer transitions as a share of employment over time, using data from the CPS, SIPP, PSID and LEHD.

CPS Panel (a) of figure 1.1 uses the basic monthly files of the CPS, and plots the share of employed workers that change jobs each month between 1994 and 2016.¹⁰ The solid blue line shows the raw data and the dashed red line shows a fitted cubic trend. The figure points to a downward trend in the transition rate starting in early 2000s; a decline from 2.7 percent per month during this period to a level around 1.7 percent per month in 2016, which marks a percentage point decrease in job mobility.

Even though the decline seems to be concentrated around the recessions of 2001 and 2008, the job mobility rate has not recovered to its level in 2000, even eight years after the National Bureau of Economic Research (NBER) announced the end of the Great-Recession.^{11,12}

SIPP The CPS is not explicitly designed as a panel survey, and its rotating panel structure allows workers to be only observed for two four-month periods with an eight-month break in between. Therefore, it is not ideal for constructing measures that require tracking workers over time. To address this concern, I turn to the SIPP, which is designed as a panel that tracks households over the course of three to five years and interviews them every four months. Panel (b) of figure 1.1 plots the monthly E-E rate constructed from the 1993, 1996, 2001, 2004 and 2008 SIPP panels. Since the end of one SIPP panel does not necessarily overlap with the beginning of the following panel, the time-series display some gap months. The blue solid line plots the raw data and the red dashed line shows the fitted cubic trend. The data point to a percentage point decline from two percent to one percent between 1993 and 2014. Job mobility rates in the SIPP are lower than in the CPS, but are largely parallel. The common downward trend corroborates findings from the CPS that aggregate E-E rate has substantially declined in the last two decades.

¹⁰ Unfortunately, the CPS allows direct measures of job mobility only after its 1994 redesign.

¹¹ See <http://www.nber.org/cycles.html> for business cycle start and end dates as determined by the NBER. According to the NBER, the end of the Great-Recession was June 2009. Even though the labor market recovered from the recession long after 2009, the E-E rate is 1.7 percent as of July 2017, where unemployment rate is comparable to its level before the recession of 2001.

¹² Jaimovich and Siu 2014 studies how secular changes might manifest themselves during recessions. I do not study such an interaction in this paper.

PSID The earliest measure of job mobility I construct from the CPS and SIPP dates back to 1993. An important aspect of the analysis is to determine whether the downward trend in job mobility has in fact started in the early 2000s or if it is just a manifestation of a much longer trend.¹³ To this end I turn to the PSID, which is available between 1988 and 1997.¹⁴ Panel (c) of figure 1.1 plots the monthly E-E rate of household heads between 1988 and 1997 together with a fitted cubic trend. PSID data reveal that employer transitions were stable in the late 1980s and 1990s at around 2 percent per month. This suggests that the decline has been a recent phenomenon.

ASEC Supporting evidence for stable E-E transitions pre-2000 and a steady decline afterwards comes from the Annual Social and Economic Supplement (ASEC) to the CPS, commonly known as the March Supplement. The ASEC asks interviewees the number of jobs they held in the previous year. Panel (d) of figure 1.1 plots the share of employed workers that report to have held more than one job in the preceding year. The plot reveals a stable share between the 1980s and late 1990s, after which it exhibits a steep drop. Although the share of multiple job holders is not a direct measure of job mobility, it can proxy for the frequency of E-E transitions to the extent that employer transitions with an *observed* non-employment spell in between stayed stable within a year.

LEHD Measures of job mobility based on administrative data sources also point to a decline in transitions since 2000. Panel (e) of figure 1.1 plots the seasonally-adjusted quarterly E-E rates using the LEHD.¹⁵ The blue solid line depicts the rate of hires following a separation with short or no non-employment spell since last employment. The red dashed line with circles plots the same rate for separations. Both point to a two percentage point decline between 2000 and 2016 in agreement with evidence from surveys.

Sub-samples The aggregate time-series evidence suggest that job mobility took on a downward turn beginning in 2000 and despite the recovery in the U.S. labor

¹³ As discussed earlier, a downward trend can be observed in a number of indicators of labor market fluidity. For some of these indicators, the start of the decline can be dated back to as early as the 1980s. See Molloy et al. 2016.

¹⁴ 1988 is the earliest wave that allows constructing monthly employment spells. Furthermore, the PSID was redesigned following its 1997 wave. To avoid complications associated with the biannual data, I only include waves from 1988 to 1997.

¹⁵ Data files are available at https://lehd.ces.census.gov/data/j2j_beta.html.

market after the Great Recession, it now remains at a lower level. This phenomenon is not specific to one particular geographic location, demographic group or firm type.

Figure 1.2 plots E-E rate time-series by various subsets of the worker population and reveals that the change is broad based. Panel (a) shows E-E rate by worker gender and points to a common decline among men and women using the CPS. Panel (b) considers three major U.S. states, Florida, California and New York, and plots their job mobility rates over time. A parallel downward trend in California and Florida is of particular interest since they have different laws regulating their labor markets in regards to the enforcement of non-competition clauses, which contractually prevents workers from switching to an employer’s competitor.¹⁶ The decline can be observed across broad categories of occupations as well. I use a categorization of occupations that is based on the distinction of a job’s skill requirement along two dimensions: “cognitive” versus “manual”, and “routine” versus “non-routine”.¹⁷ Panel (c) plots job mobility rates by workers’ current occupation type in one of these four categories and points to a common downward trend. Panels (d) and (e) plot E-E rates from the LEHD based on matched employee-employer data by various firm sizes and age categories.¹⁸ Except for workers in very young firms, the job mobility behavior shows a similar decline across workers in firms that are young and old, as well as in firms that employ a small number of workers compared to those that employ hundreds of workers.¹⁹

Summary The decline in job mobility starting around 2000 is a prevalent and robust phenomenon as measured by various distinct datasets. It is common across workers employed in different regions of the U.S. and in different types of firms. This broad-based change calls for an explanation that does not solely resort to the compositional shifts in worker demographics and firm structures observed in the U.S.

¹⁶ One of the proposed explanations for the decline in E-E transitions is the increasing prevalence of non-competition clauses in employment contracts. Even though non-compete clauses have become more common in the last 20 years, their enforcement is not uniform within the U.S. California is known to be a state where non-compete clauses are not enforced, whereas Florida is known to be where such contractual clauses are enforced to the fullest extent. See Garmaise 2011 for a discussion of non-competition agreements and a state level index of enforceability.

¹⁷ I categorize occupations into these four groups based on Autor and Dorn 2013 and according to the adaptation in Jaimovich and Siu 2014.

¹⁸ The same pattern emerges using the seasonally-adjusted job-to-job separation rates from the LEHD. I do not report these results.

¹⁹ As discussed before, the firm start-up rate has also been decreasing, which implies that young firms constitute a smaller share of the firm stock in recent years compared to the 1990s. Therefore this outlier is less of a concern.

It suggests a common force that explains the decline in employer transitions such as the information mechanism I propose and investigate in the rest of this paper.

A New Fact: The Flattening of E-E Tenure Profile

Motivated by insights from the theoretical and empirical literatures emphasizing the early career worker behavior, I study if and how E-E tenure profile has changed over the last two decades, during which the aggregate job mobility rate has declined. To this end, I split my samples into two; an *early period* covering 1996 to 2000 when the average E-E rate was stable around 2.7 percent per month, and a *late period* covering 2010 to 2016 when the E-E rate dropped to 1.7 percent per month.

Tenure Profile To construct the E-E tenure profile, I first calculate the tenure upon a job switch for each worker, and then calculate the share of employed workers that make an employer transition at each tenure duration. Figure 1.3 plots this job mobility tenure profile using data from the CPS and SIPP.²⁰ The blue solid lines present the profiles for the early period. The negative relationship between the hazard rate of E-E transition and tenure is a well established fact.²¹ Most job transitions occur when a worker is has just started a job. With longer tenure, the hazard rate of employer change decreases and settles to a constant rate.

My particular interest is in the worker behavior during the late period relative to that of the early period. The red dashed lines in figure 1.3 show the tenure profile of E-E transitions during the late period using data from the CPS and SIPP. The two panels point to a similar finding; the decline is more pronounced in the early stages of a job's life-cycle. For instance, the E-E rate in the first month of a job dropped from around 5 percent to around 3 percent in the CPS sample, marking a 2 percentage point decline, whereas the the change in longer tenures is negligible.

Shift-Share Analysis To formally gauge the effect of the flattening of E-E tenure profile on the overall decline in E-E transitions, I undertake an accounting exercise.

²⁰ The CPS and SIPP are the two data sources that allow me to measure E-E rates by tenure, and compare worker behavior between 1996 – 2000 and 2010 – 2016. LEHD does not provide tenure information. The change in PSID's design after 1997 limits my sample to years between 1988 and 1997.

²¹ Farber 1994 establishes this fact using the National Longitudinal Survey of Youth. The paper finds that the hazard rate is not monotonic, but slightly increases for the first 3 months on a job and then decreases. I also see a similar pattern in some of my samples, however explaining this pattern is out of the scope of my paper. See Menzio, Telyukova, and Visschers 2016, Jung and Kuhn 2016 and Nagypál 2007, which also document the negative relationship between hazard rate of job change and age/tenure, among many other papers.

Let c index a worker cell, where a cell can represent different worker characteristics such as tenure and age. Mechanically, one can express the overall E-E transition rate at time t as a weighted average of group level transition rates:

$$ee_t = \sum_c ee_{ct} \times s_{ct}$$

where ee_{ct} and s_{ct} are cell specific E-E rate and employment shares, respectively. It follows that the change in E-E rate between periods 0 and t can be expressed as the sum of three components:

$$\Delta ee_t \equiv ee_t - ee_0 = \underbrace{\sum_c \Delta ee_{ct} \times s_{c0}}_{\text{within-cell component}} + \underbrace{\sum_c ee_{0t} \times \Delta s_{ct}}_{\text{between-cell component}} + \underbrace{\sum_c \Delta ee_{ct} \times \Delta s_{ct}}_{\text{interaction}}$$

The first term I call the *within-cell component* captures the share of the aggregate decline that can be attributed to the change in cell specific behavior, keeping the employment shares fixed to their initial level. The second term, the *between-cell component*, is the part of the decline that can be explained by the changes in employment shares keeping flows fixed to their initial level. Letting c denote tenure durations, one can further split the within-cell component into:

$$\sum_c \Delta ee_{ct} \times s_{c0} = \underbrace{\sum_{c=1}^K \Delta ee_{ct} \times s_{c0}}_{\text{early tenure}} + \underbrace{\sum_{c=K+1}^C \Delta ee_{ct} \times s_{c0}}_{\text{late tenure}}$$

where the first term is the part of within-cell component accounted by the first K tenure cells. A way to measure the disproportionate impact of the change in new match behavior is to calculate how much these first K cells account for in the overall within-cell component. Plotting $\frac{\sum_{c=1}^K \Delta ee_{ct} s_{c0}}{\sum_c \Delta ee_{ct} s_{c0}}$ and $\sum_{c=1}^K s_{c0}$ against K then provides a way to quantify the effect of the flattening E-E tenure profile on aggregate changes.²²

Figure 1.4 plots the share in the within-cell component together with the cumulative employment share against the first K tenure cells used in the decomposition. The figure indicates that 50 percent of the within component can be directly attributed to the change in E-E behavior of workers in jobs with tenure less 12 months

²² Note that a large within-component implies a broad-based change across cells. I am interested in the relative weights of the cells in this component. If the rate changed by the same amount for each worker cell, the ratio $\frac{\sum_{c=1}^K \Delta ee_{ct} s_{c0}}{\sum_c \Delta ee_{ct} s_{c0}}$ would simplify to $\frac{\sum_{c=1}^K s_{c0}}{\sum_c s_{c0}} = \sum_{c=1}^K s_{c0}$: the cumulative employment share of the first K cells. Any disproportionate change in the early cells is reflected as a steeper curve than the cumulative employment curve.

based on the CPS sample. The within component accounts for about 80 percent of the overall decline, therefore the direct effect of the changes in E-E rates in the first 12 months of matches can explain about 40 percent of the aggregate change.

Regression Analysis To test the statistical significance of the change in E-E tenure profile, I also run simple regressions. Concretely, I pool my early (1996 Panel) and late (2008 Panel) period samples of employed workers from the SIPP.²³ I regress an employer-to-employer transition indicator on a dummy for the late period sample, including tenure, age, gender, marital status, disability, education, race and state dummies for workers. Table 1.1 presents the results. The first column shows that the E-E transition rate is lower on average in the late period relative to the early period (coefficient -0.0037 with t-stat -16.1), consistent with the aggregate decline in job mobility plotted in figure 1.1. To see if the decline is more pronounced among recently formed jobs, I interact the late period dummy with an indicator of jobs with less than 12 months of tenure. The second column shows that, the decline in E-E transitions is much larger for jobs with less than 12 months of tenure compared to jobs with longer tenure (coefficient -0.0081 with t-stat -10). This indicates that the flattening of the E-E tenure profile is indeed statistically and economically significant, corroborating the findings presented in figure 1.3. Columns four and five present analogous results excluding observations between 2008 and 2010, the immediate aftermath of the Great Recession. The coefficient on the late period dummy in column four indicates that even after excluding the recovery years, E-E rate is on average lower (coefficient -0.0038 with t-stat -17.68) compared to the early period. The difference-in-difference specification in column 5 points to a more pronounced decline among workers with tenures shorter than a year (coefficient -0.0078 with t-stat -10.8). These results point to an even stronger change in the years after the recovery from the recession, and address any concern that the decline observed in the 2008 panel reflects a cyclical decline in job mobility.

Age Profile Age is a proxy for worker experience and one might expect any force that is changing worker behavior observed in the E-E tenure profile to manifest itself in the E-E age profile as well. To complement my findings from the previous section, I study if and how the E-E tenure profile has changed from the early to the late period.

²³ SIPP allows me to construct a larger sample, and measure tenure and wages at a greater level of detail than the CPS. The reason is that, in the CPS, wages can be measured only twice during the time that a worker is in the survey and job tenure is only available at two-year intervals for a subset of workers interviewed. To get more statistical power, I therefore use the SIPP in my analysis using individual level data.

To construct the age profile of job mobility, I first group employed workers between ages 20 and 65 into five-year age bins at the time of an E-E transition. I then calculate the average monthly job mobility rate for each group. Figure 1.5 plots this E-E age profile using data from the CPS and SIPP. The blue solid lines present the profiles for the early period. The red dashed lines show the job mobility age profile in the late period, and reveal that the decline in job mobility is more pronounced among young workers. In the CPS, the decline is around two percentage points for workers in the 20 – 25 age bin, from 5 percent to 3 percent, whereas it is less than a percentage point for older workers. This finding questions proposed explanations attributing the decline in E-E rate to compositional shifts in the labor market, i.e., the aging of the labor force.

I undertake an analogous shift-share analysis to decompose the contribution of various age groups to the aggregate decline in job mobility. Figure 1.6 plots the share in the within-cell component together with the cumulative employment share against the first K age cells in this decomposition. Panel (a) of the figure indicates that around 40 percent of the within-cell component can be directly attributed to the change in E-E behavior of workers younger than 30 years. The within-cell component accounts for about 95 percent of the overall decline in the CPS, therefore the direct effect of the changes in E-E rates among workers aged between 20 and 30 can explain close to 40 percent of the aggregate decline.

Summary I interpret the disproportionate job mobility declines in early tenure and age groups as consistent with increased availability of information and decreased need to experiment on a job. These findings reveal that changes in worker behavior during the experimentation phase of a job has an important role in accounting for the aggregate decline in E-E.

1.3 Model

This section formalizes the link between job mobility and the information channel. Specifically, I build a search model with heterogenous match quality and on-the-job search. Match quality is imperfectly observed and agents receive noisy signals about potential matches, and based on the beliefs they form, decide whether to accept or reject offers. Once they form a job, by observing a random output, they further update their beliefs about their match quality. An increase in the signal precision of potential matches leads to a decline in worker experimentation and employer-to-employer transitions.

Environment

Time is discrete and runs forever. Firms and workers in the economy are risk-neutral. Workers live T periods, and exit the model at age $T + 1$. Their age is denoted by $a \in \{1, \dots, T\}$. Each exiting cohort is replaced by a new group with age 1, and worker mass is normalized to unity for each cohort, implying a total worker mass T . Agents discount the future with a common factor $\beta < 1$.

Matches are destroyed with exogenous separation rate δ . Of the workers that are separated, a share ρ have the opportunity to switch to another employer without an intervening unemployment spell, which I call a *reallocation shock*. The complementary $1 - \rho$ share of separated workers go to unemployment directly. The idiosyncratic reallocation shocks are necessary to generate job mobility at long tenures, otherwise there would be no E-E transitions left in the model given that uncertainty is fully resolved over time. This prediction would be at odds with the data.

Matching Workers search for potential matches with differing intensities depending on their employment status. Firms post vacancies by paying a flow cost κ . Meetings are determined randomly by 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 $\theta \equiv \frac{V}{S}$. The mass of job seekers includes both employed, unemployed and reallocated workers. The meeting rate for an unemployed worker is $f^U(\theta) = \frac{M(S, V)}{S} = M(1, \theta)$. I assume that employed workers search on-the-job with fixed intensity $\lambda < 1$, therefore contact rate for an employed worker is $f^E(\theta) = \lambda f^U(\theta)$. Contact probability for a firm is $q(\theta) = \frac{M(S, V)}{V} = M(1/\theta, 1)$. The mass of job seekers is $S = (u + (\lambda(1 - \delta) + \delta\rho)(1 - u))T$, and u denotes aggregate unemployment rate.

Match Quality and Learning When a worker and firm meet, the productivity of their potential match μ is randomly drawn from two types: High quality with productivity μ_h and low quality with productivity μ_L where $\mu_H > \mu_L$ as in Moscarini 2005. The unconditional probability of drawing μ_H is p_H and common knowledge. However, firms and workers do not observe their μ directly. Instead, by observing noisy signals about their potential productivity, they form an initial belief on which they base their decision whether to consummate the match or not. In an active match, agents observe their random output every period and update their beliefs about the underlying match productivity. The initial belief that the firm and worker form before starting production is denoted by p_0 . In an active match, their current prior about having a high quality match is denoted by p , which will differ from initial prior p_0 due to the repeated updates following each realization of output.

Timing The timing of the model is as follows. Matched workers and firms bargain over how to split the surplus they generate, before they observe their current period output. Unemployed workers consume an unemployment benefit and employed workers consume their bargained wage. After the consumption/production phase, agents observe the output and update their priors about the underlying match quality. With the exogenous probability δ , some matches are destroyed. From the remaining matches, workers decide whether to continue the match or end it based on their updated belief. Subsequently, the search phase takes place. Unemployed and recently separated workers meet potential employers and observe a signal about the underlying productivity. They then decide whether to accept or reject the offer. Similarly, employed workers engage in on-the-job search and receive outside offers. Depending on the signal about the potential match and their belief of the current match they decide to switch or stay. Figure 1.7 summarizes the timing of the model from the worker’s viewpoint.

Production and Bargaining

I assume that match quality μ captures the average output from a match. Once matched, the firm and worker bargain over their expected output. If the agents have prior p about their match quality, their expected match output is a weighted average of low and high type productivities given by:

$$\mathbb{E}[\mu|p] = p\mu_H + (1 - p)\mu_L.$$

Wages are defined as piece-rate contracts and are adapted from Bagger et al. 2014. Flow wage in a match is given by

$$w = r\mathbb{E}[\mu|p]$$

where $r \in (0, 1)$ is the endogenous, bargained piece-rate.

To lay out the wage protocol, here I introduce notation that I formally define in section 1.3. I denote the value of an employed worker with prior p , age a and piece-rate r by $W(p, a, r)$, value of unemployment by $U(a)$ and the value of a filled position to the firm by $J(p, a, r)$. Surplus from a match is then defined as²⁴

$$S(p, a) \equiv J(p, a, r) + W(p, a, r) - U(a). \quad (1.1)$$

²⁴Note that here I use the result I formally derive in section 1.3, that surplus is independent of piece-rate wage r . The intuition for this is that wage rules only determine how surplus is shared among the worker and firm but do not impact the overall surplus from a match. For a similar argument under perfectly observable match types see Jarosch 2015.

Suppose that a worker is employed with state (p, a, r) and receives an outside offer which results in prior p_0 . If $p_0 > p$, then the poacher wins the bargain by offering r' that satisfies

$$W(p_0, a, r') - U(a) = S(p, a) + \phi[S(p_0, a) - S(p, a)] \quad (1.2)$$

where $\phi \in (0, 1)$ is an exogenous parameter.

Bargaining between a firm and unemployed worker is nested in equation 1.2 as a special case if one considers unemployment as a job with zero surplus, $S(p, a) = 0$.

If $p_0 < p$, there are two possible cases. If the offer is high enough, the worker can credibly threaten the firm to switch to the poacher. This induces a re-bargaining of the wage but the worker stays with the incumbent firm. When this is the case, the rebargained wage satisfies

$$W(p, a, r') - U(a) = S(p_0, a) + \phi[S(p, a) - S(p_0, a)]. \quad (1.3)$$

If p_0 is too low, the offer is simply discarded and the match is kept with the same wage rate. The cutoff prior $q(p, a, r)$ below which offers are discarded is characterized by the following indifference condition

$$W(p, a, r) - U(a) = S(q, a) + \phi[S(p, a) - S(q, a)]. \quad (1.4)$$

Figure 1.8 summarizes the wage bargaining protocol. A couple of comments on wage determination are in order here. First, in this setting wages are history dependent. Two workers with the same prior and age might have different piece rates depending on the outside offers they faced over the course of their employment spells. Second, this wage determination protocol can lead to wage losses upon switching employers, which is a true feature in the data.²⁵ The intuition for this is that workers, by moving to a match they believe is of higher productivity, trade off a lower current wage with the expectation of more wage increases induced by outside offers in the new match.

Value Functions

In this section, I outline the worker and firm problems. I use two distributions to take expectations in the value functions presented below. Namely, new job offers are sampled from a distribution $G(p_0)$ and in active matches, posterior p' conditional on prior p follows a distribution $G(p'|p)$. I characterize these distributions in section 1.3. Since contact rates are exogenous to the worker and the firm, I suppress their dependence on market tightness θ in the value functions for notational simplicity.

²⁵ See Bagger et al. 2014 and Tjaden and Wellschmied 2014 for a discussion of this fact, and alternative ways of generating this pattern theoretically.

Worker's Value Functions A worker with age a has unemployment value defined by the following Bellman equation

$$U(a) = b + \beta \left[(1 - f^U)U(a + 1) + f^U \int_0^1 \max \{U(a + 1), W(p_0, a + 1, r)\} dG(p_0) \right] \text{ for } a \leq T. \quad (1.5)$$

An unemployed worker consumes unemployment benefit b . She contacts a firm with probability f^U and decides whether to take or reject the offer based on prior p_0 sampled from distribution $G(p_0)$. If she fails to meet a firm or rejects the offer, she continues to the next period as unemployed, having aged by one period.

A worker with prior p , age a and piece-rate wage r has employment value defined by the following Bellman equation

$$W(p, a, r) = r\mathbb{E}[\mu|p] + \beta \left[\delta(1 - \rho)U(a + 1) + \delta\rho \int_0^1 \max\{U(a + 1), W(p_0, a + 1, r')\} dG(p_0) + (1 - \delta) \int_0^1 \max \left\{ U(a + 1), (1 - f^W)W(p', a + 1, r) + f^W \int_{p'}^1 W(p_0, a + 1, r') dG(p_0) + f^W \int_{q(p', a+1, r)}^{p'} W(p', a + 1, r') dG(p_0) + f^W W(p', a + 1, r) \int_0^{q(p', a+1, r)} dG(p_0) \right\} G(dp'|p) \right] \text{ for } a \leq T \quad (1.6)$$

where posterior p' given prior p is sampled from the distribution $G(p'|p)$. Following the consumption/production phase, the worker and firm observe the random output of their match and update their belief p to p' . With an exogenous probability δ the match is destroyed. With probability $(1 - \rho)$ the worker directly separates into unemployment and with the complementary probability ρ she contacts another employer; thus, she has the opportunity to find a new job without an intervening unemployment spell. In a surviving match, the worker decides whether to quit or continue the match with her updated prior p' . In the search phase the worker receives

an outside offer with rate f^W and decides whether to switch to this new job or stay with her current employer. If outside offer p_0 is higher than her updated belief p' then she switches to the new match with this prior p_0 . In this case, the poacher and the worker bargain the wage according to equation 1.2 and the worker continues with a new piece-rate. If p_0 is lower than p' , then the worker stays with the incumbent firm. However if the offer provides a high enough prior, that is if $p_0 > q(p', a + 1, r)$, then the incumbent firm and worker re-bargain the wage according to equation 1.3. Otherwise the match continues with the same piece-rate wage r .

Firm's Value Functions The value of a filled job to a firm with prior p , worker age a and piece-rate r is defined by the following Bellman equation

$$\begin{aligned}
J(p, a, r) = & (1 - r)\mathbb{E}[\mu|p] + \beta(1 - \delta) \left[\int_0^1 \max \left\{ 0, \right. \right. \\
& (1 - f^W)J(p', a + 1, r) \\
& + f^W \int_{q(p', a+1, r)}^{p'} J(p', a + 1, r') dG(p_0) \\
& \left. \left. + f^W J(p', a + 1, r) \int_0^{q(p', a+1, r)} dG(p_0) \right\} G(dp' | p) \right] \text{ for } a \leq T.
\end{aligned} \tag{1.7}$$

A firm pays a share r of the expected output to the worker and retains the remaining $(1 - r)$. If there is an exogenous separation, i.e. quit into unemployment or reallocation, the value of firm becomes zero. Otherwise the match continues with an updated prior. If the outside offer provides a sufficiently high belief about match quality, the worker and firm can re-bargain the wage according to equation 1.3 and continue the match with an updated rate r' . If not, the worker simply discards the offer and they keep the same piece-rate r .

The model features free entry, therefore the value of posting a vacancy is driven to zero in equilibrium. Hence, I omit the Bellman equation that characterizes the value of a vacancy and instead directly present the free entry condition below.

Surplus It is convenient to work with the match surplus directly rather than individual value functions. Using the definition of surplus in equation 1.1, worker and firm value functions in equations 1.5, 1.6 and 1.7, and bargaining rules in equations

1.2 and 1.3, one can express the surplus as

$$\begin{aligned}
S(p, a) = & (p\mu_H + (1 - p)\mu_L) - b & (1.8) \\
& - \beta f^U \phi \left[\int_0^1 \max\{0, S(p_0, a + 1)\} dG(p_0) \right] \\
& + \beta \left[\delta \rho \phi \int_0^1 \max\{0, S(p_0, a + 1)\} dG(p_0) \right. \\
& + (1 - \delta) \int_0^1 \max\{0, S(p', a + 1)\} \\
& \left. + f^W \phi \int_{p'}^1 (S(p_0, a + 1) - S(p', a + 1)) dG(p_0) \right] G(dp' | p) \text{ for } a \leq T.
\end{aligned}$$

From equation 1.8, one can readily observe that surplus has no term containing the piece-rate r which justifies the notation used in presenting the bargaining protocol in section 1.3.²⁶ This also offers the advantage of not having to determine the level of wages to solve the model. Since the level of wages are only a determinant of how surplus is split between the firm and worker within a match, it does not play a role in worker flows.

Free Entry Firms post vacancies until the value of a vacancy is driven down to zero, i.e. market tightness satisfies θ

$$\kappa = \beta q(\theta) \mathbb{E}[J(p, s, a, r)].$$

The expectation in the free entry condition is taken with respect to the stationary distribution of workers over state variables. Let u_a denote the mass of unemployed workers with age a . Similarly let $e_{p,a}$ denote the mass of workers employed with prior p and age a . Since the mass of workers is normalized to unity for each age group, the following identity holds

$$1 = \left(\int e_{pa} dp + u_a \right) \text{ for } a \leq T.$$

I present the flow equations that characterize u_a and e_{pa} in Appendix A.2. Defining aggregate unemployment rate as

$$u \equiv \frac{1}{T} \sum_a u_a \quad (1.9)$$

²⁶ See Appendix A.2 for the derivation.

and using the bargaining rule in equation 1.2, the free entry condition can be explicitly written as

$$\begin{aligned}
\kappa = & \frac{\beta q(\theta)(1-\phi)}{(u + ((1-\delta)\lambda + \delta\rho)(1-u))T} \left(\underbrace{\sum_a u_a \int_0^1 \max\{0, S(p_0, a)\} dG(p_0)}_{\text{meeting with unemployed workers}} \right. & (1.10) \\
& + \underbrace{(1-\delta)\lambda \sum_a \int_{\tilde{p}} e_{\tilde{p}a} \left[\int_{\tilde{p}}^1 (S(p_0, a) - S(\tilde{p}, a)) dG(p_0) \right] d\tilde{p}}_{\text{meeting with employed workers}} \\
& \left. + \underbrace{\delta\rho \sum_a \int_{\tilde{p}} e_{\tilde{p}a} \left[\int_0^1 \max\{0, S(p_0, a)\} dG(p_0) \right] d\tilde{p}}_{\text{meeting with reallocating workers}} \right)
\end{aligned}$$

where the first term in parenthesis captures workers that the firm contacts from unemployment. The second term captures workers who are making an employer-to-employer transition and the last term captures workers that have been subject to the reallocation shock.

Learning

In this section I characterize the posterior distributions $G(p_0)$ and $G(p'|p)$ used in the firm and worker value functions. I adapt the learning structure in Gorry 2016, which modifies the filtering problem in Moscarini 2005 to discrete time. In this framework, agents observe consecutive output realizations from their match and infer the type of their match quality using Bayes' rule. Similarly, when a worker contacts a firm for a potential job, they have access to n output "observations" to form their initial prior and decide whether to consummate the meeting and form a match. I will capture an increase in access to information by an increase in the parameter n .

Updating Beliefs

A firm and worker in an active match do not observe the underlying match productivity μ , but observe a match output that is normally distributed around the average output of the match. The random output has standard deviation σ_Y ; thus, the realized output has distribution

$$y|\mu \sim N(\mu, \sigma_Y).$$

Agents who enter a period with prior p and observe output y , update their beliefs according to Bayes' rule, that is,

$$p' = \frac{p \exp[-\frac{1}{2}(y - \mu_H)^2/\sigma_Y^2]}{p \exp[-\frac{1}{2}(y - \mu_H)^2/\sigma_Y^2] + (1 - p) \exp[-\frac{1}{2}(y - \mu_L)^2/\sigma_Y^2]}. \quad (1.11)$$

When agents are facing a potential match, unlike in active matches, they form their beliefs about the quality of the match by observing n consecutive output signals before making a decision. This implies a similar prior formation rule for the agents. More concretely, by repeatedly substituting one period's posterior as the next period's prior, one can obtain the n -period-ahead posterior. Since agents are rational and the unconditional probability of having a high productivity type is p_H , all agents have this probability as their starting prior. Thus, the prior formed after having received n signals about a potential match is given by²⁷

$$p_0 = \frac{p_H \exp[-\frac{1}{2}(\bar{y}_n - \mu_H)^2/(\sigma_Y^2/n)]}{p_H \exp[-\frac{1}{2}(\bar{y}_n - \mu_H)^2/(\sigma_Y^2/n)] + (1 - p_H) \exp[-\frac{1}{2}(\bar{y}_n - \mu_L)^2/(\sigma_Y^2/n)]} \quad (1.12)$$

where $\bar{y}_n \equiv \sum_{t=1}^n y_t/n$.²⁸

Figure 1.9 presents an intuitive summary of this learning structure. Panel (a) plots the density of observed output y for high and low productivity matches. Depending on the match quality, each period the worker and firm sample their random output from one of these distributions. Panel (b) plots how their expected output evolves over the course of the match, and how it converges to the true productivity. p_0 is the match's initial prior and corresponds to the intercept of the dashed green line.

Posterior Distributions

Equations 1.11 and 1.12 laid out in section 1.3 induce distributions for the initial prior p_0 and posterior p' conditional on prior p .

Deriving $G(p'|p)$ To derive the posterior distribution, first observe that in active matches output is a mixture of two normal random variables where the mixing parameter is the prior. Let $\phi(\cdot; \mu_i, \sigma_Y)$ denote the normal probability density function

²⁷ I provide formal derivations of equations 1.11 and 1.12 in Appendix A.2.

²⁸ Note that due to the assumption of normality of output y , n does not have to be an integer. One can think of n as parametrizing the precision of the signal observed for potential matches where a higher n implies a more precise signal for the match quality.

with mean μ_i and standard deviation σ_Y . The density of random output y is then given by

$$\psi(y|p) \equiv p\phi(y; \mu_H, \sigma_Y) + (1-p)\phi(y; \mu_L, \sigma_Y)$$

and let the corresponding cumulative density function be denoted by $\Psi(y|p; s)$.

By inverting the updating rule for active matches in equation 1.11, one can derive output y necessary to yield posterior p' given prior p . This inverse function is defined as

$$f(p'|p) \equiv \frac{\sigma_Y^2}{(\mu_H - \mu_L)} \log \left(\frac{p'(1-p)}{(1-p')p} \right) + \left(\frac{\mu_L + \mu_H}{2} \right).$$

Using the definitions for $\psi(y|p)$ and $f(p'|p)$, one can derive the cumulative density function of the posterior as follows

$$\begin{aligned} G(p'|p) &\equiv Pr[\tilde{p} < p'|p] \\ &= Pr[f(\tilde{p}|p) < f(p'|p)|p] \\ &= \Psi(f(p'|p)|p). \end{aligned}$$

Therefore, the density of the posterior conditional in prior is

$$g(p'|p) \equiv \psi(f(p'|p)|p) \frac{\partial f(p'|p)}{\partial p'}.$$

Deriving $G(p_0)$ One can derive the distribution of n -step-ahead prior p_0 analogously. First noting that n parameterizes the precision of observed potential output realizations, and one only needs to know the average y observed over the n signal realizations, the density of \bar{y}_n can be expressed as

$$\hat{\psi}(\bar{y}_n; p, n) \equiv p\phi(\bar{y}_n; \mu_H, \sigma_Y/\sqrt{n}) + (1-p)\phi(\bar{y}_n; \mu_L, \sigma_Y/\sqrt{n})$$

and similarly by inverting the updating function given in equation 1.12, average output needed to yield posterior p_0 with starting prior p_H and access to n observations is given by

$$\hat{f}(p_0; p_H, n) \equiv \frac{\sigma_Y^2/n}{(\mu_H - \mu_L)} \log \left(\frac{p_0(1-p_H)}{(1-p_0)p_H} \right) + \left(\frac{\mu_L + \mu_H}{2} \right).$$

Therefore, the density of n -step ahead posterior is

$$\hat{g}(p_0; p_H, n) \equiv \hat{\psi}(\hat{f}(p_0; p_H, n); p_H, n) \frac{\partial \hat{f}(p_0; p_H, n)}{\partial p_0}.$$

The probability density function for the initial prior that I use to take expectations in the Bellman equations is defined as $g(p_0) \equiv \hat{g}(p_0; p_H, n)$ with the corresponding cumulative density denoted by $G(p_0)$, where I suppress the dependence of g on p_H and n for notational simplicity.

The Information Channel and the Role of n

The model counterpart of “better information” is captured by a higher n , where n measures the precision of the initial signal that firms and workers receive about a prospective match. To see this intuitively, note that the density of the initial signal, $\hat{\psi}(\bar{y}_n; p_H, n)$, is a mixture of two normal distributions; therefore, the variance of this signal is given by

$$\sigma_{\hat{\psi}}^2 = p_H(1 - p_H)(\mu_H - \mu_L)^2 + \frac{\sigma_Y^2}{n}.$$

A higher n implies a lower variance, and thus a signal more concentrated around the underlying match quality. This means the worker and firm start with an initial belief that is closer to the true productivity.

An alternative is to interpret n literally, as the number of output realizations that the worker and firm observe before making a decision. This would imply that, when new jobs are formed, it is as if they have already had an employment relationship for n periods. In other words, newly formed jobs start with an n -period tenure. Given that learning models generate a downward sloping E-E tenure profile, this implies that in a high- n regime, new matches have lower labor turnover compared to a low n -regime.

There is an additional effect of higher n on the variance of the posterior distribution, $G(p'|p)$. In contrast to Jovanovic 1979, which has normally distributed match qualities and signals, the standard deviation of $G(p'|p)$ is *not monotonically* decreasing in p ; however, it decreases on *average* as beliefs get closer to 0 or 1.²⁹ A high n , by bringing beliefs closer to the truth, reduces uncertainty, and leads to fewer ex-post negative surprises.³⁰

Equilibrium

The stationary equilibrium of the model is a set of value functions $W(p, a, r)$, $U(a)$, $J(p, a, r)$, re-bargaining cutoff $q(p, a, r)$, and market tightness θ such that:

²⁹ For a discussion of this result see Moscarini 2005 and Gorry 2016.

³⁰ In appendix A.3, I present suggestive evidence for the negative correlation between ex-post negative surprises and separations.

- Value functions solve the worker and firm problems given in equations 1.5, 1.6 and 1.7.
- The value of a vacant firm is zero due to free entry and market tightness satisfies equation 1.10.
- Piece-rate r is determined according to the bargaining protocol given by equations 1.2 and 1.3, and $q(p, a, r)$ solves the indifference condition in equation 1.4.
- The state (p, a, r) evolves according to the laws of motion induced by the worker and firm problems. The worker distribution over (p, a) satisfies flow equations A.2.2 and A.2.3 presented in appendix A.2.

1.4 Quantitative Analysis

In this section I discuss the choice of parameters and the calibration strategy. Then, I use the calibrated model to evaluate the role of information about potential jobs in explaining the secular decline in employer-to-employer transitions.

Calibration

Functional Forms To solve the model I need to choose a functional form for $M(S, V)$. I assume a constant elasticity of substitution matching function as proposed by Haan, Ramey, and Watson 2000:

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

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

$$f^U(\theta) = \frac{\theta}{(1 + \theta^l)^{1/l}}, \quad q(\theta) = \frac{1}{(1 + \theta^l)^{1/l}}$$

where l is the elasticity parameter.³¹

³¹ An advantage of this functional form is that, contact rates f^U and q always lie between zero and one. The standard Cobb-Douglas form requires ensuring contact probabilities do not exceed one.

Calibration Strategy There are 13 parameters in the model. I choose eight parameters without solving the model and jointly estimate the remaining five to be consistent with a number of average labor market outcomes during the *early* period between 1996 and 2000. I set a model period to one month, consistent with the frequency of observations from the CPS and SIPP.

Parameters Set Outside the Model I set the monthly discount factor to $\beta = 0.9967$ to yield an annual interest rate of 4 percent. I fix the life of workers to $T = 540$ which is equivalent to a 45 year work-life. In the baseline calibration, I normalize the number of signals received by the firms and workers about potential jobs to $n = 1$.

All match qualities are discovered when tenure is sufficiently high. In my simulations, I find that a tenure of $\tau = 60$ months to be sufficient for most of uncertainty to be resolved, as average prior becomes very close to one. This means, all workers that make an E-E or E-U transition at this tenure do so due to the exogenous separation shock. The baseline parameterization for n also ensures that all offers provide a high enough prior for workers to accept the job upon a reallocation shock. Therefore the employer-to-employer and employment-to-unemployment flow rates at this tenure level identify the exogenous separation and reallocation rates. The E-E rate after all uncertainty resolves is the share of employed workers that are subject to the reallocation shock, $\delta\rho$, and the E-U rate is the share of workers that flow directly into unemployment, $\delta(1 - \rho)$. The empirical counterparts of these rates are one percent and 0.5 percent respectively in the CPS for the 1996 – 2000 period, which imply parameter values of $\delta = 0.015$ and $\rho = 2/3$.

I normalize the low and high quality match productivities, μ_L and μ_H , to zero and one respectively. I take the value of ϕ from Bagger et al. 2014 which estimates a worker bargaining share around 0.3. I set the elasticity parameter of the matching function to 0.4, as estimated in Hagedorn and Manovskii 2008 for the U.S. Table 1.2 summarizes the choice of parameters set without solving the model.

Parameters Set via the Simulated Method of Moments I calibrate the remaining five parameters to minimize the distance between model moments and their empirical counterparts. To compute model moments, I simulate 100,000 individuals for 540 months (45 work-years). Below I discuss estimated parameters together with the target moments that they are most closely related to, although they are estimated jointly via the Simulated Method of Moments.

The unconditional probability of drawing a high quality match, p_H , determines the initial composition of matches. Since workers are less likely to quit from good jobs, this parameter is closely linked to the average duration of jobs. To discipline

p_H , I follow the calibration strategy in Gorry 2016 and target the average duration of a job, as measured by Farber 1994, of 13.7 months for workers with a maximum potential experience of 10 years. Therefore, when calculating the average job duration I drop workers whose tenures exceed 10 years.

The standard deviation of stochastic output, σ_Y , is closely linked to job mobility. The signal to noise ratio, $\frac{\mu_H - \mu_L}{\sigma_Y}$, determines the speed of learning and thus, the shape of the E-E tenure profile. When the difference between high and low match productivities is small or the standard deviation is high, it becomes harder to distinguish between match types. In the limiting case, when there is no information contained in the signals, the E-E tenure profile is flat at a rate dictated by the exogenous separation and reallocation shocks, given by $\delta\rho$. Given the choice of μ_H and μ_L , I target the smoothed E-E tenure profile up to 60 months of tenure to discipline σ_Y .³²

The exogenous reallocation rate determines the lower bound on job mobility, whereas the standard deviation of match output determines the shape of the E-E tenure profile. The on-the-job search intensity is another factor that affects job mobility. To discipline λ , I target the average E-E rate between 1996 and 2000, which is 2.7 percent.

The model features free entry and the cost of posting a vacancy κ determines market tightness θ given the match values 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. Therefore, I calibrate κ to match an average monthly unemployment rate of 4.46 percent.

The estimation minimizes the equally weighted sum of squared percent deviations of simulated moments from their empirical counterparts. I elaborate on computational details regarding the solution and calibration of the model in Appendix A.2. Table 1.3 reports the parameters estimated via the Simulated Method of Moments. Table 1.4 presents the empirical moments used in the estimation together with the fit of the model. The model does a fairly good job at matching the calibration targets. The dashed red line with diamonds in panel (a) of figure 1.10 plots the empirical E-E profile, whereas the solid blue line with circles plots its simulated counterpart for the baseline calibration. Thus, the model replicates a critical feature of the worker behavior observed in the data. The baseline calibration implies a 2.1 percent equilibrium E-E rate, compared to 2.7 percent in the data. This discrepancy is due to the fact that I target the smoothed E-E tenure profile in my baseline calibration. The raw data exhibits a much steeper decline than the fitted tenure profile in the CPS. Considering the large mass of employment with short tenures, this results in

³²Smoothing is done using a locally weighted regression with bin width 0.8.

an underestimate of the aggregate E-E rate calculated based on raw data.³³

Quantitative Exercises

The goal of the model is to quantify the role of information about potential jobs in declining E-E transitions. There are two forces that can generate this decline in my model. First, an increase in information can lower mobility by reducing costly worker experimentation to find good matches. I capture this in the model as an increase in the precision of the initial signal about match quality, n . Second, job mobility can decline simply due to a lower efficiency of on-the-job search. I model this as a decrease in λ . This is a reduced form way of capturing any additional friction that inhibits job mobility, such as the growing prevalence of non-competition clauses in employment contracts, increasing occupational specificity and licensing restrictions of jobs.

The fundamental challenge in this exercise is that both information and on-the-job search efficiency are unobserved. I first show that two features of the data provide enough information to distinguish the relative role of each factor: the change in the E-E tenure profile and the change in the wage growth of job switchers. I discuss this identification approach in section 1.4. In section 1.4, I discuss the measurement of wage gains conditional upon E-E transition. In section 1.4, I implement a structural estimation using this identification strategy and back out the changes in information and on-the-job search efficiency, which I then use to quantify the contribution of each channel to the decline in job mobility.

An Informal Identification Discussion

I establish identification by showing that the decline in job mobility induced by a decline in λ has a qualitatively different implication for wage growth patterns compared to the equivalent decline induced by an increase in n . More specifically, I focus on average wage gains for job switchers. I show that a decline in λ generates decreases in wage gains for job switchers, whereas a higher n results in larger wage gains conditional on E-E transitions.

Information Channel (n only) I first set all parameters of the model except for n to the baseline calibration. Then I choose n to match the E-E tenure profile in the 2010 – 2016 period. The estimation requires n to increase to 24.5. Panel (a) of figure

³³ See figure panel (a) of figure 1.3. E-E rate for jobs with a month of tenure is almost seven percent in the raw data, whereas it is 4.5 percent in the smoothed E-E tenure profile.

1.10 presents the resulting E-E tenure profile. The green line with triangles plots the simulated E-E tenure profile with $n = 24.5$ and the orange line with squares plots its smoothed empirical counterpart from the 2010 – 2016 period.

Frictions Channel (λ only) I repeat the exercise by allowing only λ to change from the baseline calibration. To match the E-E profile in the late period, the estimation requires λ to decline from 0.282 to 0.095. Panel (b) of figure 1.10 presents the resulting E-E tenure profile. The green line with triangles plots the simulated E-E profile with the new λ . As this exercise shows, both an increase in n and a decrease in λ are capable of explaining the decline in job mobility observed in the last two decades.

Wage Implications The changes induced by changes in n and λ have strikingly different implications for wage growth of job switchers. To compute this object in the model, I pool simulated data from the baseline calibration and the parameterizations corresponding to the 2010 – 2016 period. Then, I regress the change in the log wages of job switchers on a late period dummy controlling for a full set of tenure and age dummies.³⁴ The coefficient on the late period dummy captures the change in average wage gains. Column (3) of panel (a) in table 1.6 reports these regression coefficients. If the entire decline in job mobility was due to an increase in n , this would have caused a 17.6 percentage point *higher* average wage gain for job switchers in the late period. If lower mobility was entirely due to a smaller λ , then conditional wage growth would have been 5 percentage points *lower*.

The changes in parameters capturing information and on-the-job search intensity channels make conflicting predictions about the change in wage growth of job switchers. I use this key moment in the data to assess quantitatively the relative contribution of each force. To this end, I target jointly the late period E-E tenure profile as well as the observed change in conditional wage growth. In the section below, I describe the measurement of this moment.

Measuring Changes in Wage Growth of Job Switchers

I utilize two sources to measure the wage growth of job switchers. In particular, using individual level observations from the SIPP, I establish that average wage gains have become 7.5 percentage points higher in the late period compared to the early

³⁴In the model, I construct annual age dummies from monthly ones to mimic the empirical setup, which reports ages in years.

period.³⁵ Then, I use public tabulations of the LEHD to establish that conditional wage growth has increased by around four percentage points since 2001, which supports my findings from the SIPP. These two distinct sources point to qualitatively similar findings that are consistent with the implications of the information channel in the model.

SIPP To measure wage growth conditional on job mobility in the SIPP, I first residualize log of hourly wages by controlling for worker’s age, gender, marital status, disability, education level, race, number of kids and state of residence. I also include experience and its square as controls in the regression. To calculate conditional wage growth, I take the difference between log wages observed immediately after and before the reported E-E transition.

Panel (a) in figure 1.11 shows a stark increase of average wage gains. Compared to 1995, conditional wage growth is almost 15 percentage points higher.

Finally, I use individual level data to exclude any possible observable factor that might change the conditional wage growth behavior during this period. Specifically, I regress worker level conditional wage growth on a dummy for the late period sample together with the dummies in the Mincer regression I use to residualize wages. The third column in table 1.1 shows that average conditional wage growth is 7.5 percentage points higher in the 2008 Panel of the SIPP compared to that in the 1996 panel. I use this regression coefficient as an additional target in the indirect inference approach that I explain in the next section.

LEHD I undertake a similar exercise using data from the LEHD. LEHD Job-to-Job Flows by Origin and Destination files provide average monthly earnings prior to and following a job change by origin and destination state, including job changes within the state. The data are further broken down by age groups and gender. Observations are quarterly and cover the period between 2001 and 2015.³⁶

I use the information contained in these files to study if and how average wage growth of job switchers changed over time. I take the log difference between monthly earnings following and prior to a job transition and regress that quantity on a linear trend, controlling for a full set of age group (ages 19–24, 25–34, 35–44, 45–54 and 55–64) and gender dummies. Table 1.5 presents the results from this regression. The first column shows that there is a positive and statistically significant trend in wage growth. The coefficient on the trend implies that between 2001 and 2015 wage

³⁵ In the SIPP, the early period refers to the period between 1996 and 1999 (1996 Panel). The late period refers to the period between 2008 and 2013 (2008 Panel).

³⁶ Details are provided in appendix A.1.

growth has increased approximately by 4 percentage points. Furthermore, the second column shows that the trend is larger for younger workers and gets flatter as workers become older. Wage gains of job switchers in the LEHD point to a qualitatively similar trend observed in the SIPP. Panel (b) of figure 1.11 plots annual time series of conditional wage growth by age groups. The figure points to a positive trend in wage gains upon job change for each age group, which is consistent with the wage implications of “better information” in the model.

Quantifying the Role of Information in the Decline of Job Mobility

As discussed above, a decrease in on-the-job search intensity or an increase in the precision of initial signals about the quality of a potential match have observationally similar implications for job mobility. The conditional wage growth moment allows me to quantify the contributions of n and λ to the aggregate decline in E-E transitions. To this end, I re-estimate the model by setting all parameters to their baseline values except for n and λ , and target the flattening E-E profile together with the regression coefficient from column 3 of table 1.1. The model counterpart of this coefficient is computed as discussed in section 1.4.

To match these targets, the estimation requires λ to decline to 0.17 from 0.28 and n to increase from one to 6.77. Figure 1.12 plots the E-E profile corresponding to these values. The green line with triangles shows the new profile under the jointly estimated values of n and λ , which is close to its empirical counterpart. Panel (b) of table 1.6 reports the fit on the regression coefficient. The coefficient estimated from simulated data is 0.0747 and is remarkably close to its empirical counterpart of 0.0749. The average E-E rate in the model is 1.3 percent, slightly lower than the observed job mobility rate of 1.7 in the 2010 – 2016 period. This marks a sizable decline from the baseline E-E rate of 2.1 percent. In other words the two factors combined explain 0.8 percentage points of the one percent point decline in the data.

To quantify the contribution of the information channel, I start from the baseline calibration and then feed the estimated values of n and λ corresponding to the 2010 – 2016 period one at a time. Table 1.7 summarizes the resulting average E-E rate from this exercise. Change in n alone generates an E-E rate of 1.6 percent, explaining 62 percent of the total decline. Conversely, the change in λ reduces mobility rate to 1.7 percent, explaining 50 percent of the total decline, which means the remaining 50 percent is due to the change in n . I conclude that the increase in information about potential matches accounts for 50 to 60 percent of the decline in the employer-to-employer transition rate.³⁷

³⁷ Because this is a non-linear model there are interactions between the two forces; therefore, the order of decomposition affects the share of the decline attributed to information.

Finally, I turn to aggregate implications of the decline in job mobility. E-E transitions improve the the average productivity in the labor market by allocating workers to more productive matches. Therefore, one might think that lower mobility might be associated with lower labor productivity. Column (3) of table 1.7 shows that in contrast to this conventional wisdom, average labor productivity is higher when mobility is lower. In fact the model generates a rise in labor productivity of about 10 percent, from 0.745 to 0.824. This happens in the model, precisely because more information about potential matches facilitates a better initial allocation of workers across jobs, and thus also throughout their life cycle. This result is similar to that of Ates and Saffie 2016, which finds that the quality of entrants rises through selection in episodes of declining firm entry.

1.5 Conclusion

In this paper, I investigated the decline in job mobility observed in the United States during the last two decades. This decline has raised concerns in the academic literature as well as among policy makers that the U.S. labor market has become less flexible. I showed that the decline in employer-to-employer transitions is common across many subsets of the worker population and more pronounced among jobs that have been recently formed. In particular, I established that the decline in E-E transitions from jobs less than a year of tenure can explain about 40 percent of the aggregate decline between 1996 and 2016. To interpret these facts, I built a model of on-the-job search that allows for learning about match quality. I estimated this model to quantify the relative roles of improvements in information about potential matches and changes in frictions that hinder job mobility. I established identification of these two forces by studying their predictions for wage growth of job switchers. In particular, increases in information push up wage gains of job switchers, whereas increases in frictions have the opposite implication. Turning to the data, I documented a novel fact: Wage growth conditional on E-E transitions has increased over the period of my study, lending support to the information hypothesis. My estimation attributed 50 to 60 percent of the aggregate decline in job mobility to better information about potential matches. In other words, matches in the labor market in the past used to be “experience goods,” meaning that workers had to experiment to find out the right jobs for them. Changes in information reduced the need for experimentation and turned matches into “inspection goods.”

My results have shown that it is crucial to ascertain the factors behind falling job mobility before concluding that the decline is inherently undesired. In particular, in my model at least 50 percent of this decline is benign, as it implies better initial

matches resulting in higher labor productivity. Therefore, it is not clear that declining labor mobility is a sign of a less flexible labor market and it is less clear what the role for policy would be, if any. This conclusion might extend to other parts of the economy, as job mobility is not the sole indicator that is exhibiting a downward trend. While these declines may suggest a less flexible labor market, careful analysis is needed to understand their welfare consequences.

An important avenue for future research is to document if and how job mobility rates have changed across the world. In particular, my proposed explanation would imply a job mobility decline common to many countries as the increased use of information technologies in job search and recruitment activities is a world-wide phenomenon. In particular, with the increasing availability of matched employer-employee datasets in Europe and South America, it will be fruitful to study E-E rates, which would provide even greater measurement accuracy than is possible in the U.S. I plan to undertake this analysis in future work.

1.6 Tables

Table 1.1: Significance Test for the Flattening of the E-E Profile

	2008-2013		2011-2013			
	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{I}(E-E)$	$\mathbb{I}(E-E)$	$\Delta \log(w)$	$\mathbb{I}(E-E)$	$\mathbb{I}(E-E)$	$\Delta \log(w)$
$\mathbb{I}(2008 \text{ Panel})$	-0.00372*** (0.000203)	-0.00278*** (0.000179)	0.0749*** (0.0157)	-0.00378*** (0.000234)	-0.00254*** (0.000209)	0.0830*** (0.0212)
$\mathbb{I}(\tau \leq 12)$		0.0492*** (0.00203)			0.0501*** (0.00251)	
$\mathbb{I}(2008 \text{ Panel}) \times \mathbb{I}(\tau \leq 12)$		-0.00745*** (0.000669)			-0.00815*** (0.000811)	
Dummies						
Tenure	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes
Sex	Yes	Yes	Yes	Yes	Yes	Yes
Marital Status	Yes	Yes	Yes	Yes	Yes	Yes
Disability	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes
Race	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
Number of Kids	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1612644	1612644	4200	1042086	1042086	3153

Notes: This table reports individual level regression results from the SIPP. The dependent variable in columns (1) and (2) is an indicator for E-E transition. The dependent variable in column (3) is the change in residual log wage upon an E-E transition. The last three columns run identical specifications, but excluding the observations between 2008 and 2010 from the 2008 SIPP panel. Standard errors are reported in parenthesis and clustered at the individual level. *** p<0.01, ** p<0.05, * p<0.1.

Table 1.2: Externally Set Parameters

Parameter	Description	Value	Source
β	Discount factor	0.9967	4% annual interest rate
T	Working life	540	45 year work-life
l	Matching function parameter	0.4	Hagedorn and Manovskii 2008
ϕ	Worker bargaining parameter	0.3	Bagger et al. 2014
μ_L	Low match quality	0	Normalization
μ_H	High match quality	1	Normalization
δ	Exogenous separation rate	0.015	E-E and E-U rate
ρ	Reallocation rate	2/3	at $\tau = 60$
n	Number of signals	1	Normalization

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

Table 1.3: Internally Set Parameters

Parameter	Description	Value
p_H	Unconditional probability of high type	0.45
σ_Y	Standard deviation of signals	3.11
λ	On-the-job search intensity	0.28
b	Unemployment benefit	0.37
κ	Vacancy posting cost	0.067

Notes: This table reports parameters chosen via the Simulated Method of Moments in the baseline calibration.

Table 1.4: Targets and Model Fit

Moment	Target Moment	Simulated Moment
Average unemployment rate	0.046	0.045
Average E-E rate	0.027	0.021
E-E rate at tenure = 60	0.01	0.01
E-U rate at tenure = 60	0.005	0.005
Average job duration	13.7	16.7

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

Table 1.5: Trend in Wage Growth in the LEHD

	(1)	(2)
	$100 \times \Delta \log(w)$	$100 \times \Delta \log(w)$
Trend	0.0647*** (0.00542)	
Trend \times $\mathbb{I}(19 - 24)$		0.0941*** (0.00939)
Trend \times $\mathbb{I}(25 - 34)$		0.0730*** (0.00617)
Trend \times $\mathbb{I}(35 - 44)$		0.0512*** (0.00643)
Trend \times $\mathbb{I}(45 - 54)$		0.0244*** (0.00712)
Trend \times $\mathbb{I}(55 - 64)$		0.0611*** (0.00885)
Age Group Dummy	Yes	Yes
Sex Dummy	Yes	Yes
Constant	Yes	Yes
Observations	1182510	1182510

Notes: This table reports regression results from the LEHD. The dependent variable is the log difference between annual earnings prior to and following an E-E transition by origin-destination state, worker gender and age groups multiplied by a hundred. Data are quarterly and covers between 2001 and 2015. Column (1) shows a positive trend in conditional wage growth. Column (2) shows that the trend is steeper for younger workers. Standard errors are reported in parenthesis and clustered around the origin-destination state pairs. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.6: Calibration to the 2010 – 2016 Period

(a) Independent Calibrations

Parameter	Value	E-E Rate		$\Delta\log(\text{wage})$	
		(1) Model	(2) Data	(3) Model	(4) Data
n	24.52	0.013	0.017	0.176	0.0749
λ	0.095	0.014	0.017	-0.051	0.0749

(b) Joint Calibration

Parameter	Value	E-E Rate		$\Delta\log(\text{wage})$	
		(1) Model	(2) Data	(3) Model	(4) Data
n	6.77	0.013	0.017	0.0747	0.0749
λ	0.17				

Notes: This table reports the re-calibrated values of n and λ , setting other parameters to their baseline values. Panel (a) reports values from calibrating n and λ separately to match the E-E tenure profile in the late period. Panel (b) reports values from the joint estimation of the parameters targeting the E-E tenure profile and the regression coefficient on the late period dummy from column (3) of table 1.1. The last two columns report the simulated E-E rates and the coefficients on the late period dummy from a pooled regression of conditional wage growths on a later period dummy, controlling for a full set of tenure and annual age dummies.

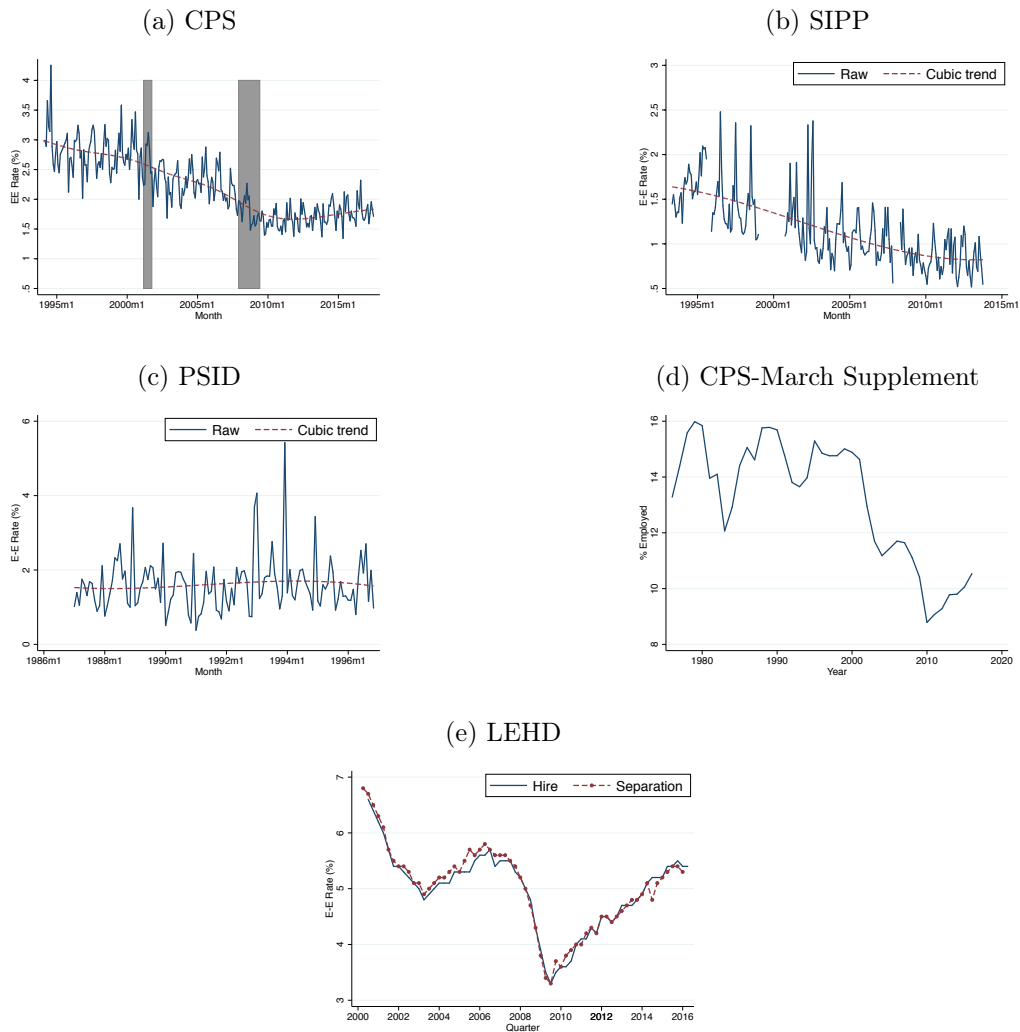
Table 1.7: Decomposition

		E-E Rate		ALP
		(1) Model	(2) Data	(3) Model
Baseline	$(n = 1, \lambda = 0.28)$	0.021	0.027	0.745
Joint	$(n = 6.77, \lambda = 0.17)$	0.013	0.017	0.824
n only	$(n = 6.77, \lambda = 0.28)$	0.016	–	0.823
λ only	$(n = 1, \lambda = 0.17)$	0.017	–	0.747

Notes: This table reports average job mobility rates from various parameterizations of the model. The first row is the outcome from the baseline calibration, whereas the second row reports outcomes from the joint estimation of n and λ , targeting the late period E-E tenure profile and change in wage growth of job switchers. The last two rows summarize the exercises when only one of the parameters is changed to its re-estimated value. First column reports average E-E rates. The second column reports resulting average labor productivities.

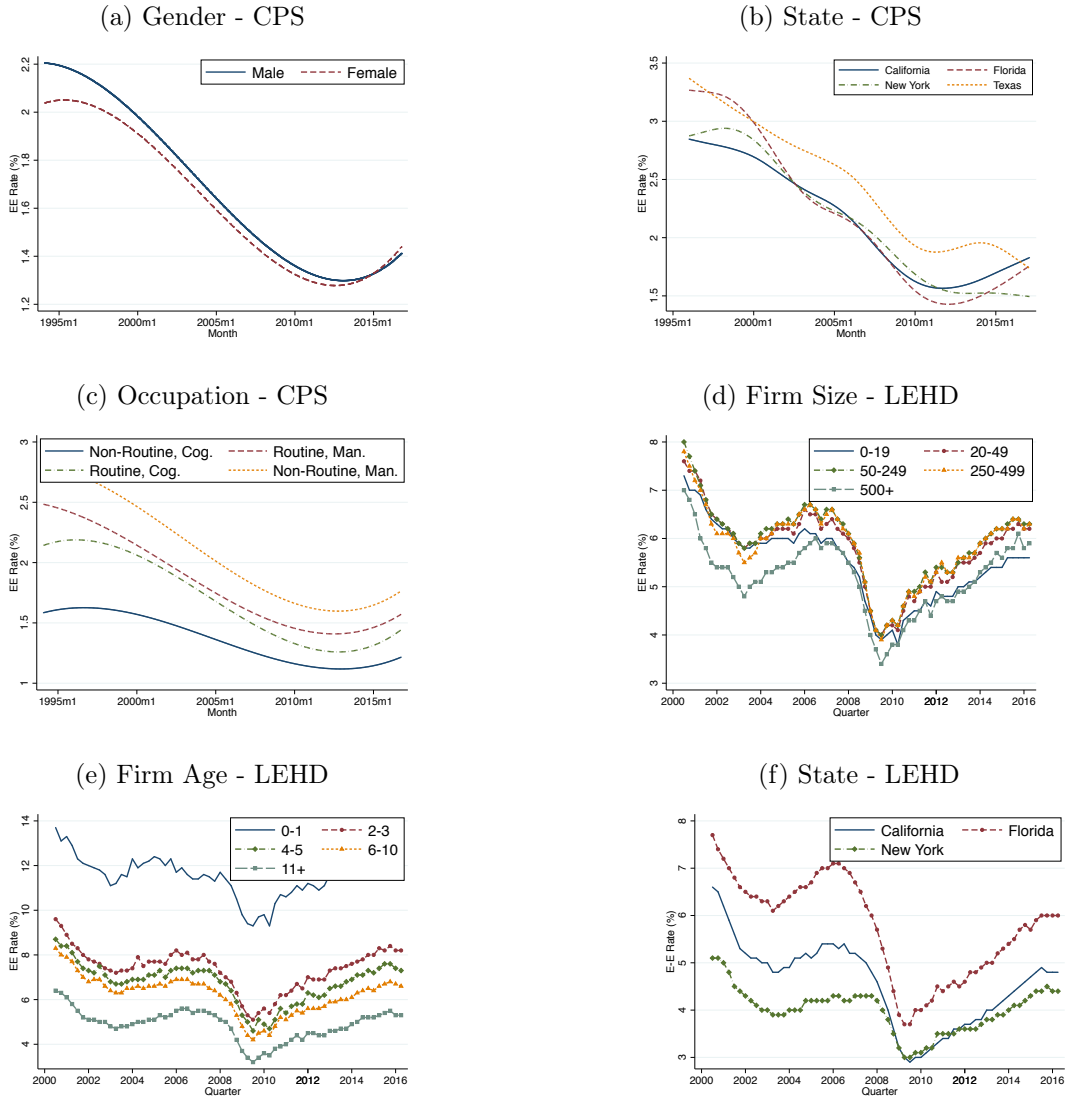
1.7 Figures

Figure 1.1: Aggregate Decline in E-E Transitions



Notes: This figure plots various measures of job mobility. Panel (a) shows the decline in E-E transitions using matched monthly CPS files over the last 2 decades. Panel (b) shows the decline in E-E rate using SIPP. Since the end of a particular SIPP panel does not necessarily coincide with the beginning of the following panel, there are missing months. Panel (c) plots the E-E rate for the pre-2000 period using the PSID. The first three panels show raw data as well as fitted cubic trends. Panel (d) plots the share of employed workers who held more than one job in a year using the CPS March Supplement. Panel (e) plots the quarterly seasonally adjusted E-E hiring and separation rates using the LEHD.

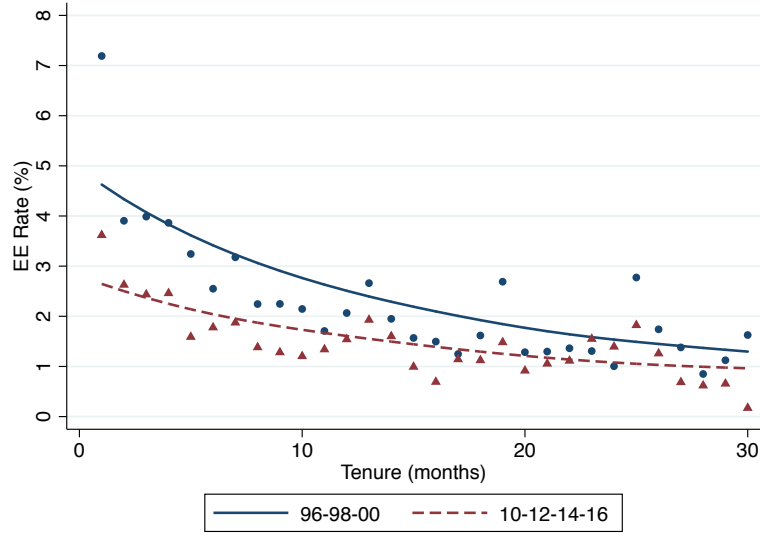
Figure 1.2: Decline in E-E Transitions Across Worker Groups



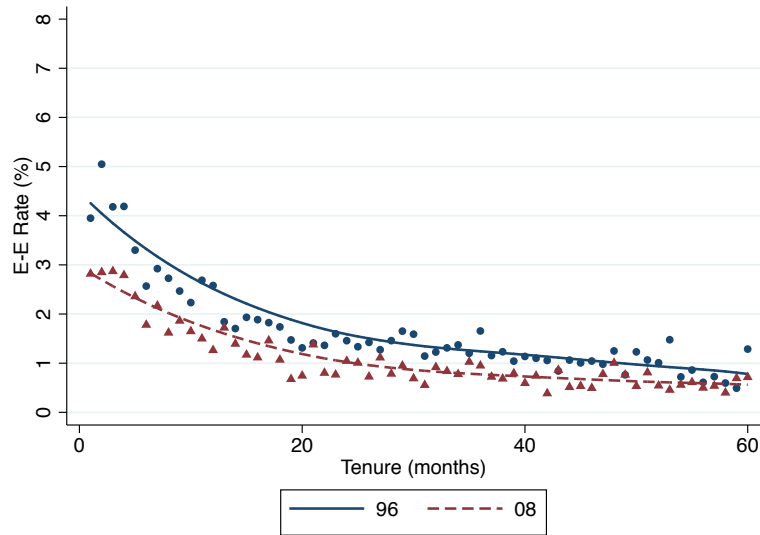
Notes: This figure plots measures of job mobility by various subsets of the data. Panel (a) shows the E-E rate for men and women. Panel (b) shows the E-E rate in three major states, California, Florida and New York. Panel (c) shows employer transitions by occupation. The first three series are computed from monthly CPS files, and each panel plots H-P trends of the raw data. Panels (d) and (e) plot E-E hiring rates by firm size and age. Panel (f) plots E-E hiring rates for three large states California, Florida and New York using the LEHD. Series in the last three panels are seasonally adjusted.

Figure 1.3: Tenure Profile

(a) CPS



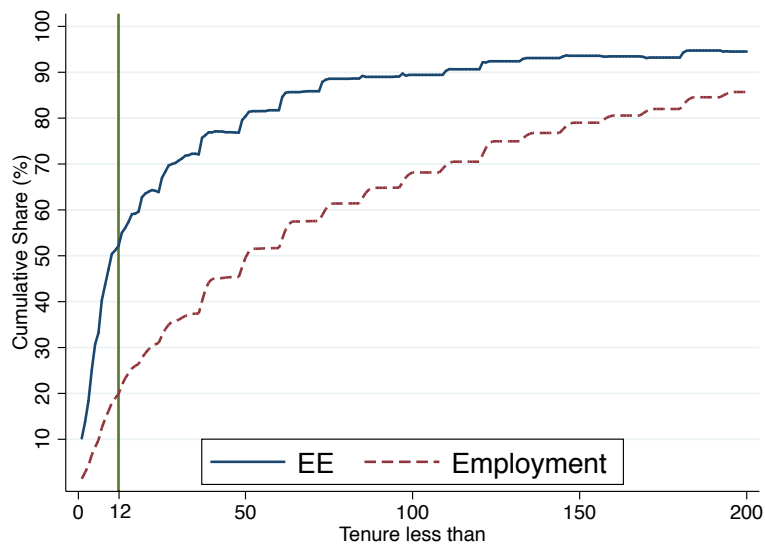
(b) SIPP



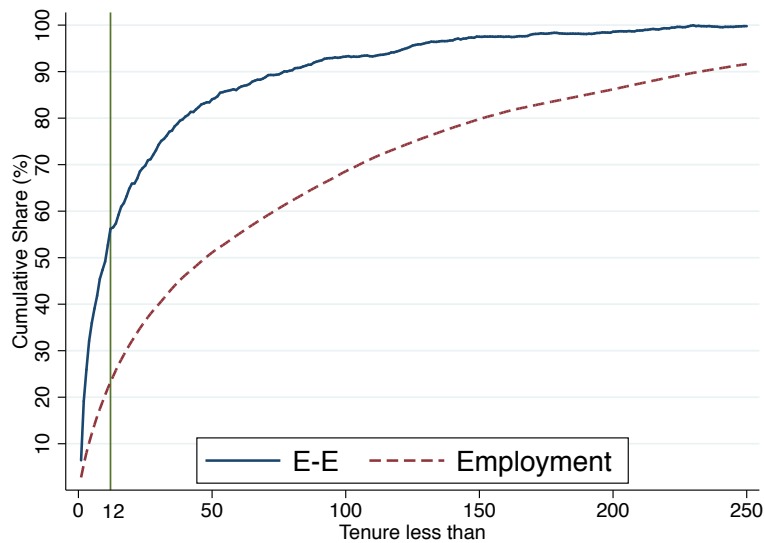
Notes: This figures plots the E-E tenure profiles in the early and late periods. Panel (a) shows E-E rate by tenure using data from the CPS. The early period sample pools CPS Tenure Supplements for years 1996,1998 and 2000. The late period pools years 2010, 2012, 2014 and 2016. Panel (b) shows E-E rate by tenure using 1996 and 2008 SIPP panels. Both plots include LOWESS lines fitted to the raw data.

Figure 1.4: Share of Tenure Cells in Within Component

(a) CPS



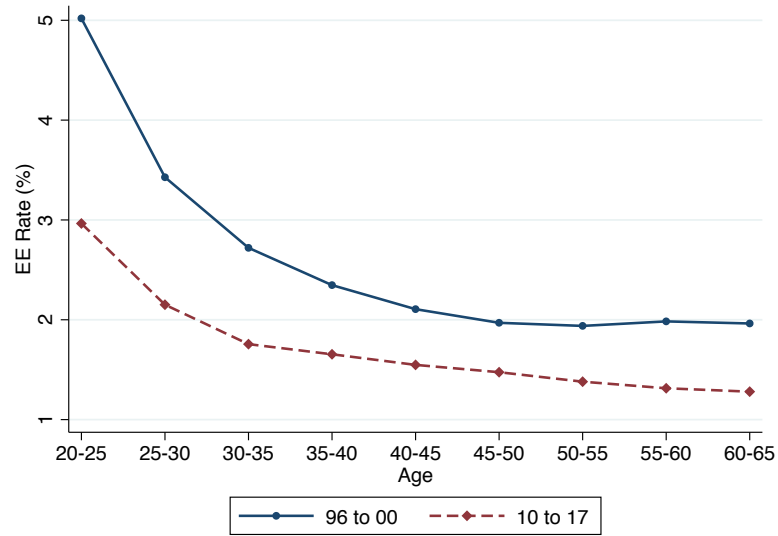
(b) SIPP



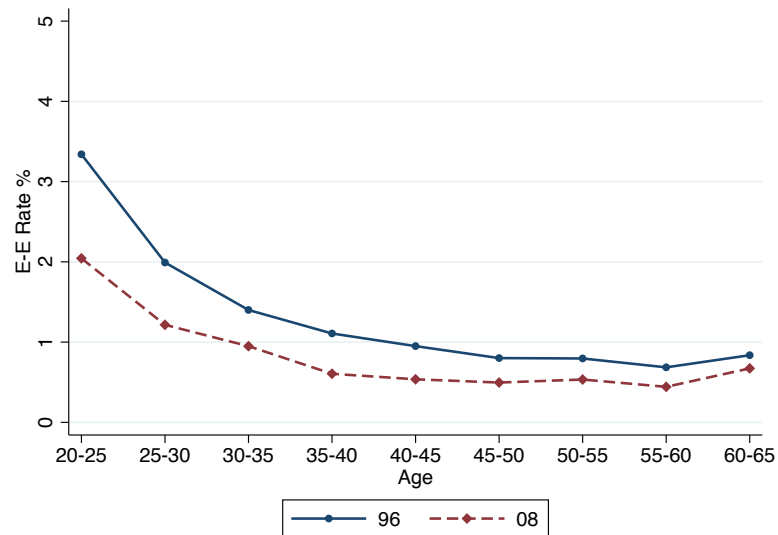
Notes: This figure plots the share of the within-cell component that tenure cells less than a given duration (x-axis) can explain together with the cumulative employment share of these tenure cells. Panel (a) uses CPS tenure supplements between 1996 – 2000 and 2010 – 2016. Panel (b) uses 1996 and 2008 SIPP panels.

Figure 1.5: Age Profile

(a) CPS



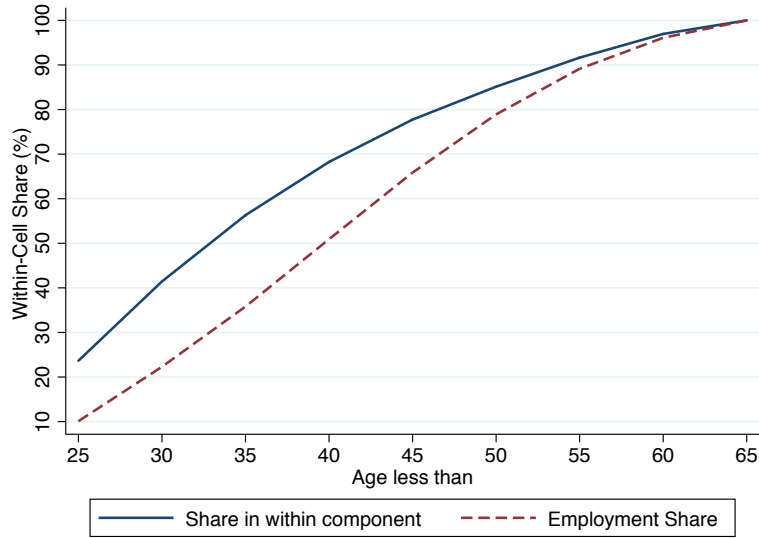
(b) SIPP



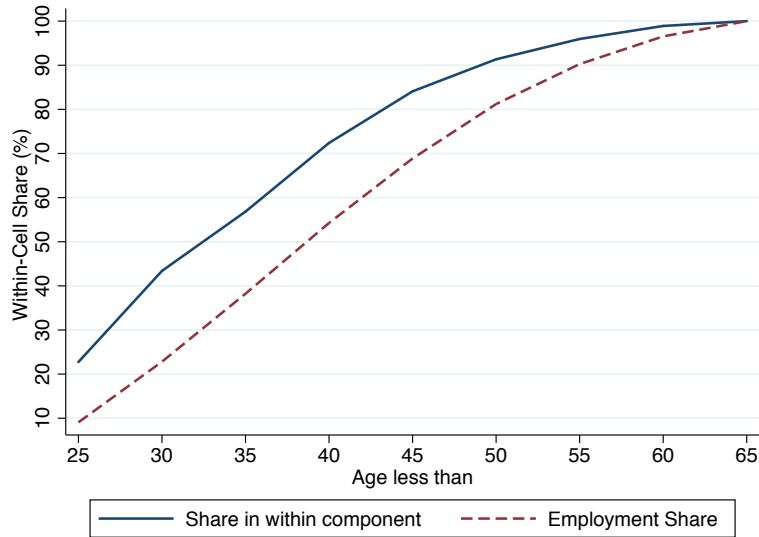
Notes: This figure plots E-E rates by age groups. Panel (a) shows E-E rate by 5 year age bins using data from the CPS for the periods 1996 – 2000 and 2010 – 2017. Panel (b) shows the age profile using the 1996 and 2008 SIPP panels.

Figure 1.6: Share of Age Cells in Within Component

(a) CPS

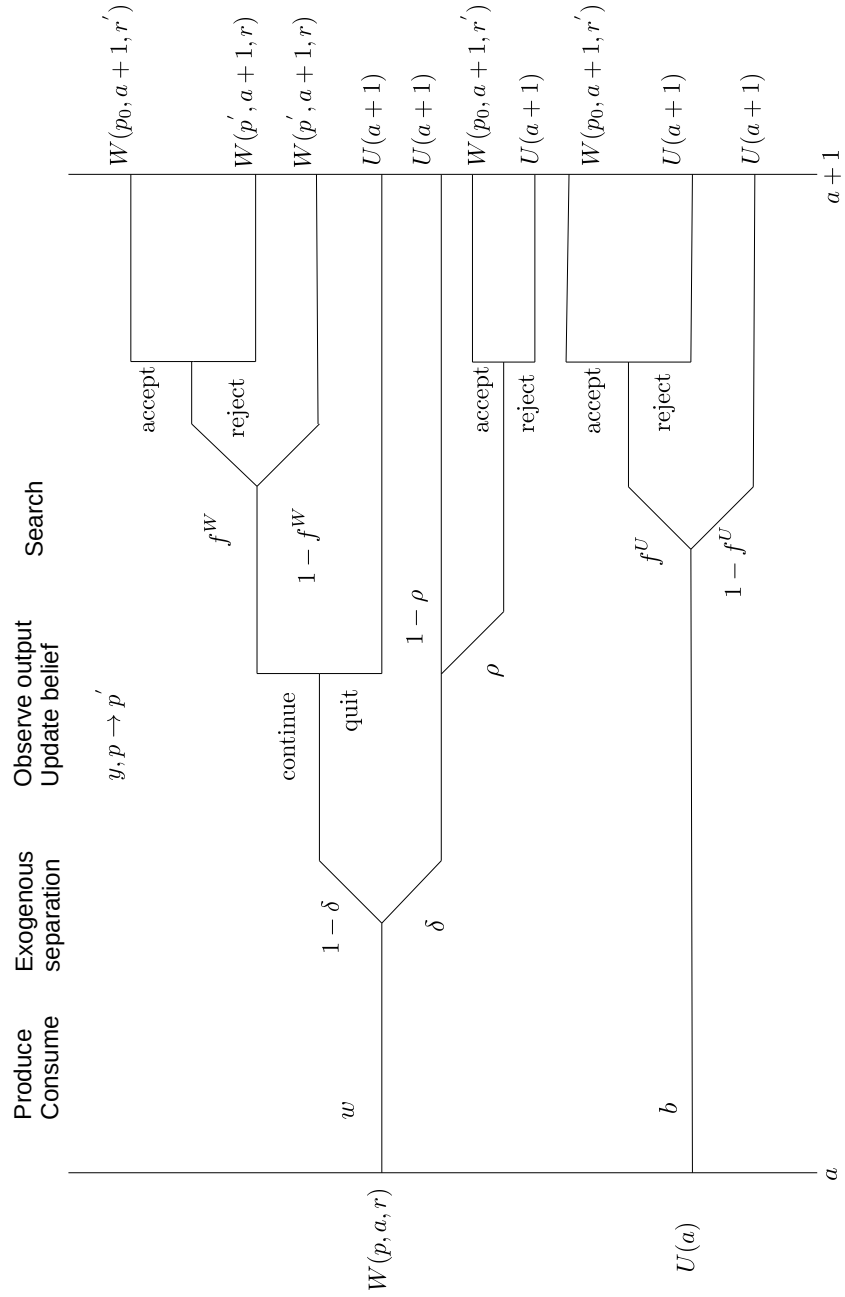


(b) SIPP



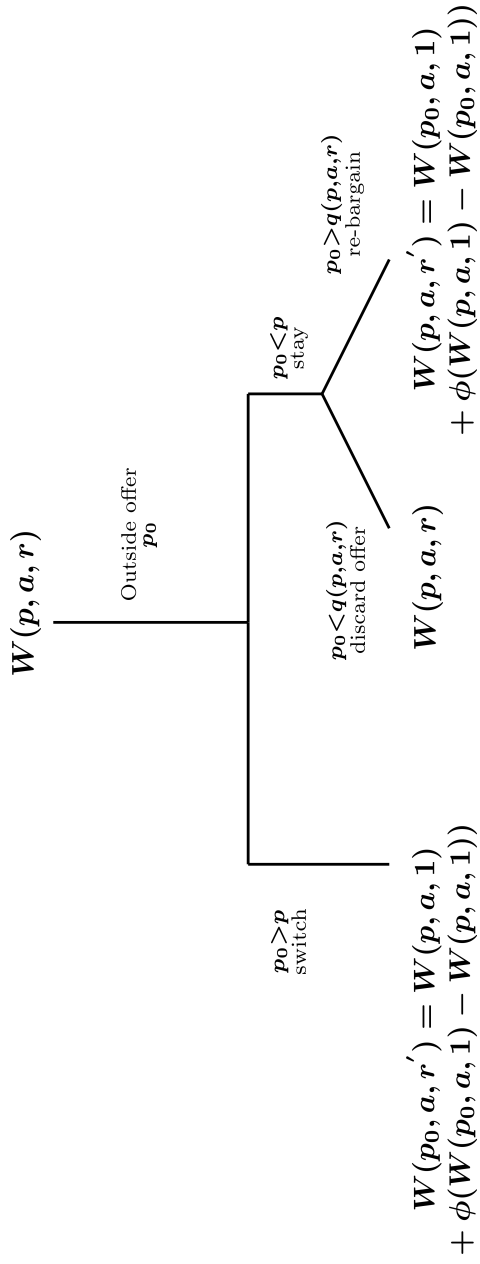
Notes: Panel (a) plots the share of within-component that workers that are younger than a certain age can explain using monthly CPS files between the 1996 – 2000 and 2010 – 2016 periods. Panel (b) is the SIPP analogue based on panels 1996 and 2008.

Figure 1.7: Worker Timing



Notes: This figure summarizes the model timing from the worker's perspective.

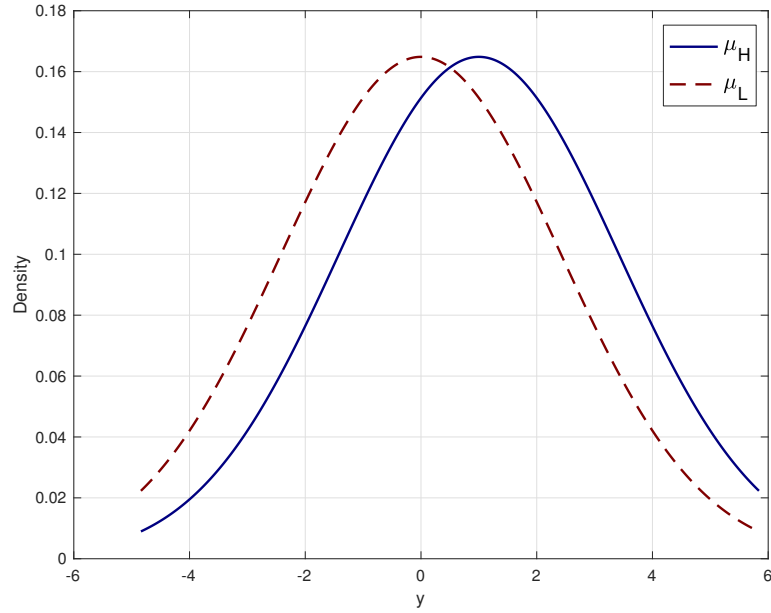
Figure 1.8: Wage Bargaining



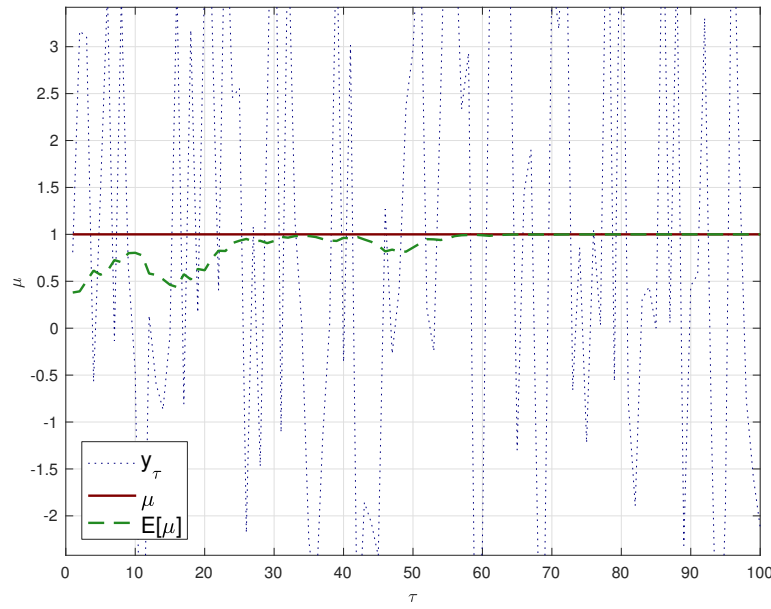
Notes: This figure summarizes the wage determination protocol.

Figure 1.9: Learning

(a) Observed Output Densities



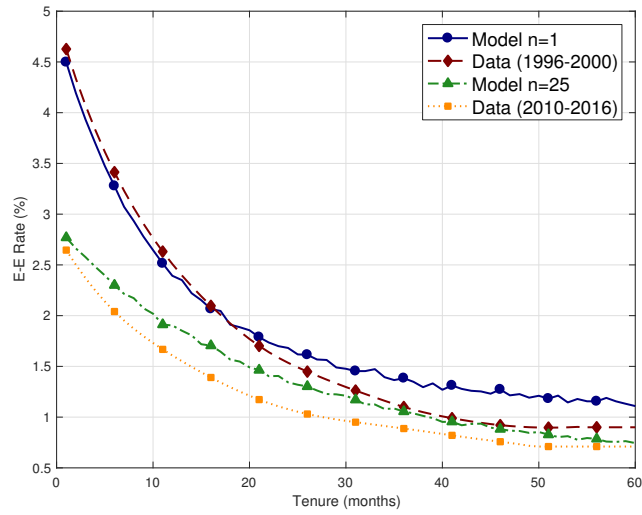
(b) Evolution of Prior



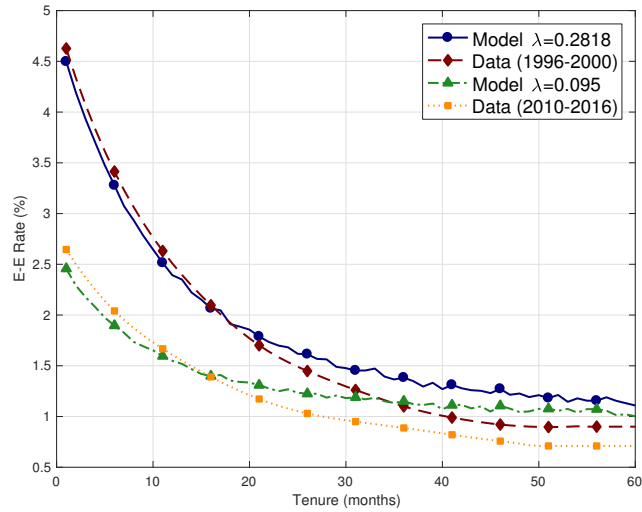
Notes: Panel (a) plots the density of output observations for a high type and a low type match. Panel (b) demonstrates how beliefs evolve based on the underlying match type μ and observed outputs y_τ for a hypothetical case where match productivity is high with $\mu = \mu_H$.

Figure 1.10: Simulated Tenure Profiles

(a) Information

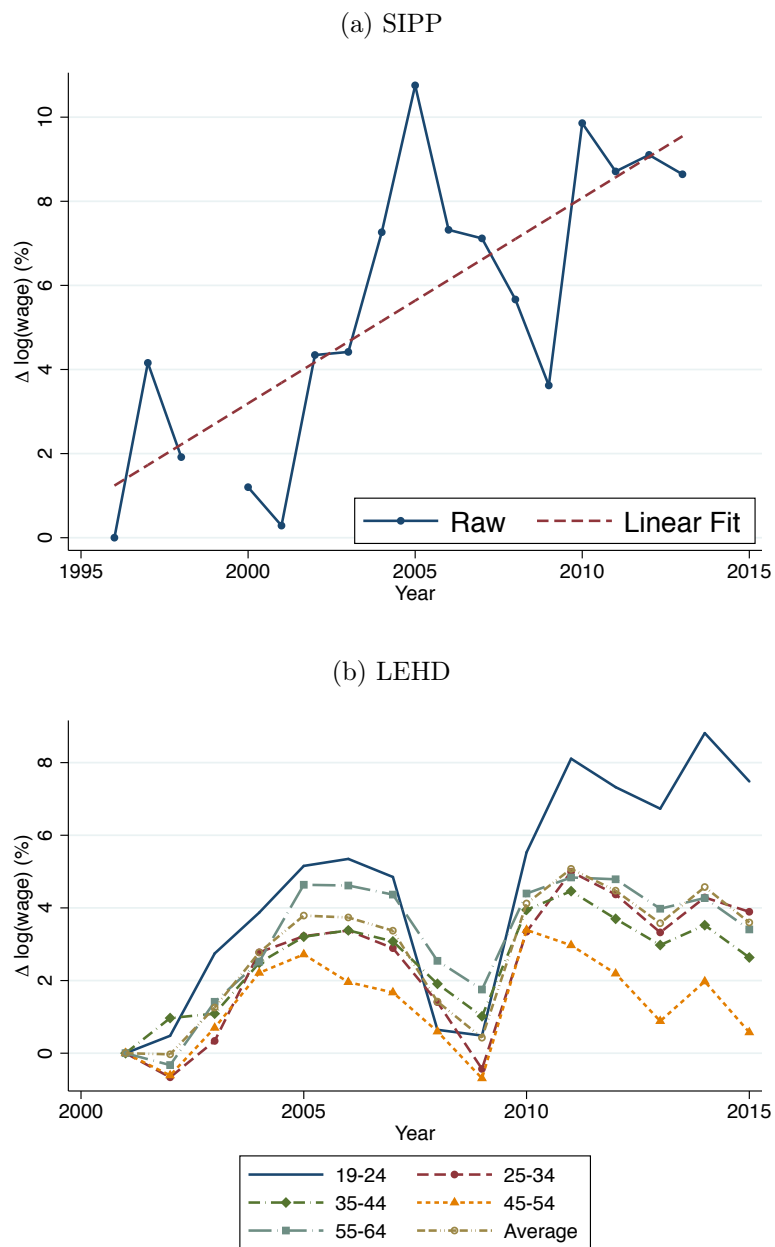


(b) On-the-Job Search Intensity



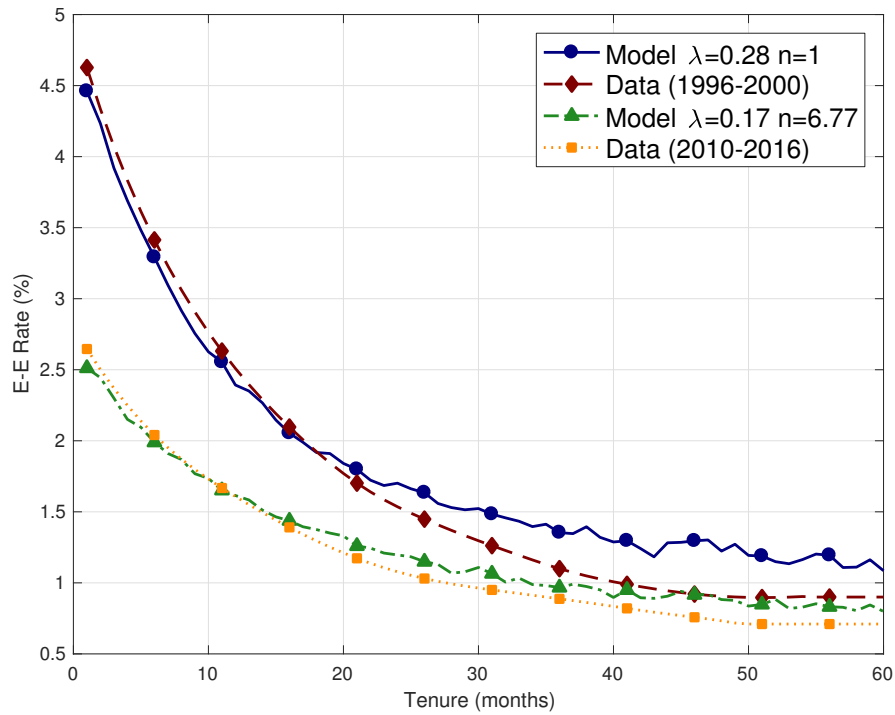
Notes: This figure plots simulated and empirical E-E tenure profiles in the early and late periods. Panel (a) shows the baseline calibration and the exercise where n is estimated to match the E-E tenure profile in the late period. Panel (b) shows the E-E profile resulting from estimating λ to match the late period profile. In both of the exercises the remaining parameters are set to their baseline values. The empirical profiles are smoothed using a locally weighted regression.

Figure 1.11: Conditional Wage Growth



Notes: This figure plots time-series of average conditional wage growth upon E-E transition. Panel (a) uses data from the LEHD and shows annual averages of growth rates between 2001 and 2015 by various age groups as well as the aggregate. Panel (b) uses the SIPP to plot average residual wage growth of job switchers between 1995 and 2013. All growth rates are normalized to zero at initial observation.

Figure 1.12: Joint Calibration of n and λ



Notes: This figure plots simulated and empirical E-E tenure profiles in the early and late periods. For the late period, n and λ are jointly estimated to target both the new E-E profile and the change in wage growth conditional on job mobility.

Chapter 2

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

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Benjamin Schoefer (UC Berkeley)

2.1 Introduction

Labor markets are characterized by large degrees of wage dispersion between otherwise similar workers and jobs.² Through the lens of frictionless labor market models, such wage dispersion is puzzling because workers should sort into firms offering the highest wage.³ *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:

¹ This chapter will form the theoretical basis of a broader research agenda conducted jointly with Simon Jäger, Damian Osterwalder and Josef Zweimüller, with whom we will undertake an empirical test of the framework we develop here. The research presented in this chapter contains solely material from collaboration between Yusuf Mercan and Benjamin Schoefer, and is intended for inclusion as a dissertation chapter.

² See e.g. Hornstein, Krusell, and Violante 2011; Card, Heining, and Kline 2013; Sorkin 2018.

³ Alternative explanations appeal to amenity differences or compensation differentials.

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 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.⁴ 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 administrative 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 2.2 provides motivating facts on job mobility and unemployment risk. Section 2.3 presents our model, and Section 2.4 discusses the calibration strategy, Section 2.5 presents a quantitative analysis of the model, and Section 2.6 provides quantitative exercises. Section 2.7 concludes.

⁴ Except for equilibrium adjustments.

2.2 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.⁵

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.⁶ 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 months with a change in employer-employee match ID.⁷

⁵ 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.

⁶ We exclude spells of individuals enrolled in school or in the army, and of the self-employed.

⁷ 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

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.⁸

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 2.1 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 2.1 shows that starting a new job exposes newly hired workers to excess nonemployment risk, compared to their higher-tenure colleagues.

Companion Figure 2.2 casts these monthly transition rates into *annually-cumulated* separation rates. It preserves the monthly tenure bins and summarizes the probabil-

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.

⁸ The tenure gradient of the separation rate has previously be documented by Farber 1994 using the National Longitudinal Survey of Youth. See Menzio, Telyukova, and Visschers 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.

ity of separation into unemployment during the upcoming 12 months rather than the single month.⁹ 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 2.3 presents the tenure profile of EU separations for each sample separately for the monthly transition probability; Figure 2.4 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.

⁹ 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.

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 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 2.5 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 five 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 2.6 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 2.6 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.¹⁰ We plot $\rho_{\tau}^{(E)EU}$ for these two groups of workers separately in Figure 2.7. Figure 2.7 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.¹¹

¹⁰ Wage loss upon job change is an important feature of the data as documented by Tjaden and Wellschmied 2014.

¹¹ This conclusion depends on the extent that we can interpret wage gains pointing to a voluntary job switch.

2.3 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.

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 $\mu \in \{\mu_1, \dots, \mu_m\}$ with $\mu_1 < \dots < \mu_m$, 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 $\vec{q}_i \in \{\vec{q}_1, \dots, \vec{q}_n\}$ 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 $\sum_{j=1}^m q_{ij} = 1 \forall i \in \{1, \dots, n\}$. 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 2.8 depicts the timing of the model from the worker's point of view.

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

$$U = b + \beta \left[(1 - f)U + f \sum_{i=1}^n Pr(\vec{q}_i) \max \left\{ U, \vec{q}_i \max \{ W(\mu'), U \} \right\} \right]. \quad (2.1)$$

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

$$\begin{aligned}
W(\mu) = & w(\mu) + \beta \left[\delta U \right. \\
& \left. + (1 - \delta) \left((1 - \lambda f) W(\mu) + \lambda f \sum_{i=1}^n Pr(\vec{q}_i) \max \left\{ W(\mu), \vec{q}_i \max \{ W(\vec{\mu}'), U \} \right\} \right) \right].
\end{aligned} \tag{2.2}$$

An employed worker in a type- μ job consumes 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

$$\begin{aligned}
J(\mu) = & \mu - w(\mu) \\
& + \beta(1 - \delta) \left((1 - \lambda f) J(\mu) + \lambda f \sum_{i=1}^n Pr(\vec{q}_i) \mathbb{I} \left\{ W(\mu) \geq \vec{q}_i \max \{ W(\vec{\mu}'), U \} \right\} J(\mu) \right).
\end{aligned} \tag{2.3}$$

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 0.¹²

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

$$S(\mu) \equiv J(\mu) + W(\mu) - U. \tag{2.4}$$

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

$$W(\mu) - U = \phi S(\mu) \tag{2.5}$$

$$J(\mu) = (1 - \phi) S(\mu). \tag{2.6}$$

¹² We assume that there is free entry, therefore the outside value of a firm is 0.

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 2.1, 2.2, 2.3, definition of surplus in Equation 2.4, and the linear sharing rules in Equations 2.5 and 2.6, we arrive at the surplus value given by the following Bellman equation

$$\begin{aligned}
S(\mu) = & \mu - b + \beta(1 - \delta) \left[(1 - \lambda f)S(\mu) + \phi \lambda f \sum_{i=1}^n Pr(\vec{q}_i) \max \left\{ S(\mu), \vec{q}_i \max\{S(\vec{\mu}'), 0\} \right\} \right. \\
& + (1 - \phi) \lambda f \sum_{i=1}^n Pr(\vec{q}_i) \mathbb{I} \left\{ S(\mu) \geq \vec{q}_i \max\{S(\vec{\mu}'), 0\} \right\} S(\mu) \left. \right] \\
& - \beta \phi f \sum_{i=1}^n Pr(\vec{q}_i) \vec{q}_i \max\{S(\vec{\mu}'), 0\}.
\end{aligned} \tag{2.7}$$

We note that Equation 2.7 does not depend on the level of wages and its solution, given a market tightness value, is sufficient to determine worker decisions. We provide details of the derivation of $S(\mu)$ in Appendix B.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 $S = u + \lambda(1 - \delta)(1 - u)$, where u denotes the share of unemployed workers. Firms post vacancies until the value of a vacancy becomes zero. The free-entry condition implies

$$\begin{aligned}
\kappa &= \beta q(\theta) \mathbb{E}[J(\mu)] \\
&= \beta q(\theta) (1 - \phi) \mathbb{E}[S(\mu)] \\
&= \beta q(\theta) \frac{(1 - \phi)}{u + \lambda(1 - \delta)(1 - u)} \left(u \sum_{i=1}^n Pr(\vec{q}_i) \sum_{j=1}^m q_{ij} \mathbb{I}\{S(\mu_j) > 0\} \right. \\
&\quad \left. + \lambda(1 - \delta) \sum_{k=1}^m e(\mu_k) \sum_{i=1}^n Pr(\vec{q}_i) \mathbb{I}\{S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'), 0\}\} \sum_{j=1}^m q_{ij} \mathbb{I}\{S(\mu_j) > 0\} \right)
\end{aligned} \tag{2.8}$$

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 2.6. 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 B.1.

Equilibrium

We solve the model in steady state.¹³ 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 2.7.
- Distribution of workers over employment states, $(u, \{e(\mu_j)\}_{j=1}^m)$, evolves according to the laws of motion in Equations B.1.1 and B.1.2, and is time-invariant.
- Market tightness θ satisfies the free-entry condition in Equation 2.8.

2.4 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.

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, Ramey, and Watson 2000:

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

¹³For most of our quantitative exercises, we compare steady states of the model under different unemployment insurance regimes. In Section B.2 we outline an algorithm used to study the transition behavior of our model to one time unanticipated shocks to the unemployment insurance level.

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.¹⁴

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. $Pr(\vec{q}_i) = \frac{1}{n} \forall i \in \{1, \dots, n\}$.

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 $\begin{bmatrix} q_{11} & \dots & q_{1m} \\ \vdots & & \vdots \\ q_{n1} & \dots & q_{nm} \end{bmatrix}$, whose i th 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 $b = 0$.

Table 2.1 summarizes the choice of parameters set without solving the model, together with their values.

¹⁴ 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.

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 now functions of our augmented model of job lotteries:

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

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:

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

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:

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

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 2.5.

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.2 and B.2. Table 2.2 reports the parameters estimated by solving the model. Table 2.3 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.

2.5 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

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

An example job lottery Figure 2.9 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 2.10 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:¹⁵

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

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 : $W(\bar{\mu}) = U$.

¹⁵ 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:

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

The quit-into-unemployment option therefore limits the downside of the job offer. Figure 2.10 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.

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

$$r_i \equiv \sum_{j \in \{j: S(\mu_j) < 0\}} q_{ij} \quad (2.9)$$

This probability is simply the sum of probabilities in the flat part of Figure 2.10, 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 2.10. 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 2.11 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: $\mathbb{I}\left\{W(\mu_k) < \overbrace{\bar{q}_i}^{\Omega_i} \max\{W(\vec{\mu}'), U\}\right\}$. 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 2.12 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):

$$\sigma(\mu_j) = \sum_{i=1}^n Pr(\bar{q}_i) \mathbb{I}\{W(\mu_j) < \Omega_i\} \quad (2.10)$$

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 2.13 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 2.14 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 2.15 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/ \bar{q}_i -specific sampling probability and takes a weighted

average using the McCall job lottery distribution:

$$\sum_{i=1}^n Pr(\vec{q}_i) \sum_j \frac{e(\mu_j)}{1-u} \mathbb{I}\{W(\mu_j) < \Omega_i\} \quad (2.11)$$

Since Figure 2.11 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 2.16 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 2.11.

2.6 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.¹⁶ We will use the estimate as an additional empirical target for our calibrated model.

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 2.17 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 2.18 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 downside risk i.e. put more weight on U to begin with. To see this, recall that lottery value is $\Omega_i = \bar{q}_i \max\{W(\mu), U\}$. 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 2.19 plots our risk measure in Equation 2.9 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

¹⁶ This planned extension of our work will be coauthored work with Simon Jäger, Damian Osterwalder and Josef Zweimüller.

regimes. Clearly, lotteries that put more weight on bad states of the world, i.e. U , have a lower expected value.¹⁷

Figure 2.20 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

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

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.¹⁸ Figure 2.16 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 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

¹⁷ 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 2.11 plots the expected lottery value conditional on it resulting in employment. As the figure shows, this expected value is independent of lottery risk.

¹⁸ 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.

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 2.22 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 2.23 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.

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.2.

Figure 2.24 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 over the transition period; both proxies for job risk taking initially spike but ultimately settle as lower steady states.

The intuition is simply selection. Figure 2.25 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 2.23 already described for the steady states in a histogram of μ levels in employment.

2.7 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.

2.8 Tables

Table 2.1: 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
μ_{\min}	Minimum match productivity	0	-
μ_{\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 2.2: 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.

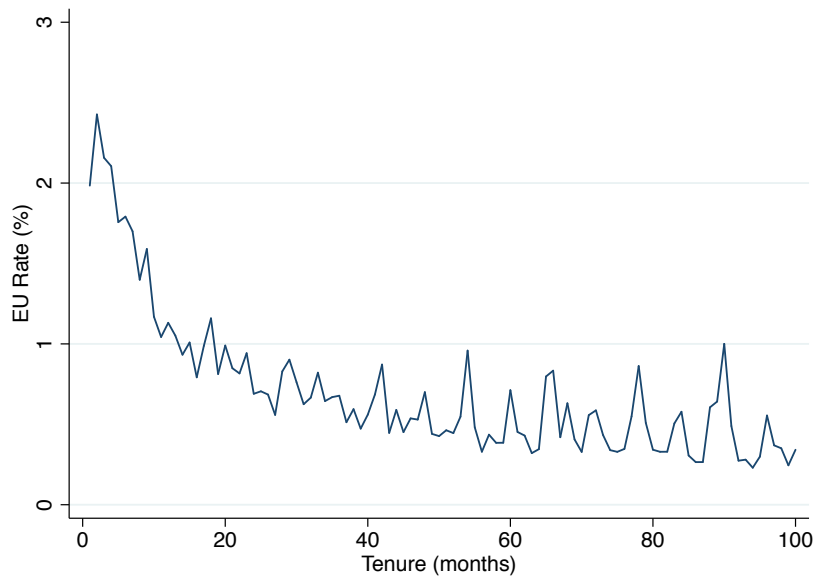
Table 2.3: Targets and Model Fit

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

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

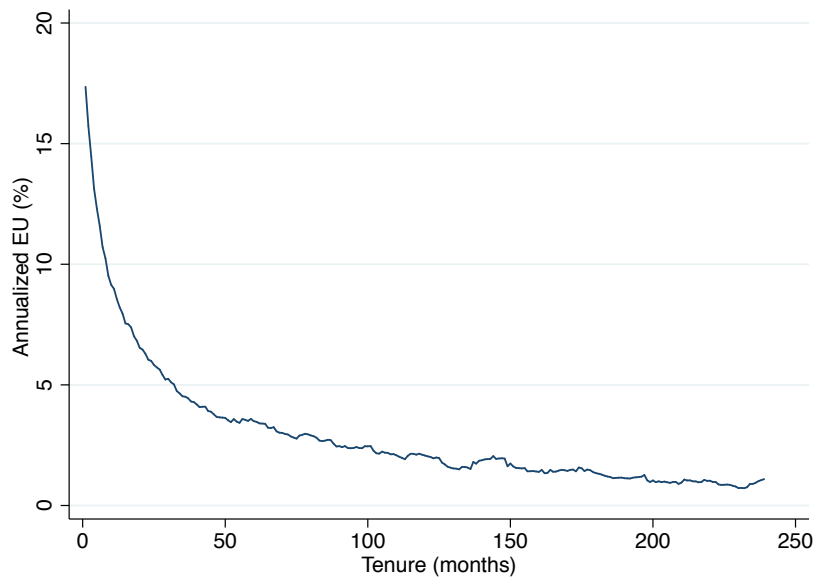
2.9 Figures

Figure 2.1: Monthly EU Rate by Tenure



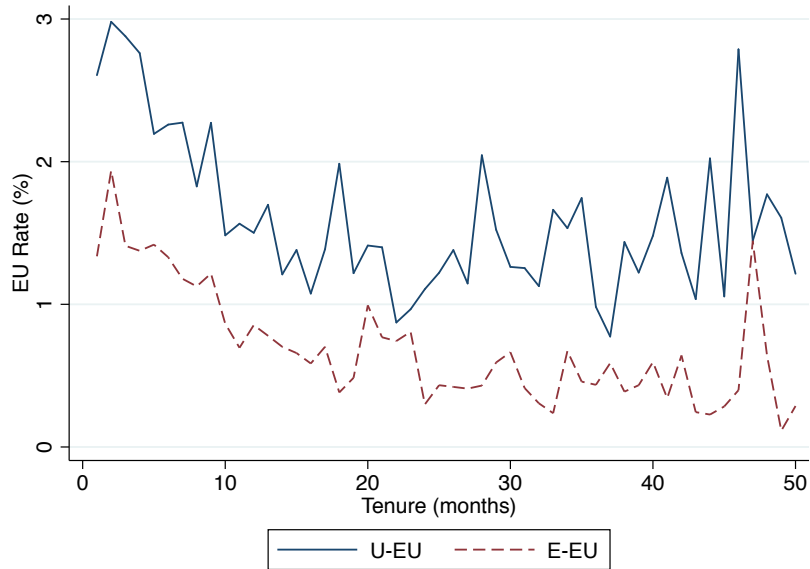
Notes: This figure plots the monthly share of employed workers that separate into nonemployment by tenure, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 2.2: Annualized EU Rate by Tenure



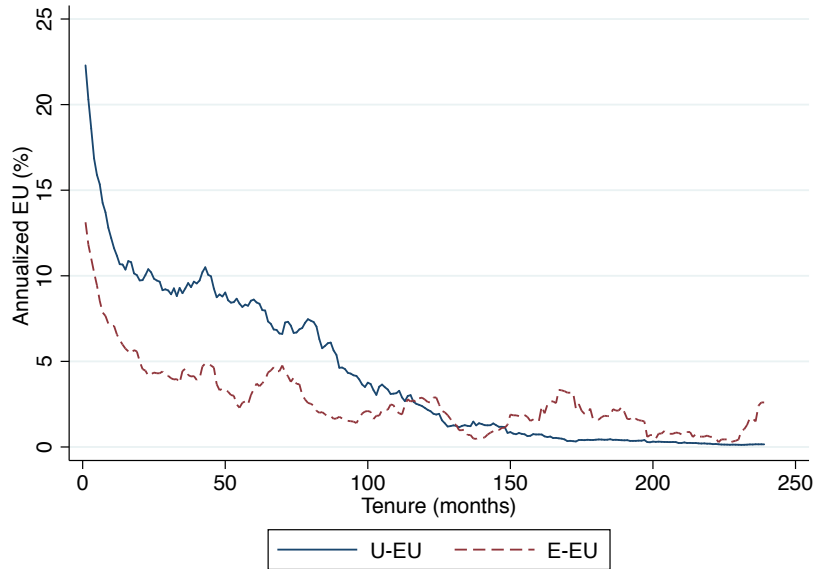
Notes: This figure plots the probability of making an employment-to-nonemployment transition within the next 12 months by tenure, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 2.3: Monthly EU Rate by Tenure and Origin



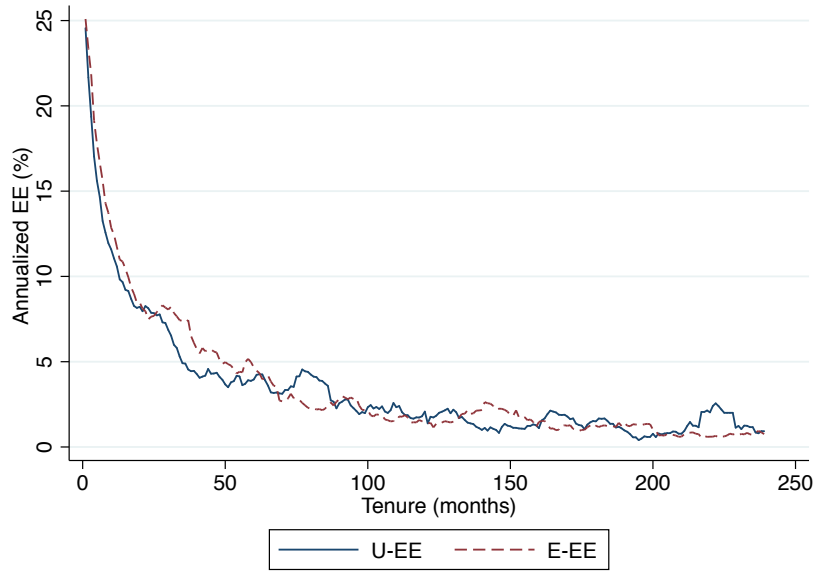
Notes: This figure plots the monthly share of employed workers that separate into nonemployment by tenure and labor market status prior to finding current job, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 2.4: Annualized EU Rate by Tenure



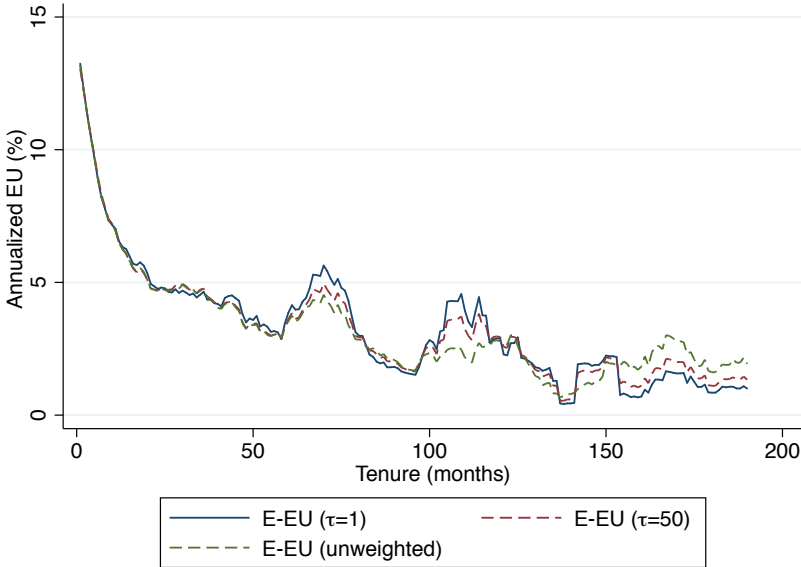
Notes: This figure plots the probability of making an employment-to-nonemployment transition within the next 12 months by tenure and labor market status prior to finding current job, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 2.5: Annualized EE by Tenure



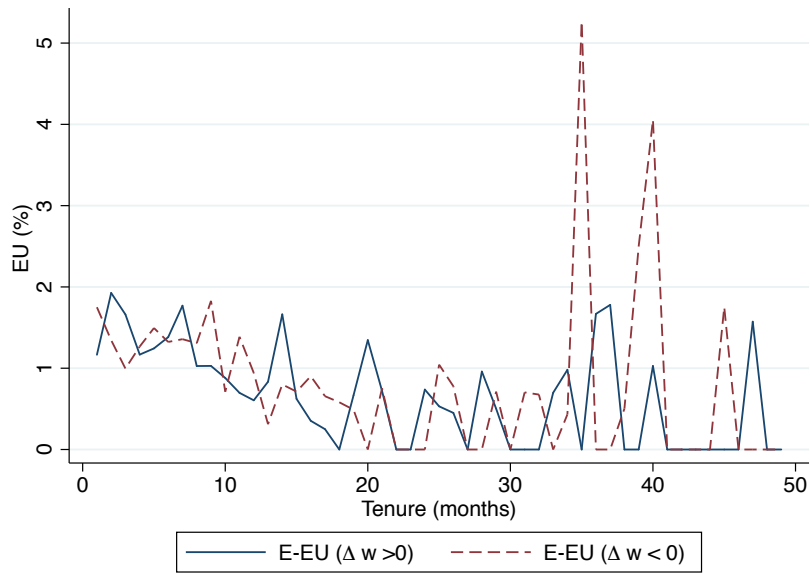
Notes: This figure plots the probability of making an employment-to-employment transition within 12 months by tenure and labor market status in previous employment spell using data from the SIPP.

Figure 2.6: Reweighted Annualized EU Rate by Tenure



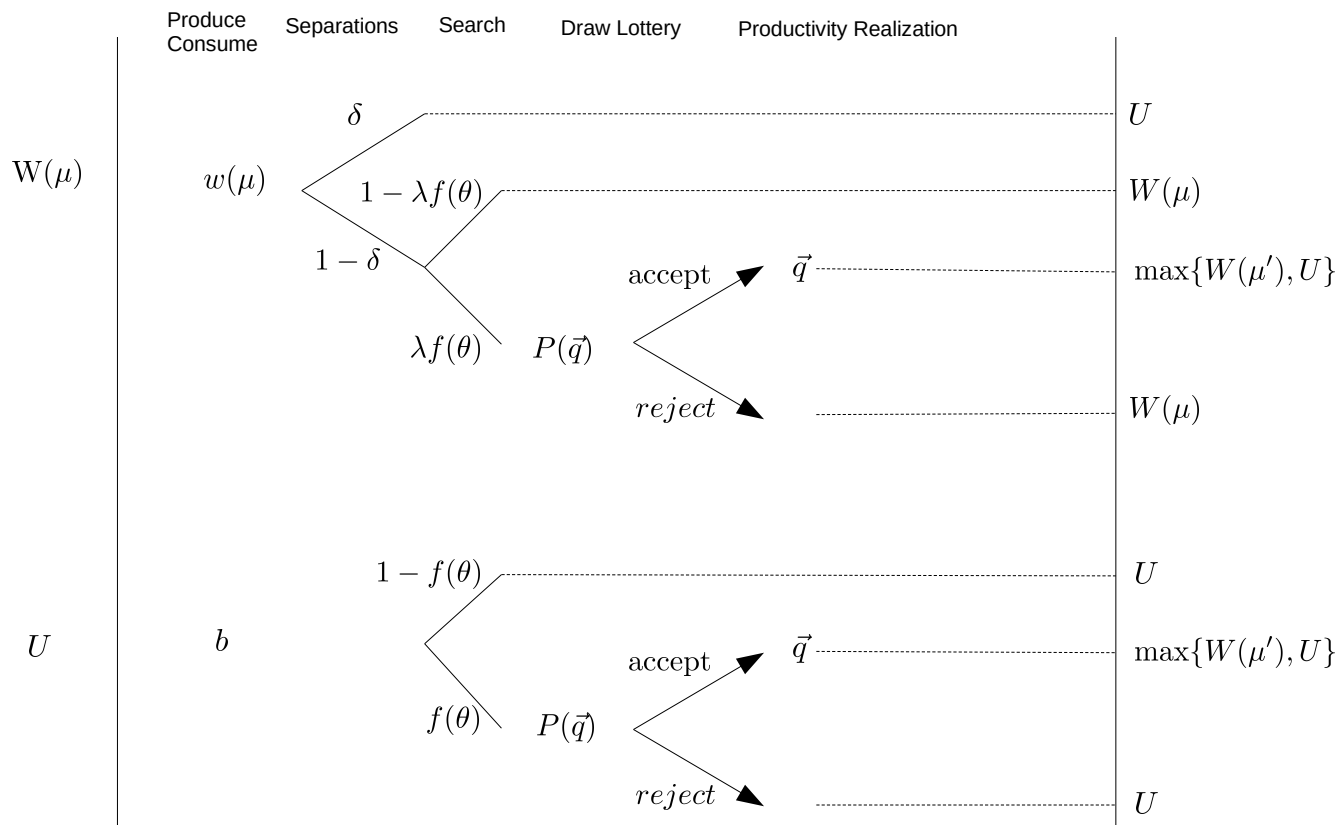
Notes: Notes: This figure plots the probability of making an employment-to-nonemployment transition within the next 12 months by tenure for workers who found their current job through a job-to-job transition, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels. The solid blue line 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 2.7: Monthly EU Rate by Tenure for Jobs Originating from Direct EE-Transition With Wage Increases and Decreases



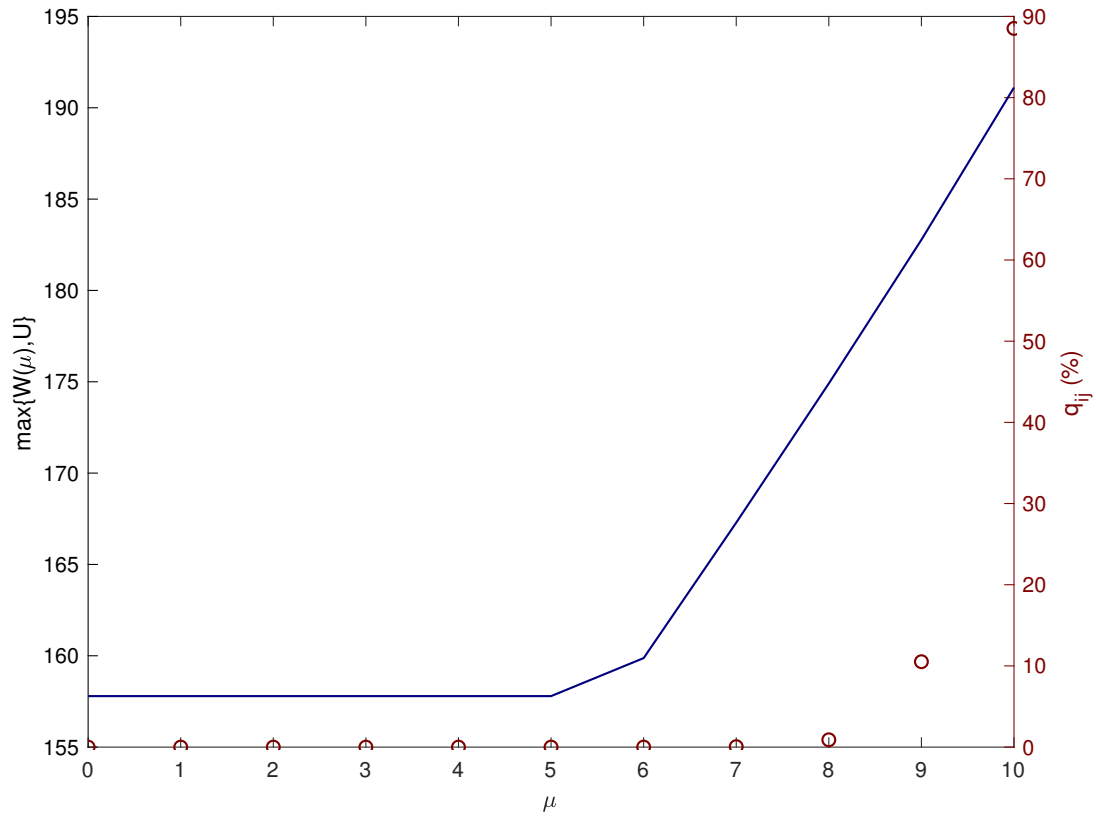
Notes: This figure plots the monthly share of employed workers that separate into nonemployment for workers that started their current through a job-to-job transition by tenure and sign of wage growth at job transition, using data pooled from the 1993, 1996, 2001, 2004 and 2008 SIPP panels.

Figure 2.8: Model Timing



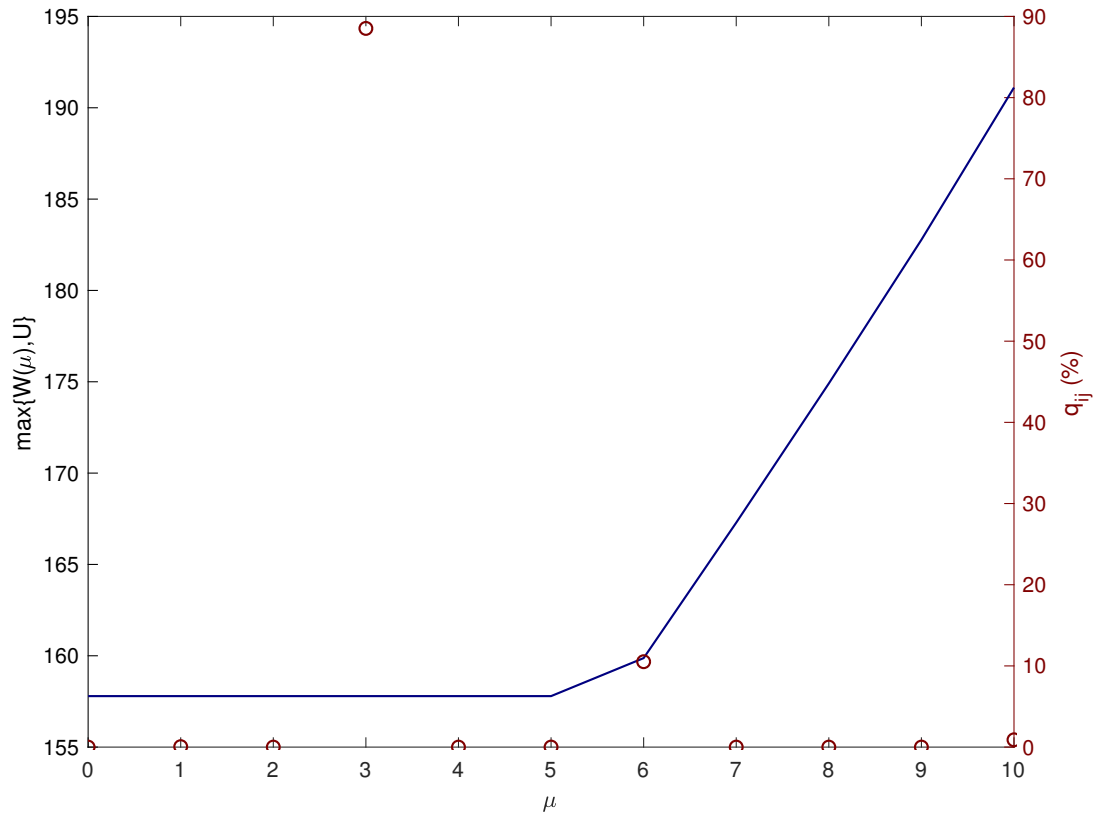
Notes: This figure summarizes the timing of the model from the worker's point of view.

Figure 2.9: Base Lottery Profile vs Payoffs



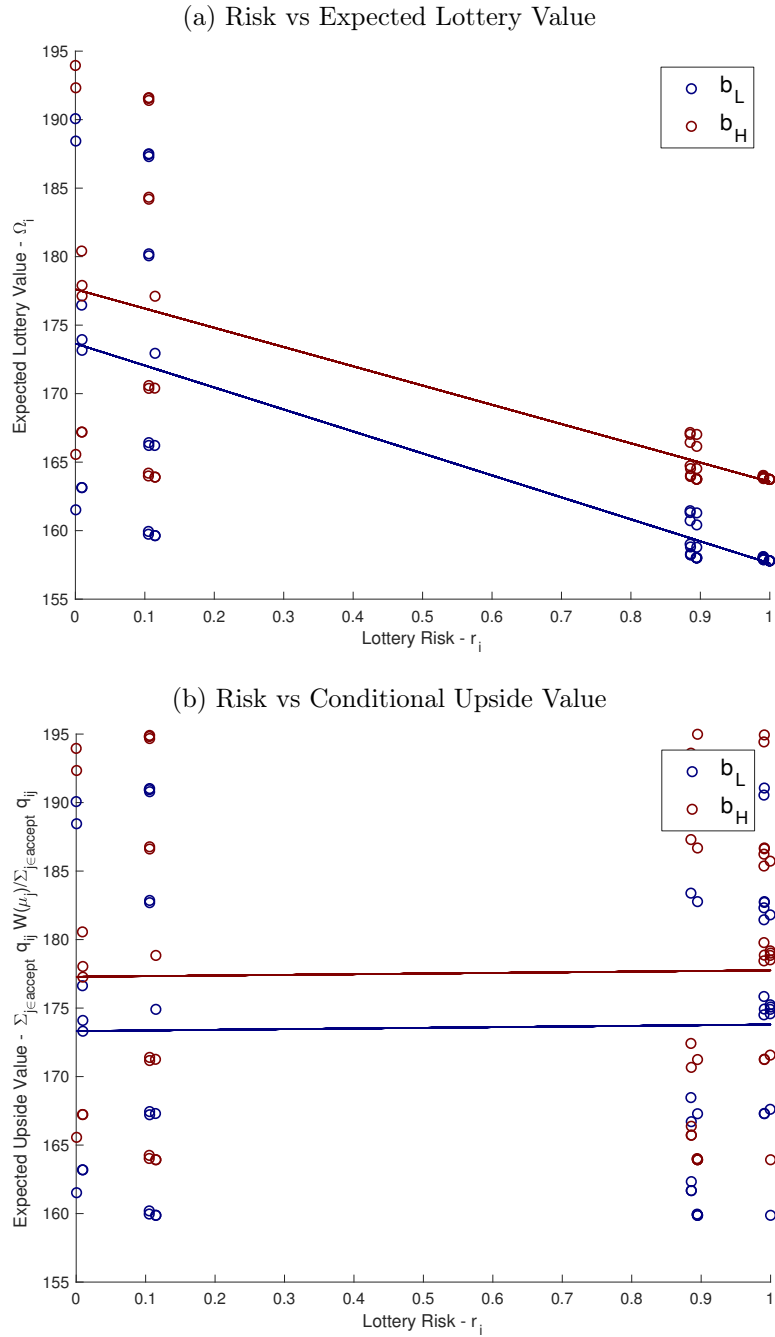
Notes: This figure plots the base “placement probabilities”, q_{0j} , superimposed on the lottery payoff structure.

Figure 2.10: Lottery Profile vs Payoffs



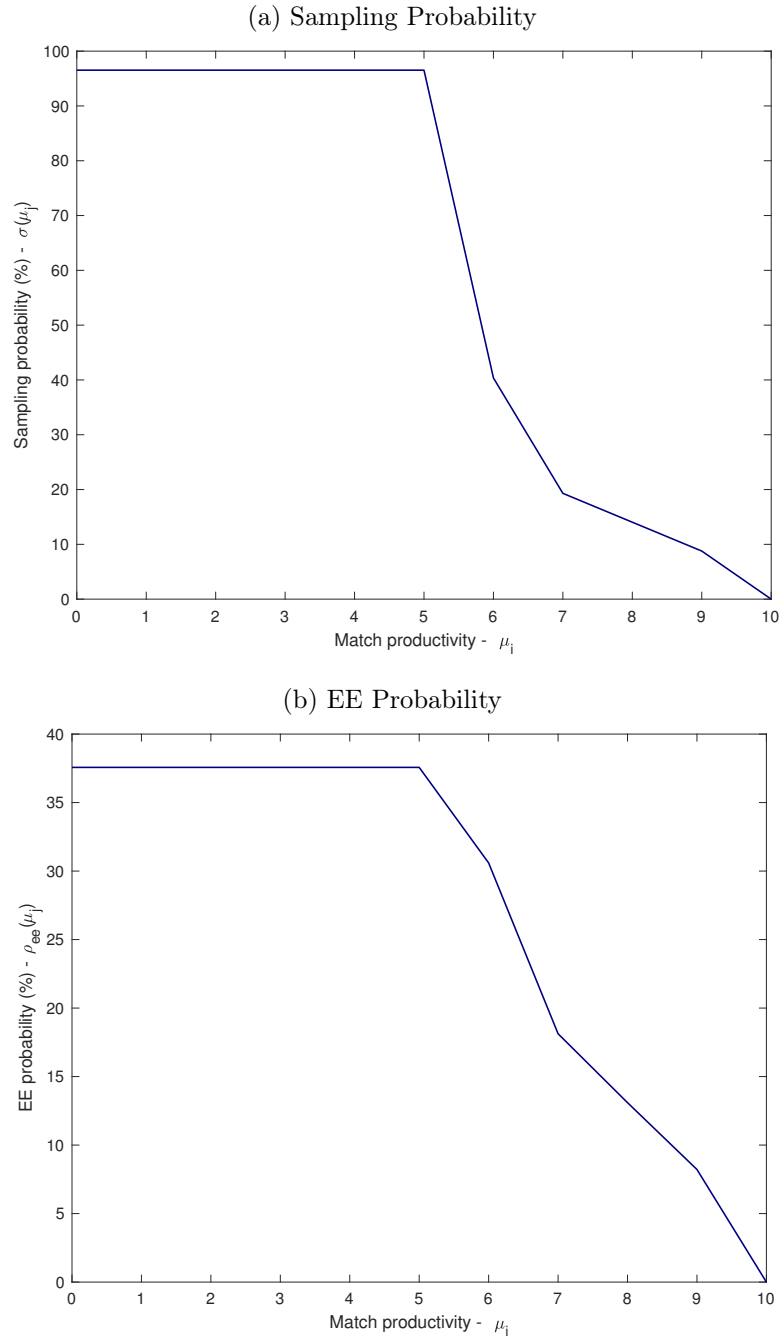
Notes: This figure plots a typical lottery, a random permutation of q_{0j} , superimposed on the lottery payoff structure.

Figure 2.11: Lottery Values by Risk



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.

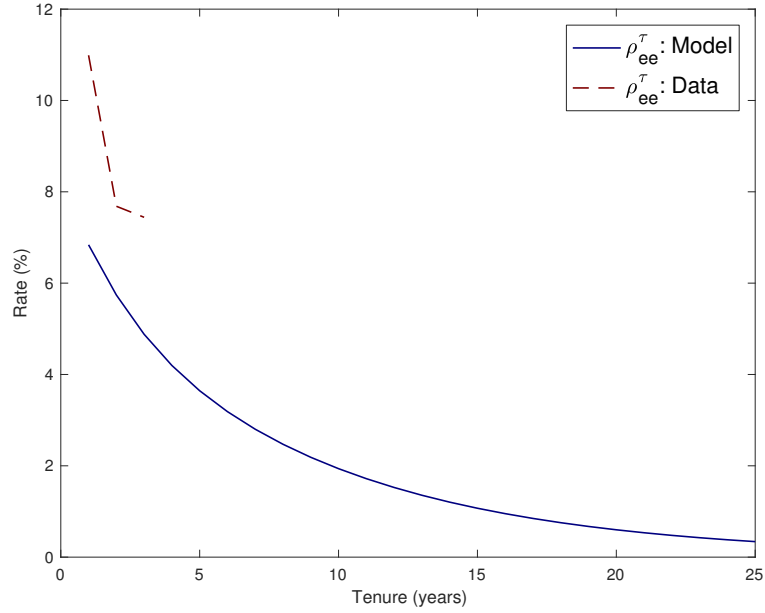
Figure 2.12: EE and Lottery Sampling Probabilities by μ



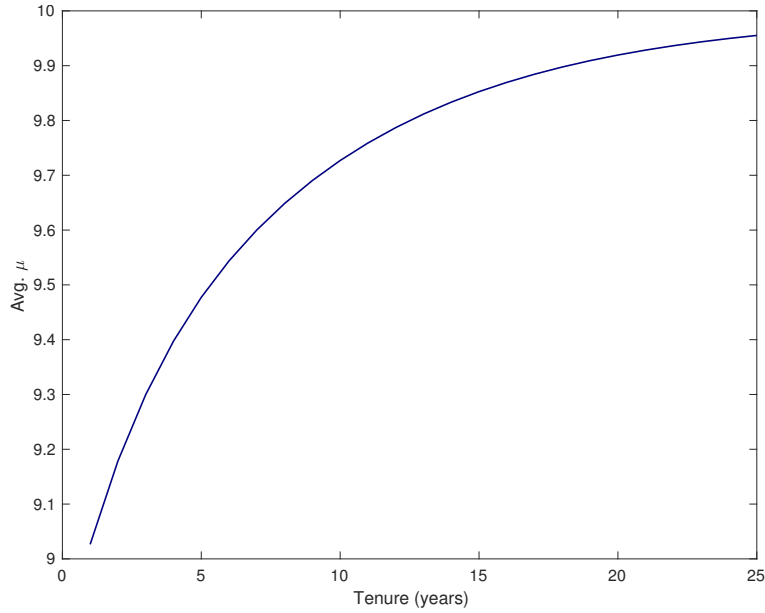
Notes: Panel (a) plots the probability of sampling a lottery conditional on contact against match quality μ . Panel(b) plots the probability of making a successful job-to-job transition, conditional on having sampled the lottery against match quality.

Figure 2.13: Tenure Profiles

(a) (E)EE by Tenure

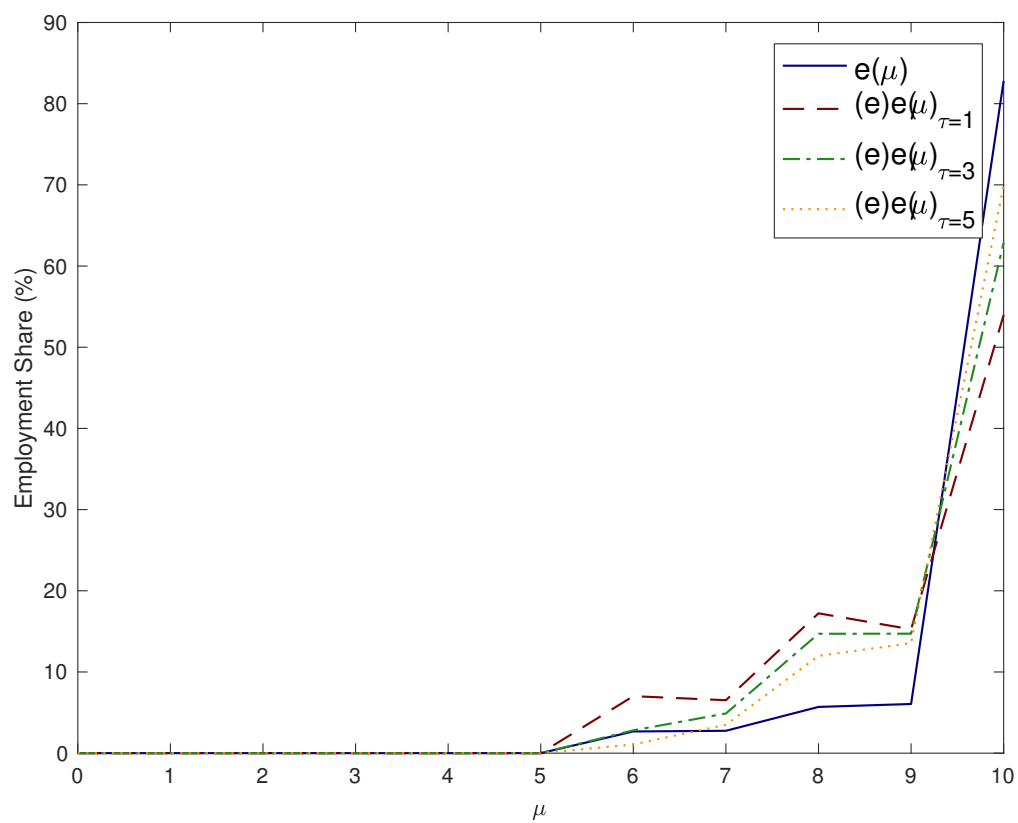


(b) Average Productivity by Tenure among (E)EE



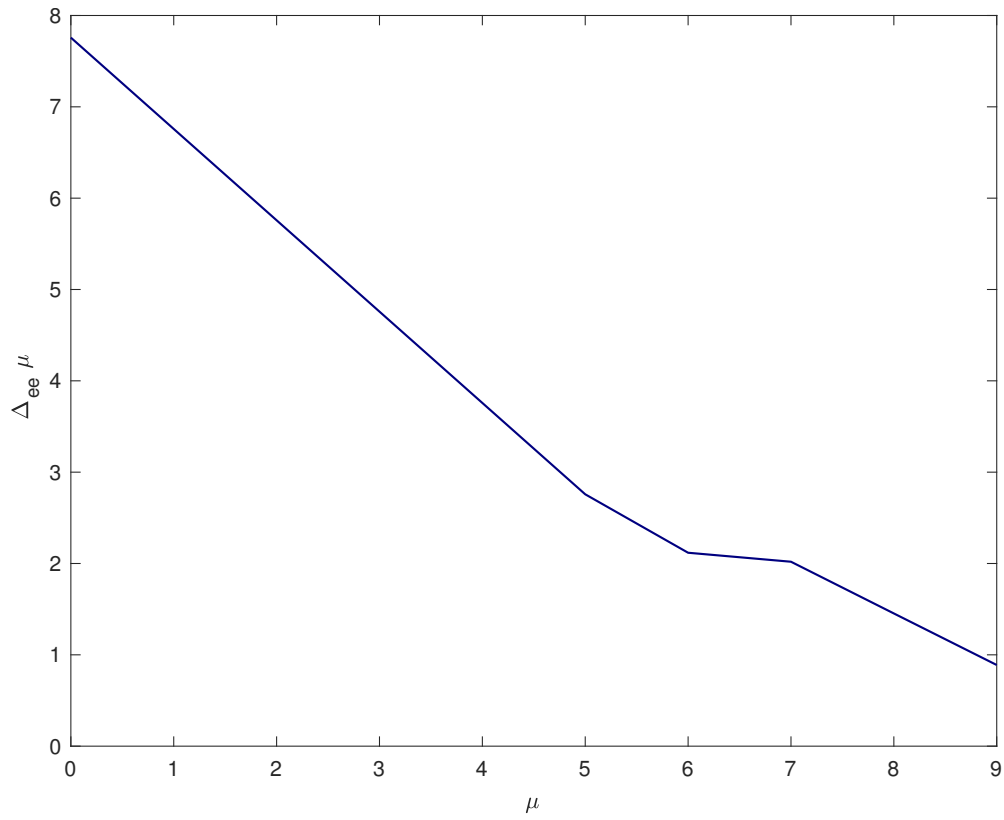
Notes: Panel (a) plots the job-mobility rate of a worker by tenure in a job, together with its data counterparts for the first 3 tenure years. Panel(b) plots the evolution of average match productivity by tenure.

Figure 2.14: Employment Distribution



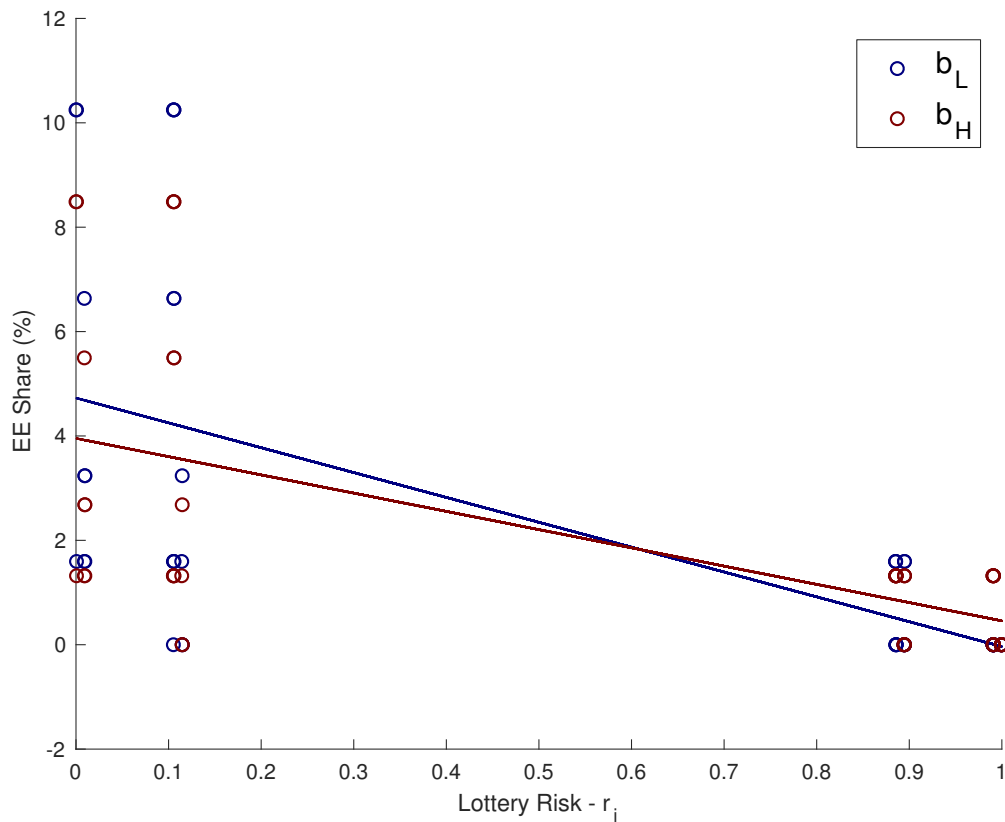
Notes: This figure plots the share of employed workers by match productivity in the steady state, and for workers who started their current job through a job-to-job transition at tenures 1, 3 and 5 years.

Figure 2.15: Average Change in μ upon Job Switch



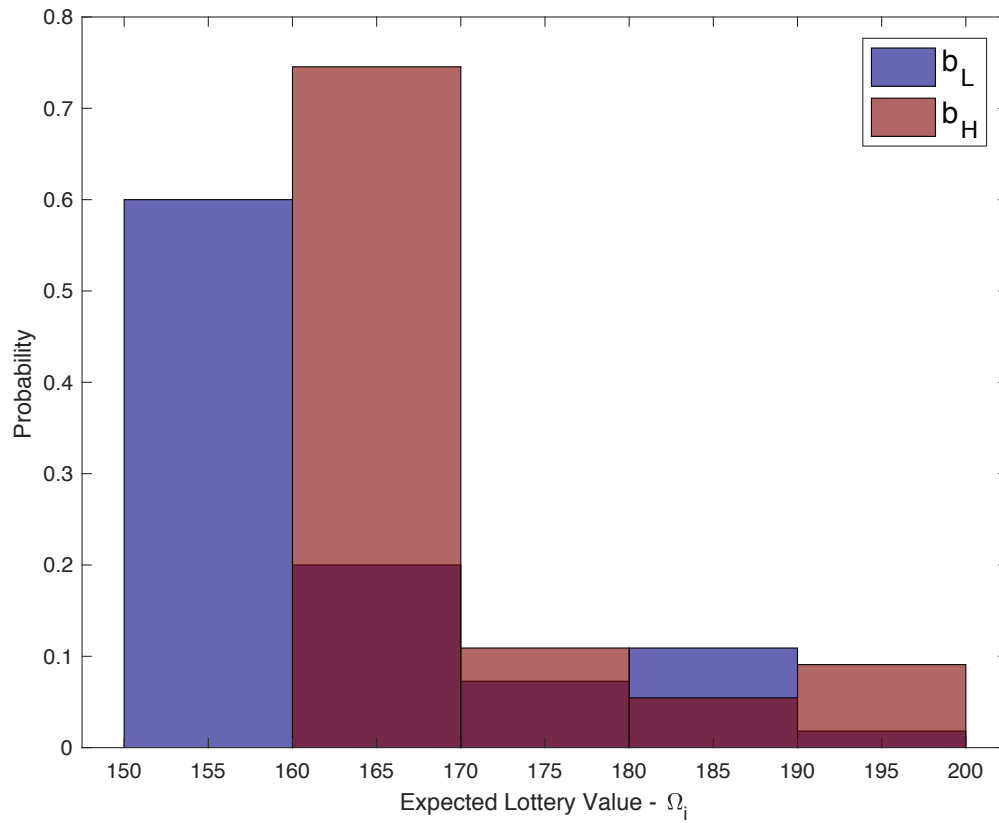
Notes: This figure plots the average change in match productivity upon job switch for different against match productivity of the current job.

Figure 2.16: Risk - Experimentation



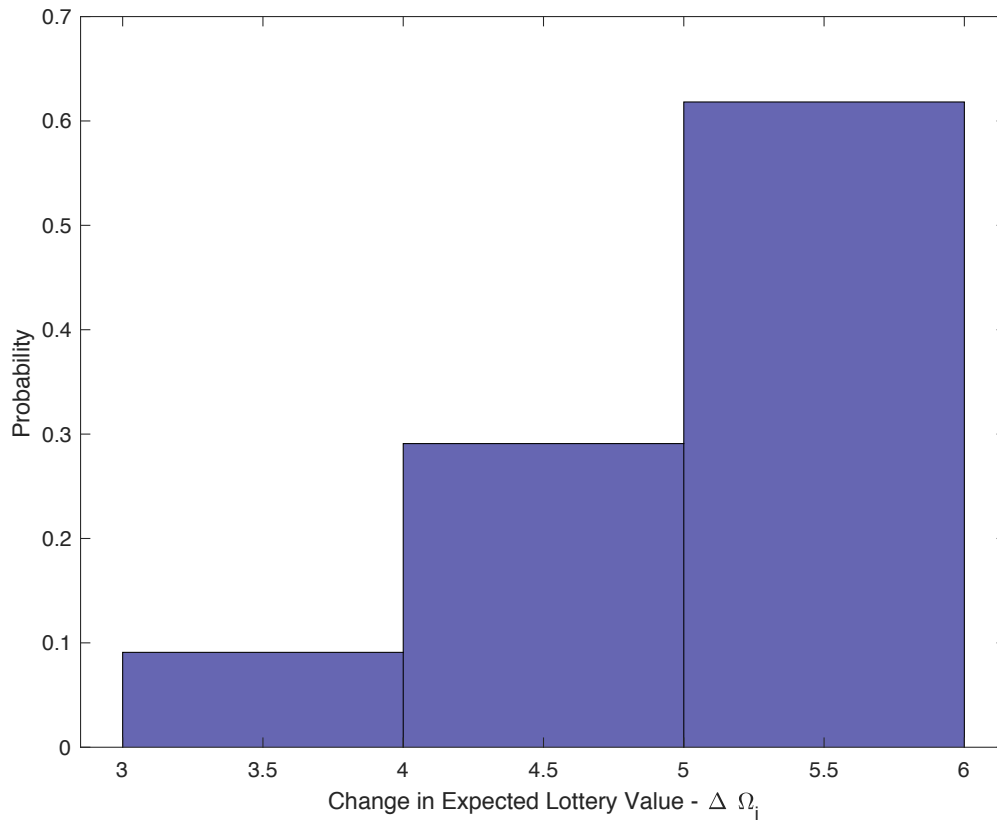
Notes: This figure plots lottery take-up rates vs lotteries' probability of yielding a match productivity over which worker prefers unemployment.

Figure 2.17: Histogram of Lottery Values



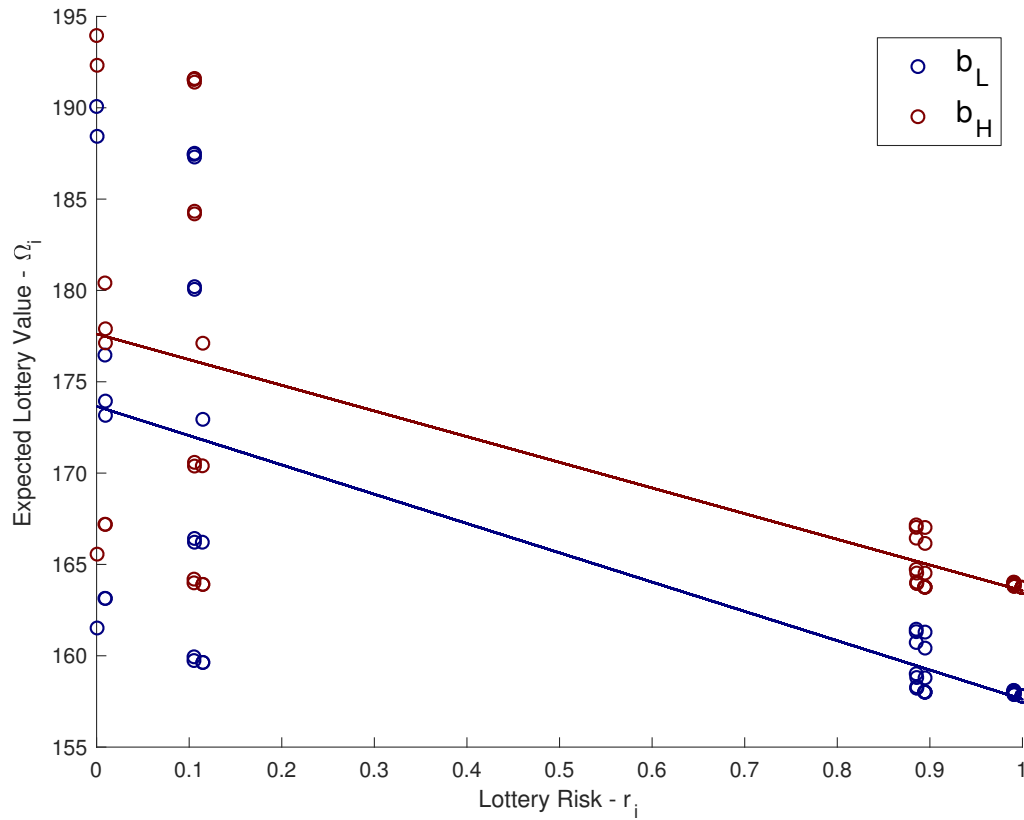
Notes: This figure plots the distribution of expected lottery values given by $\sum_j q_{ij} \max \{W(\mu_j), U\}$ under high and low unemployment benefit level regimes.

Figure 2.18: Histogram of Lottery Value Changes



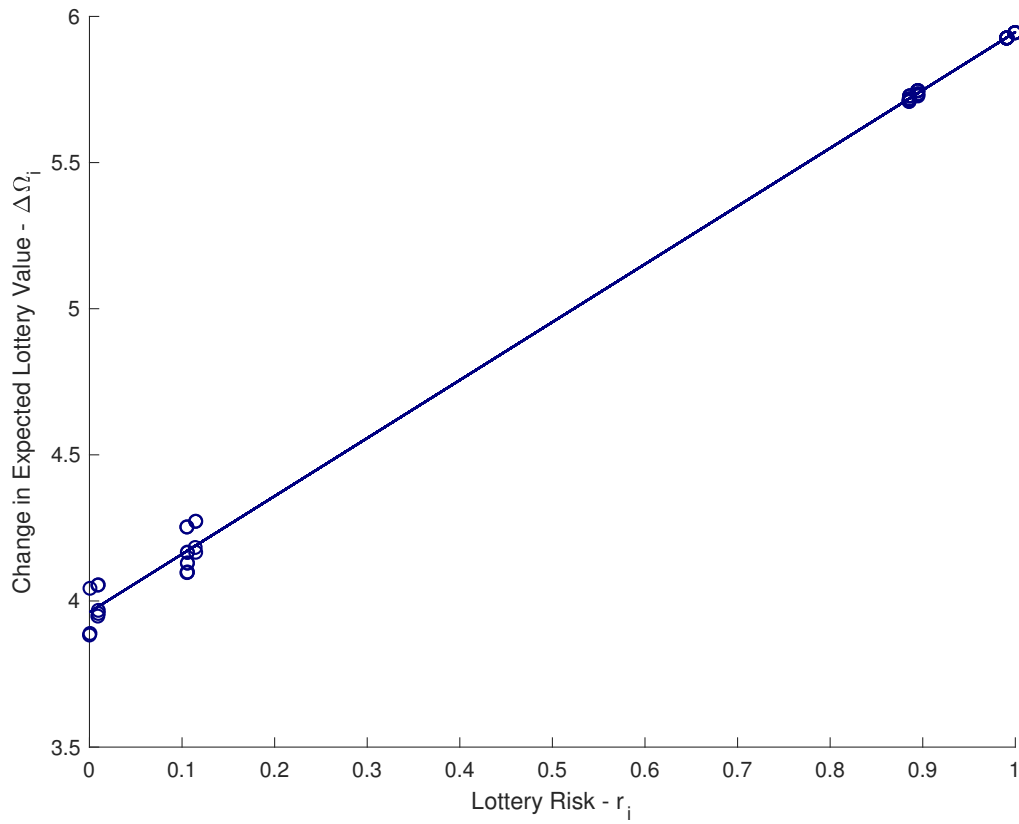
Notes: This figure plots the distribution of the change in expected lottery values moving from a low to high unemployment insurance benefit regime.

Figure 2.19: Risk vs Expected Lottery Value



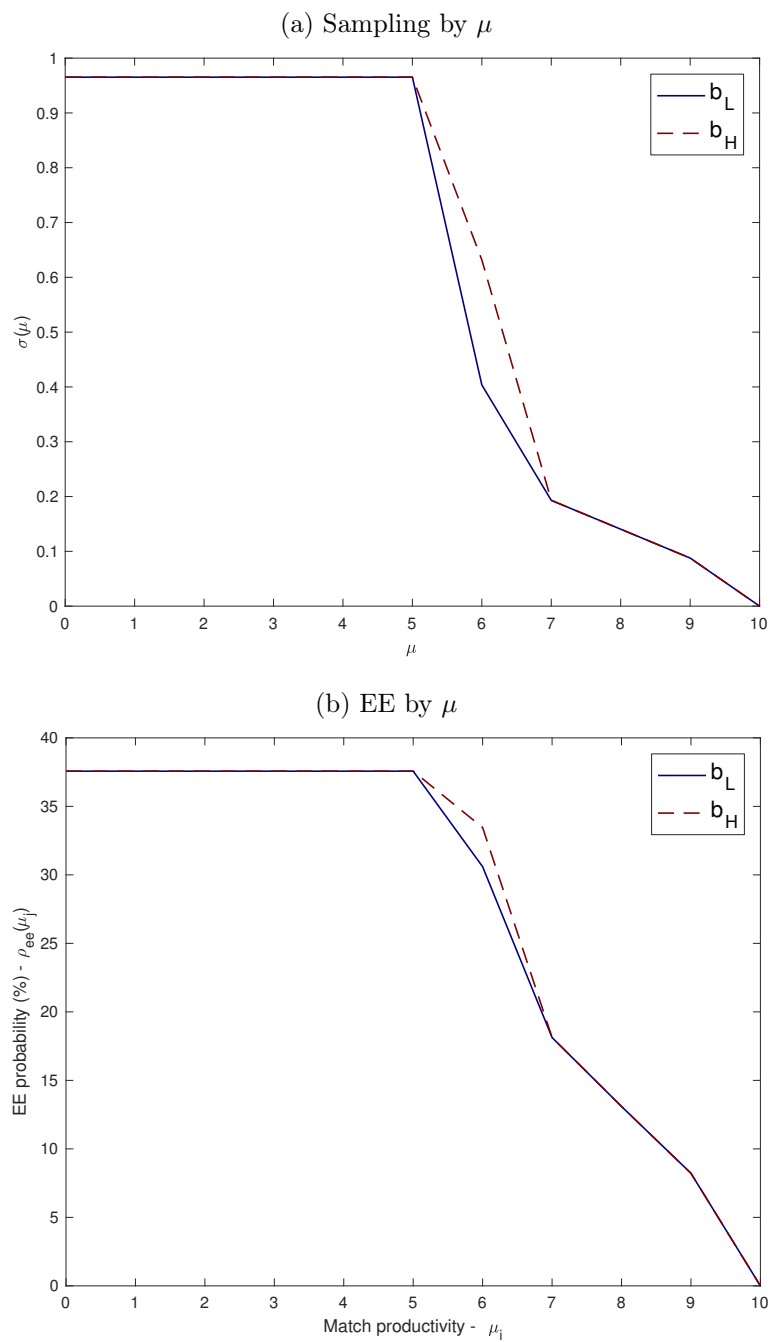
Notes: This figure plots the expected value of lotteries against their ex-ante downside risk under low and high unemployment benefit regimes. Risk is calculated under the low unemployment benefit regime. Market tightness is kept fixed across regimes.

Figure 2.20: Risk vs Change in Value



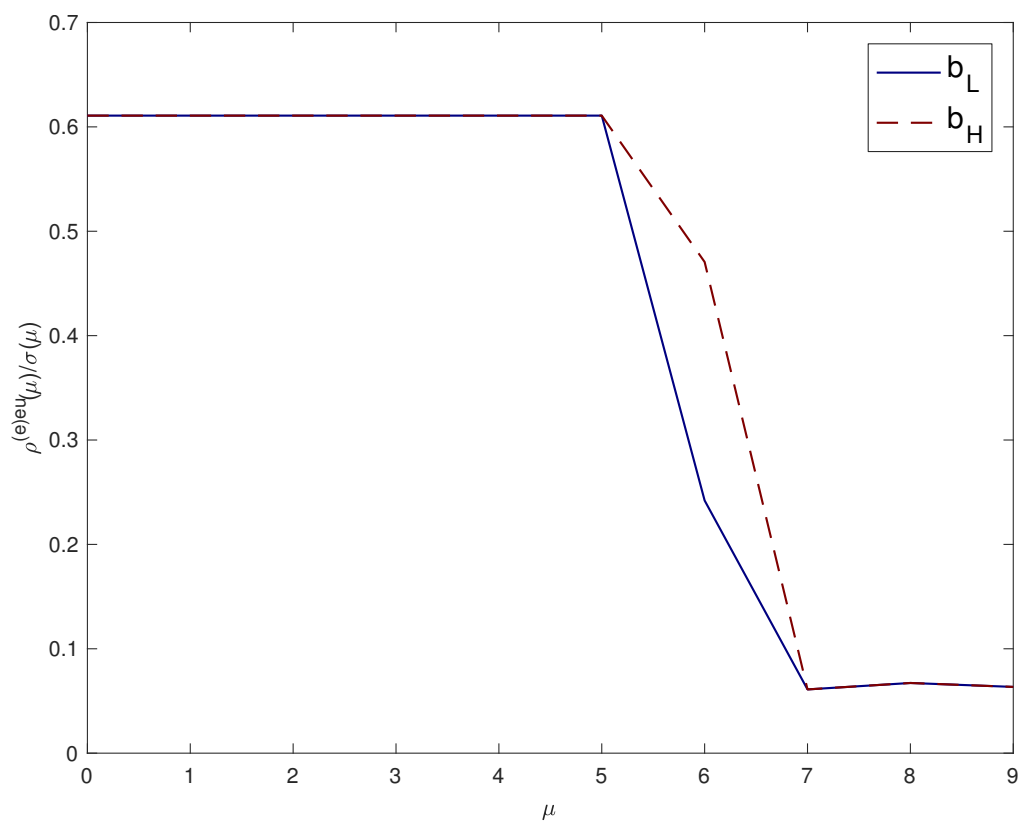
Notes: This figure plots the change in expected lottery value from the low to the high UI regime against lottery risk.

Figure 2.21: Sampling and Job Mobility Probabilities by Productivity



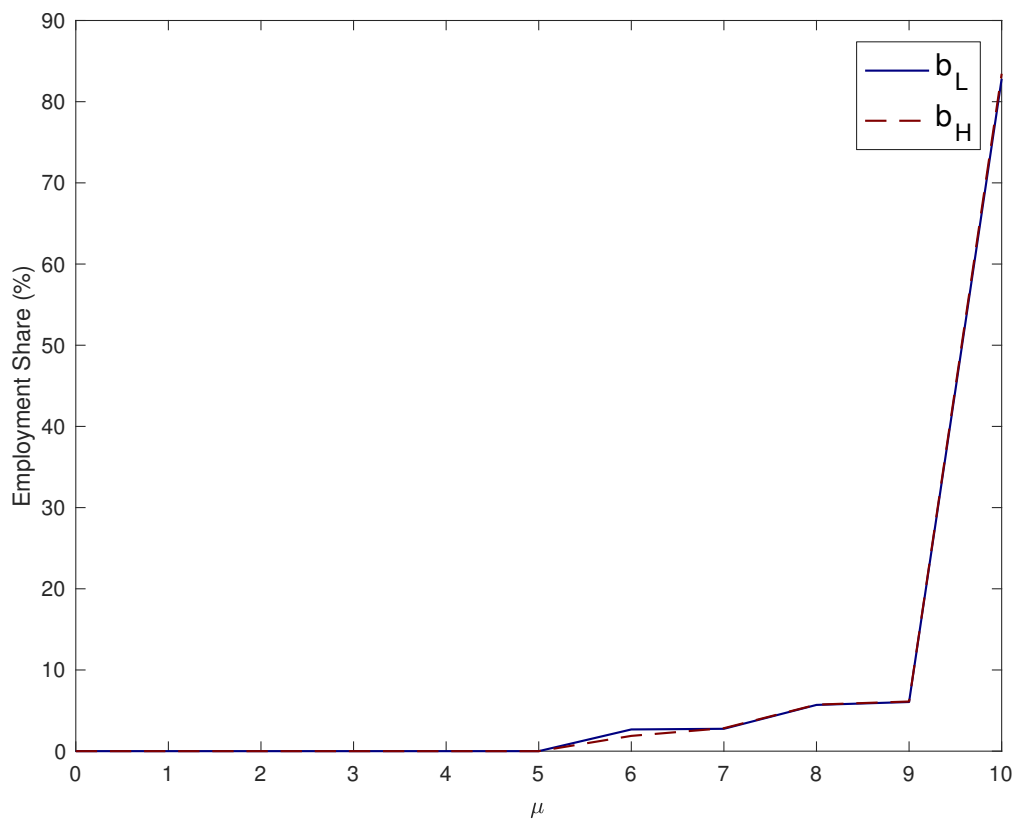
Notes: Panel (a) plots the sampling rate of a worker by μ . Panel(b) plots the job mobility rate by μ .

Figure 2.22: Share of Quits in Sampled Lotteries



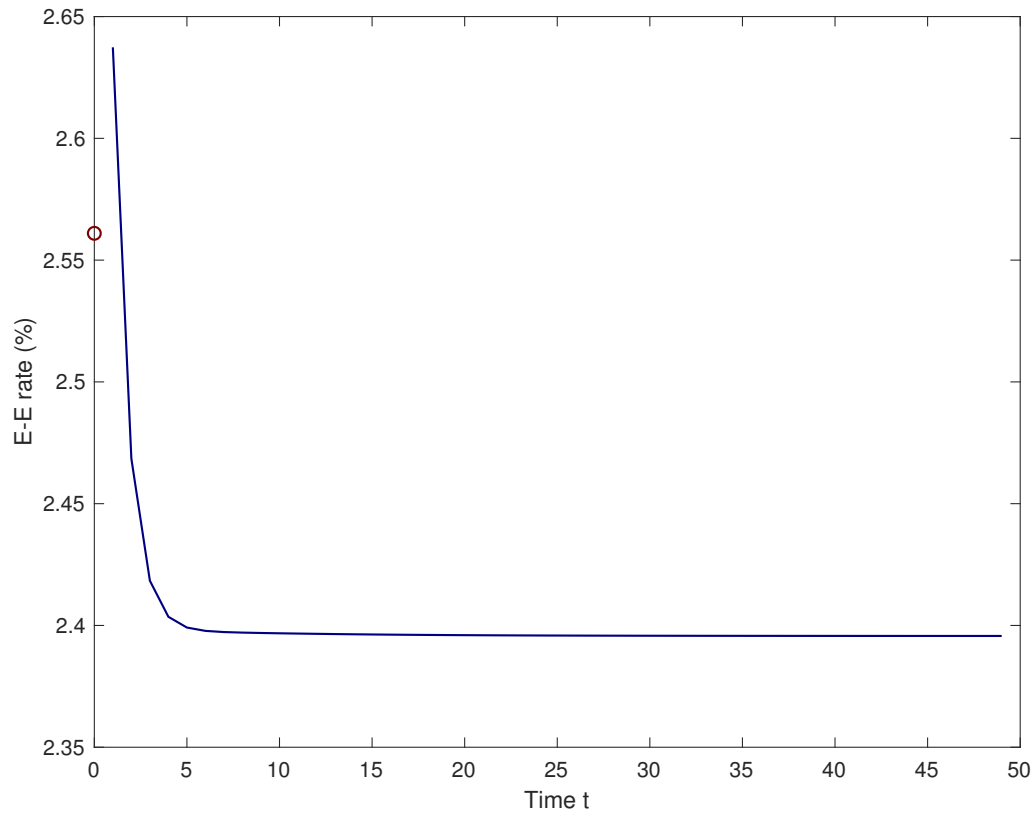
Notes: This figure plots the share of sampled lotteries that result in a quit to unemployment by match productivity.

Figure 2.23: Employment Distribution



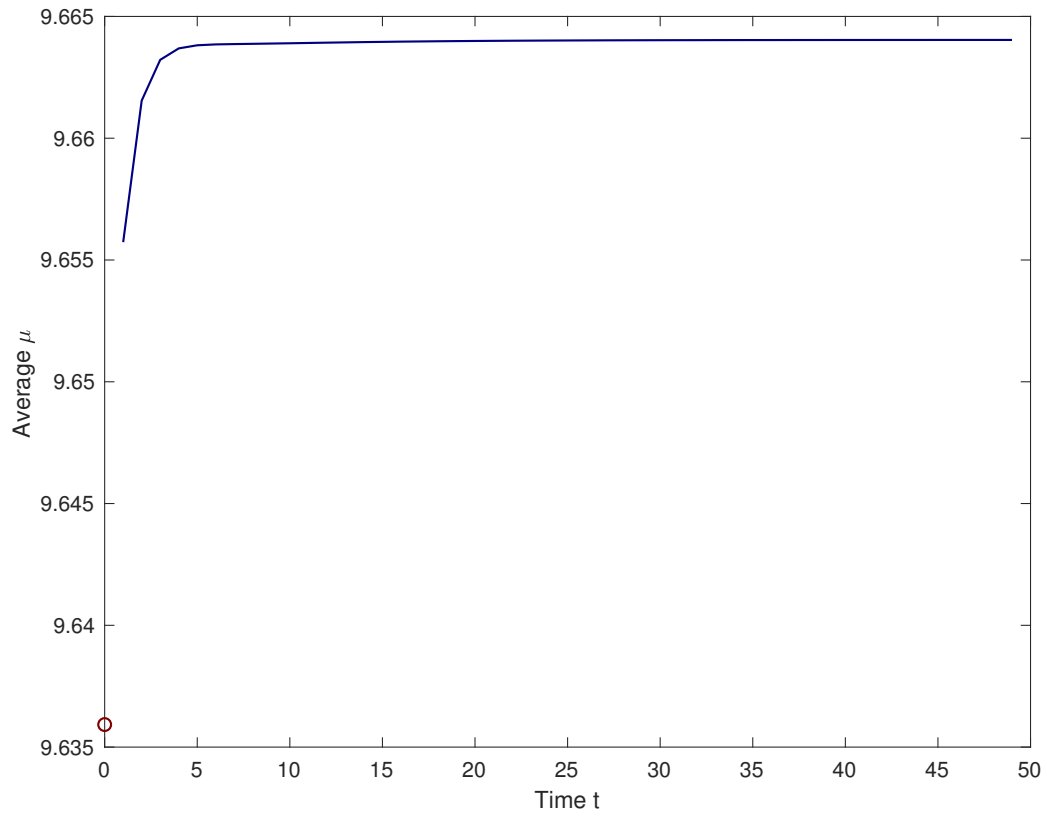
Notes: This figure plots the employment share by match productivity under the low and high UI regimes.

Figure 2.24: 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 2.25: Average μ



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

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Appendix A

Appendix to Chapter 1

A.1 Appendix: Data

In this section I discuss data sources used in my empirical analysis.

Current Population Survey (CPS) The CPS is not strictly a panel, but its rotating panel structure allows tracking individuals over a limited duration. In the CPS, interviewees are surveyed for four consecutive months, and then take an eight month break followed by another four months of interviews. I use the basic monthly files of the CPS starting from 1994, when a redesign of the survey made it possible to measure employer-to-employer transitions directly. Specifically, a new question was introduced that asks individuals whether they are employed at the same employer as in the previous month.¹ I define an employer-to-employer transition as an event where a worker is employed in two consecutive months but reports a change in employer in the latter month.

Basic monthly CPS files do not provide a start date for the current job nor a measure of tenure. Therefore, I turn to the Employee Tenure and Occupational Mobility Supplements of the CPS administered every two years. I use the supplements from 1996 to 2016. To construct E-E transitions by tenure I merge the monthly files and tenure supplements and record the tenure at the time of an E-E event. My early period sample pools data from the 1996, 1998 and 2000 supplements, whereas the late period pools data from the 2010, 2012, 2014 and 2016 supplements. All CPS data are obtained from the Integrated Public Use Microdata Series (Flood et al.

¹ See Fallick and Fleischman 2004 for the details of the redesign of the CPS and measuring E-E transitions.

n.d.).²

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 (called a “reference period”). A new set of households are sampled every two to four years (called “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 possibly up to four years, whereas in the CPS this is much shorter.³

In my analysis, I use the 1993, 1996, 2001 and 2008 panels in calculating measures of E-E transitions. I construct my sample similar to Nagypál 2008 in order to make indicators of labor market status consistent with the CPS. I use the reported status of workers in the last week of each month to categorize them as employed, unemployed and out of the labor force.

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.⁴ Using this information, I determine which employer the worker held a job at in each month of the reference period. In case of multiple jobs, I define worker’s main job to be the one where she has worked the most hours. If hours worked are equal then I choose the job that was held the longest.

Using the monthly employment status and job identifier variables, I define an employer-to-employer transition as an event where a worker is employed in two consecutive months with a change in job ID. I compute the tenure at transition using the job start and separation dates. I exclude individuals who are enrolled in school or in the army. In my analysis of the job mobility and age/tenure profiles I use the panels of 1996 and 2008 for the early and late periods. The 1996 panel covers the period between December 1995 and January 1999. The 2008 panel covers the period between May 2008 and November 2013.

CPS does not provide a measure of earnings at the monthly frequency. Therefore, to study the wage dynamics upon job change I create a panel of hourly wages from the SIPP. To do so, I further exclude individuals who report to be non-profit or family workers. I also drop observations where wages are imputed. For earnings

² Data can be downloaded from <https://cps.ipums.org/cps/>.

³ Furthermore, 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.

⁴ These variables are `een01` and `een02`. SIPP also provides identifiers for spells of self-employment but I exclude them from my analysis. Job IDs in the 1993 panel are subject to miscoding as identified in Stinson 2003 and pointed out in Fujita and Moscarini 2017. I correct for miscoding by using the revised job IDs.

reported at the monthly level, I convert them to an hourly basis by dividing earnings by the total number of hours worked. I deflate nominal hourly wages by the personal consumption expenditures price index to calculate real wages. To compute residual wages, I follow Tjaden and Wellschmied 2014 and I regress the logarithm of real hourly wages on dummies for worker age, gender, disability status, education level (less than high-school, high-school, some college, college and higher), race (white, black, hispanic, other), marital status, number of kids and state. I also control for potential experience and experience squared. The R^2 from the Mincer regression in my sample, which covers the period between 1996 to 2013, is 0.3591 and the variance of residual wages is .188, which is comparable to the same statistics, 0.37 and 0.21 respectively, from the Tjaden and Wellschmied 2014 sample which covers the 1993 – 1996 period.

Panel Study of Income Dynamics (PSID) CPS data only allow direct measures of job mobility starting from February 1994. I turn to the PSID to construct a longer time-series of E-E transitions.

The PSID is an annual panel survey of households that started in 1968. In this regard it is well-suited to track individuals for long periods of time. Unfortunately, data before 1988 do not allow for constructing monthly employment spells. In addition, PSID started administering the survey bi-annually after 1997, which intensified concerns about respondent recall bias. To keep my job mobility measure as consistent as possible with the CPS and SIPP, I limit my analysis to 10 waves of the PSID between 1988 and 1997.

Questions related to labor market status are retrospective. Employed individuals are asked to report the date that they started their current job as well as the months they were with their current employer in the previous year. In case they held another main job, they are also asked to provide which months they were employed at that employer together with the start and end dates. A similar set of questions are asked to currently unemployed workers. They report the end date of their last job together with the months in which the job was held. In addition, they report the start and end dates of the job they held before their last one. This enables me to keep track of the employment status of an individual and identify job switches at a monthly frequency.

I use the algorithm provided in Upward 1999 to create a monthly panel of workers between 1988 and 1997. I restrict my sample to male household heads between ages 20 and 65 and I only include individuals belonging to the core sample. I define an E-E transition analogously to the CPS and SIPP samples.

Longitudinal Employer-Household Dynamics (LEHD) Job-to-Job Flows

LEHD is a linked employer-employee panel that covers over 95 percent of U.S. private sector jobs. The data are collected with a federal-state data sharing collaboration called the Local Employment Dynamics (LED) partnership. The Census integrates different sources and provides a number of publicly available statistics based on the micro data.⁵ Earliest data are available starting from the second quarter of 2000.

I use the quarterly Job-to-Job (J-J) Flows that Census publishes on hires and separations.⁶ In this data set, J-J hires are defined as “hires that are part of a job-to-job move with little to no non-employment between jobs” and similarly, J-J separations are defined as “separations that are part of a job-to-job move with little to no non-employment between jobs”. The rates are simply calculated as the share of hires and separations in average employment over the quarter. In addition to national averages, Census constructs job mobility measures by worker and firm characteristics, as well as geographical location. Publicly available data also report job mobility from an origin to a destination state by gender and age group together with average monthly earnings prior to and following job-to-job flows. This information allows me to analyze any trend in wage growth conditional on a job change since 2000.

Employment Opportunities Pilots Project (EOPP)

EOPP is an establishment level survey conducted in 1980 with a follow-up conducted in 1982, sponsored by the National Institute of Education and the National Center for Research in Vocational Education. In the 1982 survey, sampled establishments were asked to provide information about their last hire prior to August 1981, together with resources allocated for screening and interviewing to fill the position.

To test the relationship between perceived productivity and match stability, I use a number of variables pertaining to the last hired worker’s income and productivity. Specifically, establishments are asked to provide a current productivity score (or the last productivity score if the worker had left at the time of the survey) for the worker, relative to their most productive worker in a similar position. They also provide the productivity score for a typical worker who has been in this job for two years. In addition, they provide the starting hourly wage as well the current wage for this worker. Finally, I use information whether the last hired worker is still with the firm, and if not the reason for her separation. See Barron and Bishop 1985 for more details.

⁵ They are available at <https://lehd.ces.census.gov/data/>.

⁶ Available at https://lehd.ces.census.gov/data/j2j_beta.html.

A.2 Appendix: Model

In this section I elaborate some of the derivations omitted in the main text and provide computational details. Section A.2 derives the surplus equation from the individual value functions. A.2 derives the prior updating formulas using Bayes' rule. A.2 explains how I simulate wages. A.2 presents the flow equations I use to obtain the stationary worker distribution. A.2 presents the algorithm I use for solving and simulating the model.

Deriving Surplus

Rearranging individual value functions 1.5, 1.6 and 1.7 and making use of the bargaining rule for the poacher in equation 1.2; W , U and J can be expressed as the following three equivalent value functions:

$$\begin{aligned}
 W(p, a, r) = & r\mathbb{E}[\mu|p] + \beta U(a + 1) \\
 & + \beta \left[\delta \rho \phi \int_0^1 \max\{0, S(p_0, a + 1)\} dG(p_0) \right. \\
 & + (1 - \delta) \int_0^1 \max \left\{ 0, \right. \\
 & (1 - f^W + f^W G(q(p', a + 1, r))) (W(p', a + 1, r) - U) \\
 & + f^W \int_{p'}^1 (W(p_0, a + 1, r') - U(a + 1)) dG(p_0) \\
 & \left. \left. + f^W \int_{q(p', a + 1, r)}^{p'} (W(p', a + 1, r') - U(a + 1)) dG(p_0) \right\} G(dp' | p) \right] \text{ for } a \leq T.
 \end{aligned}$$

$$\begin{aligned}
 U(a) = & b + \beta U(a + 1) \\
 & + \beta \left[f^U \phi \int_0^1 \max \{0, S(p_0, a + 1)\} dG(p_0) \right] \text{ for } a \leq T.
 \end{aligned}$$

$$\begin{aligned}
 J(p, a, r) = & (1 - r)\mathbb{E}[\mu|p] + \beta(1 - \delta) \left[\int_0^1 \max \left\{ 0, \right. \right. \\
 & (1 - f^W + f^W G(q(p', a + 1, r))) J(p', a + 1, r) \\
 & \left. \left. + f^W \int_{q(p', a + 1, r)}^{p'} J(p', a + 1, r') dG(p_0) \right\} G(dp' | p) \right] \text{ for } a \leq T.
 \end{aligned}$$

Now, using the definition of surplus in equation 1.1 and making use of the wage rule in equation 1.2 again, it is then straightforward to reach the desired expression in equation 1.8. Note that in this derivation all terms involving the piece rate r cancels out.

Forming Beliefs

In a match, let the firm's and worker's information set after having observed random output y_τ be denoted by $I_\tau = (y_\tau, I_{\tau-1})$. Suppose the agents enter period τ with a prior $p_{\tau-1}$. The agents use Bayes' rule to update their belief about the underlying match being high productivity. Formally,

$$\begin{aligned}
p_\tau &\equiv Pr[\mu = \mu_H | I_\tau] \\
&= \frac{Pr[\mu = \mu_H \cap I_\tau]}{Pr[I_\tau]} \\
&= \frac{Pr[\mu = \mu_H \cap y_\tau \cap I_{\tau-1}]}{Pr[I_\tau]} \\
&= \frac{Pr[y_\tau | \mu = \mu_H \cap I_{\tau-1}] Pr[\mu = \mu_H \cap I_{\tau-1}]}{Pr[I_\tau]} \\
&= \frac{Pr[y_\tau | \mu = \mu_H] Pr[\mu = \mu_H | I_{\tau-1}] Pr[I_{\tau-1}]}{Pr[I_\tau]} \\
&\stackrel{a}{=} \frac{\frac{1}{\sqrt{2\pi\sigma_Y^2}} \exp[-\frac{1}{2}(y_\tau - \mu_H)^2/\sigma_Y^2] p_{\tau-1} Pr(I_{\tau-1})}{Pr(I_\tau)} \\
&\stackrel{b}{=} \frac{p_{\tau-1} \exp[-\frac{1}{2}(y_\tau - \mu_H)^2/\sigma_Y^2] Pr(I_{\tau-1})}{p_{\tau-1} \exp[-\frac{1}{2}(y_\tau - \mu_H)^2/\sigma_Y^2] Pr(I_{\tau-1}) + (1 - p_{\tau-1}) \exp[-\frac{1}{2}(y_\tau - \mu_L)^2/\sigma_Y^2] Pr(I_{\tau-1})} \\
p_\tau &= \frac{p_{\tau-1} \exp[-\frac{1}{2}(y_\tau - \mu_H)^2/\sigma_Y^2]}{p_{\tau-1} \exp[-\frac{1}{2}(y_\tau - \mu_H)^2/\sigma_Y^2] + (1 - p_{\tau-1}) \exp[-\frac{1}{2}(y_\tau - \mu_L)^2/\sigma_Y^2]}
\end{aligned}$$

where steps a and b use the normality of the conditional distribution of y_τ . This yields the desired result in equation 1.11.

Now suppose the firm and worker observe match output $y_{\tau+1}$ in the subsequent

period. The posterior in period $\tau + 1$ is then

$$\begin{aligned}
p_{\tau+1} &= \frac{p_{\tau} \exp\left[-\frac{1}{2} \frac{(y_{\tau+1} - \mu_H)^2}{\sigma_Y^2}\right]}{p_{\tau} \exp\left[-\frac{1}{2} \frac{(y_{\tau+1} - \mu_H)^2}{\sigma_Y^2}\right] + (1 - p_{\tau}) \exp\left[-\frac{1}{2} \frac{(y_{\tau+1} - \mu_L)^2}{\sigma_Y^2}\right]} \\
&= \frac{p_{\tau-1} \exp\left[-\frac{1}{2} \frac{(y_{\tau} - \mu_H)^2}{\sigma_Y^2}\right] \exp\left[-\frac{1}{2} \frac{(y_{\tau+1} - \mu_H)^2}{\sigma_Y^2}\right]}{p_{\tau-1} \exp\left[-\frac{1}{2} \frac{(y_{\tau} - \mu_H)^2}{\sigma_Y^2}\right] \exp\left[-\frac{1}{2} \frac{(y_{\tau+1} - \mu_H)^2}{\sigma_Y^2}\right] + (1 - p_{\tau-1}) \exp\left[-\frac{1}{2} \frac{(y_{\tau} - \mu_L)^2}{\sigma_Y^2}\right] \exp\left[-\frac{1}{2} \frac{(y_{\tau+1} - \mu_L)^2}{\sigma_Y^2}\right]} \\
&= \frac{p_{\tau-1} \exp\left[-\frac{1}{2} \frac{(\frac{\sum_{t=\tau}^{\tau+1} y_t}{2} - \mu_H)^2}{\sigma_Y^2/2}\right]}{p_{\tau-1} \exp\left[-\frac{1}{2} \frac{(\frac{\sum_{t=\tau}^{\tau+1} y_t}{2} - \mu_H)^2}{\sigma_Y^2/2}\right] + (1 - p_{\tau-1}) \exp\left[-\frac{1}{2} \frac{(\frac{\sum_{t=\tau}^{\tau+1} y_t}{2} - \mu_L)^2}{\sigma_Y^2/2}\right]}.
\end{aligned}$$

By induction, the n -step ahead posterior is simply

$$p_{\tau+n} = \frac{p_{\tau} \exp\left[-\frac{1}{2} \frac{(\frac{\sum_{t=\tau+1}^{\tau+n} y_t}{n} - \mu_H)^2}{\sigma_Y^2/n}\right]}{p_{\tau} \exp\left[-\frac{1}{2} \frac{(\frac{\sum_{t=\tau+1}^{\tau+n} y_t}{n} - \mu_H)^2}{\sigma_Y^2/n}\right] + (1 - p_{\tau}) \exp\left[-\frac{1}{2} \frac{(\frac{\sum_{t=\tau+1}^{\tau+n} y_t}{n} - \mu_L)^2}{\sigma_Y^2/n}\right]}.$$

By realizing that the starting prior of firms and workers is p_H due to rationality, one gets the desired result in equation 1.12.

Simulating Wages

Even though the level of wages is not necessary to solve the model and simulate worker flows, I still need to characterize the re-bargaining threshold $q(p, a, r)$ to study the income related implications of the model.

To obtain an expression for wages, subtract unemployment value from employment value for a given piece-rate r . Defining the survival function as $\bar{G}(x) \equiv 1 - G(x)$ and using bargaining rules presented in section 1.3, this yields

$$\begin{aligned}
W(p, a, r) - U(a) = & r\mathbb{E}[\mu|p] - b \\
& - \beta \left[f^U \phi \int_0^1 \max\{0, S(p_0, a+1)\} dG(p_0) \right] \\
& + \beta \delta \rho \phi \left[\int_0^1 \max\{0, S(p_0, a+1)\} dG(p_0) \right] \\
& + (1 - \delta) \beta \mathbb{E}_{s'|s,e} \left[\int_0^1 \max\{0, \right. \\
& (1 - f^W \bar{G}(q'))(W(p', a+1, r) - U) + f^W \bar{G}(q')S(p', a+1) \\
& + f^W \phi \int_{p'}^1 (S(p_0, a+1) - S(p', a+1)) dG(p_0) \\
& \left. + f^W (1 - \phi) \int_{q(p', a+1, r)}^{p'} (S(p_0, a+1) - S(p', a+1)) dG(p_0) \right\} G(dp'|p) \right] \text{ for } a \leq T.
\end{aligned}$$

To characterize the cutoff prior q below which offers are discarded, substitute in the indifference condition in equation 1.4. Noting that the piece-rate r stays the same on both sides of the previous expression, one obtains

$$\begin{aligned}
(1 - \phi)S(q(p, a, r), a) + \phi S(p, a) = & r\mathbb{E}[\mu|p] - b \tag{A.2.1} \\
& - \beta \left[f^U \phi \int_0^1 \max\{0, S(p_0, a+1)\} dG(p_0) \right] \\
& + \beta \delta \rho \phi \left[\int_0^1 \max\{0, S(p_0, a+1)\} dG(p_0) \right] \\
& + \beta(1 - \delta) \left[\int_0^1 \max\{0, (1 - \phi)S(q(p', a+1, r), a+1) + \phi S(p', a+1) \right. \\
& + (1 - \phi)f^W \bar{G}(q(p', a+1, r))(S(p', a+1) - S(q(p', a+1, r), a+1)) \\
& + f^W \phi \int_{p'}^1 (S(p_0, a+1) - S(p', a+1)) dG(p_0) \\
& \left. + f^W (1 - \phi) \int_{q(p', a+1, r)}^{p'} (S(p_0, a+1) - S(p', a+1)) dG(p_0) \right\} G(dp'|p) \right] \text{ for } a \leq T.
\end{aligned}$$

This equation may be solved by backward iteration, starting from the latest period with all values set to 0. As a result, one obtains a mapping from a combination of p, a, r values to a cutoff value q . Using this mapping, one can then simulate piece-rate r given the workers p, a and threshold q . The flow wage level is simply $r\mathbb{E}[\mu|p]$.

Worker Flows

All workers are born unemployed. Therefore, $u_1 = 1$ and $e_{p1} = 0 \forall p \in (0, 1)$.

A worker rejects/quits her job if her surplus drops below zero, then the prior cutoff below which workers quit/reject jobs is characterized by

$$S(p^*(a), a) = 0.$$

To differentiate employed and unemployed workers, I use subscripts U and Q . Employed workers whose prior fall below $p_Q^*(a)$ quit their jobs and unemployed workers who receive an offer below $p_U^*(a)$ reject the match.

Unemployment The flow equation for unemployed workers is defined for $a \leq T$ by

$$\begin{aligned} u_a = & \delta(1 - \rho)e_{a-1} + (1 - f^U \bar{G}[p_U^*(a-1)])u_{a-1} & (\text{A.2.2}) \\ & + (1 - \delta) \left(\int_p e_{pa-1} G[p_Q^*(a-1)|p] dp \right) \\ & + \delta \rho \left(\int_p e_{pa-1} G[p_U^*(a-1); s] dp \right) \text{ for } 2 \leq a \leq T. \end{aligned}$$

The first term captures exogenous separations from employment into unemployment. The second term corresponds to workers who stay unemployed from the previous period. The third term corresponds to endogenous separations into unemployment. The fourth term captures workers who receive a reallocation shock, reject their offer and move into unemployment. All flows account for aging of workers.

Employment The flow equation for employed workers is defined for $a \leq T$ by

$$\begin{aligned} E_{pa} = & f^U (G[p] - G[p_U^*(a-1)])u_{a-1} & (\text{A.2.3}) \\ & + (1 - \delta)(1 - f^W) \left\{ \int_{\tilde{p}} e_{\tilde{p}a-1} (G[p|\tilde{p}] - G[p_Q^*(a-1)|\tilde{p}]) d\tilde{p} \right\} \\ & + (1 - \delta)f^W \times \\ & \left\{ \int_{\tilde{p}} e_{\tilde{p}a-1} \left[\int_{p_Q^*(a-1)}^p G[\tilde{p}'] g[\tilde{p}'|\tilde{p}] d\tilde{p}' + \int_{p_Q^*(a-1)}^1 (G[p] - G[\tilde{p}']) g[\tilde{p}'|\tilde{p}] d\tilde{p}' \right] d\tilde{p} \right\} \\ & + \delta \rho \left\{ \int_{\tilde{p}} e_{\tilde{p}a-1} (G[p] - G[p_U^*(a-1)]) d\tilde{p} \right\} \text{ for } 2 \leq a \leq T. \end{aligned}$$

The left hand side is the share of workers employed with age a that have a prior less than p , that is $E_{pa} = \int_0^p e_{\tilde{p}a} d\tilde{p}$. The first term on the right hand side corresponds to flows from unemployment into employment. The second term is workers who do not receive outside offers and whose priors evolve to be less than p . The following two terms are workers who receive outside offers, who switch to a new job with $p_0 < p$ or those who reject the outside offer and their priors evolve to be lower than p . The last term captures workers who receive a reallocation shock and take the outside offer. All flows account the aging of workers.

Computational Details

This section provides details on how I solve and simulate the model.

Solution

Rather than solving the individual worker and firm value functions, I directly work with the value of joint surplus from a match. Therefore, I do not have to determine the level of wages at the solution phase. I discretize the state space of prior p and use value function iteration with linear interpolation to solve the model. The algorithm I use is outlined 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) Start from terminal value of surplus $S(p, T + 1) = 0$ for all p .
 - b) Iterate on equation 1.8 backward to solve $S(p, a)$ for $1 \leq a \leq T$.
 - c) Using a much finer grid than used for the value functions, iterate on the laws of motion in equations A.2.2 and A.2.3 to compute the steady-state values of employment and unemployment shares by prior and age, e_{pa} and u_a .
 - d) Solve the market tightness level $\tilde{\theta}_{n+1}$ that satisfies the free entry condition in equation 1.10. Calculate its percent deviation from θ_n .
 - e) If the percent deviation is less than the tolerance level of 10^{-3} , 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 $\omega = 0.7$.

Simulation and Calibration

For the baseline calibration of the model, I first create a coarse grid over the parameter space $(p_H, \sigma_Y, \lambda, b, \kappa)$. Then for each parameter combination in this space, I solve the decision problem of workers according to the algorithm outlined above, simulate the model with 100,000 workers and compute simulated moments. Afterward, I calculate the sum of squared percent deviations between the model moments and their empirical counterparts. I determine a number of candidate solutions from this grid search. Finally, using these points as initial values, I use a derivative free optimization method to find the parameter combination that yields the best fit. In all parameterization, I ensure that $b < p_H\mu_H + (1 - p_H)\mu_L$ to have a non-trivial equilibrium.

For the joint estimation of n and λ , I need to simulate wages. To do this, I create a grid for r and solve the cutoff prior q for each combination of p , a and r according to equation A.2.1 using the solution for S . This gives me a one-to-one mapping between q and p, a, r tuples. By inverting this mapping, I obtain a mapping from p, a, q tuples to r . For off grid values, I linearly interpolate this piece-rate wage function. This allows me to simulate piece-rates given a worker's age, the prior about the productivity of her match (incumbent or poacher, depending on the winner of the auction) and her bargaining benchmark (her current job's prior if switching, her prior for the outside offer if re-bargaining or the cutoff prior for accepting a job if moving from unemployment). With the simulated piece-rates, obtaining wages is straightforward.

A.3 Appendix: Additional Tables and Figures

Perceived Productivity and Match Stability

Table A.1: Regression Results from the EOPP

	(1)	(2)	(3)	(4)	(5)
	$\Delta \log(w)$	$\Delta \log(w)$	$\mathbb{I}(Promoted)$	$\mathbb{I}(Fired)$	$\mathbb{I}(Quit)$
$\Delta \log(p)$	0.0887*** (0.0120)	0.0634*** (0.0138)	0.287*** (0.0346)	-0.538*** (0.0492)	-0.220*** (0.0375)
$\mathbb{I}(Promoted)$		0.0881*** (0.0126)			
Dummies					
Industry	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes
Observations	1420	1407	1607	1612	1612

Notes: This table presents results from worker-level regressions using the EOPP survey. Standard errors are in parenthesis and clustered at the two digit SIC industry level. *** p<0.01, ** p<0.05, * p<0.1.

My model predicts a negative relationship between bad surprises about a match's productivity and stability. In this section, I use the Employment Opportunities Pilot Project establishment survey (EOPP) to link separations and perceived worker productivity, and provide suggestive evidence for this mechanism of the model.

The EOPP asks a number of questions about the last hire (prior to August 1981) of a sample of establishments.⁷ One of the questions in the survey asks the employer to assign a current productivity score for the last hire with respect to the most productive worker that the establishment employs. The survey also provides a productivity score for the typical worker who has been working in that position for

⁷ Data available at https://ciser.cornell.edu/ASPs/search_athena.asp?IDTITLE=427. I elaborate on the EOPP in appendix A.1.

two years. Furthermore, this worker’s starting and current wage, and her employment status with the firm (and if she left, her reason for separation) are available.

I interpret the difference between the last hire’s and the typical worker’s productivity scores as a revelation of information about the match quality. That is, if the perceived productivity of the hire turns out to be higher than the typical worker’s, the match is revealed to be more productive than what was expected initially, and vice versa. To the best of my knowledge, the EOPP is the only data source that provides information on separations by reason, together with the perceived productivity of a match.

Using data from the EOPP, I run regressions of the form

$$y_{i(j)} = \alpha + \beta \Delta \log(p) + \gamma_j + \eta_i + \phi_i + \delta_i + \epsilon_{ij}$$

where $y_{i(j)}$ is an outcome for worker i employed at an establishment in industry j . $\Delta \log(p)$ is the log difference of current perceived productivity of the last hire and the typical worker. $\gamma_j, \eta_i, \phi_i, \delta_i$ are industry, gender, education and age fixed effects, respectively. The dependent variables are the log difference of the worker’s current and starting wage, indicators for promotion, being fired, or quitting.

Table A.1 reports results from these regressions. Specifically, columns (1) and (2) show that a positive surprise in worker productivity is associated with an increase in wages, even after controlling for promotions. Column (3) shows that workers perceived to be more productive than expected are more likely to be promoted. Columns (4) and (5) show that an increase in perceived productivity is associated with a decrease in fires and voluntary quits. These results indicate that negative revelations about match quality are associated with separations, and positive surprises are related to wage increases and match stability.

Figures

Figure A.1: Measures of Resources Allocated to Hiring and Job Search



Note: This figure presents different measures of resources spent on hiring and job search. Panel (a) plots normalized log real values of production by a number of service industries against GDP in the U.S., based on BLS Labor Productivity and Costs database. Panel (b) plots the employment share of Employment Placement Agencies and Executive Search Services industry in total employment using ACS samples. Panel (c) plots the employment share of occupations related to human resources in total employment based on Census/ACS samples. Panel (d) plots the share of workers in the labor force that use internet for job search conditional on having internet access at home, based on CPS Internet and Computer Use supplements.

Appendix B

Appendix to Chapter 2

B.1 Appendix: Model

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

Derivation of Surplus

We use worker value functions in Equations 2.1 and 2.2 to calculate worker surplus, $W(\mu) - U$. Simple algebraic manipulation yields the following

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

We add firm's value, $J(\mu)$ to the expression above, and use the definition of match surplus in 2.7 to arrive at

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

Finally using the linear surplus sharing rules in Equations 2.5 and 2.6, we cast everything in terms of total match surplus

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

Eliminating the redundant max operator in the final term, we arrive at the desired expression in Equation 2.7.

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.

$$\begin{aligned}
u = & \left[(1 - f) + f \sum_{i=1}^n Pr(\vec{q}_i) \vec{q}_i \mathbb{I}\{S(\vec{\mu}') < 0\} \right] u \\
& + \delta(1 - u) \\
& + (1 - \delta)\lambda f \times \\
& \sum_{k=1}^m \left[\sum_{i=1}^n Pr(\vec{q}_i) \mathbb{I}\left\{ S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'), 0\} \right\} \sum_j q_{ij} \mathbb{I}\{S(\mu_j) < 0\} \right] e(\mu_k)
\end{aligned} \tag{B.1.1}$$

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

$$\begin{aligned}
e(\mu_j) = & (1 - \delta) \left[(1 - \lambda f) + \lambda f \sum_{i=1}^n Pr(\vec{q}_i) \mathbb{I}\left\{ S(\mu_j) > \vec{q}_i \max\{S(\vec{\mu}'), 0\} \right\} \right] e(\mu_j) \\
& + (1 - \delta)\lambda f \times \\
& \sum_{k=1}^m \left[\sum_{i=1}^n Pr(\vec{q}_i) \mathbb{I}\left\{ S(\mu_k) < \vec{q}_i \max\{S(\vec{\mu}'), 0\} \right\} q_{ij} \mathbb{I}\{S(\mu_j) > 0\} \right] e(\mu_k) \\
& + f \left[\sum_{i=1}^n Pr(\vec{q}_i) q_{ij} \mathbb{I}\{S(\mu_j) > 0\} \right] u.
\end{aligned} \tag{B.1.2}$$

The first line captures employed workers in type- μ_j jobs, who do not 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.2 Appendix: Computational Details

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

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 2.7 to solve $S(\mu)$.
 - b) Iterate on the laws of motion in equations B.1.1 and B.1.2 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 2.8. 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 $\omega = 0.85$.

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.

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 $\max_{1 \leq t < T} |\theta_t^1 - \theta_t^0| < \epsilon$. 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.