

Business Cycles, Unemployment and Job Search

Essays in Macroeconomics and Labor Economics

Andreas Mueller





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Abstract

This thesis consists of four essays.

The first essay, "Separations, Sorting and Cyclical Unemployment", establishes a new fact about the compositional changes in the pool of unemployed over the U.S. business cycle and evaluates a number of theories that can potentially explain it. Using longitudinal micro data from the Current Population Survey 1979-2008, it documents that in recessions, the pool of unemployed shifts towards workers with high wages in their previous job. Moreover, it shows that these changes in the composition of the unemployed are mainly due to the higher cyclicalities of separations for high-wage workers, and not driven by differences in the cyclicalities of job-finding rates. A search-matching model with endogenous separations and worker heterogeneity in terms of ability has difficulty in explaining these patterns. But an extension of the model with credit-constraint shocks does much better in accounting for the new facts. The reason is that at the productivity threshold where separations occur, matches with high-ability workers produce more negative cash flows and separations of these workers are thus more sensitive to a tightening of credit than separations of low-ability workers.

The second essay, "The Lot of the Unemployed: A Time Use Perspective", provides new evidence on the time use of employed and unemployed individuals in 14 countries. It devotes particular attention to characterizing and modeling job search intensity, measured by the amount of time devoted to searching for a new job. Job search intensity varies considerably across countries, and is higher in countries with higher wage dispersion. It also examines the relationship between unemployment benefits and job search.

The third essay, "Job Search and Unemployment Insurance: New Evidence from Time Use Data", provides new evidence on job search intensity of the unemployed in the U.S. The major findings are: 1) the average U.S. unemployed worker devotes about 41 minutes to job search on weekdays, which is substantially more than their European counterparts; 2) workers who expect to be recalled by their previous employer search substantially less than the average unemployed worker; 3) across the 50 states and D.C., job search is inversely related to the generosity of unemployment benefits, with an elasticity between -1.6 and -2.2; 4) job search intensity for those

eligible for Unemployment Insurance (UI) increases prior to benefit exhaustion; and 5) the time devoted to job search is fairly constant regardless of unemployment duration for those who are ineligible for UI.

The fourth essay, "On-the-Job Search and Wage Dispersion: New Evidence from Time Use Data", provides new evidence on the job search intensity of the employed in the U.S. As recently emphasized by Fallick and Fleischman (2004), around 2.6% of employed individuals change employment each month without going through a spell of unemployment. Why do so many employed workers change jobs each month? A model of on-the-job search and wage dispersion predicts that search effort should decrease with the current wage since the benefits of searching for a better job are higher the further down the worker is on the wage ladder. With data from the American Time Use Survey (ATUS), the implication of the model is tested, modeling search effort as time allocated to job search activities. The results show a negative and highly significant effect of the current wage on job search intensity, with an elasticity between -0.7 and -1.3.

To Helga Margrét

Acknowledgments

I very well remember the day when I decided to go to Geneva to study International Relations for my undergraduate degree. I was very excited; I was going to learn about the world and the big questions in international politics. The interdisciplinary character of the degree was what attracted me, but rapidly led to a big frustration. There were so many angles to each question, but no clear methodology in answering them. Luckily, one branch of the degree was international economics, and soon I was fascinated by the economist's approach to world affairs.

Towards the end of my studies in Geneva, I decided to apply for a PhD program in Economics, and it was one of my professors, Charles Wyplosz, who pointed me towards the IIES and the program in Stockholm. I was very excited when I came to Sweden to learn everything in Economics and, after nearly six years, I can say that my experience as a PhD student here was simply outstanding. The PhD program offers many great courses in the first years but, more importantly, I have greatly benefited from the unique intellectual environment at the Institute and the excellent supervision and advice from its faculty.

First and foremost, I would like to thank my advisor Per Krusell for his invaluable input into my research and thesis work and for devoting his time to answering my numerous questions, listening to my ideas and calming my insecurities. In many ways, Per has been crucial in the development of my research. I went to Princeton in the academic year 2007-08, where I took part in his macro group and thus could present my research to a small group of students and professors. This was a unique experience and greatly improved my research and presentation skills. The interaction with Per also sharpened my senses to look out for the important and unanswered questions. Needless to say, his comments and advice for the development of the job market paper as well as the job market process itself were immensely valuable.

I also owe special thanks to my co-author Alan B. Krueger, without whose enthusiastic support and guidance my academic path would have looked very different. Per Krusell introduced us in December 2007, and we hit it off immediately and embarked on an extremely productive collaboration. We started working together on a project that studied the time-use patterns of the unemployed for a conference in Amsterdam in April 2008, but very soon we discovered that there was room for more, wrote a follow up paper and collected our own time-use survey in New Jersey (the results of which unfortunately did not make it into this thesis). The collaboration with Alan was and still is a tremendous learning experience, and it opened my

eyes to empirical analysis in economic research.

I am indebted to Torsten Persson and John Hassler, whose advice and support were extremely valuable for my research and the job market, for having their doors open at all times and for taking the time to listen to my ideas and questions. I also benefited from many interesting discussions with other faculty at the IIES, especially Almut Balleer, Ethan Kaplan, Lars Calmfors, Tobias Broer and Emilia Simeonova. I am also grateful to Christina Lönnblad for excellent editorial assistance and all-encompassing support, to Karl Eriksson for superb computer assistance and to Annika Andreasson for her help in getting this thesis to print. Thanks also go to the faculty at the Stockholm School of Economics, where I spent the first one and a half years of my PhD. In particular, I very much valued the interaction with Martin Flodén and David Domeij.

My time here and in Princeton were great fun, thanks to my fellow graduate students and office mates, especially Shon Ferguson, David von Below, Dario Caldarà, Erik Meyersson, Erik Mohlin, Eva Ranehill, Ronny Freier, Marta Lachowska and Daniel Spiro. I am also indebted to my friend and co-author Mirko Abbritti, with whom I pursued a separate research project, for the productive meetings and many interesting conversations.

I would like to thank my parents Ivo and Regula for their love and support throughout the years, for encouraging me to develop my talents and for igniting in me that intellectual curiosity that is so crucial in academia. Special thanks go to all my friends and family who have been a source of inspiration as well as a basis for relaxation from academic stress and pressure. And I am grateful to my son Theodór for putting a smile upon my face every day and reminding me of the important things in life.

None of this, however, would have been possible without the unconditional love, patience and strength of my wife Helga Margrét. I am truly grateful to her for standing by me all this time, for accompanying me to Sweden, and to New York next year, for carrying on in difficult times and for cheering me up in moments of self-doubt. Her support and belief in me carried me through my studies and made me strive for the best. In deep love and admiration, it is to her that I dedicate this thesis.

Stockholm, April 2011

Andreas Mueller

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Chapter 1

Introduction

This thesis consists of four essays in macroeconomics and labor economics. Even though the essays are self-contained and differ in the methods used, the common denominator is the focus on the labor market and, more specifically, on the topic of unemployment. Chapter 2 studies the cyclical changes in the composition of the unemployment pool over the business cycle and Chapters 3 and 4 examine the allocation of time of unemployed individuals, with a focus on the time spent on job search activities. Chapter 5 slightly departs from the main topic of unemployment, but is tightly connected to Chapters 3 and 4 as it examines the job search process of the already employed.

There are many theories of unemployment and economists have long debated the true nature of unemployment. According to Lucas and Rapping's (1969) theory, unemployment is a period where workers efficiently substitute leisure for market work because their wage income is temporarily low. Other theories have pointed towards market failures as the source of unemployment and describe workers as involuntarily unemployed in the sense that they would be willing to work at the prevailing wage rate. Finally, search and matching theory views unemployment as the result of the workers' and firms' imperfect knowledge about suitable jobs and available workers. However, search and matching theory is not necessarily inconsistent with other theories of unemployment. Rather it is distinct in its basic approach of describing unemployment as the outcome of bilateral trade between workers and firms and the costly search for trading opportunities. As aptly described by Pissarides in the introduction to his book:

"... the decomposition of unemployment into frictional, cyclical, voluntary, involuntary, and so on is unhelpful in the theoretical and empirical analysis of un-

employment. In this book unemployment consists of workers who lose their jobs because it is not to their advantage (and to their employer's advantage) to continue employed, and who find another job after a length of time that depends on aggregate events, on institutional constraints and on what they, firms, and other workers do." (Pissarides, 2000)

A related but unresolved question is why unemployment varies so much over the business cycle. As pointed out by last year's Nobel Prize committee, search and matching theory has become "the leading paradigm in macroeconomic analysis of the labor market" (The Royal Swedish Academy of Sciences, 2010), not the least because it provides a rigorous microeconomic foundation of unemployment. Yet, some people have also documented some important shortcomings of this theory. In particular, Shimer (2005) showed that the standard search-matching model only predicts small movements in unemployment over the business cycle. Chapter 2 follows this line of research and studies the cyclical nature of unemployment in a search-matching model. The approach taken, however, is different as it analyzes the changes in the *composition* of the unemployed over the business cycle. The ambition is - by studying the composition of unemployment over the business cycle - eventually, to learn something about the nature of unemployment and its behavior over the business cycle.

Chapters 3-5 do not follow the macroeconomic approach taken in Chapter 2, but focus on the evaluation of partial equilibrium models of job search with micro data. A large literature has examined duration data and found support for some of the main predictions of search theory. E.g., it has been found that more generous unemployment benefits are associated with longer unemployment spells. Similarly, employed workers in lower paying jobs have been found to transition more frequently to other jobs, consistent with the view that they are searching for better paying jobs. Unemployment duration as well as job-to-job transitions are expected to be affected by the worker's search effort, but this variable has rarely been studied directly. Chapters 3-5 attempt to fill this gap by modeling job search intensity as the time employed and unemployed workers allocate to job search activities using data from time-use surveys. In time-use surveys, respondents report in great detail how they spent their time on the previous day or days and Chapters 3-5 use these diary data to test the predictions of search models such as, e.g., Mortensen's (1977) canonical model of job search and unemployment insurance.

Chapter 2 "**Separations, Sorting and Cyclical Unemployment**" uncovers a new fact about the compositional changes in the pool of unemployed over the U.S. business cycle and evaluates a number of theories that can potentially explain it.

Using longitudinal micro data from the Current Population Survey (CPS) 1979-2008, it documents that in recessions, the pool of unemployed shifts towards workers with high wages in their previous job. This cyclical pattern is robust to many different empirical specifications. Controlling for observable characteristics such as education, age, occupation etc. in the wage, it shows that the share of unemployed with high residual wages still increases in recessions, although the magnitude of the increase is smaller than for the raw wage measure. This finding suggests that both observed and unobserved factors explain the shift towards high-wage workers in recessions. The chapter also investigates whether the compositional shift is due to differences in the cyclical nature of separation or job-finding rates across wage groups, and finds that the compositional shift is almost entirely driven by separations.

These empirical findings have potentially important implications for models of aggregate fluctuations of the labor market, as the compositional changes in the pool of unemployed feed back into the firms' incentives for hiring people. The reason is that when the pool of unemployed shifts towards the more able, the probability for a firm of finding a worker of high ability increases and thus, there is an increase in the returns to posting vacancies. This poses an additional challenge to the recent literature on the "unemployment volatility puzzle" (see Shimer, 2005), as shifts towards high-ability workers in recessions may dampen the response of hiring and unemployment to aggregate productivity shocks.

Given the importance of the documented facts, the second part of the chapter tries to explain them. For this purpose, it sets up a search-matching model with match-specific productivity shocks, endogenous separations and worker heterogeneity in terms of ability. The baseline model, however, implies shifts in the pool of unemployed towards low-ability workers in recessions, which is inconsistent with the new facts. I also explore other calibrations of the model, as well as models with different types of worker heterogeneities such as differences in bargaining power or home production. All these models, however, have difficulties in replicating the key facts summarized above. Therefore, I offer two extensions of the model that can potentially explain the more cyclical nature of separations for high-ability workers.

One explanation is that many layoffs in downturns occur due to firm and plant death. These shocks affect workers indiscriminately of type and thus lead to larger increases in separations in percentage terms for those with lower average separation

rates (i.e., high-ability workers). However, the model cannot fully explain the higher cyclicity of separations for high-ability workers. Another extension of the model with credit shocks, where firms are constrained to produce positive cash flows in recessions, also produces more cyclical separations for high-ability workers. The idea is that it is more difficult to obtain outside financing in recessions as liquidity dries up in financial markets. In the baseline model with efficient separations, worker-firm matches produce negative cash flows at the productivity threshold where separations occur. The firm is willing to pay the worker above current match productivity, because it is compensated by expected positive future cash flows. Thus, if firms face constraints on their cash flows in recessions, workers and firms may separate even though it would be in the interest of both parties to continue the relationship. This mechanism is stronger for high-ability workers, because they produce larger negative cash flows at the efficient (unconstrained) separation threshold. Therefore, separations of these workers are more sensitive to a tightening of credit. As a result, the model produces more cyclical separations for high-ability workers, consistent with the empirical patterns in the U.S. data.

Chapter 3 "**The Lot of the Unemployed: A Time Use Perspective**" (co-authored with Alan B. Krueger) analyzes the lives of the unemployed using time-use data for 14 countries. A new purchase on the experience of unemployment is made possible by the accumulation of comparable time-use data on large representative samples for several countries. In time-use surveys, individuals keep track and report their activities over a day or a longer period. We acquired time-use data from several sources, including government statistical agencies, the Multinational Time Use Study (MTUS) data from Oxford University's Center for Time Use Research, and the Harmonized European Time Use Survey (HETUS).

We relate the amount of time spent on job search to demographic variables such as age, education, gender and marital status and find evidence that is broadly consistent with predictions from search theoretic models. At the national level, we do not find much evidence that parameters of a country's unemployment benefit system affect the amount of time devoted to job search, although our sample of countries is small and we cannot rule out some economically significant effect. We do find, however, that inequality is a strong predictor of the amount of time the unemployed devote to job search. While it is possible that this finding is emblematic of a tendency for lower job search in countries with a strong social welfare state and compressed wages, the fact that controlling for unemployment benefits does not attenuate the

effect of the 90-10 wage differential on job search suggests that inequality per se matters. Our tentative interpretation of this finding is that job search has a higher payoff in labor markets with greater wage dispersion.

Chapter 4 "**Job Search and Unemployment Insurance: New Evidence from Time Use Data**" (co-authored with Alan B. Krueger) examines the relationship between Unemployment Insurance and job search intensity, by using time-use data from the U.S.

It is well known that since the early 1980s, the unemployment rate has been lower in the U.S. than in Europe. Our tabulations of international time-use data also indicate that unemployed Americans tend to devote much more time to searching for a new job than their European counterparts. On weekdays, for example, the average unemployed worker spent 41 minutes a day searching for a job in the U.S., as compared to only 12 minutes in the average European country with available data. One explanation for the comparatively low unemployment rate and high search time in the U.S. is the relatively modest level and short duration of Unemployment Insurance (UI) benefits in most states in the U.S. In this paper, we examine the effects of UI on the amount of time devoted to job search by unemployed workers in the U.S., using features of state UI laws for identification.

The major finding is that, across the 50 states and D.C., job search is inversely related to the generosity of unemployment benefits, with an elasticity between -1.6 and -2.2. We also test the predictions of Mortensen's (1977) model regarding job search and unemployment duration and find mixed support. Consistent with the model, job search intensity for those eligible for Unemployment Insurance (UI) increases prior to benefit exhaustion. Moreover, the time devoted to job search is fairly constant regardless of unemployment duration for those who are ineligible for UI. However, one finding that is inconsistent with Mortensen's model is that search intensity appears to decline after the exhaustion of unemployment benefits. One possible explanation for the decline is that unemployed workers become discouraged if they fail to find a job despite substantial search effort, a feature that is absent from most search models and that deserves further attention.¹

Chapter 5 "**On-the-Job Search and Wage Dispersion: New Evidence from Time Use Data**" provides new evidence on the job search intensity of the employed in the U.S.

Why do so many employed workers change jobs each month? One explanation is

¹See Krueger and Mueller (2011) for further research on this issue.

that in the face of wage dispersion, employed workers search for better paying jobs. Christensen et al. (2005), e.g., provide a search model of the labor market with on-the-job search, wage dispersion and endogenous search effort. Their model predicts that search effort decreases with the wage since returns to search for a better job are higher the further down the worker is on the wage ladder.

With data from the American Time Use Survey (ATUS), the essay tests the predictions of this model by modeling search intensity as the amount of time spent on job search activities. It finds a negative and highly significant effect of the current wage on search intensity, consistent with the model predictions. The estimated elasticity of job search with respect to the wage lies between -0.7 and -1.3.

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Chapter 2

Separations, Sorting and Cyclical Unemployment^{*}

1 Introduction

This paper establishes a new fact about the compositional changes in the pool of unemployed over the U.S. business cycle and evaluates a number of theories that can potentially explain it. Using longitudinal micro data from the Current Population Survey (CPS) 1979-2008, I document that in recessions the pool of unemployed shifts towards workers with high wages in their previous job. This cyclical pattern is robust to many different empirical specifications. Controlling for observable characteristics such as education, age, occupation etc. in the wage, I show that the share of unemployed with high residual wages still increases in recessions, although the magnitude of the increase is smaller than for the raw wage measure. This finding suggests that both observed and unobserved factors explain the shift towards high-wage workers in recessions. I also investigate whether the compositional shift is due to differences in the cyclicity of separation or job-finding rates across wage groups, and find that the compositional shift is almost entirely driven by separations.

These empirical patterns may appear to contradict findings from a related literature on the cyclicity of real wages. Specifically, Solon, Barsky and Parker (1994)

^{*} I am grateful to Per Krusell, John Hassler, Torsten Persson, Alan B. Krueger, Thijs van Rens, Fabrizio Zilibotti, Almut Balleer, Phillippe Aghion, Valerie A. Ramey, Yongsung Chang, Tobias Broer, Ethan Kaplan, Mirko Abbritti, Toshihiko Mukoyama, Gueorgui Kambourov, Guillermo Ordonez, Steinar Holden, Shon Ferguson, David von Below, Erik Meyerson, Daniel Spiro, Ronny Freier and participants at the Econometric Society European Winter Meeting and the IIES macro group for very helpful comments and ideas, and to Handelsbanken's Research Foundations and the Mannerfelt Foundation for financial support.

documented that the measured cyclicality of aggregate real wages is downward biased, because the typical *employed* person is of higher ability in recessions. Hines, Hoynes and Krueger (2001), however, showed that Solon, Barsky and Parker's result relies on the weighting of aggregate real wages by hours worked. With unweighted wage data, composition bias has almost no effect on the cyclicality of real wages, suggesting that it is not the composition of the employed that changes over the business cycles but rather the hours worked by different skill groups. Moreover, changes in the composition of the employed do not necessarily translate into changes in the pool of unemployed in the opposite direction if the average quality between the pools differs. In fact, I show that large shifts towards high-wage workers in the pool of unemployed are fully consistent with small shifts towards high-wage workers in the pool of employed.

My empirical findings have potentially important implications for models of aggregate fluctuations in the labor market, as changes in the pool of unemployed feed back into firms' incentives for hiring. Contrary to Pries (2008), who assumes that the pool of unemployed shifts towards low-ability workers, shifts towards high-ability workers in recessions lead to a dampening of productivity shocks. The reason is that when unemployment shifts towards the more able, the probability that a firm finds a worker of high ability goes up, which raises the returns to posting vacancies. This poses an additional challenge to the recent literature on the "unemployment volatility puzzle" (see Shimer, 2005), as shifts towards high-ability workers in recessions may dampen the response of hiring and unemployment to aggregate productivity shocks.

Given the importance of the new fact I document in the first part of the paper, the second part of the paper tries to explain it. For this purpose, I first set up a search-matching model with match-specific productivity shocks, endogenous separations and worker heterogeneity in terms of ability.¹ The baseline model, however, implies shifts in the pool of unemployed towards low-ability workers in recessions, which is inconsistent with the new facts. I also explore other calibrations of the model, as well as models with different types of worker heterogeneities such as differences in

¹ Bilts, Chang and Kim (2009) also study the cyclicality of separations for different wage and hours groups. However, they pay little attention to compositional changes in the pool of unemployed in terms of ability. See also Section 2 below for a discussion of their empirical results from the Survey of Income and Program Participation (SIPP).

bargaining power or home production. All these models, however, have difficulties in replicating the key facts summarized above. Therefore, I offer two extensions of the model that can potentially explain the more cyclical nature of separations for high-ability workers.

One explanation is that many layoffs in downturns occur due to firm and plant death. These shocks affect workers indiscriminately of type and thus lead to larger increases in separations in percentage terms for those with lower average separation rates (i.e., high-ability workers). The model, however, cannot fully explain the higher cyclicity of separations for high-ability workers because, with such death shocks, differences in the cyclicity of separation rates between low-wage and high-wage individuals are limited by differences in the average separation rates between the two groups.

Thus, I propose another extension of the model with credit shocks, where firms are constrained to produce positive cash flows in recessions. This also produces more cyclical separations for high-ability workers. The idea is that it is more difficult to obtain outside financing in recessions as liquidity dries up in financial markets. In the baseline model with efficient separations, worker-firm matches produce negative cash flows at the productivity threshold where separations occur. The firm is willing to pay the worker above current match productivity, because it is compensated by expected positive future cash flows. Thus, if firms face constraints on their cash flows in recessions, workers and firms may separate even though it would be in the interest of both parties to continue the relationship. This mechanism is stronger for high-ability workers, because they produce larger negative cash flows at the efficient (unconstrained) separation threshold. Therefore, separations of these workers are more sensitive to a tightening of credit. As a result, the model produces more cyclical separations for high-ability workers, consistent with the empirical patterns in the U.S. data.

The remainder of the paper is organized as follows. Section 2 describes the CPS data and carries out the empirical analysis. Section 3 sets up the search-matching model, discusses alternative calibration strategies, and studies the model with firm and plant death. Section 4 extends the model with credit-constraint shocks and Section 5 concludes the paper.

Figure 1: *CPS panel structure by month and interview number*

Month	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Interview	1	2	3	4									5	6	7	8
	Wage												Wage			

2 Data

I use U.S. micro data from the Current Population Survey (CPS) for the period 1979-2008 to estimate monthly transition probabilities from employment to unemployment and vice versa. The CPS is the main labor force survey for the U.S., representative of the population aged 15 and older. It has a rotating panel structure, where households are surveyed in four consecutive months, rotated out of the panel for eight months, and then surveyed again for another four consecutive months, as illustrated in Figure 1. Note that the CPS records the labor-force status for each person in the sample each month. Weekly hours and earnings, however, are collected only in the fourth and eighth interview of the survey, referred to as the Outgoing Rotation Groups (ORG).

2.1 Sample Criteria and Measurement

I am interested in the wage of those who lose their job and become unemployed. Wage data is available only for the fourth and the eighth interview of each household. I restrict my sample to all individuals with available wage data from the fourth interview and analyze the employment outcomes in subsequent months. I do not use wage data from the eighth interview as this is the final interview in the CPS panel and I want to avoid possible selection effects associated with including wages after job loss.²

I restrict my sample to individuals aged 19 to 64 who worked in the private sector, are not self-employed and not self-incorporated. I also trim the sample for outliers excluding individuals with a wage above the 99.75th or below the 0.25th percentile each year and individuals with weekly hours below 5 or above 80. The

² The main concern is that individuals who separate in recessions tend to have lower wages on their *new* job, because it has been documented that wages for new hires are more responsive to the business cycle. See, e.g., Bils (1985) or, more recently, Haefke, Sonntag and van Rens (2009).

sample size is 1,369,741 individuals, where each individual has up to three monthly transitions between labor market states (between interviews 5 to 6, 6 to 7 and 7 to 8).

The CPS does not follow individuals who move out from an address surveyed in a previous month.³ This gives rise to substantial attrition between the fourth interview when individuals report their wage and the interviews 9, 10, 11 and 12 months later (as shown by Figure 1, there is a gap of 8 months between the 4th and the 5th interview): 27% of the individuals in my sample had no match in interviews 5-8. Similarly to Bleakly, Ferris and Fuhrer (1999), I adjust the survey weights to account for attrition. More precisely, I run a logit regression of the likelihood of remaining in the sample for interviews 5 to 8 on observable characteristics (such as sex, age, education, race and marital status) for each year, and multiply the existing survey weight with the inverse of the predicted value of the logit regression. This deflates the weight for groups and years with low attrition rates.⁴

The selected sample excludes unemployed individuals who have been unemployed for more than 12 months. This may lead to biases in the estimates of the average and the cyclicity of job findings rates (in particular, if job-finding rates are duration dependent). Notice, however, that the median duration of unemployment was less than three months for the entire sample period according to official statistics of the Bureau of Labor Statistics (BLS), and the fraction of those with unemployment durations above one year averaged only 8.8% over the sample period with a maximum of 13.3% in 1983.⁵ This suggests that the constraint imposed by the sample-selection criterion is relatively minor.

Finally, the sample does not include those who were classified as out of the labor force at the time of their 4th CPS interview. For this reason, movements from out of the labor force into unemployment and employment are not included in my

³ See Madrian and Lefgren (1999) for details about merging CPS files. Due to moves into and out of given household addresses, matches must be eliminated based on demographic information. I use the s|r|a criterion of Madrian and Lefgren, because it appears to yield a relatively good trade-off between accepting invalid matches and rejecting valid matches. The criterion keeps as valid matches only those with the same sex, race and an age difference of 0-2 years.

⁴ Abowd and Zellner (1985) propose a procedure of reweighing the data that minimizes the difference between the stocks implied by the matched worker flow data and the official CPS stocks. Unfortunately, this procedure is not available here because the CPS does not report the stocks of unemployed workers by wage on the previous job.

⁵ These numbers are taken from the OECD's statistics of "Incidence of unemployment by duration".

sample. As argued by Shimer (2007) and others, movements between out of the labor force and unemployment are relatively acyclical and contribute little to the overall variation in unemployment. Naturally, it is still possible that movements into and out of the labor force are different across groups and that these differences cancel out in the aggregate. In any event, movements between out of the labor force and unemployment are another potential margin of cyclical changes in the composition of the pool of unemployed, which is omitted from my analysis.

2.2 The Cyclicalities of the Wage of Job Losers

Does the composition of the unemployed change over the business cycle? In particular, are there changes in the pool by ability? To answer these questions, I use the wage on the previous job as an indicator of ability. Figure 2 plots the average wage of those who lost their job in the previous year, as well as the average wage of those who remained employed. More precisely, I plot the yearly average wage for those who were employed in interview 4 but unemployed in interview 8 of the CPS, as well as the average wage of those who remained employed. As is apparent from the plot, the average wage of the unemployed is strongly and positively correlated with the aggregate unemployment rate (the correlation coefficient is 0.55).⁶

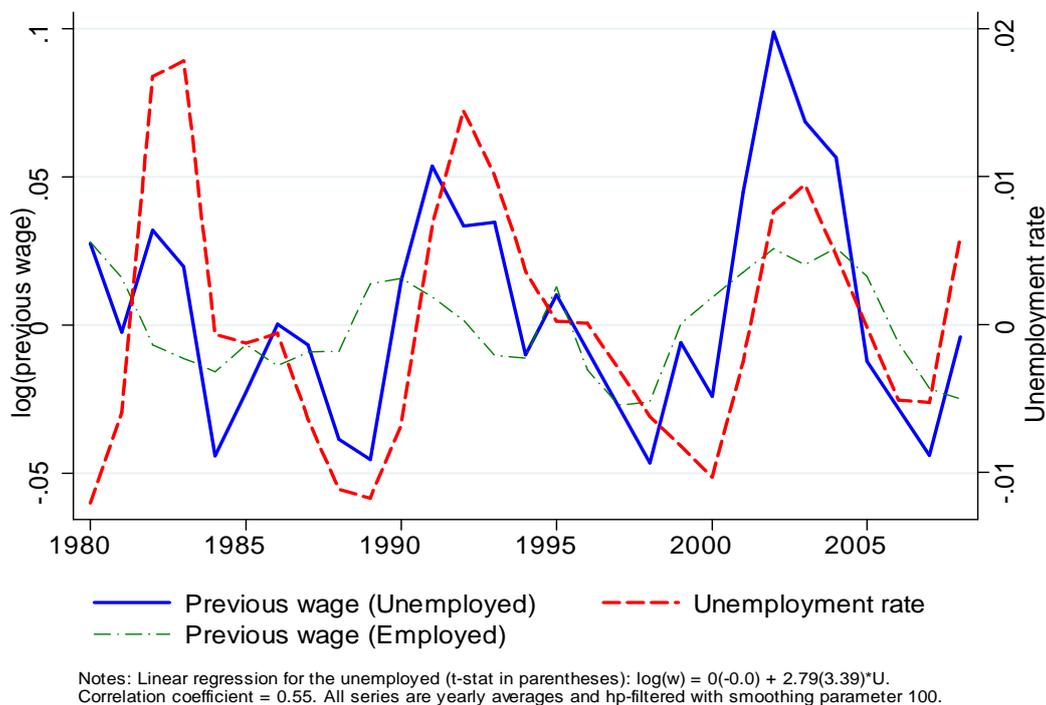
Figure 3 shows that, when I remove year effects, the average wage for the unemployed is even more closely correlated with the unemployment rate, with a correlation coefficient of 0.72, suggesting that the results are not driven by the cyclical behavior of real wages.⁷

Figure 4 shows the same plot but for the residual of a Mincer-style regression of the wage on observable characteristics such as age, gender, marital status, education and race, and dummies for state, industry, occupation and year. The average wage residual is still strongly counter-cyclical for those who lost their job in the previous year, with a correlation with the unemployment rate of 0.62. The magnitude is smaller as a percentage-point increase in the unemployment rate leads to a 1.1% increase in the average residual wage of the unemployed, as compared to a 2.8% increase in the average (not residual) wage in Figure 2. This suggests that both

⁶ The unemployment rate is taken from the official tables of the Bureau of Labor Statistics.

⁷ By definition, the average wage residual is zero for each year for the full sample and close to zero for the employed as they represent over 90 % of the full sample.

Figure 2: Average wage from the previous year by employment status

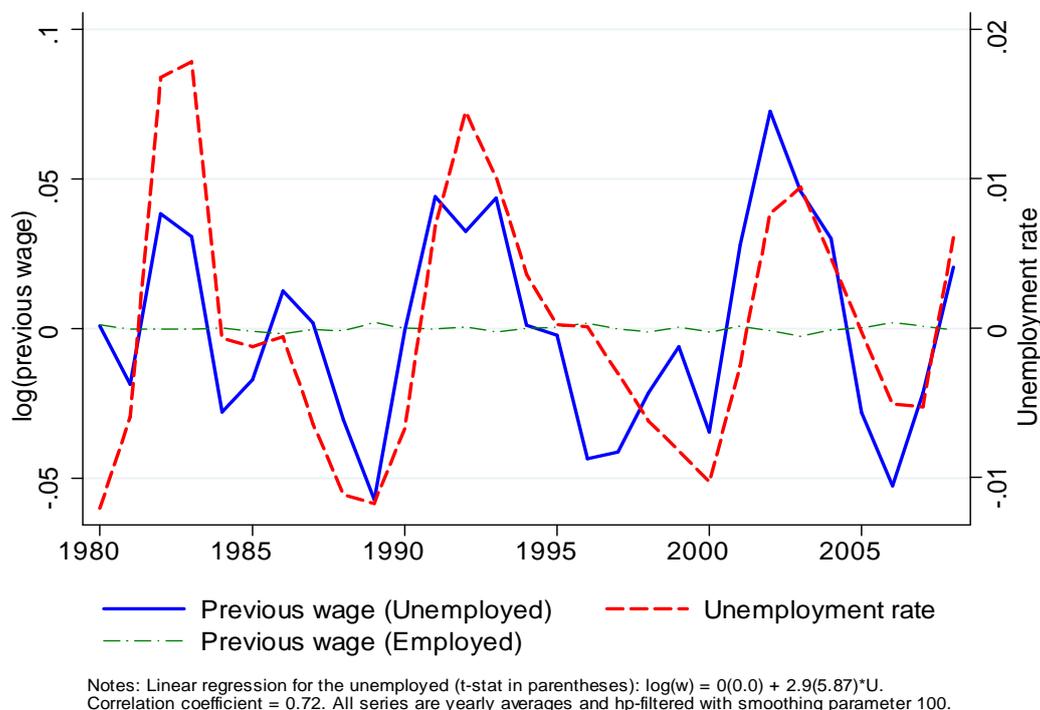


observed and unobserved factors contribute to the compositional changes in the unemployment pool over the business cycle.

One thing to keep in mind is that the reported series are HP-filtered such that the mean is zero for both the employed and unemployed over the entire sample period. The mean of the unfiltered series is, however, considerably lower for those who lose their job, as opposed to those who remain employed. This suggests that the unemployed are on average of lower quality, but become more similar to the employed in a recession.

One might be concerned about wage compression and argue that the wage differential between those who lose their job and those who remain employed narrows in a recession, simply because overall wage dispersion becomes smaller at the same time. To evaluate this possibility, I attribute an ordinal wage rank to each individual in my data set (the rank in the wage distribution in a given year is defined by lining up all individuals according to their current wage from the lowest to the highest on the unit interval). If wage compression drives the patterns in Figures 2-4, then the average wage rank should show no correlation with the aggregate unemploy-

Figure 3: Average wage from the previous year by employment status (residuals from a regression of the log wage on year dummies)



ment rate. However, Figure 5 shows a very strong correlation of the average wage rank of the unemployed with the aggregate unemployment rate. The correlation coefficient is 0.72, suggesting that wage compression plays no role. In terms of the magnitude, a percentage-point increase in the unemployment rate is associated with a 1.5 percentage-point increase in the average wage rank of the job losers, which represents a substantial shift in the composition of the pool of unemployed.

2.3 The Cyclicity of Separations and Job Findings by Wage Group

Changes in the composition of the pool of unemployed over the business cycle can arise because of different behavior of inflows into and/or the outflows from unemployment. For this reason, I analyze in more detail the worker *flow* data from my CPS sample to determine whether the patterns documented in the previous section are due to job separations or job findings. In particular, I divide the sample in each

Figure 4: Average wage from the previous year by employment status (residuals from a regression of the log wage on year dummies and observable characteristics)



Notes: Linear regression for the unemployed (t-stat in parentheses): $\log(w) = 0(0.0) + 1.1(7.33) \cdot U$. Correlation coefficient = 0.62. All series are yearly averages and hp-filtered with smoothing parameter 100.

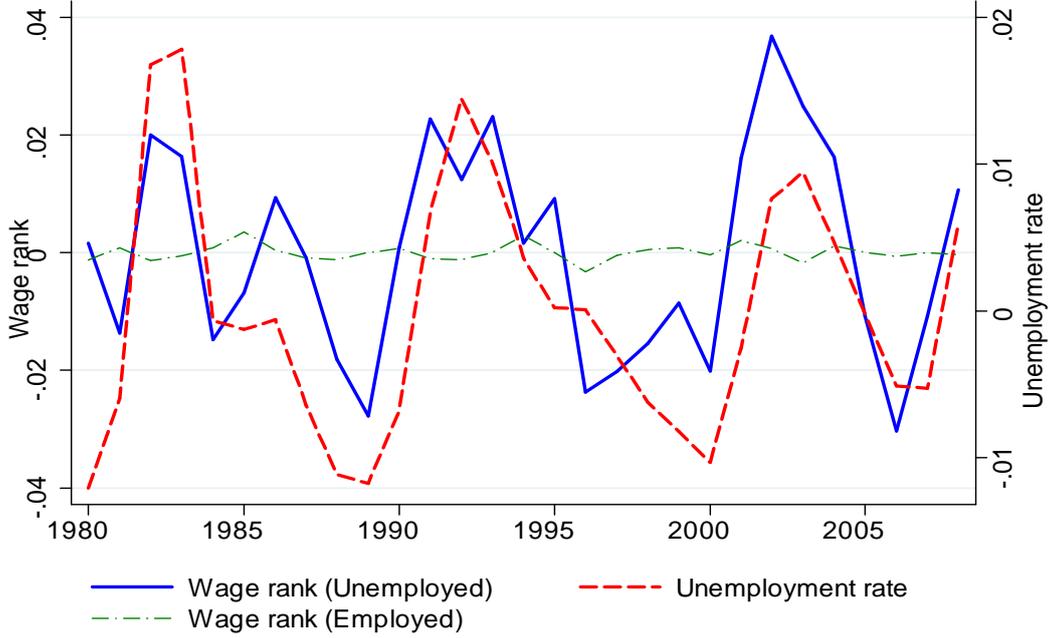
year into those below and above the median wage and analyze the cyclical behavior of the separation and job-finding rate for each of these groups. Job separations and findings are defined as the percentage of those who changed their employment status (from E (employment) to U (unemployment) or from U to E). The groups are divided into below or above the median wage in interview 4, and the transitions are analyzed for subsequent interviews (i.e., monthly transitions between interviews 5 to 6, 6 to 7 and 7 to 8).

Measurement

Elsby, Michaels and Solon (2009) show that one can decompose the contributions of separations (s) and job findings (f) to changes in the unemployment rate approximately into

$$dU_t \approx U_t(1 - U_t) [d \ln s_t - d \ln f_t]. \quad (2.1)$$

Figure 5: Average wage rank by employment status



Notes: Linear regression for the unemployed (t-stat in parentheses): Wage rank = 0(0.0) + 1.54(5.92)*U. Correlation coefficient = 0.72. All series are yearly averages and hp-filtered with smoothing parameter 100.

Now, the share of group i in the pool of unemployed is defined as

$$\phi_{it}^U = \psi_i^U \frac{U_{it}}{U_t}, \quad (2.2)$$

where U_{it} is the unemployment rate of group i at time t and ψ_i^U is the population share for group i (assumed to be constant). Given equations (2.1) and (2.2), it can be shown that changes in the share of group i in the pool of unemployed can be decomposed into

$$d\phi_{it}^U \approx \phi_{it}^U \left(\begin{array}{l} (1 - U_{it}) [d \ln s_{it} - d \ln f_{it}] \\ -(1 - U_t) [d \ln s_t - d \ln f_t] \end{array} \right), \quad (2.3)$$

which implies that changes in the share of group i are related to changes in the *log* of the separation and job-finding rate of group i relative to the average. More importantly, since $(1 - U_{it})$ is very similar across groups, one can directly conclude from the magnitude of the changes in the log separation and job-finding rates which margins are more important for the changes in the composition of the pool. To

Table 1. CPS 1979-2008: The cyclicalities of separation and job-finding rates, by wage group

		Log(hourly wage)		Mincer residual	
		low	high	low	high
Separations	Average	0.012	0.007	0.010	0.008
	Cyclicity (s.e.)	0.40 (0.082)***	0.75 (0.099)***	0.45 (0.063)***	0.67 (0.085)***
Job findings	Average	0.318	0.301	0.309	0.313
	Cyclicity (s.e.)	-0.57 (0.059)***	-0.72 (0.069)***	-0.68 (0.073)***	-0.61 (0.077)***
Unemployment	Average	0.036	0.023	0.033	0.025
	Cyclicity (s.e.)	0.81 (0.024)***	1.25 (0.030)***	0.91 (0.027)***	1.11 (0.035)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000. The cyclicity is measured as the coefficient β in the regression $\log(x_{it}) = \alpha + \beta \log(U_t) + \varepsilon_{it}$, where x_{it} is the separation, job-finding or unemployment rate of group i at time t and U_t is the sample unemployment rate. Similar to Bils, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment rate because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

understand how separations and job findings relate to cyclical changes in the unemployment rate, one thus has to relate the changes in the log of the separation and job-finding rate to the aggregate unemployment rate (or other cyclical indicators). For this reason, I run the following regressions:

$$\ln x_{it} = \alpha_i^x + \beta_i^x \ln U_t + \varepsilon_{it}^x, \quad (2.4)$$

where x_{it} stands for s_{it} (separation rate), f_{it} (job-finding rate) or U_{it} (unemployment rate) for group i at time t and the measure of cyclicity is the percentage increase in x_{it} in response to a 1% increase in the aggregate unemployment rate (the coefficient β_i^x). All series are monthly, seasonally adjusted, and detrended with an HP-filter with smoothing parameter 900,000.

Results

Table 1 summarizes the main results for different groups in terms of the average as well as the cyclicity of separation and job-finding rates. The first two columns split the sample into those below and above the median wage. Columns 3 and 4 report the results for those below and above the median residual wage.

Not surprisingly, separations are on average lower for high-wage workers than for low-wage workers. The main result is that the cyclicality of separations is almost twice as large for individuals with high wages compared to those below the median. The difference is somewhat smaller when looking at the cyclicality of separations for those below and above the median residual wage: The ratio of $\frac{\beta_{low}^{sep}}{\beta_{high}^{sep}}$ is 0.68 compared to 0.54 for the cyclicality with the raw wage measure.

Job-finding rates are of similar size, on average, for both groups, and also their cyclicality is very similar across groups: The cyclicality of job findings is slightly more cyclical for those above the median wage, but the pattern reverses for the residuals and the differences are not statistically significant. Overall, I conclude that changes in the composition of the pool in terms of the previous wage are driven:

1. almost entirely by the different cyclicality of separations as opposed to job findings and
2. by observable as well as unobservable characteristics of the unemployed.

These facts are robust across a large range of different specifications and sample selection criteria. Appendix Tables A.1, A.2 and A.3 show very similar results for different sample restrictions (age 25-54, men only, full-time workers only, college educated only, years 1990-2008) and different filters. The patterns are also similar when one includes those OLF (out of the labor force) or excludes those on temporary layoff. Finally, I use Fujita and Ramey's (2009) adjustment for time aggregation bias and find that the differences in the cyclicality of separations are even stronger for those below and above the median wage.

Job-to-Job Transitions

The measure of job separation above does not include job-to-job transitions (in other words, job separations that do not result in an intervening spell of unemployment). The original CPS did not ask respondents about job switches, but fortunately with the redesign of the CPS in 1994, it became possible to identify those who switched jobs between two monthly interviews (see Fallick and Fleischman, 2004, for details). Table 2 shows the average and the cyclicality of job-to-job transitions for the same groups as in Table 1. As in Fallick and Fleischman, the monthly job-to-job transitions are about twice as large as the flow from E to U. The job-to-job transitions

Table 2. CPS 1994-2008: The cyclicalty of job-to-job transitions, by wage group

		<u>Log(hourly wage)</u>		<u>Mincer residual</u>	
		<u>low</u>	<u>high</u>	<u>low</u>	<u>high</u>
Job-to-job transitions	Average	0.023	0.018	0.021	0.019
	Cyclicalty	-0.22	-0.13	-0.25	-0.10
	(s.e.)	(0.058)***	(0.074)*	(0.064)***	(0.075)

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. See notes in Table 1 for further details.

are procyclical, but less so for individuals with high wages. In particular, the cyclicalty for those with high residual wages is -0.10, compared to -0.25 for those with low residual wages. Even though these differences are only marginally statistically significant (at the 10% level), this evidence does not support the view that the high cyclicalty of separations for high-wage workers is driven by the fact that direct job-to-job transitions decrease strongly during recessions for this group. On the contrary, it appears that job-to-job transitions decrease more for low-wage workers in recessions and thus one would expect separations into unemployment to be more cyclical for the *low*-wage group.

In summary, the data strongly suggests that the unemployment pool shifts towards high-ability individuals in recessions, and this shift is mainly due to job separations.

2.4 Relation to Previous Research

Bils, Chang and Kim (2009) find similar patterns in the data for low-wage vs. high-wage workers from the Survey of Income and Program Participation (SIPP), but they focus their attention on the cyclical nature of *employment* for these groups and pay little attention to the question of cyclical changes in the composition of the pool of unemployed. More precisely, they split their sample into four groups: by low or high hours and by low or high wages. Averaging the cyclicalty of separations for the wage groups, one finds that the cyclicalty of separations is about 20% lower for the low-wage group, as compared to 35-50% in the CPS data. One possible explanation for the quantitatively smaller effect is that Bils, Chang and Kim average wages before and after job loss, which introduces a potential selection effect: workers who

separate into unemployment in a recession are likely to receive lower wages on their new job and thus, are more likely to be classified in the low-wage group.^{8, 9}

Solon, Barsky and Parker (1994) show that there is a substantial composition bias when looking at the cyclicalities of aggregate real wages. The employed become *more* skilled during recessions, leading the researcher to underestimate the cyclicalities of real wages when looking at aggregate wage data. This evidence seems to be in contrast with the facts presented above, because it suggests that the proportion of high-wage workers *among the employed* increases in recessions. However, their evidence relies on the composition bias in the aggregate hourly wage, which is a weighted average by hours. Therefore, the composition bias could be driven either by a higher cyclicalities of hours for the low skilled (the intensive margin) or a higher cyclicalities of employment for the low skilled (the extensive margin). In fact, Hines, Hoynes and Krueger (2001) show that Solon, Barsky and Parker's results rely on the weighting of aggregate real wages by hours worked. They demonstrate that with unweighted wage data, composition bias has almost no effect on the cyclicalities of real wages, suggesting that it is not the composition of the employed that changes over the business cycle but rather the hours worked by different skill groups.

Another important observation is that the pool of unemployed and the pool of employed do not necessarily have to shift in the same direction if the pools differ in the average quality. Specifically, since the typical unemployed is of lower ability than the typical employed, a transition of a worker from the lower part of the distribution of the pool of employed to the upper part of the distribution of the pool of unemployed can make both pools better off. More formally, one can approximate the relationship between changes in the share of group i in the pool of unemployed ($d\phi_{it}^U$) and changes in the share of group i in the pool of employed ($d\phi_{it}^E$) as follows:

$$d\phi_{it}^E \approx \phi_{it}^E [-2U_t d\phi_{it}^U + dU_t (1 - 2\phi_{it}^U)], \quad (2.5)$$

which implies that if the shares of the two groups are the same ($\phi_{it}^U = 0.5$), then the pools must sort in opposite directions. However, in reality the share of low-wage

⁸ There is a large body of evidence that shows that wages of new hires strongly respond to the business cycle (see, e.g., Bils, 1985, or Haefke et al., 2009).

⁹ Other differences between their analysis and mine is that they use aggregate total hours as a cyclical indicator instead of the aggregate unemployment rate and they cover a smaller number of years (from 1983 to 2005, with some gaps).

workers among the unemployed is higher ($\phi_{low,t}^U = 0.61$ in my CPS sample) and thus shifts do not necessarily go in the opposite direction. Moreover, changes in the group share among the unemployed lead to much smaller changes in the group share among the employed, because the group of unemployed is so much smaller compared to the group of employed. In fact, one can compute the response of the share of the low-wage types from the estimates in Table 1, and then use the formula in equation (2.5) to compute the implied change in the share in the pool of employed. The results are as follows:

$$\begin{aligned}\frac{d\phi_{low,t}^U}{dU_t} &\approx -1.98 \\ \frac{d\phi_{low,t}^E}{dU_t} &\approx -0.05,\end{aligned}$$

which says that the share of the low-wage types decreases by almost two percentage points in response to a one percentage-point increase in the aggregate unemployment rate. These results also imply that the pool of employed shifts in the *same* direction, but the shift is of a much smaller magnitude than for the pool of unemployed. A percentage-point increase in the unemployment rate decreases the share of the low-wage types by 0.05 percentage points. To conclude, large shifts in recessions towards high-wage workers in the pool of unemployed are fully consistent with small shifts towards high-wage workers in the pool of employed.

3 Model

In this and the following section, I evaluate a number of theories that can potentially explain the compositional shifts in the pool of unemployed over the U.S. business cycle. I start with an extension of the standard search-matching model¹⁰ to worker heterogeneity and find that it has difficulties in replicating the facts summarized above. Then, I consider further extensions of this baseline model that can potentially account for the documented facts.

In the baseline model, there are two types of workers (indexed by i) who differ in their market productivity a_i and potentially other parameters. Similar to Bils,

¹⁰ The main reference is Pissarides (2000). I deviate from his model by allowing match-specific productivity shocks to be correlated across time.

Chang and Kim (2009), I assume worker ability to be observable to the potential employer and thus firms can direct their search to a particular worker type.¹¹ More precisely, there is a continuum of workers of each type and a continuum of firms, which are matched according to the matching function:

$$M_i = \kappa u_i^\eta v_i^{1-\eta}. \quad (2.6)$$

The job finding probability is $p(\theta_i) = \frac{M_i}{u_i}$ and the hiring rate $q(\theta_i) = \frac{M_i}{v_i}$.

Match productivity is defined as zxa_i where z is aggregate productivity, x match-specific productivity and a_i worker-specific productivity. Match-specific productivity is assumed to follow an AR(1) process as discussed below in the calibration strategy. I assume that all matches start at the median match productivity \bar{x} .

Let us proceed to describe the value functions of workers and firms. The value function of an unemployed worker of type i is:

$$U_i(z) = b_i + \beta E [(1 - f(\theta_i))U_i(z') + f(\theta_i)W_i(z', \bar{x}) | z], \quad (2.7)$$

where aggregate productivity z is the aggregate state. The value of being unemployed depends on the unemployment benefit, b_i , which potentially depends on worker type, and the discounted value of remaining unemployed in the next period or having a job with the value $W_i(z', \bar{x})$.

The value function of an employed worker is:

$$W_i(z, x) = w_i(z, x) + \beta E [\max \{W_i(z', x'), U_i(z')\} | z, x], \quad (2.8)$$

which depends on the utility from the current wage and the discounted future expected value. Whenever the value of the job W_i is lower than the value of being unemployed U_i , the worker will separate and thus receive the value $U_i(z')$ in the next period.

¹¹ Appendix A.1 discusses a model where worker ability is unobservable by the employer and thus search on the firm is non-directed. The results of the model with non-directed search are similar to those of the model with directed search; in particular, the assumption of non-directed search has little impact on the cyclicalities of separations for different ability groups.

The value of posting a vacancy for a firm is:

$$V_i(z) = -c_i + \beta E [(1 - q(\theta_i))V_i(z') + q(\theta_i)J_i(z, \bar{x}) | z], \quad (2.9)$$

which depends on the vacancy posting cost c_i and the discounted future expected value. Note that $q(\theta_i)$ is the firm's hiring rate, the rate at which it fills a posted vacancy.

The value of a filled vacancy is:

$$J_i(z, x) = zxa_i - w_i(z, x) + \beta E [\max \{J_i(z', x'), V_i(z')\} | z, x], \quad (2.10)$$

which depends on the cash flow (productivity minus the wage) and the discounted future expected value. Note that the firm will fire the worker whenever the value of the filled vacancy is lower than the value of posting a vacancy.

Wages are determined by standard Nash-bargaining and split the joint surplus from the employment relationship according to the Nash-bargaining solution:

$$[W_i(z, x) - U_i(z)] = \frac{\alpha}{1 - \alpha} [J_i(z, x) - V_i(z)], \quad (2.11)$$

where α is the bargaining share of the worker.

Firm-worker matches are dissolved whenever the joint surplus from the relationship ($S_i(z, x) = W_i(z, x) - U_i(z) + J_i(z, x) - V_i(z)$) is smaller than zero, which implies that the reservation match productivity $R_i(z)$, i.e., the level of match-specific productivity x below which the employment relationship is dissolved, satisfies:

$$S_i(z, R_i(z)) = 0. \quad (2.12)$$

I refer to (2.12) as the efficient-separation condition. Separations are always in the interest of both parties and never unilateral (thus efficient).

A directed search equilibrium is defined as the reservation match productivity $R_i(z)$, the wage schedules $w_i(z, x)$, the labor market tightness $\theta_i(z)$ and the value functions $U_i(z), W_i(z, x), V_i(z)$ and $J_i(z, x)$ that satisfy: 1. the Nash-bargaining solution (2.11), 2. the efficient-separation condition (2.12), 3. the zero-profit condition:

$V_i(z) = 0$ and 4. the value functions (2.7), (2.8), (2.9) and (2.10).

3.1 Calibration

The main parameters of the model are calibrated to standard values in the literature. The following tabulation summarizes the calibration strategy.

Tabulation of the calibrated values of the main parameters of the model:

Parameter	Parameter name	Source/Target
$\beta = 0.9966$	Discount factor	$r = 4.17\%$
$c_{\text{high}} = 0.64 ; c_{\text{low}} = 0.20$ ⁽¹⁾	Vacancy-posting cost	Monthly job-finding rate = 0.3
$\eta = 0.5$	Elasticity of matching function	Micro studies
$\kappa = 0.3$	Matching efficiency	$\theta = 1$
$\alpha = 0.5$	Worker's bargaining power	Hosios condition
$b = 0.6$	Unemployment benefit	Shimer (2005); Hagedorn and Manovskii (2008)
$\ln(x_{t+1}) = 0.98\ln(x_t) + \varepsilon_t$	Match-specific productivity	Bils, Chang and Kim (2009)
$\sigma_\varepsilon = 0.03$	Std of match-specific shocks	Monthly separation rate = 0.01
$z_g = 1.02; z_b = 0.98$	Aggregate state	Shimer (2005)
$\pi_{gb} = \pi_{bg} = 1 / 24$	Transition probabilities	Duration of recession = 2 years
$a_{\text{high}} / a_{\text{low}} = 1.2 / 0.8$	Ratio of worker productivity	Wage dispersion in CPS data

(1) The vacancy posting costs are chosen to match a monthly job-finding rate of 0.3. Therefore, the values change for alternative calibrations of the model.

The parameters are chosen to be the same for both groups of workers unless otherwise noted. The vacancy posting cost c_i is calibrated internally to match a monthly job-finding rate of 0.3 for both groups (as in the CPS data). The elasticity of the matching function η is in accordance with estimates from micro studies and is set to 0.5. The matching efficiency κ is a free parameter in the model and chosen such that $\theta = 1$. The worker's bargaining power is set equal to the elasticity of the matching function in order to satisfy the Hosios condition. The log of match productivity is assumed to follow an AR(1) process with the autocorrelation coefficient 0.98. The standard deviation of match productivity shocks is set to match

an average monthly separation rate of 0.01, as in the CPS data. I discretize the state space in terms of match productivities x with Tauchen's (1986) algorithm. Aggregate productivity z is assumed to take on two values, set to match a standard deviation of aggregate labor productivity of 0.02, as reported by Shimer (2005). The productivity parameters a_{low} and a_{high} are assumed to be 0.8 and 1.2. In the CPS data the ratio of the wage of the group below and above the median wage is around 0.4. Thus, the assumption of $a_{high}/a_{low} = 1.2/0.8$ is a conservative estimate of differences in worker productivities. The unemployment benefit is assumed to be constant and equal to 0.6 (somewhere in between the extreme assumptions of Shimer (2005) and Hagedorn and Manovskii (2008)). The assumption of a constant benefit by worker type implies that, at the median match productivity $\bar{x} = 1$, the ratio of benefits over worker productivity is 0.75 for the low types and 0.5 for the high types. This strategy is motivated by two main observations: First, wages are generally replaced only up to a specified limit. In the U.S., the maximum unemployment benefit is binding for approximately 35% of the unemployed workers (see Krueger and Meyer, 2002). Second, the parameter b should also capture the utility derived from additional leisure during unemployment as well as consumption provided by additional home production, which is likely to be less than perfectly correlated with market ability, a . For these reasons, the replacement rates should be higher for the low-ability group.

3.2 Results

Table 3 reports results for the baseline calibration. The same filtering methods as for the empirical results from the CPS are applied to the simulated time series. Evidently, the model generates higher average separation rates for low-ability workers. However, the model does not do well in capturing the cyclical nature of separations as it generates a higher, not lower, cyclical nature of separations for the low-ability types.

The reason for this failure is related to the cyclical behavior of the worker's outside option. The efficient-separation equation (2.12), rewritten for convenience, is

$$W_i(z, R_i(z)) + J_i(z, R_i(z)) = U_i(z),$$

where the left-hand side is the value of the match and the right-hand side is the value

Table 3. Baseline model: The cyclical of separation and job-finding rates, by ability type

		<u>Baseline</u>		<u>Alternative calibration</u>	
		low a	high a	low a	high a
Separations	Average	0.0126	0.0075	0.0112	0.0065
	Cyclical	0.839	0.760	0.688	1.143
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclical	-0.631	-0.367	-0.510	-0.493
Unemployment	Average	0.041	0.025	0.037	0.021
	Cyclical	1.109	0.822	0.879	1.212

Notes: The series are HP-filtered with a smoothing parameter of 900,000 and the cyclical is measured as in the CPS data (see notes in Table 1 for details). Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers.

of the outside option. When aggregate labor productivity increases, the value of the match increases proportionally, whereas the value of being unemployed increases by less than one-for-one because b is constant over the business cycle. Therefore, staying employed becomes more attractive as aggregate productivity increases and thus R_i decreases. For workers with low ability, the outside option fluctuates less as the constant term of U_i (the unemployment benefit b) is large relative to the non-constant term (the expected value in the next period) and thus R_i changes *more* in response to an aggregate productivity shock. For this reason, separations are more cyclical for low-ability workers.

Table 3 also shows the results for an alternative calibration strategy where I assume that the unemployment benefit is proportional to worker ability ($b_i = ba_i$) and the variance of match productivity is higher for low-ability workers¹². More precisely, I assume that σ_ε is twice as large for the low-ability group ($\sigma_\varepsilon^{high} = 0.02$; $\sigma_\varepsilon^{low} = 0.04$). In line with the data, this model generates higher average separation rates for low-ability workers. More importantly, this model also generates a higher cyclical of separation rates for high-ability workers. The reason is that the density of matches with $x = R_i$ is higher for the low-variance (high-ability) group, and thus, changes in the reservation match productivity translate into larger changes in the

¹² This is essentially the calibration strategy used by Bilts, Chang and Kim (2009). More precisely, they choose the variance of match-specific productivities to match the average separation rate for each group.

Table 4. Wage dispersion by wage and education group

By wage group	sd(lw)	sd(dlw)
Below median	0.32	0.40
Above median	0.37	0.40
By education group	sd(lw)	sd(dlw)
HS degree or less	0.48	0.38
Some college or more	0.56	0.44

separation rate.¹³

This second calibration strategy generates both lower separations and a higher cyclicity of separations for the high-wage group. However, it is unclear why the variance of match-specific productivity shocks should be higher for low-ability workers. One way of evaluating whether high-wage workers have a lower variance of match productivity shocks is to look at the yearly wage changes between the two outgoing rotation groups of the CPS (in interviews 4 and 8). If the log wage in the model is decomposed into $w_i^a + w_{it}^x + w_t^z$, where w_i^a is a worker-specific effect, w_{it}^x a match-specific productivity effect and w_t^z an aggregate productivity effect, then we get that

$$d \log w_{it} = dw_{it}^x + dw_t^z.$$

Further, assuming that the distributions of match productivity shocks and aggregate shocks are constant over time and independent of each other, we get:

$$Var(d \log w_{it}) = 2Var(w_{it}^x)(1 - \rho_x) + 2Var(w_t^z)(1 - \rho_z),$$

where ρ_x and ρ_z are the autocorrelations of match-specific and aggregate productivity shocks. If the variance of match productivity shocks differs across wage groups, we should observe differences in the variance of wage changes. However, in the CPS

¹³ Formally, it can be shown that the change in the separation rate in response to aggregate productivity shocks is

$$\left. \frac{d \ln F(R_i)}{d \ln z} \right|_{z=1} = \frac{f_i(R_i)}{F_i(R_i)} \frac{dR_i}{dz},$$

where $\frac{f_i(R_i)}{F_i(R_i)}$ is the inverse Mills ratio for the empirical distribution of match productivity. Note that for many distributions and, in particular, for the (log) normal distribution, the inverse Mill ratio is $\frac{f_i(R_i)}{F_i(R_i)}$ is decreasing in the variance of match productivities. Therefore, for a given $\frac{dR_i}{dz}$, the cyclicity of the separation rate is *decreasing* in the variance of match productivities.

data, the variance of wage changes is very similar across the two wage groups. Table 4 shows that the standard deviation of the yearly wage growth rate is exactly the same across the two wage groups (and higher for those with some college education or more). To sum up, there seems to be little justification for assuming a higher variance of match productivity shocks for the *low*-ability group.

3.3 Other Types of Heterogeneity

Could other types of heterogeneity drive the patterns observed in the CPS data? To answer this question, I simulated the benchmark model above with different assumptions on the group-specific parameters.

1. Workers may differ in the utility derived from unemployment ($b_l < b_h$), but have the same ability ($a_l = a_h = 1$). With Nash-bargaining, workers with high b have higher wages as the value of their outside option is higher. This model generates more cyclical separations for high-wage workers (high b), but counterfactually high average separation rates for high-wage workers. The reason is that those workers with a high b have a better outside option and thus separate at higher match productivities than those with a low b .
2. Workers may differ in their bargaining power ($\alpha_l < \alpha_h$) but have the same ability ($a_l = a_h = 1$). This model generates counterfactually high average separation rates, as well a counterfactually lower cyclical separations for high-wage workers (those with high bargaining power). The reason for the latter is that the outside option U_i fluctuates less for workers with low bargaining power and thus separations become much more attractive in recessions.

3.4 Wage Rigidity

How about other prospective explanations for the different cyclical separations of low and high-wage workers? One possible explanation is that wage rigidity leads to more cyclical separations for high-wage workers as the failure of adjusting the wage in response to an aggregate shock results in the firm firing the worker. The rigid-wage hypothesis, however, faces several difficulties in explaining the pattern in the CPS data. First, the wage observations in the CPS sample are 9-12 months prior

to the the observed separation. Gottschalk (2005) shows that wages are usually renegotiated one year after the last change, which implies that for most records in my sample wages were renegotiated between interview 4 and the subsequent interviews 9-12 months later. Naturally, it is possible that wages are renegotiated but still display substantial rigidity if the renegotiation only results in a small wage adjustment.

Second, wage rigidity does not necessarily lead to more cyclical separations for high-wage workers. In particular, if the contribution of match-specific productivity shocks x to the variance of total match productivity zxa_i is large, it is very difficult to generate a model where wage rigidity leads to more cyclical separations for high-wage workers. If wages fail to adjust in response to match-specific productivity shocks, then high-wage workers should also be more likely to be fired in good times. In the data, aggregate shocks to labor productivity are rather small and, in particular, small compared to match-specific shocks. In my baseline calibration above, the standard deviation of match-specific shocks is 7.5 times higher than the standard deviation of aggregate shocks. Match-specific shocks are not observed but inferred from wage data, and reducing the standard deviation of match-specific productivity shocks would be at odds with data on cross-sectional wage dispersion.

Finally, sticky wages affect separations because wages fail to adjust when they fall outside the bargaining set (the range within which the surplus for both parties is positive). This implies that separations may occur even if the *joint* surplus is positive: when wages are too high, the firm fires the worker, whereas when wages are too low the worker quits. In both cases, however, the parties would be better off by renegotiating the wage and thus these separations are bilaterally inefficient. Another possibility would be to let wages adjust to the boundary of the bargaining set whenever they are about to leave it. In such a model, however, wage rigidity has little impact on separations as this type of wage rigidity affects how the surplus is split, but only has a limited impact on the total surplus.¹⁴ As long as separations occur only when the total surplus is negative – i.e., as long as separations are efficient – the model is similar to a model with flexible wages and thus unlikely to explain the empirical patterns of separations I have documented in the CPS data.

¹⁴ Naturally, wage rigidity may have an allocative role on hiring, as emphasized in a recent literature by Hall (2005), Hall and Milgrom (2008), van Rens et al. (2009) and others.

Table 5. Model with firm death shocks: The cyclical of separation and job-finding rates

		<u>λ shock only</u>		<u>λ and productivity shocks</u>	
		low a	high a	low a	high a
Separations	Average	0.0153	0.0098	0.0151	0.0097
	Cyclical	0.892	1.300	0.826	1.144
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclical	-0.073	-0.045	-0.164	-0.114
Unemployment	Average	0.048	0.032	0.048	0.031
	Cyclical	0.851	1.229	0.897	1.160

Notes: The series are HP-filtered with a smoothing parameter of 900,000 and the cyclical is measured as in the CPS data (see notes in Table 1 for details). Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers.

3.5 Firm and Plant Death

Another reason why separations are more cyclical for workers with high ability could be that separations in recessions are driven by the death of firms and plants. In fact, there is ample evidence that firm and plant death is countercyclical (see Davis, Haltiwanger and Schuh, 1996; Figura, 2006). If workers of different ability are randomly distributed across firms, then plant death will increase separations for workers of all types by the same absolute number, and more in percentage terms for those with low average separation rates (high-ability workers). A simple way of modeling such shocks is to introduce an exogenous firm death shock. In the benchmark model with one employee per firm, this is equivalent to an exogenous separation shock. Figura (2006) shows that the yearly plant death rate increased from bottom to peak by approximately 5 percentage points in the 1981/1982 recession and by 7 percentage points in the 1991 recession. The average of these two recessions corresponds to an increase in the monthly death rate of approximately 0.5 percentage points. For this reason, I extend my benchmark model from above by assuming that firms are hit by a death shock (λ) with a 0.5% probability per month in recessions and with zero probability in booms. As expected, Table 5 shows that separations in this model are more cyclical but on average lower for high-ability workers, as in the CPS data. However, the model fails in fully accounting for the differences in the cyclical of separations between low- and high-ability workers. With firm and plant death shocks, differences in the cyclical of separations only come from differences in the

average separation rates. More precisely, it can be shown that in the presence of such shocks alone, the ratio of the cyclicity of separation rates is $\frac{\beta_{low}^{sep}}{\beta_{high}^{sep}} \approx \frac{\bar{s}_{high}}{\bar{s}_{low}}$, where \bar{s}_i denotes the average separation rate of group i . The ratio of the average separation rates between low- and high-wage workers in the CPS is 0.61, whereas the ratio of the cyclicity of separation rates in the CPS is 0.53. In other words, a model with only firm and plant death shocks cannot fully explain the differences in cyclicity of separations in the CPS. As explained above, productivity shocks tend to shift separations in the opposite direction and thus, they make it even more difficult to fully match the differences found in the data.

4 Credit-Constraint Shocks

Recessions are often periods where access to credit becomes more difficult.¹⁵ Because of a shortfall of productivity in the short term, firms might therefore be forced to close down projects that would be profitable in the long term. How does such a credit-tightening affect job separations? And, in particular, does it affect matches with workers of low and high ability in a different way?

To more formally evaluate these questions, I incorporate credit-constraint shocks into my benchmark model. I use a short-cut by assuming that in recessions, worker-firm matches face a constraint to produce cash flows above some negative number $\gamma(z)$:

$$zxa_i - w_i(z, x) \geq \gamma(z). \quad (2.13)$$

Naturally, workers may be willing to deviate from the Nash bargained wage and take a wage cut in order to continue the relationship. For this reason, wages are assumed to satisfy the Nash-bargaining solution $w_i^{NB}(z, x)$ as long as the cash-flow constraint (2.13) can be met, but otherwise adjust to meet the constraint:

$$w_i(z, x) = \begin{cases} w_i^{NB}(z, x) & \text{if } zxa_i - w_i^{NB}(z, x) \geq \gamma(z) \\ zxa_i - \gamma(z) & \text{if } zxa_i - w_i^{NB}(z, x) < \gamma(z), \end{cases} \quad (2.14)$$

¹⁵ See, e.g., Lown and Morgan (2004) who provide evidence that banks strongly tighten commercial credit standards in recessions. Moreover, Kiyotaki and Moore (1997) provide a theoretical rationale for cyclical variations in borrowing constraints. In their model, small aggregate shocks lead to tighter borrowing constraints through a price effect on collaterals. These effects on borrowing constraints can be large as a reduction in the price of the collateral can lead to a further decline in demand for these assets and thus to a further reduction in the value of the collateral.

If the cash-flow constraint cannot be met at any acceptable wage for the worker, worker-firm matches will dissolve. The separation condition now states that the worker and the firm are willing to remain in the relationship if their share of the surplus is non-negative:

$$W_i(z, R_i^w(z)) - U_i(z) = 0 \quad (2.15)$$

$$J_i(z, R_i^f(z)) - V_i(z) = 0, \quad (2.16)$$

where $R_i^w(z)$ is the worker reservation match productivity and $R_i^f(z)$ is the firm reservation match productivity. By (2.15) and (2.16), the reservation match productivities differ between worker and firm and separations may occur even if the joint surplus is positive.¹⁶ Actually, firms never unilaterally fire a worker since cash-flow constraints only impose an upper limit on the wage but not a lower limit (i.e. $R_i^w(z) \geq R_i^f(z)$).

If workers are willing to take wage cuts to continue the relationship, one may wonder whether cash-flow constraints will ever result in separations. It should be kept in mind, however, that workers are willing to take wage cuts only as long as their share of the surplus remains positive. At the efficient-separation level of match productivity $R_i(z)$, for example, workers are not willing to take any wage cut because their surplus from the match is zero. Therefore, a binding cash-flow constraint will always lead to the separation for the matches whose productivity is at, or below, the efficient-separation level of match productivity $R_i(z)$.¹⁷ For worker-firm matches with $x > R_i(z)$, there is some room for wage adjustment. However, the actual wage cut that the worker may be willing to take is small, because the surplus for those x close to $R_i(z)$ is small.

The value functions in this model extension are the same as in the baseline model, except for the value function of the filled vacancy:

¹⁶ The assumption here is that wages are renegotiated in every period. In fact, if the firm could commit to pay higher wages in the future when the constraint is no longer binding, the worker-firm match could always be sustained if the total current surplus is positive. However, it is questionable whether such commitment devices exist, especially because it requires a state contingent path for future wages.

¹⁷ See Appendix A.2 for a formal proof of this statement.

$$J_i(z, x) = zxa_i - w_i(z, x) + \beta E \left[\frac{\sigma_i^w(z', x') \max \{J_i(z', x'), V_i(z')\}}{(1 - \sigma_i^w(z', x'))V_i(z')} \mid z, x \right], \quad (2.17)$$

where $\sigma_i^w(z', x')$ takes a value of 1 if the worker stays with the firm and 0 if the worker quits.¹⁸

4.1 Results

I use the same calibration as in the baseline model of Section 3. The only parameter left to calibrate is $\gamma(z)$. Table 6 shows the simulation results for three different values of $\gamma(z)$. I assume it to be 100%, 250% or 400% of the average cash flow in the unconstrained economy (these values correspond to $\gamma(z) = -0.02$, $\gamma(z) = -0.05$ and $\gamma(z) = -0.08$, respectively). The average cash flow in this economy is about 2.0% of average labor productivity. This is similar to other models; e.g., the cash flow in the model of Shimer (2005) is around 1.5% of average labor productivity. It may be argued that these constraints are very tight as a firm would need just one to four months of average productivity (depending on the calibration of γ) to repay current losses. Note, however, that in this model, match productivity shocks are highly correlated across time and thus, the chances of recovering current losses are far smaller than that.

All my calibrations yield more cyclical separations for high-ability workers. The calibration with the tightest constraint ($\gamma(z) = -0.02$), however, seems unrealistic as it leads to aggregate separations that are far too cyclical relative to aggregate job findings. The reason is that the constraint is relatively tight, which makes aggregate separations very volatile. The calibrations where $\gamma(z) = -0.05$ and $\gamma(z) = -0.08$ do better in that respect and, at the same time, produce more cyclical separations for high-ability workers. Quantitatively, the model even overpredicts the cyclicity for high-ability workers when $\gamma(z) = -0.05$, whereas it exactly matches the ratio of the cyclicity of separations of low- and high-ability workers in the CPS data when $\gamma(z) = -0.08$ (i.e. $\frac{\beta_{low}^{sep}}{\beta_{high}^{sep}} = 0.54$).

¹⁸ A directed search equilibrium is defined as $R_i^w(z)$, $R_i^f(z)$, $w_i(z, x)$, $\theta_i(z)$ and the value functions $U_i(z)$, $W_i(z, x)$, $V_i(z)$ and $J_i(z, x)$ that satisfy: 1. the Nash-bargaining solution subject to the cash-flow constraint (2.13), 2. the separation equations (2.15) and (2.16), 3. the zero-profit condition:

Table 6. Model with credit-constraint shocks: The cyclicality of separation and job-finding rates

		$\gamma = -0.02$		$\gamma = -0.05$		$\gamma = -0.08$	
		low a	high a	low a	high a	low a	high a
Separations	Average	0.0144	0.0091	0.0131	0.0084	0.0128	0.0077
	Cyclicality	1.114	1.380	0.669	1.658	0.702	1.279
Job findings	Average	0.30	0.30	0.30	0.30	0.30	0.30
	Cyclicality	-0.025	-0.008	-0.205	-0.122	-0.397	-0.257
Unemployment	Average	0.046	0.030	0.042	0.028	0.041	0.025
	Cyclicality	0.916	1.133	0.690	1.477	0.847	1.246

Notes: The series are HP-filtered with a smoothing parameter of 900,000 and the cyclicality is measured as in the CPS data (see notes in Table 1 for details). Sample size: 1000 monthly observations where each observation is estimated from a cross-section of 30,000 workers.

4.2 Discussion

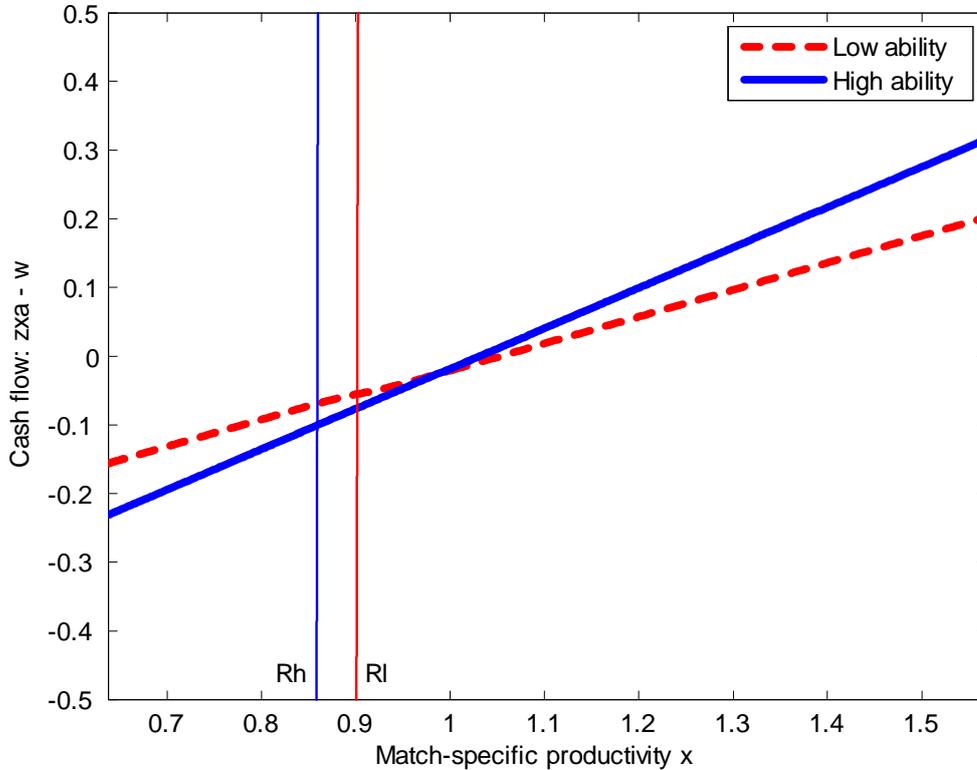
The important insight of this last model extension is that in the baseline model outlined in Section 3, each worker-firm match produces negative cash flows at the efficient reservation productivity level. As shown in Appendix A.2, the firm's cash flows at the reservation productivity level $R_i(z)$ can be written as:

$$CF_i(z, R_i(z)) = -\beta E \left[\max \{ (1 - \alpha) S_i(z', x'), 0 \} \mid z, R_i(z) \right], \quad (2.18)$$

This says that cash flows at the reservation productivity level $R_i(z)$ are equal to minus the expected future discounted match surpluses S_i (times the bargaining share of the firm). Therefore, as long as the firm receives a positive share of the surplus (i.e. $1 - \alpha > 0$), cash flows are negative at $R_i(z)$. This can also be seen in Figure 6, which plots cash flows by match-specific productivity. Importantly, cash flows are more negative at the reservation match productivity level for high-ability workers than for low-ability workers because the expected future surplus is higher.¹⁹ For this reason, separations of high-ability workers are more sensitive to a tightening of

$V_i(z) = 0$ and 4. the value functions (2.7), (2.8), (2.9) and (2.17).

¹⁹ This can be attributed to two effects: First, because high-ability workers face lower replacement rates, the reservation match productivity $R_i(z)$ is lower and thus cash flows are more negative at $R_i(z)$. Second, match surpluses at a given level of x and z are increasing in ability, which implies that at $R_i(z)$, cash flows are more negative for high ability workers even if $R_i(z)$ is the same for both types (this can also be easily seen in Figure 6). Appendix A.2 shows that if both types of workers face identical replacement rates, then $S_i(z, x) = a_i \tilde{S}(z, x)$ where $\tilde{S}(z, x)$ is a function that is independent of ability type.

Figure 6: *Cash flows by match-specific productivity and worker type*

credit.

One potential concern may be that, in the model, firms are small in the sense that they only have one employee. It may be argued that if firms had more than one worker, the above mechanism would produce different results because the cash-flow constraint would be operating at the firm and not at the match level. In particular, high-ability workers generate a higher surplus for the firm (because of high expected future productivity) and thus, the firm might prefer to lay off low-ability workers in order to keep its high-ability workers. Notice, however, that getting rid of low-ability workers may not always relax the constraint sufficiently to keep the high-ability workers. More generally, in a multi-worker firm, each worker-firm relationship has a shadow value of relaxing the cash-flow constraint. This shadow value is larger for matches with high-ability workers, because these workers produce more negative cash flows at the productivity threshold where separations occur. In other words, firing one high-ability worker would allow keeping many low-ability workers, whereas

the firm would have to fire many low-ability workers to keep one high-ability worker. For reasonable assumptions regarding the substitutability between the two types of workers, the mechanism in my model should therefore also be expected to be operative in a multi-worker firm setup.

Ideally, one should set up a multi-worker firm model to investigate the qualitative and quantitative effects of cash-flow constraints on the cyclicity of separations for low- and high-ability workers. However, such a model is very complicated as the wage bargained by one worker affects the firm-level cash-flow constraint and thus, the wage bargained by other workers. Stole and Zwiebel's (1996) intrafirm bargaining game would be a good starting point, but further complicated by the presence of low- and high-ability types. This important work is left for future research.

5 Conclusion

This paper provides new facts about the composition of the unemployment pool over the U.S. business cycle. In recessions, the pool of unemployed shifts towards workers with high wages in their previous job. Moreover, this change is driven by the higher cyclicity of separations for high-wage workers. These empirical patterns are difficult to explain with a standard search-matching model with endogenous separations and worker heterogeneity, since it predicts shifts in the pool of unemployed in the opposite direction of the data.

I offer two extensions of the model that work better at replicating these new facts. The first extension introduces firm death shocks, which affect all workers indiscriminately of type. However, these shocks cannot fully account for the more cyclical separations of high-ability workers because, with such death shocks, differences in the cyclicity of separation rates between low-wage and high-wage individuals are limited by differences in the average separation rates between the two groups. The second extension with credit-constraint shocks, on the other hand, can fully match the differences in the cyclicity of separations between low- and high-ability workers. It is somewhat difficult to exactly pin down the magnitude of these credit-constraint shocks, but my simulations show that the separations of high-ability workers are more cyclical for a broad range of parameter values.

Shifts towards high-ability workers among the unemployed in slumps have im-

portant implications for models of aggregate fluctuations of the labor market and pose an additional challenge to the recent literature on the "unemployment volatility puzzle" (see Shimer, 2005). Specifically, these compositional changes aggravate the apparent lack of an amplification mechanism in the standard search-matching model, as they dampen the response of the firms' recruiting behavior to aggregate productivity shocks. Moreover, the shifts may have a large impact on the welfare costs of business cycles as high-ability workers are better able to self-insure against unemployment shocks (see, e.g., Mukoyama and Sahin, 2006). To conduct a proper welfare analysis, however, I have to model the savings and consumption choices of the employed and unemployed. I leave this important task to future research.

Another avenue for future research is to extend my empirical analysis with other data sources. Matched employer-employee data is particularly promising as it allows us to determine the importance of firm death for separations. Moreover, it makes it possible to extract individual fixed effects from the wage and perform the same type of analysis with the average individual effect instead of the average previous wage. It will also be interesting to extend my empirical analysis to other countries. Many European countries have an extensive employment protection legislation, which may affect the sign as well as the magnitude of the shifts in the unemployment pool. E.g., seniority rules make it harder for firms to lay off more experienced workers. But it is unclear how these rules interact with the business cycle. On the one hand, seniority rules imply that separations in recessions should be concentrated on the less experienced workers. On the other hand, these rules might be circumvented or inapplicable in recessions (e.g., because of firm and plant death) and thus, the shift towards high-wage workers may be even stronger than in the U.S.

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Appendix

A.1 A Search-Matching Model with Non-Directed Search

If search on the firm side is non-directed to a particular worker type, then there is only one aggregate matching function:

$$M = \kappa u^\eta v^{1-\eta}. \quad (2.19)$$

Note that in this model, there is an important interaction between the labor markets of low- and high-ability types, as the composition of the pool of unemployed is of importance for the firm's chances of meeting the high-ability types and thus affects the incentives for posting vacancies.

The value functions of the worker are the same as before:

$$U_i(Z) = b_i + \beta E[(1 - f(\theta_i))U_i(Z') + f(\theta_i)W_i(Z', \bar{x}) | Z] \quad (2.20)$$

$$W_i(Z, x) = w_i(Z, x) + \beta E[\max\{W_i(Z', x'), U_i(Z')\} | Z, x], \quad (2.21)$$

whereas the value functions of the firm are now:

$$V(Z) = -c + \beta E[(1 - q(\theta))V(Z') + q(\theta)(\pi J_l(Z', \bar{x}) + (1 - \pi)J_h(Z', \bar{x})) | Z] \quad (2.22)$$

$$J_i(Z, x) = zxa_i - w_i(Z, x) + \beta E[\max\{J_i(Z', x'), V(Z')\} | Z, x], \quad (2.23)$$

where the important difference is that the value of the vacancy is now independent of type, as firms post vacancies for all types of workers. This implies that the value of posting a vacancy depends on the share of the low-ability types in the pool of unemployed (π).

A *non-directed* search equilibrium is defined as $R_i(Z)$, $w_i(Z, x)$, $\theta(Z)$ and the value functions $U_i(Z)$, $W_i(Z, x)$, $V(Z)$ and $J_i(Z, x)$ that satisfy: 1. the Nash-bargaining solution (2.11), 2. the efficient-separation equation (2.12), 3. the zero-profit condition: $V(Z) = 0$ and 4. the value functions (2.20), (2.21), (2.22) and (2.23).

Note that in the non-directed search equilibrium, the group-specific unemployment rates and the distribution of types across match productivities are aggregate

state variables. The reason is that the firms' decision to post a vacancy depends on the share of low types in the pool of unemployed in the current as well as in future periods. The distribution of worker types across match productivities x is needed to forecast the share of low types in the future, because the more workers of one type are close to the productivity threshold where separations occur, the more likely this share is to increase for that group in the future. This complicates the analysis considerably as it is generally not possible to solve a model with a highly dimensional state space such as with the distribution of worker types across match productivities. For this reason, I only do the comparative statistics for the non-directed search model because in the steady state, the distribution of worker types is constant across time. I leave it to future work to compute an approximate equilibrium with a limited set of aggregate state variables similar to Krusell and Smith's (1998) method in models with heterogeneity in asset holdings. Appendix Tables A.4, A.5 and A.6 show the comparative statics results for the directed and non-directed search model. The results between the two models are similar; in particular, the differences in the cyclicity of separations between the low- and high-ability types are not affected to any considerable extent by the modeling choices on non-directed or directed search.

A.2 A Search-Matching Model with Cash-Flow Constraints

This appendix provides formal propositions and proofs of the intuition explained in the text.

Proposition 1 *At the efficient reservation match productivity $R_i(z)$, the firm's cash flows are negative if the firm's bargaining share is larger than 0.*

Proof. At $R_i(z)$, the joint surplus of the match is zero, as well as the surplus share of the firm. Because of the zero-profit condition, we get:

$$\begin{aligned}
 0 &= J_i(z, R(z)) - V_i(z) \\
 &= J_i(z, R(z)) \\
 &= CF_i(z, R(z)) + \beta E \left[\max \{ J_i(z', x'), 0 \} \mid z, R_i(z) \right],
 \end{aligned}$$

and thus

$$\begin{aligned} CF_i(z, R_i(z)) &= -\beta E \left[\max \{J_i(z', x'), 0\} \mid z, R_i(z) \right] \\ &= -\beta E \left[\max \{(1 - \alpha)S_i(z', x'), 0\} \mid z, R_i(z) \right], \end{aligned}$$

which says that cash flows have to be negative at the efficient reservation match productivity level if the firm expects a surplus from the match in the future, i.e., if the firm's surplus share is positive ($1 - \alpha > 0$). This holds for any process of match productivity with some positive probability of a higher match productivity in future periods. ■

Proposition 2 *At the efficient reservation match productivity $R_i(z)$, wages do not adjust in response to a credit-constraint shock, and matches separate if the constraint is binding.*

Proof. At the efficient reservation match productivity, the total match surplus as well as the worker share of the surplus is zero. Therefore, the worker is not willing to take a wage cut, because it would result in a negative surplus share for the worker. ■

Proposition 3 *If $b_i = ba_i$ and $f(\theta_i) = f$, then, at the efficient reservation match productivity $R_i(z)$, cash flows are more negative for high-ability workers.*

Proof. From the proposition above, we know that the cash flow at the reservation match productivity level depends on the discounted future expected surplus. So if the expected surplus is higher for high-ability workers, then cash flows are more negative at $R_i(z)$. If $b_i = ba_i$, then the surplus can be written as:

$$\begin{aligned} S_i(z, x) &= W_i(z, x) - U_i(z) + J_i(z, x) \\ &= a_i(zx - b) + \beta E \left[\max \{S_i(z', x'), 0\} \mid z, x \right] \\ &\quad - \beta f(\theta_i) \alpha E \left[\max \{S_i(z', \bar{x}), 0\} \mid z \right], \end{aligned}$$

and if $f(\theta_i) = f(\theta)$, then

$$S_i(z, x) = a_i \tilde{S}(z, x),$$

where $\tilde{S}(z, x) \geq 0$ is independent of ability. This implies that the surplus is increasing proportionally to ability and thus cash flows at $R_i(z)$ are more negative for high-ability workers. ■

It follows that if $\frac{db_i}{da_i} = 0$, cash flows at the reservation match productivity level are even more negative for high-ability workers, since the surplus is even higher for high-ability workers. Note that the assumption that the job-finding rates are the same for the two groups is not necessarily met: the model calibration targets the average job-finding rate to be 0.3 for both groups, but the job-finding rates are allowed to differ over the cycle.

Table A.1 The cyclicalities of separation rates, by wage group (robustness checks)

		<u>Log(hourly wage)</u>		<u>Mincer residual</u>	
		low	high	low	high
E--> U (Baseline)	Cyclicalities (s.e.)	0.40 (0.082)***	0.75 (0.099)***	0.45 (0.063)***	0.67 (0.085)***
E --> U + OLF	Cyclicalities (s.e.)	0.05 (0.043)	0.30 (0.055)***	0.10 (0.046)**	0.21 (0.056)***
E --> U (not on temporary layoff) (1988-2008 only)	Cyclicalities (s.e.)	0.38 (0.086)***	0.77 (0.146)***	0.40 (0.096)***	0.73 (0.112)***
Subsample: age 25-54	Cyclicalities (s.e.)	0.43 (0.089)***	0.75 (0.081)***	0.46 (0.072)***	0.73 (0.077)***
Subsample: men	Cyclicalities (s.e.)	0.46 (0.080)***	0.74 (0.084)***	0.50 (0.064)***	0.73 (0.098)***
Subsample: full-time workers	Cyclicalities (s.e.)	0.38 (0.088)***	0.74 (0.102)***	0.44 (0.066)***	0.67 (0.090)***
Subsample: Some college or more	Cyclicalities (s.e.)	0.42 (0.121)***	0.74 (0.108)***	0.45 (0.100)***	0.76 (0.093)***
Subsample: 1990-2008	Cyclicalities (s.e.)	0.35 (0.083)***	0.78 (0.111)***	0.45 (0.078)***	0.64 (0.110)***
Filtering: HP-filtered with smoothing parameter 14400	Cyclicalities (s.e.)	0.54 (0.174)***	1.08 (0.171)***	0.61 (0.109)***	1.01 (0.200)***
Filtering: Not filtered, but controlling for linear trend	Cyclicalities (s.e.)	0.39 (0.054)***	0.76 (0.068)***	0.44 (0.055)***	0.69 (0.062)***
Adjusted for time aggregation bias	Cyclicalities (s.e.)	0.28 (0.084)***	0.61 (0.106)***	0.32 (0.069)***	0.54 (0.089)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000 (unless otherwise stated). The cyclicalities are measured as the coefficient β in the regression $\log(x_{it}) = \alpha + \beta \log(U_t) + \epsilon_{it}$, where x_{it} is the separation, job-finding or unemployment rate of group i at time t and U_t is the sample unemployment rate. Similar to Bils, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment rate because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

Table A.2 The cyclical job-finding rates, by wage group (robustness checks)

		<u>Log(hourly wage)</u>		<u>Mincer residual</u>	
		low	high	low	high
U --> E (Baseline)	Cyclical (s.e.)	-0.57 (0.059)***	-0.72 (0.069)***	-0.68 (0.073)***	-0.61 (0.077)***
U + OLF --> E	Cyclical (s.e.)	-0.38 (0.074)***	-0.48 (0.060)***	-0.41 (0.064)***	-0.43 (0.060)***
U (not on temporary layoff) --> E (1988-2008 only)	Cyclical (s.e.)	-0.62 (0.067)***	-0.90 (0.117)***	-0.76 (0.094)***	-0.75 (0.078)***
Subsample: age 25-54	Cyclical (s.e.)	-0.53 (0.084)***	-0.69 (0.071)***	-0.65 (0.099)***	-0.59 (0.088)***
Subsample: men	Cyclical (s.e.)	-0.57 (0.067)***	-0.66 (0.063)***	-0.64 (0.091)***	-0.61 (0.076)***
Subsample: full-time workers	Cyclical (s.e.)	-0.57 (0.078)***	-0.69 (0.066)***	-0.69 (0.100)***	-0.58 (0.071)***
Subsample: Some college or more	Cyclical (s.e.)	-0.64 (0.085)***	-0.73 (0.088)***	-0.76 (0.078)***	-0.62 (0.096)***
Subsample: 1990-2008	Cyclical (s.e.)	-0.60 (0.087)***	-0.82 (0.088)***	-0.75 (0.098)***	-0.68 (0.079)***
Filtering: HP-filtered with smoothing parameter 14400	Cyclical (s.e.)	-0.65 (0.156)***	-0.60 (0.136)***	-0.68 (0.173)***	-0.61 (0.159)***
Filtering: Not filtered, but controlling for linear trend	Cyclical (s.e.)	-0.69 (0.049)***	-0.68 (0.058)***	-0.76 (0.061)***	-0.63 (0.048)***
Adjusted for time aggregation bias	Cyclical (s.e.)	-0.69 (0.072)***	-0.86 (0.082)***	-0.81 (0.087)***	-0.74 (0.094)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000 (unless otherwise stated). The cyclical is measured as the coefficient β in the regression $\log(x_{it}) = \alpha + \beta \log(U_t) + \epsilon_{it}$, where x_{it} is the separation, job-finding or unemployment rate of group i at time t and U_t is the sample unemployment rate. Similar to Bils, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment rate because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

Table A.3 The cyclicalities of unemployment rates, by wage group (robustness checks)

		<u>Log(hourly wage)</u>		<u>Mincer residual</u>	
		low	high	low	high
U	Cyclicalities (s.e.)	0.81 (0.024)***	1.25 (0.030)***	0.91 (0.027)***	1.11 (0.035)***
U + OLF	Cyclicalities (s.e.)	0.06 (0.044)	0.18 (0.060)***	0.09 (0.047)*	0.13 (0.056)**
U not on temporary layoff (1988-2008 only)	Cyclicalities (s.e.)	0.81 (0.048)***	1.35 (0.069)***	0.92 (0.056)***	1.19 (0.054)***
Subsample: age 25-54	Cyclicalities (s.e.)	0.80 (0.024)***	1.24 (0.027)***	0.91 (0.031)***	1.11 (0.040)***
Subsample: men	Cyclicalities (s.e.)	0.78 (0.032)***	1.18 (0.027)***	0.88 (0.032)***	1.14 (0.040)***
Subsample: full-time workers	Cyclicalities (s.e.)	0.80 (0.027)***	1.21 (0.029)***	0.92 (0.028)***	1.09 (0.032)***
Subsample: Some college or more	Cyclicalities (s.e.)	0.81 (0.045)***	1.16 (0.037)***	0.95 (0.035)***	1.07 (0.044)***
Subsample: 1990-2008	Cyclicalities (s.e.)	0.80 (0.032)***	1.27 (0.045)***	0.92 (0.030)***	1.11 (0.039)***
Filtering: HP-filtered with smoothing parameter 14400	Cyclicalities (s.e.)	0.81 (0.048)***	1.23 (0.060)***	0.86 (0.057)***	1.17 (0.076)***
Filtering: Not filtered, but controlling for linear trend	Cyclicalities (s.e.)	0.83 (0.022)***	1.22 (0.028)***	0.92 (0.022)***	1.10 (0.028)***

Notes: Newey-West corrected standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. All series are HP-filtered with a smoothing parameter of 900,000 (unless otherwise stated). The cyclicalities are measured as the coefficient β in the regression $\log(x_{it}) = \alpha + \beta \log(U_t) + \varepsilon_{it}$, where x_{it} is the separation, job-finding or unemployment rate of group i at time t and U_t is the sample unemployment rate. Similar to Bilal, Chang and Kim (2009), I instrument the sample unemployment rate with the official unemployment rate because of measurement error. Sample size: 322 monthly observations. Source: The author's estimates with data from the Current Population Survey 1979-2008.

Table A.4 Comparative statics results: baseline calibration

		<i>Non-directed search</i>		<i>Directed search</i>	
		low a	high a	low a	high a
Separations	Average	0.0120	0.0073	0.0123	0.0073
	Cyclical	0.458	-0.242	0.288	-0.014
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclical	-0.807	-0.807	-0.988	-0.560
Unemployment	Average	0.041	0.025	0.041	0.025
	Cyclical	1.265	0.565	1.277	0.546

Table A.5 Comparative statics results: model with firm and plant death

		<i>Non-directed search</i>		<i>Directed search</i>	
		low a	high a	low a	high a
Separations	Average	0.0147	0.0097	0.0146	0.0095
	Cyclical	0.788	0.944	0.715	0.952
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclical	-0.151	-0.151	-0.225	-0.140
Unemployment	Average	0.049	0.032	0.049	0.032
	Cyclical	0.939	1.094	0.940	1.092

Table A.6 Comparative statics results: model with credit-constraint shocks ($\gamma = -0.05$)

		<i>Non-directed search</i>		<i>Directed search</i>	
		low a	high a	low a	high a
Separations	Average	0.0122	0.0081	0.0122	0.0082
	Cyclical	0.512	1.136	0.316	1.111
Job findings	Average	0.30	0.30	0.30	0.30
	Cyclical	-0.240	-0.240	-0.446	-0.252
Unemployment	Average	0.041	0.027	0.041	0.027
	Cyclical	0.752	1.376	0.761	1.363

Chapter 3

The Lot of the Unemployed: A Time Use Perspective*

1 Introduction

Economists have long debated the causes and consequences of unemployment. To some, unemployment is a sign of market failure that causes some workers to be involuntarily prevented from working. To others, unemployment is a form of disguised leisure, a period when labor is voluntarily reallocated to more efficient uses. Time use data provide a new window on the lives of the unemployed. How much time do unemployed workers spend searching for a job? How much time do they spend in leisure activities and home production? Is the lot of the unemployed very different from that of the employed?

In this paper, we analyze the lives of the unemployed using time-use data for 14 countries. A new purchase on the experience of unemployment is made possible by the accumulation of comparable time-use data on large representative samples for several countries. In time-use surveys, individuals keep track and report their activities over a day or a longer period. We acquired time-use data from several sources, including government statistical agencies, the Multinational Time

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Use Study (MTUS) data from Oxford University's Center for Time Use Research, and the Harmonized European Time Use Survey (HETUS). Section 2 describes and briefly evaluates the data that we use.

In Section 3 we summarize how unemployed and employed individuals allot their time. In all of the regions for which we have data, the unemployed sleep nearly an hour more per day on weekdays than the employed. The unemployed also spend considerably more time engaged in home production, caring for others, watching TV and socializing.

The amount of time devoted to searching for a new job is of central interest in search theory and an important determinant of unemployment, yet it has rarely been studied directly.¹ We first proceed with a descriptive analysis of time devoted to job search. Key findings are: 1) The percentage of unemployed workers who search for a job on any given day varies from a low of 5% in Finland to 20% in the U.S. 2) Conditional on searching, the average search time ranges from 43 minutes in Slovenia to over 3 hours in Canada. 3) The unemployed spend considerably more time on job search than do the employed and those who are classified as out of the labor force, which suggests that conventional labor force categories represent meaningfully different states.

Section 4 provides a theoretical framework for understanding the time devoted to job search activities. We focus on Mortensen's (1977) canonical model of Unemployment Insurance (UI) and job search.² Job search intensity is modeled as time devoted to job search activities, as the opportunity cost of time is foregone leisure. The key prediction is that for a newly laid-off worker time spent on job search activities is decreasing in the level and maximum duration of UI benefits. Job search intensity should also decrease with access to other forms of insurance that provide income support during unemployment (e.g., through the spouse) and increase with mean and variance of the distribution of potential wage offers. Furthermore, time devoted to job search should increase with the expected duration of the new job, and individuals who are relatively more efficient in activities such as home production

¹ Exceptions are Barron and Mellow (1979), who use the May 1976 CPS supplement on job search activities in the last month, and find that the American unemployed searches an average of 7 hours a week, Layard, Nickell and Jackman (1991), who provide some evidence on time spent on job search by the unemployed in the U.S. and the U.K., and Holzer (1987) and Albrecht et al. (1989), who find that youth who devote more time to job search are more likely to find a job.

² Similar predictions come from labor supply models such as, e.g., Moffitt and Nicholson (1982).

should search less.

In Section 5 we evaluate the predictions of search theory with micro data from six countries and relate our measure of job search intensity to demographic variables such as age, education, gender and marital status. We find that, on average, women search significantly less than men of the same age and education, and these differences are more pronounced between married women and men. We also find that higher educated workers tend to devote more time to job search activities and that the age profile of time spent on job search is inverse U-shaped.

The unemployed in the U.S. and Canada spend more than twice as much time searching for a new job than do the unemployed in Western Europe and Eastern Europe, and eight times more time than in the Nordic countries. Understanding variability in job search time across countries is important for understanding national differences in the unemployment rate and duration of unemployment. Thus in Section 6 we use our sample of 14 countries to model the job search time as a function of country's unemployment system, wage dispersion and other variables. Although conclusions are highly speculative with such a small sample of countries, we find that income variability and the escalation of unemployment benefits are the most robust and strongest predictors of job search intensity. The finding that the unemployed devote more time to searching for a new job in countries where wage dispersion is higher, conditional on unemployment benefits, suggests that the potential gain from finding a higher paying job is an important motivator of search intensity.

2 Data Sources

We draw on data from 16 time-use surveys conducted in 14 countries between 1991 and 2006. Combined, the surveys represent 170,347 employed and 13,333 unemployed diary days. The sources are:

- Original micro time-use data files from the government statistical agencies of Austria, France, Germany, Italy, Spain, the U.K. and the U.S.A.
- The Multinational Time Use Study (MTUS) from Oxford University's Center for Time Use Research. The MTUS consists of a multitude of time-use surveys

conducted in 20 countries from 1961 to 2003. Activity codes were harmonized to a common set of 41 activities. We use data after 1991.

- The Harmonized European Time Use Survey (HETUS), which is a collection of time-use surveys conducted in 15 European countries, starting in the mid-1990s. There are 49 harmonized activity codes, in comparable format to the MTUS. HETUS does not grant access to the original micro data files, but we made use of the dynamic web application (<http://www.h2.scb.se/tus/tus/>), which produces estimated average minutes spent in various activities and participation rates for selected subsamples.

We limit our analyses to the subset of surveys that contain job search activities. For our cross-country comparisons of the time use of the employed and unemployed we harmonized the activity codes from MTUS, HETUS and the original survey files to produce comparable estimates.

Measuring unemployment and job search in time-use surveys

The definition of unemployment that we employ requires that the individual did not work in the previous week, actively looked for work in the previous 4 weeks, and was available to start work (last week or in the next two weeks, depending on the survey).³ In addition, in the U.S. individuals on layoff who expect to be recalled to their previous employer are classified as unemployed regardless of whether they searched or were available for work. This definition corresponds closely to the definition of unemployment in national labor force surveys. We restrict our sample to people age 20-54 to abstract from issues related to youth unemployment or retirement.⁴ For most of the surveys (exceptions are France, U.S. and Italy), the sample unemployment rate is slightly lower than the official unemployment rate, which is primarily due to our age restrictions. The correlation (weighted by number of job searchers) between the sample unemployment rate and the official unemployment rate in the corresponding year is 0.92.

³ For Canada, we do not have access to the original micro data and therefore we use unemployment status such as defined in MTUS (self-reported unemployed). In the German surveys, the respondents were not asked the questions listed above and therefore we also use the self-reported unemployment status.

⁴ The results are very similar for the sample of unemployed of age 20-65 (see the working paper version, Krueger and Mueller, 2008a).

Table 1. Summary statistics of the time use surveys

Country	Survey	Source: Original	Source: HETUS	Source: MTUS	# diary days	# diary days employed	# diary days unemployed
Austria	1992	x		x*	1	10,191	146
Belgium	1998-2000		x		2	6,068	428
Bulgaria	2001-02		x		2	4,980	871
Canada	1992			x*	1	4,271	286
Canada	1998			x*	1	4,402	207
Finland	1999-2000		x		2	4,872	371
France	1998-99	x	x*		1	6,874	741
Germany	1991-92	x*		x*	2	12,494	828
Germany	2001-02	x*	x*		3	13,819	922
Italy	2002-03	x	x		1	18,493	1,724
Poland	2003-04		x		2	17,029	2,577
Slovenia	2000-01		x		2	5,900	372
Spain	2002-03	x	x		1	17,400	1,884
Sweden	2000-01		x		2	4,994	176
UK	2000-01	x	x		2	8,195	219
USA	2003-06	x			1	30,365	1,581

* Unemployed defined as self-reported unemployed; elsewhere unemployed defined as not working, actively seeking work and available for work.

Sources:

- Multinational Time Use Study, version 5.5.2 (October 2005). Center for Time Use Research, Oxford University.
<http://www.timeuse.org/mtus/>

- Harmonised European Time Use Survey, online database version 2.0 (2005-2007). Statistics Finland and Statistics Sweden.
<https://www.h2.scb.se/tus/tus/>

- We obtained the original micro data files from the government statistical agencies of Austria (through the institute WISDOM), Germany, Italy, France (through the Centre Maurice Halbwachs) and Spain. The micro data files for the UK time use survey were provided by the UK Data archive and for the American Time Use Survey (ATUS) by the Bureau of Labor Statistics.

Job search activities are defined in similar ways across surveys and typically include calling or visiting a labor office/agency, reading and replying to job advertisements and job interviewing/visiting a possible employer (see the Appendix Table A.1 for more details). Table 1 lists the various surveys for which we were able to identify time spent in job search activities. The MTUS does not have an activity code identifying job search activities. However, for a number of countries in the MTUS we were able to identify job search activities because the code “time in paid work at home” (AV2) exclusively contains time allocated to job search for the unemployed. In HETUS, job search activities are included in the code “activities related to employment”, which also contains lunch breaks at work and time spent at the

workplace before and after work. The unemployed should not engage in activities related to employment except job search and thus we use this activity code in our cross-country comparisons.

We assess the accuracy of the HETUS tabulations by comparing our own estimates of job search time with those from HETUS for the subset of countries where we have access to the underlying micro data files. This enables us to check whether activities related to employment represent job search time in the HETUS. Table 2 shows that we closely reproduce the HETUS estimates of average minutes of job search and the proportion participating in job search on the diary day. The small differences for France and Spain are mainly due to the fact that we use a different definition of unemployed than HETUS. HETUS slightly overestimates job search for the UK, Germany and Italy. For countries where we have more than one source of data we use the original micro data file when that is available. If we do not have access to the original micro data, we use tabulations from HETUS or the MTUS harmonized data files, whichever is available.

3 Time Use Patterns of the Unemployed and Employed

Table 3 summarizes the number of minutes per day that employed and unemployed individuals spend in various activities for five geographic regions.⁵ Results are shown separately for weekdays, weekends and pooled over the entire week. The standard errors are quite small, so they are not reported.⁶ Not surprisingly, more pronounced differences between the employed and unemployed arise on weekdays, when most of the employed work. One word of caution is warranted, however, when comparing the unemployed to the employed because of potential selection issues (e.g., the unemployed might be disproportionately those with a strong distaste for work).

In each region, the unemployed sleep substantially more than the employed. Sleep is notably high for unemployed Americans, who average just over 9 hours

⁵ Appendix Table A.2 reports the number of minutes per day separately for men and women.

⁶ For the employed, the standard errors are usually around 1 or 2 minutes for each activity; for the unemployed they are larger, but usually no more than 5 minutes for most activities and most countries.

Table 2. Comparison of estimates from HETUS and original survey data

Country	Survey	Source	# diary days	# diary days employed	# diary days unemployed	Unemployment rate (sample)	Average job search, in minutes per day	Participation rate in job search
France	1998-99	Original	1	6,874	741	11.6%	21	19%
France	1998-99	HETUS*	1	6,865	824	12.7%	19	18%
Spain	2002-03	Original	1	17,400	1,884	10.0%	18	11%
Spain	2002-03	HETUS**	1	17,400	2,378	12.3%	16	10%
UK	2000-01	Original	2	8,195	219	2.8%	7	10%
UK	2000-01	HETUS	2	8,190	219	2.8%	8	14%
Germany	2001-02	Original*	3	13,819	922	6.4%	9	10%
Germany	2001-02	HETUS*	3	14,095	922	6.3%	10	11%
Italy	2002-03	Original	1	18,493	1,724	9.0%	9	8%
Italy	2002-03	HETUS	1	18,493	1,724	9.0%	10	8%

Note: Survey weights are used to compute percentages and averages.

* Unemployed defined as self-reported unemployed

** The survey questions to define unemployed differ for Spain between HETUS (currently looking for work) and our estimates from the original survey data (actively seeking work in the last 4 weeks).

Table 3. Average minutes per day by activity, region, employment status and day of the week
(Western Europe, Austria, Belgium, France, Germany, Italy, Spain, UK, Eastern Europe, Bulgaria, Slovenia, Poland, Nordic: Finland, Sweden)

	Employed, Weekday					Unemployed, Weekday				
	US	Canada	Western Europe	Eastern Europe	Nordic	US	Canada	Western Europe	Eastern Europe	Nordic
Sleep	474	458	470	466	463	549	511	521	540	504
Personal care	46	44	48	47	42	45	43	51	47	42
Eating	62	54	86	79	71	49	71	100	105	84
Work	410	445	398	411	368	12	50	21	10	54
Job search	1	0	0	n.a.	n.a.	41	38	16	14	5
Education	13	8	7	6	12	27	7	29	18	59
Home production and care of others	113	113	120	144	136	224	170	220	170	198
of which: childcare	37	23	22	25	28	47	43	30	37	32
Shopping and services	23	24	22	19	25	35	62	42	33	31
Voluntary, religious and civic activities	7	7	5	3	6	7	9	7	3	7
Sport	15	18	17	11	21	16	37	34	24	39
Leisure and socializing	186	180	177	175	199	344	363	313	295	316
of which: TV	108	90	88	104	89	202	165	150	159	144
Travel	85	89	87	75	86	73	79	82	72	78
Other	6	0	3	5	5	11	0	4	5	24
Employed, Weekend										
Sleep	550	520	541	527	542	571	538	551	556	565
Personal care	41	52	51	52	48	41	36	56	52	46
Eating	71	70	119	110	99	65	57	119	115	92
Work	113	129	98	141	77	6	7	7	3	14
Job search	0	0	0	n.a.	n.a.	10	3	3	2	2
Education	8	7	5	9	5	13	0	13	14	8
Home production and care of others	172	178	169	188	191	206	154	177	224	172
of which: childcare	30	32	24	29	27	43	17	24	29	29
Shopping and services	42	41	29	16	25	35	17	31	15	25
Voluntary, religious and civic activities	26	12	12	19	8	22	5	8	10	6
Sport	26	39	40	31	38	26	61	46	37	35
Leisure and socializing	298	317	289	270	313	372	471	347	330	378
of which: TV	160	125	120	148	125	207	186	155	174	176
Travel	84	86	83	72	88	65	90	79	69	79
Other	8	0	3	4	6	9	0	3	5	18
Unemployed, Weekend										
Sleep	496	475	490	484	486	555	519	530	544	522
Personal care	45	43	49	48	44	44	41	53	49	44
Eating	65	59	96	88	83	53	67	106	108	87
Work	325	356	312	334	285	10	38	17	8	43
Job search	1	0	0	n.a.	n.a.	32	28	12	11	4
Education	11	8	7	7	10	23	5	24	17	45
Home production and care of others	130	131	134	157	151	219	165	207	258	189
of which: childcare	37	26	22	26	28	46	28	28	35	37
Shopping and services	28	29	24	19	25	35	50	39	29	29
Voluntary, religious and civic activities	13	8	7	8	6	18	8	8	8	7
Sport	18	24	23	16	26	19	44	37	28	37
Leisure and socializing	218	219	209	202	232	352	303	323	305	334
of which: TV	123	100	97	117	99	204	171	157	164	153
Travel	84	88	86	74	86	71	82	81	71	78
Other	7	0	3	4	5	10	0	3	5	22

Notes: Survey weights were used to compute country averages. Region averages are weighted by the size of the labor force of each country. Universe: Labor force, age 20-54.
 Sources: HETUS, MTUS (Canada 1998, Austria, Germany 1991-92, France), ATUS, For Canada, we report the results for the more recent survey from 1998.

of sleep a night – almost as much as teenagers.⁷ Large differences in time use between the unemployed and employed are also evident for time spent in home production and taking care of others. The unemployed spend from 0.6 hours to 1.7 hours more than the employed engaged in home production and caring activities across the regions. More time is spent on personal care, eating and drinking by the employed in some regions and by the unemployed in others. The unemployed spend considerably more time than the employed in leisure and social activities.⁸ A large share of this difference is due to TV watching, which absorbs almost a quarter of the awake time of the unemployed in the U.S. The amount of time the unemployed spend socializing rises by over 10% on the weekends, possibly because it is easier to coordinate social activities with employed individuals on the weekend. In the Nordic countries, the employed spend more time in home production than in other regions, perhaps because taxes are high there and home production is not taxed. Curiously, the unemployed in the Nordic region spend less time on home production than their counterparts in most other countries. The unemployed-employed gap in time spent on child care is lower in the Nordic countries, probably because child care services are more widely available from public services.

As expected from labor force surveys of work hours, the time use data indicate that Americans and Canadians spend more time engaged in work related activities than workers in Western Europe and the Nordic countries.⁹ (The unemployed spend a small amount of time at work because in some of the surveys work includes related activities and because of classification errors.) The average unemployed worker spends about half an hour searching for a job on any given day in the U.S. or Canada, and substantially less in Europe. The unemployed spend almost as much time traveling as do the employed, which suggests that they are not sedentary.

The high sleep hours by the unemployed could result from depression or be a behavioral response to having a low opportunity cost of time.¹⁰ The greater time

⁷ Note that in the ATUS the sleep category includes time spent sleeping, tossing and turning, lying awake and insomnia. All but a few minutes of sleep are classified in the first category. The younger average age of the unemployed does not account for much of the difference in sleep between employed and unemployed individuals.

⁸ Freeman and Schetkatt (2005; Table 7) find a qualitatively similar pattern using broader activity categories for 7 countries.

⁹ In the time use data, Americans spend less time at work than Canadians, which is an interesting discrepancy from the pattern in labor force surveys of weekly work hours.

¹⁰ Interestingly, Krueger and Mueller (2008a) find that the unemployed feel less tired over the

devoted to home production and caring for others by the unemployed than the employed is also consistent with the unemployed having a lower opportunity cost of time.

Time Spent on Job Search Activities

How much time do the unemployed devote to searching for work? Table 4 reports the proportion of individuals who search for a job on any given day, called the participation rate, and the (unconditional) average duration of job search by labor force status, for all countries in our sample. As noted above, average search time is highest in the U.S.A., at 32.3 minutes per day, closely followed by Canada. Europeans search much less, but there is considerable variation across countries. In France the unemployed search around 21 minutes a day compared with 3 minutes in Finland.¹¹

The proportion participating in job search, which we consider the extensive margin, is highly correlated with the average duration of job search; the weighted correlation is 0.88.¹² The U.S.A. has the highest participation rate in job search at 20.2%, compared with a low of 5% in Finland.

The American unemployed also search more on the intensive margin – for those who engage in job search activities on a given day, the average duration of job search is 159.7 minutes in the U.S., compared to 104.6 minutes in all the other countries in our data set. One can decompose the variance of the log average search time, $Var(\log(s_i))$, into $Cov(\log(s_i), \log(p_i)) + Cov(\log(s_i), \log(s_i|p_i))$, where s_i denotes average search time in country i , p_i the average participation rate and $s_i|p_i$ the average search time conditional on participation. We find that the two terms are of similar size, suggesting that both the intensive and extensive margin contribute equally to the overall variation of search time across countries.

Figure 1 summarizes the distribution of job search times for those who searched on the diary day in a series of box plot diagrams for six countries for which we had

course of the day than the employed.

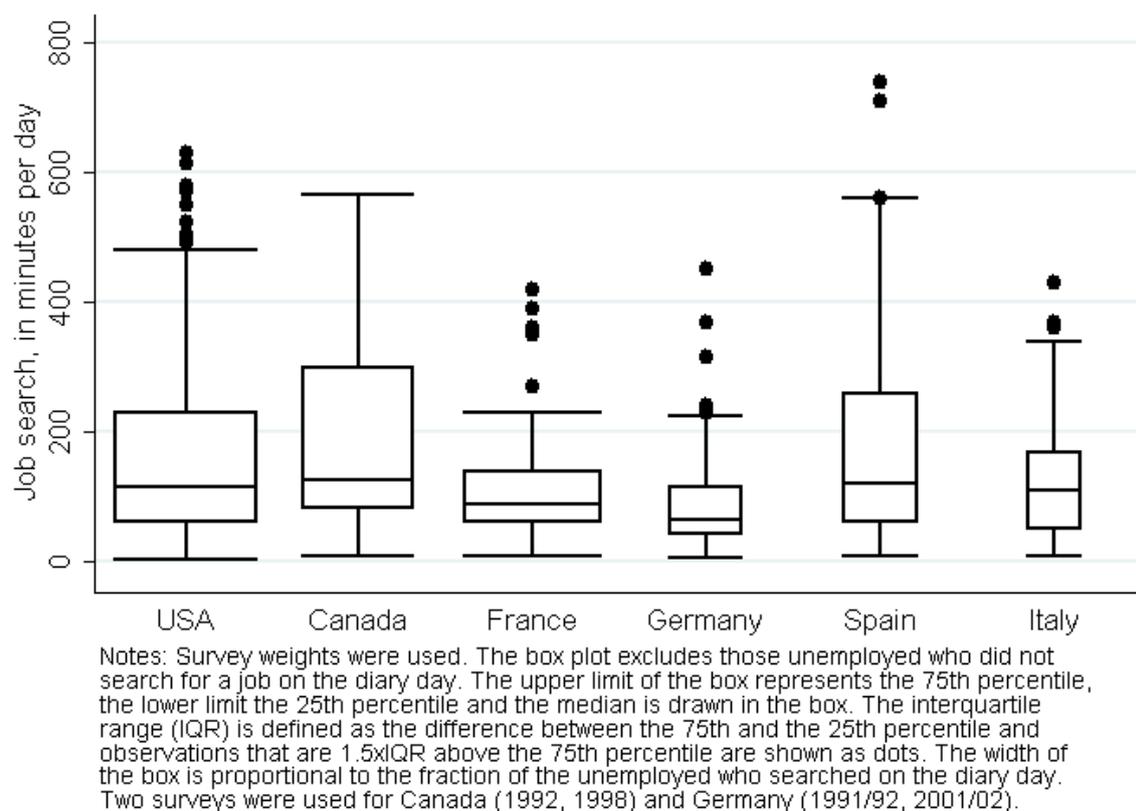
¹¹ The unemployed in the Nordic countries tend to spend much more time in education than elsewhere (around 45 minutes a day compared to 23 minutes in the U.S.). However, when we exclude from the sample of the Nordic countries those who indicate that they are a pupil, student, in further training or unpaid traineeship, time spent in education is only around 12 minutes a day, whereas time spent on job search remains unaffected at a low 3 minutes in Finland and 5 minutes in Sweden. This suggests that participation in educational programs does not explain the low job search intensity in these countries.

¹² The weights are the number of job searchers in each country's time-use data set.

Table 4. Labor force categories and job search

Country	Survey	Average job search, in minutes per day			Participation in job search		
		Employed	Unemployed	Out of labor force	Employed	Unemployed	Out of labor force
Austria	1992	0.0	10.5	0.6	0.1%	13.0%	0.6%
Belgium	1998-2000	n.a.	6 *	2 *	n.a.	9% *	1% *
Bulgaria	2001-02	n.a.	12 *	2 *	n.a.	8% *	1% *
Canada	1992	0.3	33.8	0.9	0.3%	16.3%	1.0%
Canada	1998	0.2	28.3	0.9	0.3%	15.6%	0.7%
Finland	1999-2000	n.a.	3 *	0 *	n.a.	5% *	1% *
France	1998-99	0.1	20.9	0.9	0.2%	19.4%	0.9%
Germany	1991-92	0.2	7.9	0.6	0.3%	10.5%	1.0%
Germany	2001-02	0.3	9.2	0.2	0.4%	10.2%	0.4%
Germany	2002-03	0.3	9.3	0.2	0.1%	7.8%	0.2%
Italy	2003-04	n.a.	11 *	0 *	n.a.	10% *	1% *
Poland	2000-01	n.a.	3 *	1 *	n.a.	7% *	2% *
Slovenia	2002-03	0.2	18.2	0.7	0.2%	10.7%	0.5%
Spain	2000-01	n.a.	5 *	2 *	n.a.	12% *	5% *
Sweden	2000-01	0.3	6.9	0.7	0.4%	10.5%	0.8%
UK	2003-06	0.6	32.3	0.9	0.7%	20.2%	0.7%

Note: Average search time and participation rates were computed with survey weights. Universe: Population, age 20-54.
* HE TUS rounds to the nearest integer.

Figure 1: *Box plot of job search in six countries*

access to micro data. The width of the box is drawn in proportion to the fraction of unemployed who searched on the diary day in each country. The median search time among those who searched is 115 minutes in the U.S.A. and 125 minutes in Canada, but just as high (120 minutes) in Spain and nearly as high (110 minutes) in Italy. Note, however, that there is a potential selection issue: countries with low search participation rates such as Italy might have highly motivated searchers, whereas in countries with high participation rates like the U.S.A. or Canada, more marginal searchers are included. Also, Figure 1 does not include countries with low search intensity such as Sweden and Finland as we do not have micro data for these countries.

One important feature to bear in mind is that job search is concentrated on weekdays. For the U.S., for example, participation in job search for those unemployed who are not on temporary layoff is 27.2% during weekdays and the (unconditional) average search time is 44.2 minutes, compared with 8.3% and 10.8 minutes, respec-

tively, during weekends. In the other countries, job search during the weekend is lower as well. In Spain, for example, the unemployed search on average 23.0 minutes during the week and 6.6 minutes during the weekend.

Table 4 also shows the average duration of job search and participation rates for the employed and those classified as out of the labor force. For both categories, average duration of job search is no more than two minutes in all the countries in our sample (note that HETUS rounds to the nearest integer). Moreover, participation in job search is equal or below 1%, except for Slovenia and Sweden. Even if we limit the sample in the U.S. to those who were classified as unemployed according to the CPS three months prior to the ATUS survey and classified as out of the labor force in the ATUS, average search time is only 1.9 minutes. Together, these results suggest that the unemployed spend considerably more time searching for a new job than do individuals who are classified as employed or out of the labor force. We interpret these results as evidence that the conventional labor force categories represent meaningfully different states and behavior patterns.

So far, we have only analyzed data on job search for one day. An open question is whether the unemployed who engage in job search on one day are more likely to engage in job search on another day during the same week. Most of the surveys in our sample only collect information on one diary day (or, if two diary days are collected, one is typically a weekend day). The German 2001-02 time-use survey is the only survey which included two weekday diaries for respondents. The following tabulation indicates that there is a high dependence of daily participation in job search: conditional on spending some time searching on day 1, the chance of searching on day 2 is 43%, whereas conditional on not searching on day 1, the fraction of unemployed searching on day 2 is only 7%. This reinforces the impression that the daily participation is an important determinant of the overall time spent on job search activities and that our inferences would not be very different if diary data for more than one day were collected. In particular, one would expect that, because of this high dependence, the same determinants that explain daily participation should also explain participation in job search over several days.

Cross tabulation of participants and non-participants on two weekdays:

<i>Search on day 1:</i>	<i>Search on day 2:</i>		
	No	Yes	Total
No	232	17	249
Yes	26	19	45
Total	258	36	294

Source: German Time Use Survey, 2001-02. Weighted frequencies. Sample consists of respondents with two weekday diaries. Chi-sq test of independence is 41.75 (p-value=.000).

4 Job Search: A Theoretical Framework

Theoretical search models yield clear predictions on the time devoted to job search activities as opposed to leisure activities or home production. We focus on Mortensen's (1977) canonical model of Unemployment Insurance (UI) and job search. Mortensen presents a search model with variable search effort and analyzes the effects of UI on search effort and, more generally, the escape rate from unemployment. In this model, an individual has two choice variables, search effort, s_t , and the reservation wage, w_t . Search effort is modeled as time allocated to job search, as the opportunity cost of search is foregone leisure. Given search effort, the arrival rate of job offers is constant (αs_t) and the wage is drawn from a known distribution $F(w)$ with upper bound \bar{w} . The value function of an unemployed individual who is eligible for UI benefits is:

$$V(t, b) = \frac{1}{1 + rh} \max_{0 \leq s_t \leq 1, w_t \geq 0} [hu(b, 1 - s_t) + V(t - h, b) + \alpha s_t h \int_{w_t}^{\bar{w}} (U(x) - V(t - h, b)) dF(x)], \quad (3.1)$$

where t is time until benefit exhaustion, h the length of each period, $u()$ the flow utility for the period, b the unemployment benefit, and $U(w)$ is the value of a job with wage w . There is no saving, so consumption equals the wage.

The first order conditions are:

$$(s_t) : u_2(b, 1 - s_t) = \alpha \int_{w_t}^{\bar{w}} (U(x) - V(t - h, b)) dF(x) \quad (3.2)$$

$$(w_t) : U(w_t) = V(t - h, b). \quad (3.3)$$

The optimal choice of how much time to spend searching trades off the marginal cost of foregone leisure against the increase in the probability of obtaining a job offer (times the expected gain from such an offer), and the optimal reservation wage strategy is to accept any wage offer that yields a value greater than or equal to the value of remaining unemployed at the end of the period.

The Mortensen model predicts that for a newly laid-off worker, search effort is decreasing in the maximum benefit duration T and in the benefit level b .¹³ Moreover, an increase in the average wage offer increases the value of all potential jobs and thus increases the returns to search. A higher dispersion of potential wage offers, holding the average wage offer constant, also leads to higher search effort. The intuition for this result is that, with a higher dispersion of potential wages, there is a greater benefit from searching for a high paying job, whereas if wage offers are compressed the individual might as well accept the first job offered, as the next is not likely to be much better.¹⁴ Note, however, that this conclusion depends on the curvature of the utility function: if workers are extremely risk averse, a greater mean-preserving spread in wages might actually lower the expected utility gain of getting a job and thus also the time allocated to job search.¹⁵

The Mortensen model also yields clear predictions across different demographic groups in terms of how much time these groups are expected to devote to job search activities. For example, unemployed workers with higher UI benefits or greater access to other forms of insurance that provide income support during unemployment (e.g., through a working spouse or self-insurance) should spend less time on job search activities. Home production also provides for consumption during unemployment and, therefore, unemployed workers who are relatively more efficient in home

¹³ The latter prediction requires the plausible assumption that consumption and leisure are complements.

¹⁴ Ljungqvist and Sargent (1995) make a similar observation concerning the effect of progressive taxation on job search and unemployment. See Stigler (1962) for a seminal discussion of how wage dispersion affects the payoff from search effort.

¹⁵ See Krueger and Mueller (2008b) for a calibrated version of the Mortensen model.

production are expected to devote less time to job search. Moreover, the value of a job is increasing in the expected duration of the job and thus job search intensity is expected to decrease with fewer remaining years of work before retirement. Older workers may also search less because of greater access to self-insurance through accumulated retirement savings. Finally, one should expect the highly educated to search more intensively as wages (as well as wage dispersion) tend to increase with human capital.

5 Demographic Determinants of Job Search

To evaluate the predictions of search theory for different demographic groups, we model the likelihood that an unemployed worker searches for a job on any given day as well as the amount of time spent searching, conditional on searching at all, as a function of age, education, gender and marital status. We have comparable micro data for the following six countries: the U.S.A., Canada, France, Germany, Spain and Italy.^{16,17} Because participation in job search is low (ranging from 7.8% in Italy to 20.2% in the U.S.A.), we think it is important to analyze participation and time allocated to job search separately.

Table 5a reports the results of linear probability models where the dependent variable equals one if the unemployed individual searched for a job on the reference day, and zero if he or she did not. Several regularities are apparent. First, education is an important predictor of participation in job search. In the U.S.A., for example, those with some college education or more have a 14.4 percentage point higher probability of engaging in job search on any given day than those without a high school degree. Education is associated with a greater likelihood of job search in Canada, France and Germany, but not in Spain or Italy. As outlined above, one would expect a generally higher search time among the higher educated because they reap greater returns to search (higher wages). Wage dispersion also tends to increase with education and might explain some of the observed differences in the

¹⁶ We also have micro data for Austria and the UK, but we do not report the country-level regressions because of small sample size (less than 250 diary days).

¹⁷ The three education dummies were defined as uncompleted secondary education, completed secondary education and tertiary education (completed and uncompleted). When information was available on whether a respondent was cohabiting with a partner, we defined them as married (USA, France, Germany).

effects of education across countries. Additionally, the job search process may be more time consuming in the jobs that higher educated individuals apply for.

A second observation is that women have a much lower probability of engaging in job search, and this is especially the case for married women. This may be because married women are more likely to have access to a secondary source of income from a working spouse and/or because of a comparative advantage in activities such as home production and childcare. Moreover, there are interesting cross-country differences in the effect of marriage and gender: the interaction term of married and female is an important determinant of job search for countries with traditionally low female labor supply. In Spain a married women's probability of search is 19.4 percentage points lower than a married man's and Italy the difference is 23.7 points.

Duration Conditional on Search

To examine whether the same variables explain search on the intensive margin, we estimate a linear regression of time allocated to search (in minutes), for those who engaged in job search on the reference day. Table 5b summarizes the results. Note that the samples are small since we exclude all of those who did not search from the regression.

As with engaging in job search, the higher educated unemployed tend to search more minutes (except in Spain) and women search less intensively, although the coefficients are statistically significant in only some countries. No clear pattern emerges regarding age from the regressions. Notice also that the F-tests of the joint significance of all variables cannot reject the null hypothesis at the 5% level for the U.S.A. and Canada. Overall we conclude that it is mainly the decision of whether to participate in job search on any given day that drives differences in time allocated to job search across different population groups.

Age Profile of Job Search

To examine the effect of age on total time spent searching for a job, we computed marginal effects on time allocated to job search, including non-participants. Specifically, the expectation of job search conditional on a set of characteristics, x , can be decomposed as $E(s|x) = P(s > 0|x)E(s|s > 0, x)$. Using the product rule we obtain

Table 5a. Micro data regressions for 6 countries: linear probability model

Dependent variable:							
participation in job search	Pooled	USA	Canada	France	Germany	Spain	Italy
Mean of dependent variable	0.129	0.202	0.160	0.194	0.104	0.107	0.078
Age/10	0.029 (0.020)	-0.044 (0.116)	0.224 (0.159)	-0.004 (0.122)	-0.046 (0.098)	0.008 (0.066)	0.016 (0.078)
Age ² /100	-0.003 (0.003)	0.01 (0.016)	-0.03 (0.021)	0.001 (0.017)	0.005 (0.013)	-0.004 (0.009)	-0.003 (0.011)
Uncompleted secondary education or less	---	---	---	---	---	---	---
Completed secondary education	0.005 (0.021)	0.065 (0.038)*	-0.055 (0.054)	0.062 (0.032)*	0.026 (0.022)	-0.018 (0.020)	-0.034 (0.020)*
Tertiary education	0.069 (0.031)*	0.144 (0.037)***	0.044 (0.052)	0.216 (0.051)***	0.083 (0.034)**	0.009 (0.024)	-0.006 (0.046)
Female	-0.061 (0.010)***	-0.048 (0.043)	-0.134 (0.045)***	0.002 (0.045)	-0.047 (0.037)	-0.09 (0.023)***	-0.047 (0.026)*
Married	0.012 (0.032)	-0.016 (0.047)	0.023 (0.061)	0.061 (0.049)	-0.067 (0.034)*	0.054 (0.033)	0.145 (0.062)**
Female*married	-0.066 (0.030)*	-0.053 (0.056)	0.035 (0.079)	-0.146 (0.059)**	0.009 (0.042)	-0.104 (0.035)***	-0.19 (0.061)***
Weekend	-0.127 (0.021)***	-0.174 (0.022)***	-0.214 (0.034)***	-0.257 (0.022)***	-0.102 (0.017)***	-0.106 (0.012)***	-0.072 (0.016)***
First quarter	---	---	---	---	---	---	---
Second quarter	-0.01 (0.008)	0.012 (0.043)	-0.078 (0.062)	0.031 (0.046)	-0.022 (0.029)	-0.01 (0.021)	-0.017 (0.029)
Third quarter	-0.023 (0.007)**	-0.041 (0.037)	-0.025 (0.062)	0.055 (0.050)	-0.019 (0.033)	-0.033 (0.021)	-0.034 (0.040)
Fourth quarter	-0.036 (0.015)*	-0.072 (0.039)*	-0.183 (0.052)***	0.011 (0.046)	-0.035 (0.029)	-0.023 (0.021)	-0.003 (0.041)
Constant	0.068 (0.036)*	0.235 (0.199)	-0.244 (0.272)	0.158 (0.213)	0.267 (0.176)	0.241 (0.118)**	0.116 (0.137)
Year dummies	x	x	x	x	x		x
Country dummies	x						
Observations	8,527	1,581	489	741	1,750	1,877	1,724
R-squared	0.08	0.09	0.14	0.13	0.06	0.08	0.08
Ftest	59.98 (1)	7.48	3.90	12.55	4.2	12.82	3.43
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Robust standard errors in parentheses; Standard errors are clustered at the country level in the pooled regression in column 1.

* significant at 10%; ** significant at 5%; *** significant at 1%

(1) Test of joint significance of coefficients for age, education, female, married and the interaction female*married. With clustered standard errors, the number of variables in a test of joint significance cannot exceed the number of clusters.

Note: Regressions were weighted using survey weights. Universe: Unemployed, age 20-54. The pooled regression in column 1 also includes Austria and the UK, but we do not report the country-level regressions for these two countries because the number of observations is small (less than 250 diary days).

Table 5b. Linear micro data regressions for 6 countries (participants only)

**Dependent variable:
time allocated to job search,
in minutes per day**

	Pooled	USA	Canada	France	Germany	Spain	Italy
Mean of dependent variable	136.5	159.7	197.2	107.8	83.3	169.4	118.7
Age	-3.699 (1.681)*	-4.871 (7.008)	31.533 (24.056)	-6.291 (5.197)	-2.951 (4.321)	-6.255 (9.232)	0.794 (10.686)
Age^2	0.061 (0.030)*	0.098 (0.096)	-0.476 (0.348)	0.082 (0.068)	0.046 (0.058)	0.099 (0.137)	0.001 (0.149)
Uncompleted secondary education or less	---	---	---	---	---	---	---
Completed secondary education	12.264 (13.362)	1.322 (43.246)	31.544 (58.428)	17.852 (15.443)	29.471 (14.517)**	-36.944 (31.402)	51.949 (32.574)
Tertiary education	15.69 (20.222)	6.074 (40.135)	94.609 (53.586)*	26.064 (17.346)	16.843 (15.617)	-62.545 (33.381)*	73.506 (41.428)*
Female	-27.436 (9.787)**	-9.321 (26.284)	-41.016 (58.976)	-46.569 (21.385)**	-8.386 (15.311)	-40.365 (24.348)*	-90.643 (23.822)***
Married	17.771 (15.120)	-7.99 (28.899)	95.984 (59.287)	21.911 (22.819)	-1.032 (15.211)	24.779 (37.658)	-11.857 (32.628)
Female*married	-38.901 (17.114)*	-39.727 (36.930)	141.664 (87.120)	-9.002 (24.926)	-17.173 (22.431)	-94.419 (43.683)**	3.234 (39.390)
Weekend	-10.196 (16.610)	-30.257 (21.953)	-68.261 (78.132)	54.733 (51.743)	-43.776 (11.393)***	49.379 (40.622)	23.068 (25.055)
First quarter	---	---	---	---	---	---	---
Second quarter	1.713 (14.356)	25.019 (27.420)	54.95 (67.814)	43.391 (13.552)***	-10.866 (13.526)	-47.949 (25.942)*	
Third quarter	-0.34 (17.266)	39.583 (25.132)	18.851 (50.350)	25.478 (13.698)*	10.903 (19.860)	-47.247 (30.605)	-39.852 (26.170)
Fourth quarter	6.807 (13.230)	-13.37 (22.970)	35.525 (48.381)	96.072 (23.122)***	1.621 (15.286)	-31.911 (29.879)	44.441 (27.995)
Constant	186.078 (36.780)***	185.511 (110.396)*	346.498 (354.977)	184.028 (94.114)*	116.34 (73.601)	332.594 (152.627)**	127.035 (170.595)
Year dummies	x	x	x	x	x		x
Country dummies	x						
Observations	940	276	67	142	161	181	78
R-squared	0.14	0.08	0.28	0.27	0.11	0.14	0.26
Ftest	16.02 (1)	1.58	1.29	3.74	2.23	3.47	3.35
P-value	0.001	0.076	0.251	0.000	0.013	0.000	0.001

Robust standard errors in parentheses; Standard errors are clustered at the country level in the pooled regression in column 1.

* significant at 10%; ** significant at 5%; *** significant at 1%

(1) Test of joint significance of coefficients for age, education, female, married and the interaction female*married. With clustered standard errors, the number of variables in a test of joint significance cannot exceed the number of clusters.

Note: Regressions were weighted using survey weights. Universe: Unemployed, age 20-54. The pooled regression in column 1 also includes Austria and the UK, but we do not report the country-level regressions for these two countries because the number of observations is small (less than 250 diary days).

the marginal effect

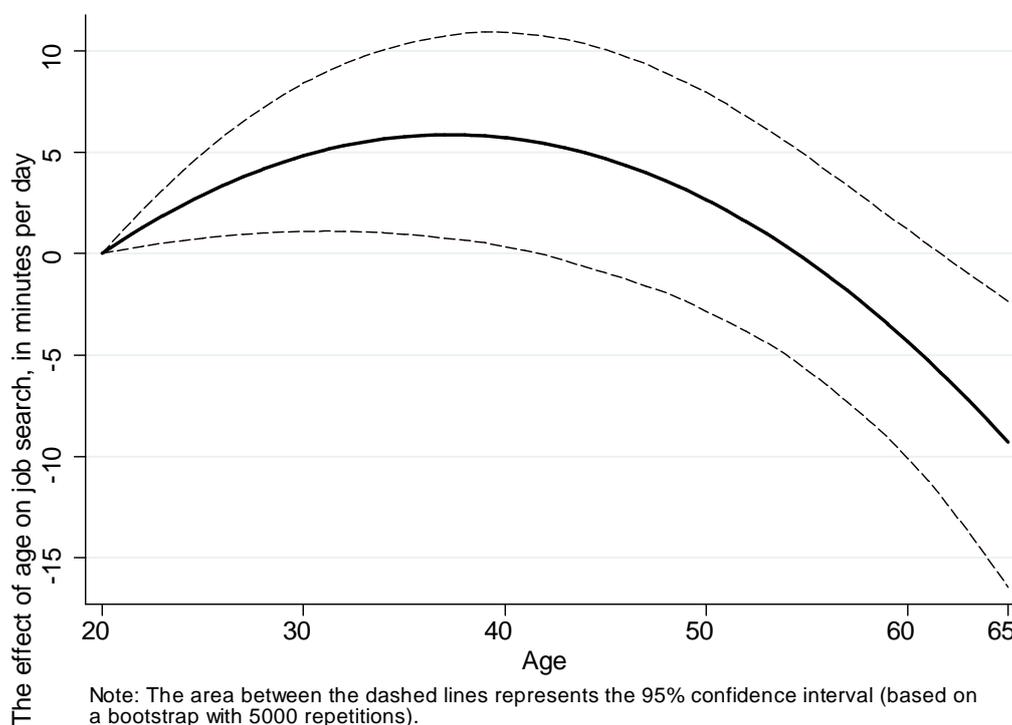
$$\frac{dE(s|x)}{dx_i} = \frac{dP(s > 0|x)}{dx_i} E(s|s > 0, x) + \frac{dE(s|s > 0, x)}{dx_i} P(s > 0|x).$$

From our regressions in Table 5a and 5b, we can substitute the coefficients for $dP(s > 0|x)/dx_i$ and $dE(s|s > 0, x)/dx_i$, and we evaluate $P(s > 0|x)$ and $E(s|s > 0, x)$ at the average x . (To make the analysis more interesting, we expand the sample to those of age 20-65 and re-estimate the coefficients in Table 5a and 5b.) Figure 2 shows the full effect of age on the duration of job search. We report the age profile of time spent on job search only for the pooled sample as we could not reject the null hypothesis that the coefficients on age and age² are the same across all countries with available micro data. The figure shows that search time is increasing in age at early stages of life but decreasing after the late 30s. One possible explanation for the inverse-U shaped age-search pattern is that the returns to search increase at younger ages because of the positive effect of work experience on wages and that older workers search less because the value of finding a high-paying job decreases with a worker's expected remaining years of work. In addition, older workers may be better able to smooth consumption over the unemployment spell because of accumulated retirement savings and thus spend less time on job search activities.

6 Institutional Factors and Job Search

What explains the large cross-country differences in the amount of time the unemployed devote to job search? Although we have data for only 14 countries, understanding differences in search effort is critical to understanding differences in unemployment across countries. Here we provide an initial analysis of two main factors: features of the Unemployment Insurance (UI) system and inequality. As time-use data become available for more countries, this analysis can be extended.

We start with some simple scatter diagrams. Figure 3 shows average job search time (including those who did not search at all) on the y-axis and an indicator of the generosity of social benefits for the unemployed on the x-axis. The size of the circles is proportional to the number of observations on unemployed individuals from the time-use survey. The benefit indicator that we use is the net replacement rate (NRR), which is the after-tax value of UI benefits, social assistance, family

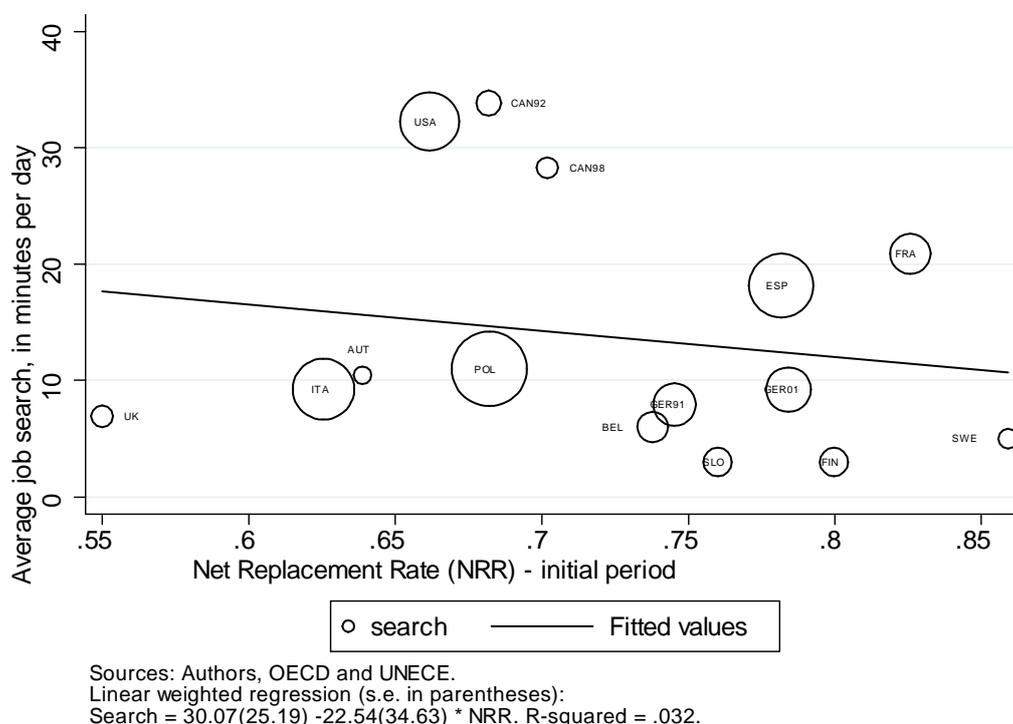
Figure 2: *The effect of age on job search*

benefits, food stamps and housing benefits relative to after-tax earnings.¹⁸ Because benefits vary over the spell of unemployment in most countries, we take the benefits available at the beginning of a spell. The bivariate relationship between job search and unemployment benefits is statistically insignificant but downward sloping, as predicted by Mortensen's model.

Note that our data contain both those eligible for UI benefits and those ineligible. Information on UI benefit receipt, however, is only available in a small number of surveys and the average time devoted to job search is usually of similar magnitude for recipients and non-recipients. In the UK survey 2000-01, for example, those unemployed who receive the "jobseeker's allowance" search 1.6 minutes more than

¹⁸ Source: OECD, Net replacement rates (NRR) during the initial phase of unemployment 2001-2004 (latest update available on the webpage of the OECD, March 2006). Specifically, we took the average of the net replacement rate for two earnings levels (the average annual wage and 67% of the average annual wage) by six family types (single, with dependent spouse, with working spouse, and those three with 2 children). Note that for Slovenia we produced our own estimate of the NRR, with information from a country chapter provided by the OECD.

Figure 3: Net replacement rates (NRRs) and job search

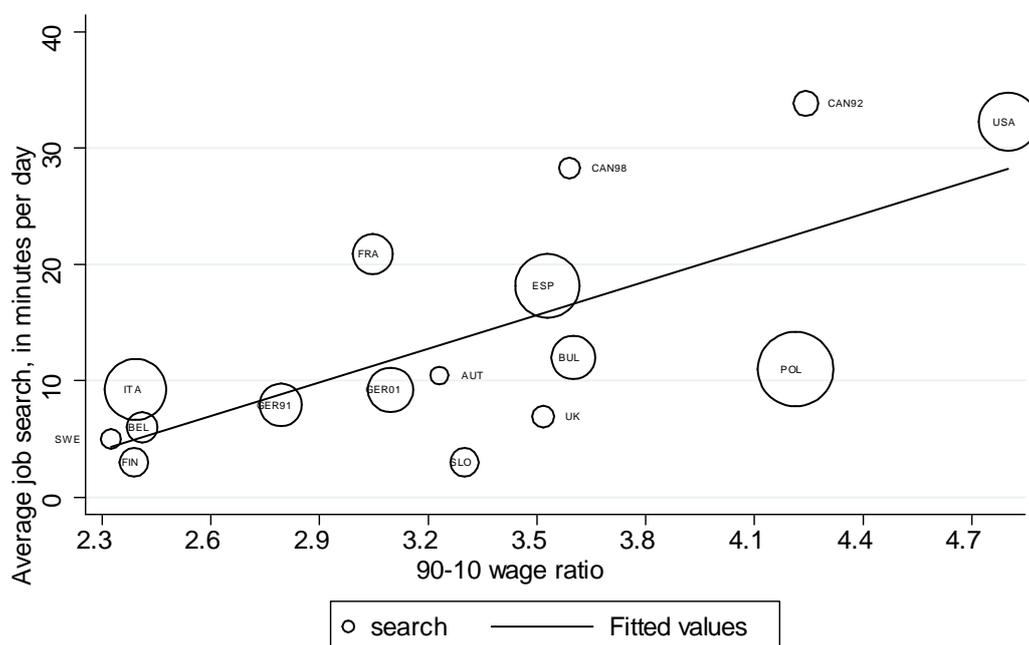


those who do not receive the allowance¹⁹, and in the French 1998-99 survey the difference between UI benefit recipients and non-recipients is less than one minute. Although we only have data for a small number of countries, these results suggest that our inferences would not be very different if we restricted the analysis to UI recipients only.

Figure 4 shows a stronger relationship between job search time by the unemployed and wage dispersion, as measured by the country's 90-10 wage ratio.²⁰ We expect wage inequality to positively influence job search time because the gain from searching for a higher paying job is greater in countries that have greater wage vari-

¹⁹ A survey on "jobseeker's allowance" recipients in the UK in 1997 found that these UI benefit recipients searched around 7 hours a week (see McKay et al., 1999), which is about 8 times more than in the UK time use survey for 2000-01 – and more than in any other survey in our sample. While it is difficult to reconcile this estimate with the time use data, one possible explanation is that benefit recipients over report their hours of job search when asked to recall how much time they spent searching in the last week, as opposed to reporting job search in a daily time diary.

²⁰ The data on the 90-10 wage ratio for OECD countries are from OECD Earnings Inequality Database and for Bulgaria and Slovenia the data are from Rutkowski (2001). We found a somewhat weaker correlation using the Gini coefficient from The World Income Inequality Database, produced by UNU-Wider (2007).

Figure 4: *Wage dispersion and job search*

Sources: Authors, OECD Earnings Inequality Database and Rutkowski (2001).
 Linear weighted regression (s.e. in parentheses):
 Search = $-18.09(8.62) + 9.64(2.56) * (90-10 \text{ wage ratio})$. R-squared = .504.

ability. Consistent with our expectation, the correlation between job search time and income inequality is positive and substantial (0.71). The correlation was even higher for the 50-10 wage ratio (0.82), which suggests that dispersion below the median is more relevant for the unemployed in our sample.²¹ When we excluded the U.S., Finland and Sweden from our sample, the correlation between average job search and the 90-10 wage ratio was 0.47, showing that the correlation between job search and wage dispersion is not entirely driven by differences between the U.S. and the Nordic region.

Of course, it is possible that income inequality is picking up the effect of factors other than the variability in wages that workers are confronted with in their potential job offer distribution. For this reason, we estimate multiple regressions to explain job search time using data at the country level in Table 6. In addition to the 90-10 wage ratio and NRR, the explanatory variables include a measure of the rate at which benefits increase or decrease over time (called benefit escalation) and average

²¹ We did not have the 50-10 wage ratio for Bulgaria and Slovenia.

Table 6. Cross-country regressions

Dependent variable: average job search, in minutes per day	Mean of variables	(1)	(2)	(3)	(4)	(5)	(6)
Mean of dependent variable	13.58						
Log(NRR - initial period)	-0.33 (0.120)	-13.808 (24.423)			-3.24 (18.375)	14.744 (18.451)	11.515 (20.119)
Benefit escalation (= GRR month 7-24 / GRR month 1-6)	0.62 (0.274)		-24.088 (7.864)***		-26.44 (8.609)***		-2.679 (17.373)
90-10 wage ratio	3.28 (0.731)			9.644 (2.558)***		11.17 (3.004)***	9.748 (5.563)
Average years of school	9.43 (1.553)						1.023 (1.901)
Constant		9.217 (8.523)	28.353 (5.267)***	-18.09 (8.618)*	29.203 (9.155)***	-17.781 (9.379)*	-22.19 (38.070)
Observations		15	16	16	15	15	15
R-squared		0.02	0.40	0.50	0.45	0.55	0.58

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Note: To adjust for differences across countries in the precision of the estimated job search time, we run weighted least squares (WLS) regressions with the weights determined in an auxiliary regression: We first run an ordinary least squares (OLS) regression and subsequently regress the squared OLS residuals on a constant and the inverse of the number of unemployed diary days. The WLS regressions then are weighted with the inverse of the predicted value from the auxiliary regression.

years of schooling from the Barro and Lee (2001) data set. The benefit escalation rate is measured by the ratio of the gross replacement rate in months 7-24 of an unemployment spell to the gross replacement rate in months 1-6.²² Again, with only 14 countries, more than the usual grain of salt is required.

Notwithstanding this caution, the 90-10 wage ratio has a relatively robust and sizable effect in the Table 6 regressions, although the coefficient is not quite significant when we include the log NRR, the escalation of benefits and average years of schooling in column 6 (with a p-value of 0.110). Going from the least to the most unequal country, the 90-10 ratio increases by about 248 percentage points. Using the coefficient in the model in column 6, this large a change in inequality is predicted to increase job search time by 24 minutes per day, which is almost twice as large as the average amount of job search time in the average country. The NRR is never statistically significant and its sign flips from negative to positive when other variables

²² In all countries in the sample, UI benefits decline over time. The underlying gross replacement rate data were provided in a correspondence with Tatiana Gordine of the OECD. For Bulgaria and Slovenia, we used data from UNECE's Economic Survey of Europe (2003, No. 1).

are included in the model, but its standard error is large and the point estimate is nontrivial. In column 1, for example, the job search-NRR elasticity is around -1 at the mean. A higher escalation of benefits is associated with less time spent searching for a job, on average, but the effect is statistically insignificant (t-ratio of 0.15) if the 90-10 wage ratio is included in the model.

In results not presented here, we experimented with including the maximum duration of benefits as an explanatory variable, but it generally had a statistically insignificant and small effect. We also estimated the specifications including the country-level unemployment rate, which usually had a negative coefficient but was not statistically significant.²³ Because of concerns about simultaneous causation – a high unemployment rate could cause fewer people to search for a job and could be caused by low job search intensity – we excluded it from the models in Table 6. However, it is reassuring that none of the variables of interest had a qualitatively different effect if the unemployment rate was included in the equation.

Lastly, we analyze the effects of NRR, benefit escalation and wage dispersion using micro data for 8 countries. The micro data allow us to simultaneously control for differences in individual characteristics across countries, such as age and gender, as well as the country-level variables. The dependent variable in Table 7 is the amount of time an unemployed individual spent searching for a job on the diary day (including 0s).²⁴ Standard errors are adjusted for correlated errors within countries and are robust to heteroskedasticity. In general, the pattern of results is similar to what we found at the country level. Most importantly, the 90-10 wage differential has an effect similar to what we found in the country-level analyses in Table 6.

Column 1 in Table 7 also shows a model with country fixed effects. The differences in job search across countries implied by the estimated country effects are similar to the differences of average job search time reported in Table 4, indicating that compositional effects explain only a small part of the total variation in time spent on job search across countries. Unfortunately, most time use surveys do not collect information on unemployment duration (exceptions are France and the U.S.) and thus we cannot control for the longer durations in Europe in our regressions in Table 7. Nevertheless, in France we find that, controlling for the same individual

²³ See Shimer (2004) for an analysis of how search intensity varies with the business cycle.

²⁴ Using the same two-step procedure as in Section 5 gives very similar results.

Table 7. Pooled micro data regressions

Dependent variable: time allocated to job search, in minutes per day						
Mean of dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Log(NRR - initial period)		-1.005 (26.613)			10.6 (18.351)	2.649 (20.132)
Benefit escalation (= GRR month 7-24 / GRR month 1-6)			-17.593 (3.335)***		-18.366 (2.317)***	0.227 (8.134)
90-10 wage ratio				8.138 (1.468)***		8.238 (3.821)*
Age	-0.056 (0.454)	-0.396 (0.549)	-0.13 (0.457)	-0.08 (0.446)	-0.137 (0.453)	-0.084 (0.447)
Age^2	0.003 (0.008)	0.006 (0.010)	0.002 (0.008)	0.002 (0.008)	0.002 (0.008)	0.002 (0.008)
Uncompleted secondary education or less	---	---	---	---	---	---
Completed secondary education	1.26 (3.186)	2.617 (3.666)	1.692 (2.549)	0.478 (3.027)	0.998 (3.029)	0.299 (3.012)
Tertiary education	10.434 (6.056)	15.877 (7.268)*	11.669 (5.160)*	10.158 (6.099)	11.064 (5.629)*	10.036 (6.012)
Female	-11.731 (2.117)***	-11.848 (2.329)***	-10.769 (2.289)***	-11.026 (2.381)***	-10.749 (2.320)***	-11.036 (2.400)***
Married	6.808 (5.802)	8.465 (5.822)	7.248 (5.866)	7.106 (5.767)	7.109 (5.649)	7.084 (5.648)
Female*married	-13.633 (5.794)*	-13.927 (5.732)**	-13.913 (5.612)**	-13.838 (5.653)**	-13.867 (5.523)**	-13.826 (5.624)**
Weekend	-17.59 (4.034)***	-17.942 (4.045)***	-17.807 (3.975)***	-17.776 (3.984)***	-17.857 (3.971)***	-17.79 (4.011)***
USA	---					
Austria	-18.244 (3.160)***					
Canada 1992	-1.142 (1.220)					
Canada 1998	-7.554 (1.093)***					
France	-8.073 (1.206)***					
Germany 1991-92	-21.633 (0.917)***					
Germany 2001-02	-21.93 (0.868)***					
Italy	-17.266 (2.333)***					
Spain	-10.322 (1.004)***					
UK	-25.132 (1.468)***					
Constant	38.473 (8.638)***	30.351 (12.147)**	39.66 (8.072)***	0.217 (8.423)	44.702 (13.172)**	0.89 (25.780)
Dummies for each quarter	x	x	x	x	x	x
Observations	8,527	8,527	8,527	8,527	8,527	8,527
R-squared	0.07	0.05	0.06	0.06	0.06	0.06

Standard errors are clustered at country level (in parentheses)

* significant at 10%; ** significant at 5%; *** significant at 1%

Note: Regressions were weighted using survey weights. Universe: Unemployed, age 20-54.

characteristics as in Table 7, those unemployed for more than six months search two minutes more per day than those unemployed for six months or less.²⁵ This suggests that the longer unemployment durations cannot explain the lower search intensity in Europe.

One caveat of our analysis is that we do not control for other potential factors such as the nature and coverage of the public employment system and the use of active labor market policies. In particular, one might wonder if the cross-country differences in time spent on job search activities are driven by the existence of well developed public employment agencies in Europe and especially in the Nordic region. Even though we cannot exclude this possibility, one should note that, in Mortensen's model, higher search efficiency is associated with higher search effort as it raises the marginal gain of time spent on job search relative to its marginal cost (see Section 4 above). In other words, if differences in search efficiency explained the cross-country patterns in time spent on job search activities, one would expect that job search, on the margin, is less efficient in Europe than in the U.S.

7 Conclusion

We have documented patterns in the amount of time devoted to searching for a new job. Job search does not take up a huge amount of time for the average unemployed person on any given day, but those who do search for a job devote considerable time to it. Compared with the employed, the unemployed tend to spend a high proportion of time sleeping, watching television, socializing, caring for others and working around the house. This pattern of activities could be explained by a mixture of lethargy and having a low opportunity cost of time.²⁶

We also related the amount of time spent on job search to demographic variables such as age, education, gender and marital status. We find evidence that is broadly consistent with predictions from search theoretic models: married women tend to search less than married men, because they are more likely to draw on a secondary source of income from a working spouse and because they may have a comparative

²⁵ See also Chapter 4 for a detailed analysis of time spent on job search by unemployment duration in the U.S.

²⁶ In some respects, this conclusion was anticipated by Jahoda, Lazarsfeld and Zeisel's (1933) study of unemployed individuals in Marienthal, Austria in the early 1930s.

advantage in home production and childcare. We also documented that the more highly educated tend to search more, which is likely due to higher wages, whereas older workers tend to search less, probably because of fewer remaining years of work before retirement and greater access to self-insurance.

Finally, at a national level we did not find much evidence that parameters of a country's unemployment benefit system affect the amount of time devoted to job search, although our sample of countries is small and we cannot rule out some economically significant effect. Another consideration is that our data include both those eligible for UI benefits and those ineligible. The UI system likely has contrasting effects on the two groups of job seekers, as the prospect of qualifying for more generous benefits should make employment more attractive for those currently ineligible for benefits (see Mortensen, 1977, and Levine, 1993).

We do find, however, that inequality is a strong predictor of the amount of time the unemployed devote to job search. While it is possible that this finding is emblematic of a tendency for lower job search in countries with a strong social welfare state and compressed wages, the fact that controlling for unemployment benefits does not attenuate the effect of the 90-10 wage differential on job search suggests that inequality per se matters. Our tentative interpretation of this finding is that job search has a higher payoff in labor markets with greater wage dispersion. If the potential wage offer distribution for an individual is compressed, the worker might as well accept the first job offer he or she receives, as the next is not likely to be much better. But if there is high variance in the potential wage offer distribution, then there is a benefit for searching for a high paying job. Notice that this interpretation requires that wage dispersion is not fully explained by personal differences in ability, as a given individual must have a chance of being offered a high paying job for inequality to affect his or her job search. In any event, the relationship between job search and inequality, which has not previously been documented, deserves further scrutiny and attention.

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Appendix

Table A.1. Definition and examples of job search activities for selected surveys

American Time Use Survey (ATUS) 2003-06

Job search activities (050401), e.g.:	writing/updating resume
contacting employer	meeting with headhunter/temp agency
making phone calls to prospective employer	picking up job application
sending out resumes	
asking former employers to provide references	
auditioning for acting role (non-volunteer)	Interviewing (050403), e.g.:
auditioning for band/symphony (non-volunteer)	interviewing by phone or in person
placing/answering ads	scheduling/canceling interview (for self)
researching details about a job	preparing for interview
filling out job application	
asking about job openings	Other activities related to job search, e.g.:
reading ads in paper/on Internet	waiting associated with job search interview (050404)
checking vacancies	security procedures rel. to job search/interviewing (050405)
researching an employer	travel related to job search (180504)
submitting applications	job search activities, not elsewhere specified (050499)

UK 2000-01

Activities related to job seeking (1391)

Definition: Activities connected with seeking job for oneself

Examples:

calling or visiting a labor office or agency
 job interviews
 updating CV
 reading and replying to job advertisements
 working on portfolio

Germany 2001-02

Activities connected with seeking job for oneself

Job search activities, not defined (150)
 Calling or visiting labor office or agency (151)
 Job search activities (152), e.g.:
 reading and replying to job advertisements
 reading ads in internet
 interviewing and visiting at a new employer
 Other specified job search activities (159)

Canada 1998

Job search; looking for work, including visits to employment agencies, phone calls to prospective employers, answering want ads. (022), e.g.:
 picked up job applications
 distributing resumes
 working on resume
 interview with prospective employer
 attended job fair at school

Harmonized European Time Use Survey (HETUS)

Activities related to employment (13) such as lunch break at work and time spent at work place before and after starting work and **activities connected with job seeking**, e.g.:
 calling or visiting a labour office or agency
 reading and replying to job advertisements
 presentation at the new employer

Table A.2. Average minutes per day by activity, region, employment status, gender and day of the week
(Western Europe: Austria, Belgium, France, Germany, Italy, Spain, UK; Eastern Europe: Bulgaria, Slovenia, Poland; Nordic: Finland, Sweden)

	Employed, Weekday (men women)								Unemployed, Weekday (men women)								
	US		Western Europe		Eastern Europe		Nordic		US		Western Europe		Eastern Europe		Nordic		
Sleep	469	480	464	477	403	470	470	456	472	553	545	534	508	550	531	502	507
Personal care	40	54	45	51	44	48	48	37	49	47	43	48	55	46	48	37	46
Eating	65	59	87	84	82	76	77	76	77	49	48	103	96	106	104	86	83
Work	447	367	447	335	450	363	363	417	317	6	6	26	17	6	6	62	46
Job search	1	1	0	0	na.	na.	na.	na.	na.	52	29	23	10	23	0	7	4
Education	11	15	7	8	5	7	7	10	14	26	28	30	28	19	16	64	54
Home production and care of others	82	148	74	181	95	204	100	173	173	181	266	144	284	201	339	140	248
of which: childcare	21	43	13	33	16	35	35	20	37	22	71	74	46	76	56	77	52
Shopping and services	16	30	16	30	16	25	20	29	29	24	46	33	50	26	40	26	34
Voluntary, religious and civic activities	7	8	6	4	3	3	6	6	5	17	17	8	7	2	4	10	5
Sport	17	12	18	15	12	8	8	24	20	19	12	42	26	33	17	56	23
Leisure and socializing	194	178	185	166	190	157	203	195	195	367	321	357	274	337	256	345	291
of which: TV	174	100	95	77	115	91	97	80	80	211	194	167	133	182	140	149	140
Travel	87	82	88	85	76	72	87	85	85	75	70	85	80	76	68	79	77
Other	5	7	3	4	5	4	5	5	5	13	9	4	4	5	5	27	22
Employed, Weekend (men women)																	
	US		Western Europe		Eastern Europe		Nordic		US		Western Europe		Eastern Europe		Nordic		
Sleep	545	556	540	541	523	532	542	542	542	569	573	546	557	561	550	570	559
Personal care	33	51	49	55	50	54	54	43	52	34	47	52	59	50	54	45	47
Eating	74	69	121	118	112	108	98	100	100	65	64	115	122	113	118	89	95
Work	129	96	110	82	168	107	84	70	70	4	7	11	3	4	3	15	13
Job search	0	0	0	0	na.	na.	na.	na.	na.	12	8	5	2	3	1	2	1
Education	0	0	5	5	8	12	4	6	na.	17	9	18	9	15	14	3	13
Home production and care of others	149	198	127	225	134	254	161	224	159	245	110	232	158	286	128	214	144
of which: childcare	26	35	19	30	24	35	23	37	25	58	22	36	76	42	76	43	43
Shopping and services	34	52	26	34	14	19	22	27	27	30	39	27	35	12	19	21	29
Voluntary, religious and civic activities	25	27	14	10	17	21	8	8	8	17	25	8	12	16	19	7	5
Sport	34	17	46	32	35	25	43	31	31	31	22	58	33	45	30	40	30
Leisure and socializing	321	271	313	257	298	237	335	291	291	428	327	399	304	385	279	435	324
of which: TV	184	132	136	99	168	123	141	107	107	246	176	185	129	201	148	195	158
Travel	83	86	87	78	75	67	92	84	84	63	66	88	70	74	64	72	86
Other	8	8	3	4	4	4	8	5	5	11	8	4	4	5	5	12	24
Unemployed (men women)																	
	US		Western Europe		Eastern Europe		Nordic		US		Western Europe		Eastern Europe		Nordic		
Sleep	490	502	486	495	480	488	481	491	491	557	553	538	523	552	537	522	521
Personal care	38	53	46	52	46	50	39	49	49	44	44	50	56	47	50	39	47
Eating	67	61	97	93	91	85	82	84	84	53	53	107	104	108	108	87	86
Work	356	289	351	263	370	290	322	246	246	14	6	21	13	11	5	49	37
Job search	1	1	0	0	na.	na.	na.	na.	na.	42	23	18	8	17	4	5	3
Education	10	13	6	7	5	8	8	12	12	23	22	27	22	19	15	47	43
Home production and care of others	101	163	89	193	106	218	117	188	188	175	260	134	268	189	324	137	239
of which: childcare	22	40	15	32	19	35	20	35	35	23	67	73	43	76	52	73	50
Shopping and services	21	36	19	31	15	23	21	29	29	26	44	31	46	22	33	24	33
Voluntary, religious and civic activities	12	14	8	6	7	8	7	5	5	17	19	8	8	6	9	9	5
Sport	22	13	26	20	19	13	29	23	23	22	15	47	28	36	20	51	25
Leisure and socializing	230	205	222	192	220	180	240	223	223	382	323	370	283	351	262	371	300
of which: TV	134	109	107	83	130	100	110	88	88	220	188	172	132	188	142	163	144
Travel	86	83	88	83	77	71	88	85	85	72	69	86	77	75	67	77	79
Other	6	7	3	4	5	4	6	5	5	12	9	4	4	5	4	22	23

Notes: Survey weights were used to compute country averages. Region averages are weighted by the size of the labor force of each country. Universe: Labor force, age 20-54.
Sources: HETUS, MTUS (Austria, Germany 1991-92, France), ATUS. We do not report the results by gender for Canada because of small sample size (less than 50 observations for some cells).

Chapter 4

Job Search and Unemployment Insurance: New Evidence from Time Use Data^{*}

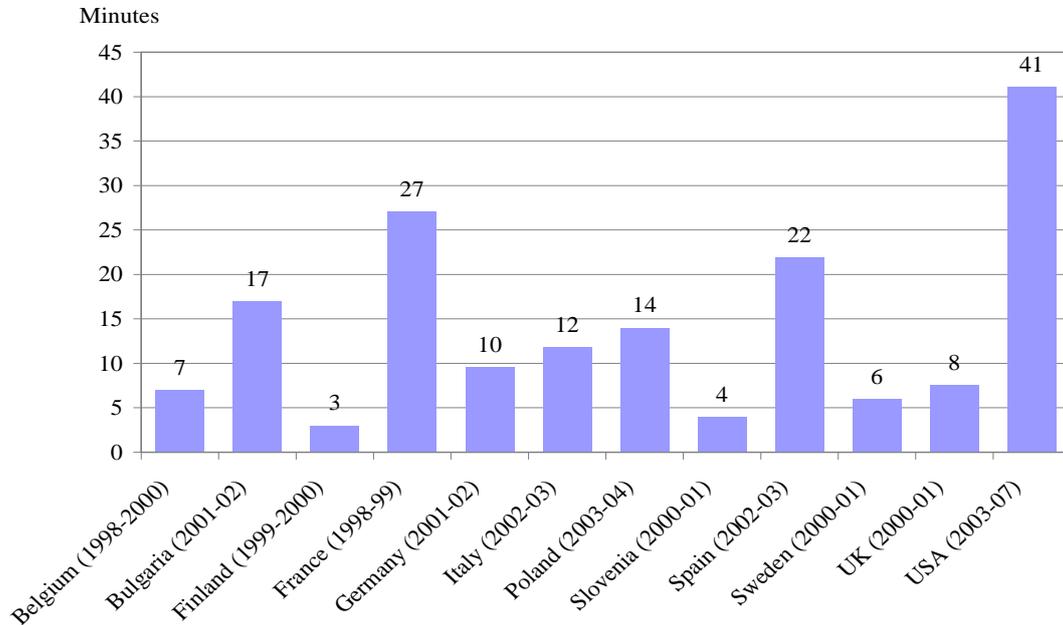
1 Introduction

It is well known that since the early 1980s the unemployment rate has been lower in the U.S. than in Europe. Our tabulations of international time use data (circa 1998-2007) also indicate that unemployed Americans tend to devote much more time to searching for a new job than their European counterparts (see Figure 1).¹ On weekdays, for example, the average unemployed worker spent 41 minutes a day searching for a job in the U.S., compared with just 12 minutes in the average European country with available data. One explanation for the comparatively low unemployment rate and high search time in the U.S. is the relatively modest level and short duration of Unemployment Insurance (UI) benefits in most states in the U.S. In this paper we examine the effects of UI on the amount of time devoted to job search by unemployed workers in the U.S., using features of state UI laws for identification.

^{*} This paper is co-authored with Alan B. Krueger, Princeton University, and is published in the *Journal of Public Economics* (Volume 94, Issues 3-4, April 2010, pp. 298-307). We have benefited from helpful discussions with Larry Katz, Per Krusell, Phil Levine, and Bruce Meyer, and seminar participants at Princeton University, the NBER, the University of Lausanne and the 2nd Nordic Summer Symposium in Macroeconomics. Alan Krueger was the Leon Levy member of the Institute for Advanced Study at Princeton when the paper was written. I gratefully acknowledge financial support from Handelsbanken's Research Foundations.

¹ See Chapter 3 for details about the underlying time use data.

Figure 1: Average number of minutes devoted to job search per day on weekdays by unemployed workers in various countries



A large and related literature examines the effects of UI on the duration of unemployment spells. For example, more generous UI benefits have been found to be associated with longer spells of unemployment, with an elasticity of about 1.0 (see Krueger and Meyer (2002) for a survey). In addition, the job finding rate jumps up around the time benefits are exhausted (Moffitt, 1985, Katz and Meyer, 1990a; see Card, Chetty and Weber, 2007 for a critical review). UI is expected to affect the duration of unemployment through its effect on the amount of effort devoted to searching for a job and the reservation wage of the unemployed, yet these variables have rarely been studied directly.² We attempt to fill this void by modeling the amount of time that unemployed individuals devote to searching for a new job over the course of unemployment spells using data from the American Time Use Surveys (ATUS) from 2003 to 2007.

Section 2 describes the ATUS data and presents summary statistics. In Section

² An exception is Barron and Mellow (1979), who used the May 1976 CPS supplement on job search activities in the last month, and find that the unemployed searched an average of 7 hours a week. See Feldstein and Poterba (1984) for related evidence on self-reported reservation wages and unemployment in the U.S. based on the same CPS data.

3, we evaluate the predictions of Mortensen's (1977) canonical model of UI and job search.³ The Mortensen model predicts that for a newly laid-off worker, search effort is decreasing in the level of UI benefits, whereas for those unemployed who are not eligible for UI or who have exhausted their UI benefits, search effort is increasing in the benefit level. This latter implication is called the entitlement effect, as higher benefits raise the value of being unemployed in the future and thus raise the value of obtaining a job.⁴ Furthermore, the model predicts that search effort is increasing in the mean wage offer and the dispersion of potential wage offers. The intuition for the latter is that, with a higher dispersion of potential wages, there is a greater benefit from searching for a high paying job.⁵ We also expect search effort to be lower for those unemployed who expect to be recalled to their previous job (see Katz, 1986).⁶ We empirically test these predictions and estimate the effect on job search of the generosity of UI benefits, job seekers' predicted wages, within-state residual wage dispersion, recall expectations and other variables. Most importantly, we find that job search intensity is inversely related to UI benefit generosity for those who are eligible for UI.

In Section 4, we evaluate the predictions of the Mortensen model regarding job search intensity and unemployment duration. The model predicts that for an eligible unemployed, job search effort increases over the unemployment spell as benefits are exhausted. After benefits are exhausted, job search effort is predicted to remain constant. An unemployed individual who is ineligible for benefits is predicted to devote a constant amount of time to job search because of the absence of learning and the assumption of stationarity in the Mortensen model. In the ATUS data, we find a striking contrast in the profiles of job search activity across those with different durations of unemployment: search activity increases as week 26 (benefit exhaustion) approaches for the UI eligible, while the profile is fairly flat for those who are ineligible for UI.

Section 5 offers some concluding thoughts as to how our results relate to search

³ Labor supply models such as, e.g., Moffitt and Nicholson (1982) yield similar predictions.

⁴ Levine (1993) provides some evidence on the entitlement effect.

⁵ See also Stigler (1962) for a seminal discussion of how wage dispersion affects the payoff from search effort, and Ljungqvist and Sargent (1995) for how progressive taxation affects job search effort through after-tax wage compression.

⁶ See also Feldstein (1976) and the empirical work of Katz and Meyer (1990a,b) on recall and job finding hazards.

theory and how time-use data can be used to further study UI and job search behavior.

2 Data and Descriptive Statistics

We use data from five consecutive years (2003-07) of the ATUS, which is a nationally representative time-use survey covering the whole civilian non-institutional population of age 15 and older. The sample is drawn from the 8th outgoing rotation group of the Current Population Survey (CPS). Respondents are interviewed within 2-5 months of their last CPS interview. The ATUS collects detailed information on the amount of time respondents devoted to various activities in the previous day. Job search activities include contacting a potential employer, calling or visiting an employment agency, reading and replying to job advertisements, job interviewing, etc. The Appendix Table provides a detailed list of activities that are identified as job search.

We restrict our sample to the population of age 20-65 to abstract from issues related to youth unemployment and retirement. The ATUS labor force recode defines unemployment in the same way as the CPS (not working in the reference week, actively looking for a job in the 4 weeks prior to the interview, and available for work in the reference week). The CPS/ATUS definition of unemployed also includes those on temporary layoff with an expectation of recall to their previous employer, regardless of whether they looked for work in the four weeks prior to the survey. Our sample consists of 2,171 unemployed individuals, of which 344 were on temporary layoff. Sample weights are used in all of our estimates. The sample unemployment rate is 5.2%, which exactly matches the official unemployment rate over the same period.

We can disaggregate the unemployed into four groups: job losers, those expecting to be recalled to their previous employer, voluntary job leavers, and re-/new entrants into the labor force. The ATUS questionnaire, however, only contains a question on whether the unemployed expect to be recalled. Thus, we use information from the final CPS interview to classify individuals into the other three groups. Specifically:

- Job losers are defined as those on layoff in the CPS, those who report in the CPS that their temporary job has ended and those who are employed at the

time of the CPS interview (and subsequently became unemployed).

- Re- or new entrants are defined as those unemployed who indicate that they were re- or new entrants in the CPS. Those who are classified as out of the labor force in the CPS but as unemployed in the ATUS are also included in this category.
- Voluntary job leavers are defined as those who indicate in the CPS that they quit their job. Note that we were able to identify voluntary job leavers only when they were already unemployed at the time of the CPS interview. We classify people who were employed in CPS and unemployed in ATUS as job losers because the share of voluntary job leavers among the unemployed in CPS is much lower than that of job losers (43% vs. 12% in our period). Consequently, compared with the CPS the proportion of the unemployed classified as job leavers is relatively low in our sample.

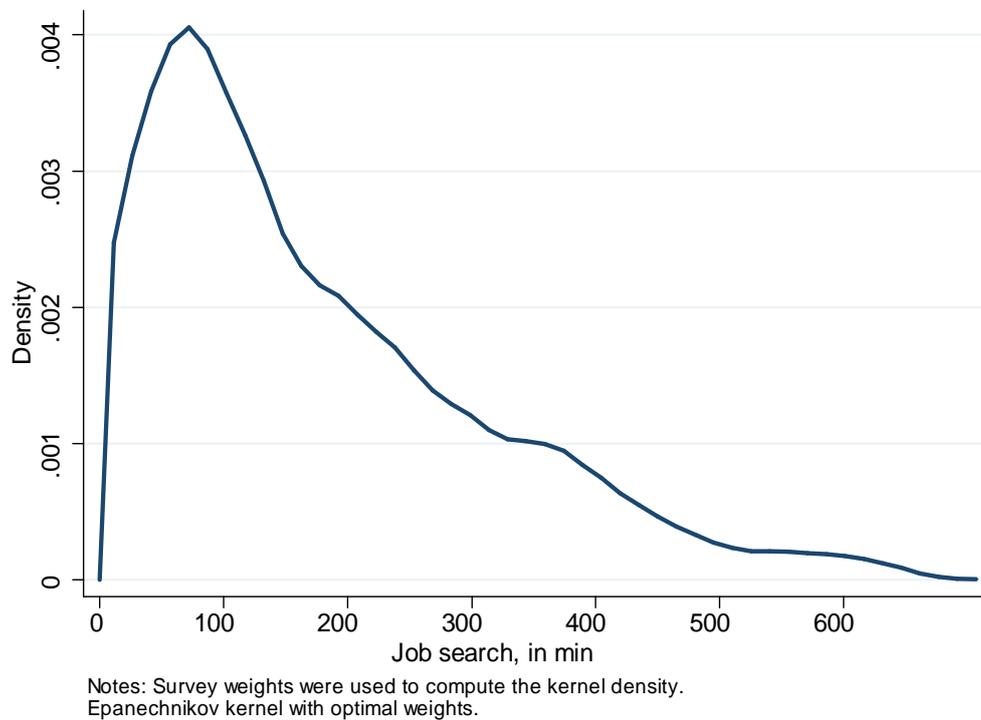
Because the ATUS lacks information on UI receipt, we infer UI eligibility from the type of unemployment and the workers' full-time/part-time status on the previous job. We classify job losers and those on temporary layoff as eligible for UI, and re-entrants, new entrants and voluntary job leavers as ineligible. In states where part-time job seekers do not qualify for UI, we classify those who worked part-time as ineligible.

We undoubtedly have some classification errors when it comes to assigning UI eligibility in our sample. Such misclassification errors are likely to lead us to underestimate the effects of UI in Sections 3 and 4 below, as the effects are expected to be of opposite sign for the UI eligible and ineligible.

Descriptive statistics of job search activities

Table 1a reports descriptive statistics on the average number of minutes devoted to job search by labor force status. It also shows the participation rate in job search, defined as the fraction of those with nonzero search time on the diary day. Several results are worth highlighting. First, the unemployed spend around 32 minutes a day (including weekends) searching for a job, whereas the employed and those classified as out of the labor force devote less than a minute a day to job search, on average.⁷

⁷ In a companion paper we found similar evidence across 14 countries (see Chapter 3).

Figure 2: *Kernel density: job search (conditional on non-zero search)*

Even if we restrict the sample to those who were classified as unemployed in the CPS interview (2-5 months prior to the ATUS interview), those classified as out of the labor force in ATUS searched for only 4.2 minutes. This suggests that the conventional labor force categories represent meaningfully different states.⁸

Second, job search is heavily concentrated on weekdays (see Table 1b). Nearly a quarter of the unemployed engage in job search activities on any given weekday, compared with 6.7% on weekends. Third, those who participate in job search on the diary day tend to devote a great deal of time to it. Figure 2 shows a kernel density diagram for the duration of job search conditional on searching on the diary day. The average duration of job search among those who searched is 167 minutes, and a quarter of job searchers spent more than 240 minutes searching for a job on the diary day. Fourth, there are large differences in job search effort depending on the reason for unemployment. Job losers search 32 minutes more than those who expect to be recalled to their previous job, and around 22 minutes more than re- or new

⁸ Corroborating evidence from job finding rates is in Flinn and Heckman (1983).

Table 1a. Descriptive statistics ATUS 2003 - 2007, by labor force status (weekdays and weekends)

	# respondents	% of total	Average job search, in min. per day	Participation in job search	Average job search (participants), in min. per day
By labor force status					
Employed	42,934	76.4%	0.6	0.6%	101.0
Unemployed	2,171	3.9%	32.1	19.3%	166.9
Not in labor force	11,091	19.7%	0.8	0.5%	152.9
By type of employed (% of employed)					
Working in CPS	40,576	94.5%	0.5	0.5%	107.6
Unemployed in CPS	824	1.9%	2.8	2.5%	115.4
Not in labor force in CPS	1,534	3.6%	0.8	1.7%	49.7
By type of unemployed (% of unemployed)					
Jobloser	943	43.4%	45.2	27.5%	164.2
On temporary layoff w/ recall expectation	344	15.8%	13.2	7.1%	185.8
Jobleaver	65	3.0%	52.9	24.9%	212.3
Re- or new entrant	819	37.7%	23.1	14.1%	163.6
By UI eligibility status (% of unemployed)					
UI ineligible	1,000	46.1%	25.4	15.6%	163.4
UI eligible	1,171	53.9%	38.0	22.5%	169.1
By type of "not in labor force" (% of not in labor force)					
Working in CPS	1,181	10.6%	2.4	1.8%	134.1
Unemployed in CPS	305	2.7%	4.2	3.2%	130.8
Not in labor force in CPS	9,605	86.6%	0.5	0.3%	176.7

Notes: Averages and participation rates are computed with survey weights. Both weekdays and weekends are included in the sample. Universe: Civilian, noninstitutional population, age 20-65.

entrants. Job leavers also have a high intensity of search, devoting almost an hour to job search a day, on average. Finally, we report average minutes of job search by UI eligibility status. Those eligible for UI search 13 minutes more on an average day than those who are not eligible. This difference, however, falls to 6 minutes when we control for observable characteristics such as age, education, sex, marital status, and a dummy for the presence of children.

Unemployment Insurance

To qualify for unemployment benefits all states require a worker to have earned a certain amount of earnings during a reference period or to have worked for a certain period of time. Most states in the US require active job search, such as a

Table 1b. Descriptive statistics ATUS 2003 - 2007, by labor force status (weekdays only)

	# respondents	% of total	Average job search, in min. per weekday	Participation in job search	Average job search (participants), in min. per weekday
By labor force status					
Employed	21,291	76.4%	0.7	0.7%	99.7
Unemployed	1,076	3.9%	41.1	24.1%	170.8
Not in labor force	5,495	19.7%	1.1	0.7%	159.8
By type of employed (% of employed)					
Working in CPS	20,141	94.6%	0.6	0.6%	106.0
Unemployed in CPS	395	1.9%	3.7	3.0%	123.3
Not in labor force in CPS	755	3.5%	0.8	1.9%	40.8
By type of unemployed (% of unemployed)					
Jobloser	488	45.4%	56.2	33.6%	167.0
On temporary layoff w/ recall expectation	171	15.9%	16.7	8.9%	188.9
Jobleaver	25	2.3%	69.6	33.7%	206.4
Re- or new entrant	392	36.4%	30.5	17.8%	171.3
By UI eligibility status (% of unemployed)					
UI ineligible	473	44.0%	33.2	19.6%	169.5
UI eligible	603	56.0%	47.9	27.9%	171.5
By type of "not in labor force" (% of not in labor force)					
Working in CPS	572	10.4%	3.5	2.4%	143.6
Unemployed in CPS	159	2.9%	5.6	4.1%	136.6
Not in labor force in CPS	4,764	86.7%	0.7	0.4%	181.4

Notes: Averages and participation rates are computed with survey weights. The estimates are based on weekdays only. Universe: Civilian, noninstitutional population, age 20-65.

certain number of employer contacts per week, to continue to qualify for UI benefits. Monitoring in the US, however, is not very strict as most states rely on postal or phone reports to enforce these job search requirements (see Anderson, 2001). The replacement rate is typically around 50% to 60% of the wage earned on the previous job, subject to a maximum benefit. The maximum weekly benefit varies widely across states, ranging from \$210 in Mississippi to \$575 in Massachusetts in 2007.⁹ Ten states provide dependents allowances beyond the maximum benefit.

In most states, the maximum duration of benefits is 26 weeks, although there are some exceptions: Massachusetts (30 weeks), Montana (28 weeks) and Washington

⁹ According to Krueger and Meyer (2002) around 35% of the unemployed receive the maximum benefit.

(30 weeks until 2007). The maximum duration of benefits may be less than 26 weeks for UI claimants who had insufficient earnings during the reference period. According to Krueger and Meyer (2002) around half of the recipients qualify for the full 26 weeks.

During 2003, UI recipients were able to receive up to 13 additional weeks of benefits through the federal Temporary Extended Unemployment Compensation Act of 2002, and benefits were extended for 26 weeks in a small number of "high" unemployment states. We exclude observations from 2003 when we examine job search behavior around 26 weeks of unemployment for the UI eligible because of complications caused by the extended benefits program.

As described below, our regression model exploits variation in the maximum weekly benefit amounts across states and number of dependents. The main source of variation in maximum benefits comes from variation across states as we take into account dependents' allowances only in those ten states that provide these allowances beyond the maximum benefit.¹⁰ The data for maximum weekly benefit amounts is taken from the U.S. Department of Labor's *Comparison of State UI Laws*.¹¹ Except for New Mexico, which introduced dependents' allowances in 2004, we take the average of maximum weekly benefit amounts across the 5 years of the ATUS by state and number of dependents. In 2003 in New Mexico, for unemployed with dependents, we set the maximum weekly benefit to the maximum weekly benefit of a single earner.

3 Relationship between Unemployment Benefits and Job Search

To evaluate the predictions of the models outlined in the introduction, we estimated micro regressions in which the total amount of time allocated to job search on the diary day was the dependent variable and the explanatory variables included the maximum weekly UI benefit, the respondent's predicted wage, a measure of wage dispersion in the state, and personal characteristics. We proceeded in two steps.

¹⁰ These states are AK, CT, IA, IL, MA, ME, NM, OH, PA and RI. The number of dependents usually includes children of age 17 and younger, and in some cases the spouse. We took differences across states in the definition of the spouse as a dependent into account.

¹¹ See <http://workforcesecurity.doleta.gov/unemploy/statelaws.asp#Statelaw>.

We first estimated the predicted wage and residual wage dispersion facing each job seeker, and then used these estimates as explanatory variables in the job search equation. Specifically, the regression models we estimated are:

$$\log(w_{is}) = a + bX_i + d_s + \varepsilon_{is} \quad (4.1)$$

$$\begin{aligned} s_{ist} = & \alpha + \beta_1 \log(wba_{ist}) + \beta_2 \log(\hat{w})_{is} + \beta_3 \text{std}(\text{resid. } w)_s \\ & + \gamma_1 X_i + \gamma_2 Z_i + d_t + \mu_{ist}, \end{aligned} \quad (4.2)$$

where w_{is} is the hourly wage of worker i in state s , s_{ist} is time allocated to job search (in minutes per day) of individual i in state s and time t , wba_{ist} is the maximum weekly benefit amount, X_i is a set of controls such as education and sex, which are included in the wage and job search equations, Z_i is a set of controls exclusively included in the search equation, d_t a time effect (month and year) and d_s a state effect. Z_i includes dummies for each group of unemployed workers (job loser, on temporary layoff, job leaver and re-/new entrant), married or cohabiting with a partner, the presence of children under age 18 in the household, interaction terms of partner and children with female, and a dummy for whether the diary day was a weekend. The maximum weekly benefit amount varies with individual characteristics in the states where dependents' allowances are provided beyond the maximum weekly benefit of a single earner. The maximum benefit varies with time only for unemployed with dependents in New Mexico. Standard errors are robust to correlated residuals within states and heteroskedasticity.

The wage equation was estimated using a sample of 319,813 workers from the CPS outgoing rotation group files for 2004 and 2005.¹² We predicted each ATUS respondent's expected log wage, denoted $\log(\hat{w})_{is}$, using the coefficients from the wage regression (4.1). We computed the standard deviation of residuals from the wage equation for each state (denoted $\text{std}(\text{resid. } w)_s$) as an indicator of the dispersion in the potential wage offer distribution.¹³

¹² The results of the wage regressions are reported in column 4 in Table 2. The hourly wage is adjusted for top coding and overtime earnings/tips. We exclude from the sample self-employed and self-incorporated, full-time and part-time students and employed with hourly earnings of less than \$1 or more than \$200.

¹³ The coefficient on the fitted log hourly wage in our regression Tables 2 and 3 shows that the fitted wage is a strong and significant predictor of job search, with an elasticity in excess of 2.5. The residual wage dispersion term is insignificant but usually positive in most of the OLS and Tobit models. This is a contrast to Chapter 3, which found that job search is higher in countries

Table 2 reports the results of estimating equation (4.2) for three separate samples. Column 1 shows the results for the full sample of unemployed individuals aged 20-65. Columns 2 and 3 report the same regressions for UI eligible and ineligible. In the full sample the coefficient on the log of the maximum weekly benefit amount is negative but not statistically significant. When we restrict the sample to those who appear eligible for UI benefits, are not on temporary layoff, and have been unemployed for 26 weeks or less (column 2), the elasticity for the maximum weekly benefit is -1.2 (the elasticity is computed by dividing the coefficient estimate by the mean of the dependent variable); this is the only sample for which the coefficient on benefits is statistically significant at the 10% level. To gauge the magnitude of this elasticity, consider the effect of changing the WBA from the state with the lowest to the highest benefit (for a person without dependents). Time devoted to job search is predicted to decrease by 54 minutes a day.

For those not eligible for benefits in column 3 the elasticity is positive but not significant. A test of the equality of the benefit coefficients for those eligible and ineligible for UI rejects at the 10 percent level, suggesting a different response to benefit generosity.

We also estimated Tobit models for the same four samples to account for the mass of workers with 0 minutes of job search on the diary day. Table 3 reports estimated coefficients of the Tobit model as well as an adjustment factor that allows one to compute the marginal effect of each variable. The marginal effect of a Tobit model is $dE(y|x)/dx_i = \beta_i \Phi(x\beta/\sigma)$ where $\Phi(\cdot)$ is the standard normal cdf and, to make the Tobit estimates comparable to the linear regression models, we evaluate the adjustment factor at the mean values of x .¹⁴ In the full sample in column 1, the coefficient on benefits is positive and not significant at conventional levels. In the subsample of eligible unemployed with spells of 26 weeks or less (column 2), the coefficient on benefits is significant at the 5% level and the implied elasticity is -0.8. Again, the contrast between the benefit effect for those eligible (column 2) and ineligible (column 3) is statistically significant.

with higher wage dispersion, controlling for benefits and other factors. One reason might be that residual wage dispersion is lower across the U.S. states than across countries, and therefore conveys less signal than in the cross-country data.

¹⁴ Note that the effect of dummy variables is different because of the non-linear nature of the Tobit model.

Table 2. Results of linear regressions

Dependent variable: time allocated to job search, in minutes per day	Mean (Std)	Full sample (1)	Subsample (2): eligible w/o recall expect. & duration <= 26	Subsample (3): ineligible	Wage equation – dep. var.: log(hourly wage)
Mean of dependent variable		32.1	49.1	25.4	2.76
Log(maximum weekly benefit amount)	5.89 (0.220)	-6.86 (11.971)	-57.275 (30.663)*	10.096 (19.864)	
Fitted log(hourly wage)	2.60 (0.329)	110.066 (48.715)**	174.048 (120.772)	105.099 (64.247)	
Std(residual of wage equation) - by state	0.490 (0.023)	92.868 (101.732)	274.379 (196.089)	83.161 (111.950)	
On temporary layoff w/ recall expectation (1)	0.15	-32.884 (4.973)***		-11.497 (12.479)	
Jobleaver	0.03	12.876 (16.585)		21.507 (20.857)	
Re- or new entrant	0.38	-13.656 (5.280)**		-3.456 (10.363)	
Age	36.75	-5.12 (3.198)	-6.816 (7.966)	-5.605 (3.691)	0.061 (0.001)***
Age^2		0.053 (0.034)	0.078 (0.086)	0.052 (0.039)	-0.001 (0.000)***
Some college or associate degree (2)	0.29	-13.133 (12.991)	-16.282 (32.615)	-14.284 (14.991)	0.209 (0.002)***
College degree (BA, MA or PhD)	0.16	-46.877 (28.113)	-59.764 (72.634)	-68.348 (37.407)*	0.573 (0.003)***
Female	0.51	14.021 (13.543)	52.805 (33.296)	-6.649 (16.080)	-0.231 (0.002)***
Female*partner	0.28	-11.09 (8.400)	-34.334 (16.167)**	9.703 (17.016)	
Female*children	0.30	-7.925 (14.362)	-26.06 (26.744)	6.872 (17.905)	
Partner	0.50	0.176 (8.911)	7.652 (13.632)	-11.682 (18.347)	
Children	0.49	7.113 (12.786)	39.751 (18.914)**	-14.717 (17.389)	
Weekend	0.28	-30.883 (3.797)***	-53.138 (6.492)***	-21.693 (4.676)***	
Constant		-115.341 (66.062)*	-71.375 (128.577)	-169.555 (100.181)*	1.2 (0.013)***
Year and month dummies		x	x	x	Year dummy
State dummies					x
Observations		2,171	671	1,000	319,813
R-squared		0.09	0.16	0.13	0.29

Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%,

(1) The base group consists of Job losers. (2) The base group consists of those with a high school degree or less.

Notes: Regressions are weighted using survey weights; Errors are clustered at state level. Universe: Unemployed, age 20-65. Source for wage equation: CPS outgoing rotation group extract, 2004 and 2005. The CEPR version of the ORG contains hourly wage series that adjust for topcoding and overtime earnings/tips. We exclude from the sample self-employed and self-incorporated, full-time and part-time students and employed with hourly earnings of less than \$1 or more than \$200.

The results shown in columns 1 to 3 are based on the following regression equation: $s_{ist} = \alpha + \beta_1 \log(wba_{ist}) + \beta_2 \log(w_{is}) + \beta_3 \text{std}(\text{resid. } w)_s + \gamma_1 X_i + \gamma_2 Z_i + d_i + \mu_{ist}$ where $\log(w_{is})$ is the fitted wage based on the coefficients estimated in the wage equation and $\text{std}(\text{resid. } w)_s$ denotes the standard deviation of the residuals from the wage equation by state.

Column 2 reports the results for the subsample of eligible without an expectation of recall to their previous employer and with a duration of unemployment of 26 weeks or less. Column 3 reports the results for the subsample of ineligible. As described in the text, we classify job losers and those on temporary layoff as eligible for UI, and re-entrants, new entrants and voluntary job leavers as ineligible. In states where part-time job seekers do not qualify for UI, we classify those who worked part-time as ineligible.

The results shown in column 4 (the wage equation) are based on the following regression equation: $\log(w_{is}) = a + bX_i + d_s + \varepsilon_{is}$.

Table 3. Tobit model regressions

Dependent variable: time allocated to job search, in minutes per day	Mean (Std)	Full sample (1)	Subsample (2): eligible w/o recall expect. & duration <= 26	Subsample (3): ineligible
Mean of dependent variable		32.1	49.1	25.4
Adjustment factor for marginal effects		0.153	0.256	0.115
Log(maximum weekly benefit amount)	5.89 (0.220)	24.344 (46.807)	-156.8 (78.173)**	117.917 (110.082)
Fitted log(hourly wage)	2.60 (0.329)	548.212 (205.572)***	652.484 (315.049)**	801.735 (334.230)**
Std(residual of wage equation) - by state	0.49 (0.023)	-12.808 (572.653)	380.496 (648.979)	-456.146 (709.477)
On temporary layoff w/ recall expectation (1)	0.15	-239.506 (38.298)***		(2)
Jobleaver	0.03	10.194 (58.054)		98.642 (88.601)
Re- or new entrant	0.38	-80.834 (24.674)***		12.685 (47.770)
Age	36.75	-24.237 (15.895)	-25.049 (23.579)	-44.41 (20.642)**
Age^2		0.245 (0.173)	0.271 (0.259)	0.421 (0.216)*
Some college or associate degree (3)	0.29	-53.855 (53.329)	-77.851 (88.886)	-119.538 (82.067)
College degree (BA, MA or PhD)	0.16	-241.132 (113.629)**	-269.902 (188.471)	-437.329 (189.517)**
Female	0.51	87.409 (57.036)	201.337 (95.916)**	75.857 (77.953)
Female*partner	0.28	-66.344 (42.073)	-88.332 (52.342)*	-34.636 (73.483)
Female*children	0.30	-38.338 (59.715)	-111.368 (81.905)	30.277 (69.874)
Partner	0.50	-4.038 (37.283)	0.006 (46.859)	-14.787 (66.825)
Children	0.49	12.663 (40.987)	120.419 (52.645)**	-93.485 (60.902)
Weekend	0.28	-218.167 (20.653)***	-223.945 (25.780)***	-175.855 (31.905)***
Constant		-1062.408 (332.084)***	-530.797 (503.571)	-1590.845 (574.960)***
sigma		264.087 (15.127)***	230.892 (11.709)***	261.18 (26.881)***
Year and month dummies		x	x	x
Observations		2,171	671	1,000
Pseudo R-squared		0.04	0.04	0.06

Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.

(1) The base group consists of Job losers. (2) We exclude the dummy for temporary layoff w/ expectation of recall for this regression, because there are only 27 of them in the sample of ineligible (part-time workers in states where part-time workers are not eligible for UI) and they all have zero search on the diary day. (3) The base group consists of those with a high school degree or less.

Notes: Regressions are weighted using survey weights; Errors are clustered at state level. Universe: Unemployed, age 20-65.

Column 2 reports the results for the subsample of eligible without an expectation of recall to their previous employer and with a duration of unemployment of 26 weeks or less. Column 3 reports the results for the subsample of ineligible. See the notes in Table 2 for details about the estimated regression equation.

Table 4. Instrumental variables (IV) regressions, marginal effect of log(average weekly benefit)

Dependent variable: time allocated to job search, in minutes per day	Full sample (1)	Subsample (2): eligible w/o recall expectation & duration ≤ 26	Subsample (3): ineligible
Mean of dependent variable	32.1	49.1	25.4
OLS			
Log(state average weekly benefit)	12.564 (16.562)	-99.696 (42.273)**	50.649 (24.731)**
IV - 2SLS (Instrument: log(maximum weekly benefit amount))			
Log(state average weekly benefit)	-12.612 (22.504)	-109.74 (58.433)*	18.109 (35.004)
Tobit			
Log(state average weekly benefit)	20.458 (11.620)*	-71.004 (34.473)**	41.583 (18.008)**
IV - Tobit (Instrument: log(maximum weekly benefit amount))			
Log(state average weekly benefit)	7.909 (13.126)	-77.511 (39.489)**	28.312 (22.004)
Observations	2,171	671	1,000
Robust standard errors in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%.			

Notes: Regressions are weighted using survey weights; Errors are clustered at state level. Universe: Unemployed, age 20-65.

The average weekly benefit is defined as benefits paid for total unemployment divided by weeks compensated for total unemployment.

Column 2 reports the results for the subsample of eligible without an expectation of recall to their previous employer and with a duration of unemployment of 26 weeks or less. Column 3 reports the results for the subsample of ineligible. See the notes in Table 2 for details about the estimated regression equation.

Note that the reported elasticities are all calculated with respect to the legislated maximum weekly benefit amount. To estimate the elasticity of job search with respect to actual UI benefits, we estimated a linear and a Tobit model with the log of the state average weekly benefit in place of the maximum weekly benefit.¹⁵ We instrument for the actual average benefit with the log maximum weekly benefit. Table 4 reports the marginal effects of the log average weekly benefits. Taking the IV estimates from column 2, the implied elasticity is -2.2 for the linear model and around -1.6 for the Tobit model. The difference between the OLS and IV estimates is small, which is not surprising given the high correlation between state average and state maximum benefit amounts (0.92).

¹⁵ The state average weekly benefit is defined as benefits paid for total unemployment divided by weeks compensated for total unemployment. We take the average of the state average weekly benefit over the years 2003-07 from <http://workforcesecurity.doleta.gov/unemploy/content/data.asp>.

To put our estimates in perspective, we can calculate the differential search time between the U.S. and the 11 European countries shown in Figure 1 that is predicted by the difference in benefit generosity and the benefit coefficients. Based on Chapter 3, benefits are 0.114 log points lower in the U.S. than in the 11 European countries over the first 26 weeks of a spell of unemployment.¹⁶ The IV-Tobit estimate in column 2 of Table 4 therefore implies that job search time would be 9 minutes longer in the U.S., and the Two-Stage Least Squares model predicts that it would be 13 minutes longer. American job seekers search about 23 minutes more per day than European job seekers (this number is slightly lower than the differences shown in Figure 1, because Figure 1 shows time spent on job search on weekdays only). The lower benefit levels in the U.S. could therefore account for from 38 percent to 54 percent of the difference in search time. Although there are some obvious limitations of this calculation – such as the fact that we were not able to restrict the European sample to UI recipients – the results suggest that UI benefit generosity can potentially explain a nontrivial share of the difference in search behavior of the unemployed in the U.S. and Europe.

The coefficient on “on temporary layoff with recall expectation” in Tables 2 and 3 also shows that unemployed workers with an expectation of recall search significantly less than job losers, consistent with Katz’s (1986) prediction. Indeed, other things equal, those with an expectation of recall hardly search at all.

In results not presented here, we tested the robustness of the findings in Tables 2 and 3 by including the state-level unemployment rate, which had a negative coefficient but was not statistically significant.¹⁷ Because of concern about simultaneous causation – a high unemployment rate could cause fewer people to search for a job and could be caused by low job search intensity – we excluded the unemployment rate and its interaction with benefits from the models in Tables 2 and 3. We also excluded the duration of unemployment because it is endogenously determined with search time. It is nonetheless reassuring that none of the variables of interest had a qualitatively different effect if these variables were included.

We also probed the robustness of our results by excluding those older than 55, as the unemployed may take into account the option to retire already in their late 50s.

¹⁶ The benefit indicator they use is the net replacement rate, which is the after-tax value of UI benefits, social assistance, food stamps and housing benefits relative to after-tax earnings.

¹⁷ See Shimer (2004) for an analysis of how search intensity varies with the business cycle.

The coefficients on the log weekly benefit remained of similar size and significance.

Finally, we used the number of job search methods used during the last 4 weeks as a dependent variable in our linear regressions of Table 2. The point estimates were consistent with our results above: For the UI eligible in column 2, a one log point increase in the weekly benefit is associated with a decrease of 0.44 methods used over the last 4 weeks, compared to a decrease of 0.05 methods for the ineligible in column 3.¹⁸ Both coefficient estimates, however, were insignificant with p-values in excess of 0.2. This highlights the utility of time use data for research on job search intensity.

Overall, the regression results provide support for Mortensen's (1977) model to varying degrees. Differences across states in the level of benefits have a negative relationship with job search in the subsample of UI eligible job seekers with unemployment duration of 26 weeks or less. Also, for the UI ineligible, the effect of benefits on job search is predicted to be positive (the entitlement effect). The coefficient has the expected sign but is not significant. However, we can reject at the 10% level the null hypothesis that the coefficient on benefits is equal for the UI eligible and ineligible (i.e., contrasting the coefficients on benefits in columns 2 and 3 in Table 2 or 3).

One word of caution, however, is warranted as our identification strategy relies on cross-state variation of maximum benefits and omitted state-level covariates could lead to biases in our estimates. Moreover, one might be concerned about endogeneity of our benefit variable as, e.g., states with high unemployment rates might enact more generous benefits. For these reasons, we would prefer to identify the effects of UI benefits on job search intensity from variation of benefits across time rather than states. Unfortunately, over the 5 years of the ATUS, changes in maximum benefits were small, providing too little variation to identify the effects of UI benefits with any reasonable precision. We leave this task for the future when more years of the ATUS become available.

Despite these limitations, we would like to mention that we control for state-level characteristics of the wage distribution and that our results are robust to the inclusion of the state-level unemployment rate. We also expect that the differential

¹⁸ The ATUS has the same categorical measures of job search as the CPS. The average number of methods used over the last four weeks is 2.4 for the UI eligible in column 2 and 2.0 for the ineligible in column 3.

effect of UI benefits on eligible and ineligible subjects is less likely due to state-level omitted variables; this provides some indirect support for our identification strategy.

Moral hazard versus liquidity effects of UI

One way to interpret our findings regarding the effects of UI benefit generosity is as a “moral hazard” effect: UI indirectly subsidizes leisure while unemployed and thus reduces the incentives to search for a new job and return to work. However, in the presence of borrowing constraints and, more generally, in the absence of insurance markets for unemployment risk, UI also enables job seekers to smooth consumption and thus reduces the pressure for them to rush back to work.

To evaluate the importance of such “liquidity effects” we follow Chetty (2008) and split the sample of UI eligible job seekers into those with a working partner (married or unmarried) and those without. Those with access to a secondary income source are more likely to maintain consumption during a spell of unemployment and thus should be less responsive to unemployment benefits. We find support for this hypothesis as the coefficient on benefits for those with a working partner is positive and statistically insignificant whereas the elasticity for those without a working partner is -2.1 and significant at the 5% level (t-ratio 2.02). Moreover, the difference between the benefit coefficients in the two samples is statistically significant at the 10% level (t-ratio 1.98).

We also split the UI eligible sample into those with annual household income below and above \$25,000. We find that the unemployed with low annual household income are more responsive to benefits with an elasticity of -2.7 (t-ratio 1.78) compared to -0.8 (t-ratio 1.29) for those with household income higher than \$25,000, but the difference is not statistically significant at the 10% level.

Although not definitive, these results suggest that liquidity constraints have a potentially important impact on many job seekers, as the search intensity of those who have less access to financial resources appears to respond more strongly to UI benefits. We also would like to estimate the elasticity of job search with respect to increases in cash on hand, such as, for example, due to severance payments. Unfortunately, there is no such information currently available in the ATUS. Future research with time-use data might be able to distinguish the liquidity effect from the moral hazard effect.

4 Relationship between Unemployment Duration and Job Search

The standard search model makes strong predictions regarding the amount of time spent searching for a job by duration of unemployment. In particular, for those eligible for benefits, job search intensity should increase as benefits approach the exhaustion date. By contrast, search intensity by the ineligible should remain constant throughout the unemployment spell. Although it would be preferable to examine these relationships with longitudinal data, we can use ATUS data to examine the cross-sectional patterns of job search across those with different durations of unemployment at the time of the survey.

To nonparametrically estimate the unemployment duration-job search profile we utilize LOWESS to plot the fitted values of a locally weighted regression of minutes spent in job search on unemployment duration at the time of the ATUS.¹⁹ We exclude those who have an expectation of recall to their previous employer, as their search behavior is different and affected by the recall strategy of the employer.

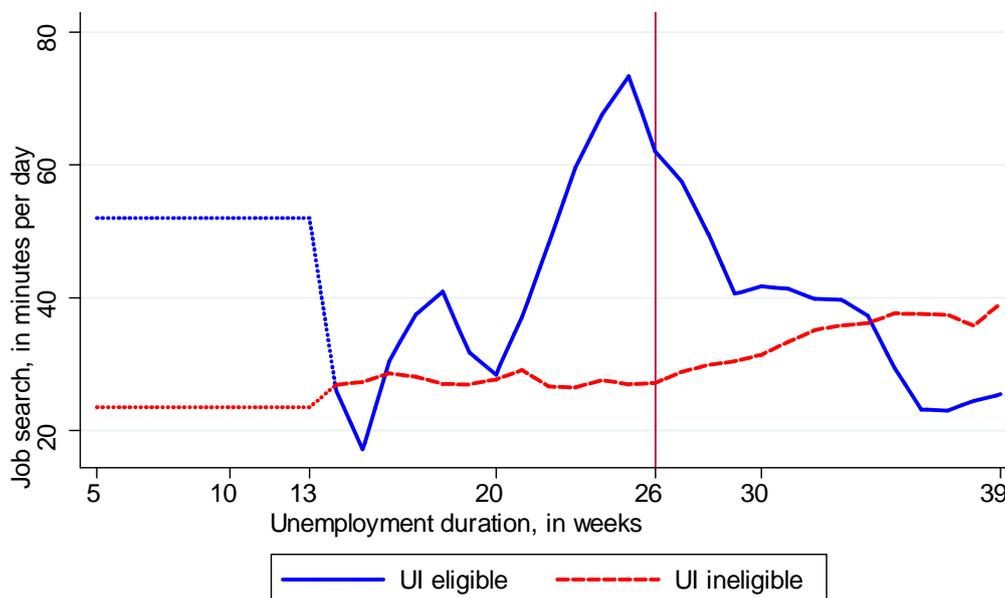
Unfortunately, the ATUS interview does not collect information on unemployment duration. Consequently, we derive unemployment duration by taking the unemployment duration reported in the last CPS interview and adding the number of weeks that elapsed between the CPS interview and the ATUS interview. The large majority of the ATUS interviews were conducted 3 months after the last CPS interview, with only 14% after 4 months or more. For those who were not unemployed at the time of the CPS interview, we impute duration of unemployment by taking half the number of weeks between the CPS and the ATUS interviews. We do not show the weekly LOWESS plot for 13 weeks or less, but simply report the average time allocated to search, as the imputed unemployment duration are quite noisy for those who become unemployed after their last CPS interview.²⁰

Figure 3 shows the LOWESS plot separately for those eligible and ineligible for UI benefits.²¹ The unemployment duration-search profile for the UI ineligible

¹⁹ Note that STATA does not allow the use of survey weights for LOWESS. For this reason, we duplicate each observation x number of times where x corresponds to the survey weight (with the “expand” command in STATA). This generates a dataset representative of the population.

²⁰ About one third of our sample of unemployed individuals (excluding those on temporary layoff) has an unemployment duration of 14 weeks or more.

²¹ Note that we exclude observations on eligible individuals from 2003 because the federal ex-

Figure 3: *Lowess: job search by unemployment duration*

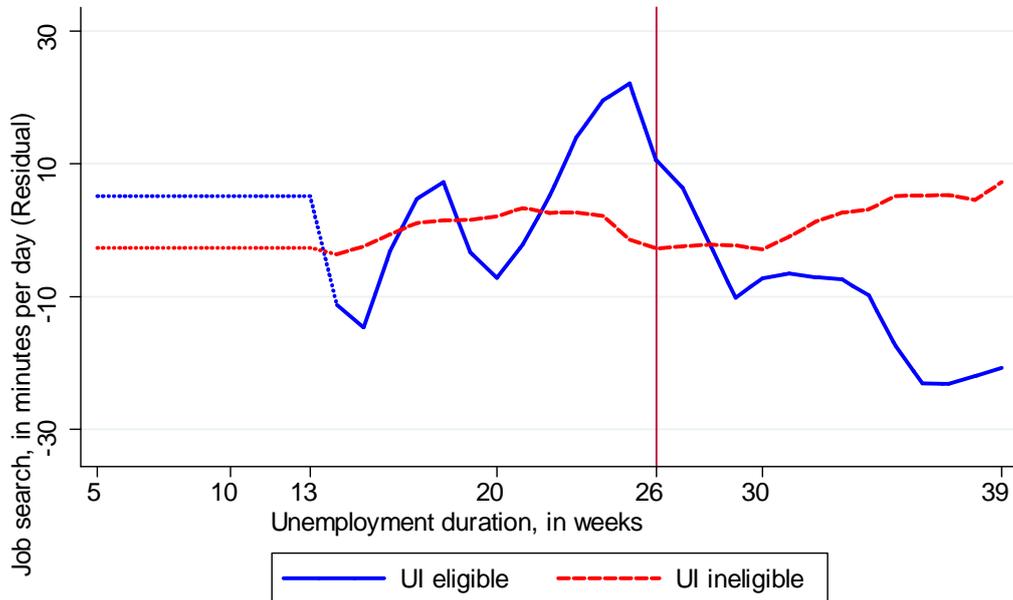
Notes: Bandwidth = 0.1. Survey weights are used to compute the lowess smoother. Unemployed with an expectation of recall to their previous employer are excluded from the sample. The dotted lines refer to the average of time spent on job search before week 14.

group is fairly flat, consistent with standard search models. For the UI eligible, however, job search increases sharply between week 15 and 26 of unemployment, from less than 20 minutes to greater than 70 minutes, and then falls back to around 25 minutes.

One problem with our measure of unemployment duration is that it does not take into account the possibility of job spells between the CPS and the ATUS interview. To assess the validity of our assumption, we matched the CPS waves 1 to 4 over the years 2003 to 2007 and looked at individuals who were unemployed and without an expectation of recall both in wave 1 and wave 4 three months later. We find that 11.8% of these individuals were employed in wave 2 and/or wave 3. To assess how this source of mismeasurement could affect our LOWESS plots, we performed simulations with our ATUS sample in which we randomly assigned job spells to 11.8% of individuals who were unemployed in the CPS as well as in the ATUS. For each individual with a simulated interim job spell we subtracted 15 weeks from unemployment duration in the ATUS. We iterated this procedure 400 times and found, on average, a slightly smaller increase of time spent on job search before

tended benefits program was in effect that year.

Figure 4: *Lowess: job search by unemployment duration (residuals from baseline regression model)*



Notes: Bandwidth = 0.1. Survey weights are used to compute the lowess smoother. Unemployed with an expectation of recall to their previous employer are excluded from the sample. The dotted lines refer to the average of time spent on job search before week 14.

week 26 for the UI eligible (from 20 to 65 minutes). The profile of search time for the UI ineligible group was hardly affected in these simulations.

As a further robustness check, we probed the robustness of the profiles in Figure 3 by removing the effects of age, sex, and other characteristics (i.e., the explanatory variables in column 1 of Table 2), and then used the residuals in the LOWESS analysis. Figure 4 provides LOWESS plots of the residuals. The general patterns in the duration-search profiles are fairly similar to those in Figure 3, although the increase in time devoted to job search between week 15 and 26 for the UI eligible sample is somewhat smaller after removing the effects of the explanatory variables.

Finally, for both the UI eligible and ineligible, we introduced quadratic polynomials for duration of unemployment with breaks at weeks 14 and 39 into the linear regression model in column 1 of Table 2.²² For the UI eligible, the linear and quadratic terms were jointly significant at the 10% level and the predicted patterns of job search by unemployment duration looked similar to the LOWESS in Figure

²² In order to be consistent with the sample used for the LOWESS, we excluded those on temporary layoff with an expectation of recall and observations on UI eligible individuals from 2003.

4: job search increases by 24 minutes between week 14 and 26 and then strongly decreases by 66 minutes as week 39 approaches. For the UI ineligible, however, the standard errors on the coefficients for the linear and quadratic terms were large, and we couldn't statistically distinguish their pattern of job search from a constant nor from the pattern of the UI eligible (i.e., we could not reject either null hypothesis).

The increase in job search in the weeks prior to benefit exhaustion for the UI eligible sample and the fairly constant amount of time devoted to job search for the UI ineligible are both consistent with Mortensen's (1977) search model. However, the decline in job search after week 26 is unexpected, as the model predicts that workers allocate a constant amount of time to job search after benefits are exhausted.

One explanation for the decline after week 26 is a potential selection issue due to unobserved heterogeneity in the propensity to search for a job: job seekers who devote a lot of effort to searching for a job are more likely to find one and exit the sample, whereas those with a low proclivity to search remain in the sample. This creates a possible "length-based sampling" bias that would tend to cause the search profiles to slope down with unemployment duration. A similar issue affects studies of the effect of UI on exit rates (e.g., Katz and Meyer, 1990a,b) and the reservation wage (e.g., Feldstein and Poterba, 1984), which analyze one unemployment spell per person or reservation wages for a cross-section of job seekers. The fact that the relationship between spell duration and job search is fairly flat for the UI ineligible sample is an indication that bias due to length-based sampling is probably small, as this group would also be subject to length-based sample bias if workers have heterogeneous commitments to job search.²³

5 Conclusion

This paper provides new evidence on job search intensity and Unemployment Insurance. We use data from the American Time Use Survey and model job search intensity as time allocated to job search activities, consistent with theoretical models. We find that time allocated to job search is inversely related to the maximum weekly benefit amount for UI eligible workers, with an elasticity of -1.6 to -2.2,

²³ See also the nonparametric Monte Carlo technique in the working paper version (Krueger and Mueller, 2008b), which suggests that the relationship between job search effort and the duration of unemployment for a cross-section of job seekers is only slightly biased by length-based sampling.

which is large enough to account for much of the gap in job search time between the U.S. and Europe. Moreover, job seekers who likely have less access to financial resources (e.g., because they do not have a working spouse) tend to respond more to UI benefits than do those with greater financial wherewithal, consistent with a role for liquidity constraints. Furthermore, we find that job search increases sharply in the weeks prior to benefit exhaustion, in line with Mortensen's (1977) model. These findings highlight the utility of simple search models for understanding job search behavior and UI.

A finding that is inconsistent with Mortensen's (1977) search model, however, is that search effort appears to decline after week 26, when benefits run out, rather than remain constant. This finding deserves further attention. One possible explanation is that the unemployed become discouraged if they fail to find a job despite substantially increasing their search effort before UI benefits run out at 26 weeks, and consequently stop searching. A related explanation is that the unemployed may feel that they have explored all of their plausible job opportunities after they sharply raised their search effort in the weeks leading up to the exhaustion of their UI benefits, and rationally feel they have little to gain from maintaining the same level of search effort over the next few months.

Our findings suggest that time-use data offer a fruitful approach for research on job search intensity. In particular, if future ATUS surveys collect data on unemployment duration, one could further investigate the link between unemployment duration and job search. Longitudinal time-use data would help to control for length-based sampling and individual heterogeneity in job search activity. Moreover, data on severance payments and asset positions of the unemployed could allow one to determine the relative importance of moral hazard and liquidity effects of unemployment benefits.

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Appendix

Appendix Table. Definition and examples of job search activities in ATUS 2006

Job search activities (050401), e.g.:

contacting employer
making phone calls to prospective employer
sending out resumes
asking former employers to provide references
auditioning for acting role (non-volunteer)
auditioning for band/symphony (non-volunteer)
placing/answering ads
researching details about a job
filling out job application
asking about job openings
reading ads in paper/on Internet
checking vacancies
researching an employer
submitting applications
writing/updating resume
meeting with headhunter/temp agency
picking up job application

Interviewing (050403), e.g.:

interviewing by phone or in person
scheduling/canceling interview (for self)
preparing for interview

Other activities related to job search, e.g.:

waiting associated with job search interview (050404)
security procedures rel. to job search/interviewing (050405)
travel related to job search (180504)
job search activities, not elsewhere specified (050499)

Chapter 5

On-the-Job Search and Wage Dispersion: New Evidence from Time Use Data^{*}

1 Introduction

The U.S. labor market features large employer-to-employer (EE) flows. As recently emphasized by Fallick and Fleischman (2004), around 2.6% of employed persons change employment each month without going through a spell of unemployment. Why do so many employed workers change jobs each month? One explanation is that in the face of wage dispersion employed workers search for better paying jobs. Christensen et al. (2005), e.g., provide a search model of the labor market with on-the-job search, wage dispersion and endogenous search effort. Their model predicts that search effort decreases with the wage since returns to search for a better job are higher the further down the worker is on the wage ladder. In Danish labor market data, they find that the job separation rate is decreasing in the wage, supporting the model's prediction.

The present paper provides direct evidence on job search intensity of the employed in the U.S., modeling job search intensity as time allocated to job search activities. I use data from the American Time Use Survey (ATUS) and find a highly

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significant effect of the wage on job search intensity, with an elasticity of between -0.7 and -1.3.

2 Model

I briefly sketch a partial equilibrium model of on-the-job search, similar to Christensen et al. (2005)¹, where the employed worker allocates a fraction s of her total available time (normalized to 1) to job search activities and faces a known wage offer distribution $F(w)$. There are no savings, so consumption is equal to the wage. The Bellman equation of the employed worker is:

$$W(w) = \max_s \left\{ u(w, 1-s) + \beta[W(w) + \alpha(s) \int_w (W(x) - W(w))dF(x) - \delta(W(w) - U)] \right\}, \quad (5.1)$$

where $W(w)$ is the value of an employed worker with wage w , $u(.,.)$ is the utility derived from consumption and leisure, β the discount factor, $\alpha(s)$ the probability of receiving a job offer for a given search effort s , δ the separation rate and U the value of being unemployed. I make the standard assumption of diminishing marginal utility of leisure ($u_{22} < 0$). Note that the employed worker never accepts a job offer that pays less than her current wage w . The first order condition for s is:

$$u_2(w, 1-s) = \alpha'(s) \int_w (W(x) - W(w))dF(x). \quad (5.2)$$

The optimal amount of time devoted to job search trades off the marginal cost of foregone leisure against the marginal increase in the probability of receiving a job offer (times the discounted expected gain from such an offer).

Proposition 4 *If the marginal utility of leisure is independent of consumption ($u_{12} = 0$) and the returns to search are constant ($\alpha'' = 0$), then s is decreasing in the wage w .*

Proof. If $u_{12} = 0$, then the left hand side of (2) is independent of w and increasing

¹ The main deviation from Christensen et al. is that I model search costs as forgone leisure whereas they assume a search cost function of the form $c(s) = gs^\lambda$.

Table 1. Descriptive statistics ATUS 2003 - 2008, by labor force status

	# respondents	% of total	Job search per day, in min	Fraction searching on diary day	Job search (conditional on searching), in min
By labor force status					
Employed	50,444	76.5%	0.65	0.6%	106.7
Unemployed	2,580	3.9%	34.99	20.0%	175.2
Not in labor force	12,954	19.6%	0.83	0.5%	154.7

Notes: Averages and participation rates are computed with survey weights. Universe: Civilian, noninstitutional population, age 20-65.

in s because of diminishing marginal utility of leisure. Moreover, if $\alpha'' = 0$, then the right hand side is decreasing in w since the worker will accept fewer job offers. Therefore, at a higher wage w , s has to be lower for (2) to hold.² ■

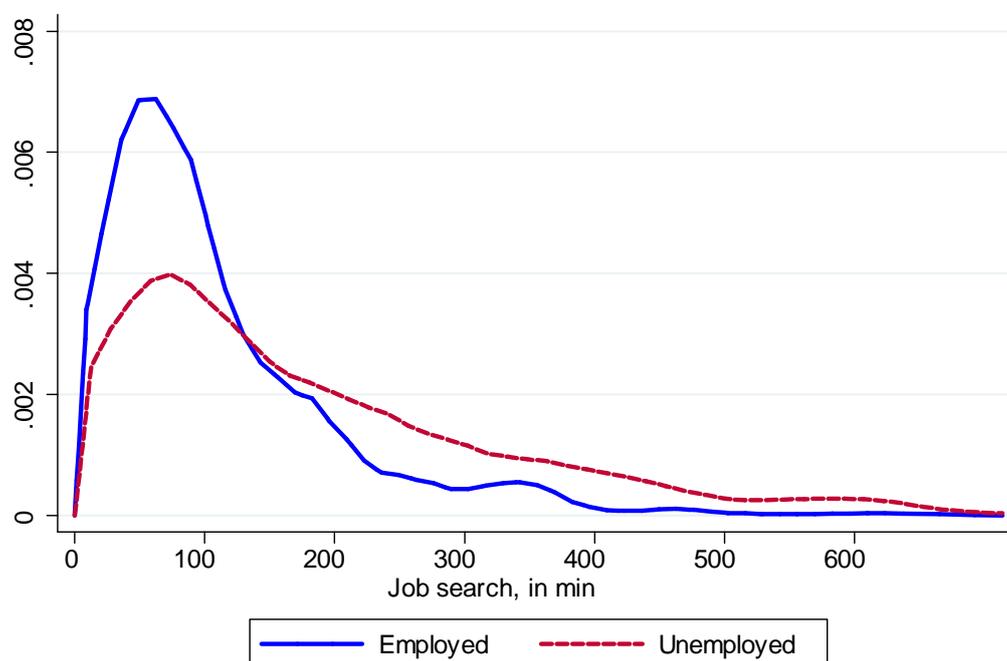
3 Data and Descriptive Statistics

I use data from six consecutive years (2003-08) of the ATUS, which is a nationally representative time-use survey, drawn from the 8th outgoing rotation group of the Current Population Survey (CPS). The ATUS collects detailed information on the amount of time respondents devoted to various activities on the previous day, including job search activities such as contacting a potential employer, calling or visiting an employment agency, job interviewing, etc.³

Table 1 provides descriptive statistics of time allocated to job search by labor force status. The average employed searches 0.65 minutes per day or 20 minutes per month, which is 54 times less than the average unemployed. Moreover, only 0.6% of the employed reported positive minutes of job search on the diary day. However, those who search on the diary day tend to spend a lot of time on job search activities. Figure 1 shows the Kernel density of time spent on job search conditional on searching on the diary day. The average duration of search is more than 100 minutes and 70% of employed job searchers spend one hour or more searching for a

² See Mortensen (1977) for a similar analysis in the case of the unemployed worker. Note also that one can generalize the proposition to the case where consumption and leisure are complements ($u_{12} > 0$) and where returns to search are non-increasing ($\alpha'' \leq 0$). When consumption and leisure are substitutes, however, job search could be increasing in the wage because at higher wages the marginal cost of search is lower.

³ See the Appendix Table in Chapter 4 for a detailed description of job search activities in the ATUS.

Figure 1: *Kernel density: job search (conditional on non-zero search)*

Notes: Survey weights were used to compute the kernel density.
Epanechnikov kernel with optimal weights.

job on the diary day.

Despite very little average time allocated to job search by the employed, there are large EE flows in the U.S. labor market: Fallick and Fleischman (2004) report that 2.6% of workers in the CPS change employer each month, compared to 28.3% of unemployed persons who find employment each month.⁴ In other words, monthly unemployment-to-employment (UE) flows are 11 times larger than EE flows. This suggests that on-the-job search is almost five times more effective in terms of time allocated to job search. As already emphasized by Blau and Robins (1990), a higher efficiency of search on-the-job could be driven either by differences in search technology (e.g., through better contacts) or unobserved heterogeneity between employed and unemployed workers in terms of job search efficiency. Also, job search activities such as defined in the time use data might be less relevant for employed workers (e.g., every lunch is a job interview).

⁴ They use data from the CPS 1994 and 1996-2003.

4 Estimation

In order to test the prediction of the model outlined above, I carry out a reduced form regression relating time devoted to job search s_i to the log hourly wage⁵ :

$$s_i = \beta_0 + \beta_1 \log(\text{hourly wage}_i) + \beta_2 X_i + \varepsilon_i, \quad (5.3)$$

where X_i includes controls for sex, age, education, race, marital status, children, interaction terms, a dummy for whether the diary day was a weekend day, a dummy for whether the person was absent from work in the reference week (for reasons other than layoff) as well as dummies for month and year of interview and state of residence. I restrict the sample to private-sector employees of age 20-65 who were not enrolled in high-school, college or university at the time of the survey. I also trim the sample in terms of the hourly wage, excluding all observations with a wage of less than \$1 or more than \$100.⁶ The sample size is 33,628. Standard errors are robust to heteroskedasticity.

One open question is whether one should include occupation and industry dummies in the regression model. Note that the assumption here is that – at given observable characteristics of the worker – the observed wage reflects the position of the worker on the wage ladder. It makes sense to include occupational dummies as they mainly reflect workers characteristics such as human capital. However, there is good reason to exclude industry dummies from the specification because they may capture features of the wage distribution faced by similar workers rather than differences in individual characteristics (see, e.g., Krueger and Summers, 1988).

Table 2 reports the results for a linear regression model: the models in column 1-3 and 5 differ only in whether state, occupation and industry dummies are included or not. The effect of the log hourly wage is negative and significant at the 1% level in

⁵ Hourly wages for non-hourly workers are computed by dividing weekly earnings by usual hours. Hours were imputed for those who indicated "varying hours" from regressions of hours on age and dummies for race, education, foreign born and citizenship for four different samples (full-time men, part-time men, full-time women, part-time women), as suggested by Schmitt (2003). To adjust for top-coding of weekly earnings (the top code is \$2885), I assumed a Pareto distribution and used the 90th percentile of the observed distribution to estimate the mean above the top-code (see Schmitt, 2003, for a discussion of adjustment for top-coding in the CPS). Hourly wages for those who work by the hour are adjusted for overtime earnings. Moreover, wages are deflated with the implicit deflator for hourly earnings in the private non-farm business sector from the BLS productivity and costs program.

⁶ I also excluded those who reported zero usual hours (3 observations).

Table 2. Results of regressions
Dependent variable: time allocated to job search, in min
Mean of dependent variable

	Mean (Std)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(hourly wage)	2.69 (0.61)	0.680 -0.912 (0.231)**	0.680 -0.938 (0.231)**	0.680 -0.858 (0.251)**	0.680 -0.865 (0.251)**	0.680 -0.845 (0.253)**	0.680 -0.473 (0.078)**	0.680 -0.384 (0.072)**
Log(usual hours)	3.69 (0.36)				-1.457 (0.480)**			-0.439 (0.083)**
Age/10	4.04 (1.18)	-0.964 (0.614)	-0.994 (0.617)	-0.982 (0.631)	-0.721 (0.620)	-0.931 (0.610)	-0.32 (0.220)	-0.157 (0.189)
Age ² /100		0.097 (0.069)	0.102 (0.069)	0.1 (0.071)	0.066 (0.070)	0.093 (0.068)	0.023 (0.028)	0.004 (0.025)
Some college or associate degree (2)	0.27	0.69 (0.270)**	0.691 (0.274)**	0.707 (0.277)**	0.716 (0.278)**	0.687 (0.269)**	0.382 (0.152)**	0.371 (0.141)**
College degree (BA, MA or PHD)	0.29	0.983 (0.231)**	0.984 (0.234)**	0.994 (0.281)**	0.994 (0.280)**	0.959 (0.286)**	0.689 (0.186)**	0.634 (0.178)**
Female	0.45	-0.539 (0.347)	-0.556 (0.351)	-0.601 (0.380)*	-0.627 (0.383)*	-0.653 (0.369)*	-0.202 (0.182)	-0.168 (0.18)
Female*partner	0.29	0.439 (0.386)	0.442 (0.385)	0.318 (0.380)	0.121 (0.338)	0.308 (0.349)	0.058 (0.181)	-0.062 (0.147)
Female*children	0.21	-0.776 (0.348)**	-0.764 (0.349)**	-0.652 (0.349)**	-0.775 (0.349)**	-0.687 (0.349)**	-0.163 (0.133)	-0.19 (0.121)
Partner	0.67	-0.418 (0.338)	-0.406 (0.328)	-0.21 (0.317)	-0.147 (0.313)	-0.199 (0.314)	-0.212 (0.169)	-0.118 (0.146)
Children	0.46	0.74 (0.298)**	0.736 (0.297)**	0.658 (0.289)**	0.652 (0.287)**	0.69 (0.294)**	0.268 (0.157)*	0.237 (0.144)*
Black (3)	0.10	0.488 (0.398)	0.607 (0.423)	0.588 (0.433)	0.594 (0.432)	0.532 (0.440)	0.089 (0.128)	0.095 (0.119)
Hispanic	0.15	-0.371 (0.239)	-0.444 (0.285)	-0.559 (0.309)*	-0.535 (0.305)*	-0.573 (0.319)*	-0.15 (0.082)	-0.127 (0.086)
Asian or other	0.05	-0.765 (0.139)**	-0.827 (0.167)**	-0.793 (0.164)**	-0.826 (0.169)**	-0.8 (0.174)**	-0.275 (0.080)**	-0.244 (0.073)**
Absent from work last week	0.03	0.419 (0.450)	0.422 (0.447)	0.372 (0.473)	0.34 (0.474)	0.36 (0.472)	0.266 (0.236)	0.239 (0.216)
Weekend	0.29	-0.368 (0.150)**	-0.369 (0.151)**	-0.415 (0.154)**	-0.401 (0.153)**	-0.447 (0.159)**	-0.225 (0.085)**	-0.193 (0.080)**
Year and month dummies		x	x	x	x	x	x	x
State dummies			x					
Occupation dummies (3-digit)				x		x		
Industry dummies (3-digit)					x			
Observations		33,628	33,628	33,628	33,628	33,628	33,628	33,628
(Pseudo-) R-squared		0.01	0.01	0.06	0.06	0.07	0.06	0.07

Robust standard errors in parentheses
 * significant at 10%, ** significant at 5%, *** significant at 1%
 Notes: Regressions are weighted using survey weights. Universe: private-sector employees of age 20-65 who were not enrolled in high-school, college or university at the time of the survey. I also trim the sample in terms of the hourly wage, excluding all observations with a wage of less than \$1 or more than \$100. (1) For dummy variables the discrete change from 0 to 1 is reported. (2) The base group consists of those with a high school degree or less. (3) The base group is White.

all 4 columns and the coefficients are of similar size. For my preferred specification (column 3), which includes state and occupation dummies, the implied elasticity of time devoted to job search with respect to the wage is -1.3.

Column 4 in Table 2 also includes the log of usual hours of work on the current job. The effect is highly significant and negative, with an elasticity of -2.1. This suggests that workers allocate more time to job search when they have more time on their hands. One may argue, however, that working hours are endogenous to the hourly wage and thus should be excluded from the regression model. It is reassuring that the estimated coefficient on the log wage changes only little between column 3 and 4.

In results not presented here, I included the monthly U.S. unemployment rate to control for the business cycle (and I excluded the month and year dummies from that specification). The estimated coefficient was positive but not significant and the coefficient on the log wage was unaffected. As a further robustness check, I restricted the sample to those of age 25-59. The implied elasticity of job search with respect to the wage was smaller (-1.0) but still significant at the 1% level. Moreover, I re-estimated column 3 without trimming the sample at the hourly wages of \$1 and \$100. The coefficient remained significant at the 1% level but the implied elasticity was smaller (-1.0). Finally, I included dummies for whether the person was unemployed or out of the labor force in the CPS interview 2-5 months prior to the ATUS interview. Those unemployed in the CPS searched 3.1 minutes more per day than those employed in the CPS, but the estimated coefficient on the log wage was virtually unaffected and remained significant at the 1% level.

I also estimate a Tobit model to account for the mass of workers with 0 minutes of job search on the diary day. Unfortunately, the log likelihood procedure did not converge when re-estimating the specifications of the linear model reported in columns 2-5. The likely reason is that the log likelihood is not well behaved due to multicollinearity in the presence of many state, industry and/or occupation dummies. Therefore, I estimate the Tobit model without state, industry and occupation effects. The results of the linear model suggest that this is innocuous, as the estimated coefficients change only little between column 1 and columns 2-5. Columns 6 and 7 report the marginal effects for the Tobit model where the latter also includes the log of usual hours. The effect of the log wage is negative and highly statistically

significant in both specifications (with t-stats in excess of 5). The estimated coefficients, however, are only about half as large as in the linear model. For column 6, the implied elasticity of time devoted to job search w.r.t. the wage is -0.7. I also confirm the significant negative effect of log hours on time devoted to job search, but with a substantially lower elasticity (-0.6).

Finally, to gauge the magnitude of the estimated effect of the wage on job search, consider the effect of reducing the log wage by one standard deviation. Decreasing the log wage by 0.61 points, increases the job search intensity by 16 minutes per month in the linear model (column 3) and 9 minutes in the Tobit model (column 6). Given that the average time allocated to job search is only 20 minutes per month this suggests an economically important effect of the wage on job search intensity.

5 Conclusion

The results presented suggest that on-the-job search effort, modeled as time allocated to job search activities, is decreasing in the wage of the current job with an elasticity of -0.7 to -1.3. One word of caution is warranted, however, as a potential bias might arise because of unobserved heterogeneity among employed workers: high ability workers might search harder because of higher returns to search, which will lead the estimated coefficient of the wage to be biased towards 0. Nevertheless, the evidence presented above supports models where similar workers face wage dispersion and invest time in order to find better paying jobs.

One open question is why job search is so much more effective on-the-job than when unemployed. In future surveys, it would be useful to collect time use data in connection with job transitions to shed further light on this issue.

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