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Systematic Job Search: New Evidence from Individual Job Application Data

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Systematic Job Search: New Evidence from Individual Job Application Data*†

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Abstract

We use novel high-frequency panel data on individuals' job applications from a job posting website to study how job seekers direct their applications over the course of a job search. We find that at the beginning of search there is sorting of applicants across vacancies by education. As the search continues, education becomes a weaker predictor of which job a job seeker applies for, and an average job seeker applies for jobs that are a first-week choice of less educated job seekers. The findings suggest that search is systematic, whereby a job seeker samples high-wage opportunities first and lower-wage opportunities later. The findings are consistent with the literature that documents declining reservation wages and provide evidence in favor of theories of job seekers' learning. (JEL Codes: E24, J64, J31, J24.)

Keywords: Job Application Process, Reservation Wage, Search-Matching, Sorting, Learning.

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1 Introduction

Equilibrium search theory provides a tractable framework for studying the functioning of the labor market.[1] At the heart of the theory is a notion of trading frictions, i.e., a notion that job search takes time. Yet, little is known empirically about the process by which workers search for jobs. How does the job search change with the length of search? Do job seekers apply for the same types of jobs throughout the duration of their search or do they direct their search to particular jobs in a systematic manner?

While the dynamics of the job search process is often treated as a black box, the relationship between the duration of search (which can be relatively easily measured in the data) and search outcomes has been studied extensively. Longer search durations are typically associated with lower reemployment wages, that is, job seekers are willing to accept less attractive jobs as search continues.[2] Different theories can rationalize this observation: In one class of theories, a job seeker samples firms in no systematic order;[3] in another class of theories, a job seeker samples high-wage opportunities first, and lower-wage opportunities later.[4] Understanding the process of the job search is important for discriminating among different explanations and enriching search theory.

In this paper, we use novel high-frequency panel data on individual applications from a job posting website to study the process of the job search. Our main focus is studying how the types of jobs a job seeker applies for change with search tenure. To our knowledge, this is the first paper that empirically examines the dynamics of the directedness of the job search.

The data consist of the matched job seeker-job posting records of all applications sent on the website between September 2010 and April 2012.[5] The raw data set is large: It contains

[1] Rogerson, Shimer, and Wright (2005) provide an excellent survey of the search theory literature.

[2] Kahn (1978), Addison and Portugal (1989), Schmieder, von Wachter, and Bender (2012).

[3] Mortensen (1970) is an early example of such models. The declining reemployment wage might result from the lower wage offers due to, for example, firms' ranking of the unemployed by duration of unemployment.

[4] Such models allow a job seeker some ex ante information about the labor market and/or relax the assumption of stationarity of the labor market environment. Examples are models with liquidity constraints or time-varying unemployment benefits (Mortensen (1977), Burdett (1978), Danforth (1979), Albrecht and Axell (1984)), imperfect knowledge of the distribution of the prevailing wages and learning (Salop (1973), Rothschild (1974), Burdett and Vishwanath (1988), Gonzalez and Shi (2010)), models of human capital depreciation, etc.

[5] We use the terms "job" and "job posting" interchangeably to refer to an open vacancy on the website.

information on the applications of more than 10 million job seekers to more than 2 million unique job postings spread across all U.S. states. The data allow tracking of a job seeker's application behavior from the first day of his search on the website and thus are uniquely suited for studying the dynamics of individual search behavior. For each job seeker, we have information about education and other basic demographic characteristics, the date when he first starts searching on the website, and the information about all applications he sends on the website during the sample period.

We start the analysis by examining whether, at the beginning of their search on the website, job seekers with different levels of education direct their search to distinct jobs. We find that this is the case, i.e., a job seeker's application decision at the beginning of search delivers a detectable pattern of sorting by education across jobs. That is, there is no single universally attractive job for which job seekers of all educational levels apply. Rather, education is an important determinant of where to apply at the beginning of the search.

The main question of our analysis is how the types of jobs a job seeker applies for change with search tenure. Our data do not contain information about wages or the job requirements of the job postings; thus, we deduce the information about jobs from the job seekers' behavior in the first week of search. For each job, we construct an educational index of the job: the average number of years of schooling of all applicants who apply for the job during their first week of search on the website. The index is revealed by each job seeker's choice of which jobs to apply for and, thus, encompasses job seekers' information about the job and about the labor market (i.e., wage, job requirements, and the probability of being hired). We use the index to characterize the job's type. Our finding that education is an important determinant of which job a job seeker applies for at the beginning of the search provides the main rationale for such a characterization.

We then examine whether there is a systematic relationship between a job seeker's educational level and the types of jobs he applies for as he continues his search on the website. First, we find that, as search continues, education becomes a weaker predictor of which job a job seeker applies for, i.e., there is less sorting by education. In particular, the correlation between a job seeker's education and our measure of the type of job he applies for drops by 33 percent from week 2 to week 26 of search, with half of the drop happening by week 5. Second, we find that an average job seeker applies for jobs of a lower type than the jobs he applies for at the beginning of the search. Third, we find that the job seekers whose total duration of search on the website is shorter have a steeper profile of the decline in the types of jobs with search tenure.

To interpret the results, it is important to understand our characterization of jobs. We have defined a high type job as one that receives applications from more highly educated job seekers in their first week of search on the website. With an additional assumption that sorting of applicants across job postings at the beginning of search is positive (in the sense that more highly educated job seekers apply for jobs with higher educational requirements), the higher type job is likely a job that pays higher wages but is harder to get because of higher educational requirements.

We then can interpret our findings as follows. At the beginning of search, a job seeker applies for the highest-wage jobs, taking into account the probability of being hired. As search continues, the job seeker applies for jobs that are the first-week choice of less educated job seekers and, thus, are likely lower-wage but easier-to-get jobs. We interpret these findings to suggest that search is systematic, whereby a job seeker samples high-wage opportunities (conditional on his belief about the probability of meeting the job requirements) first and lower-wage opportunities later.

What models can rationalize the documented systematic search pattern? The findings are consistent with a learning model whereby a negative search outcome leads to a job seeker reevaluating his job prospects and lowering the types of jobs which to apply for (as in, for example, a directed search model with learning of Gonzalez and Shi (2010)[6]). The pattern of applying for lower type jobs as search continues also appears consistent with the standard non-stationary job search model (Mortensen (1977), van den Berg (1990)), where reservation wages decline not because of learning but because job seekers exhaust their savings or unemployment insurance benefits. While the data do not contain information on job seekers' assets and thus precludes a detailed investigation, the evidence points against such liquidity constraints being the main driver of the documented pattern. First, we find that most of the adjustment takes place during the first four to five weeks of search, which is consistent with a job seeker's learning (and suggests that learning happens relatively fast) instead of with a job seeker exhausting the assets, which happens later in the search process. Second, in the standard model, if the reservation wage falls over time, job seekers should

[6] Gonzalez and Shi (2010) use the concept of "desired" wages (rather than "reservation wages") and show that, in their learning model, as search continues, the desired wage declines.

apply to more jobs, while in a learning model job seekers might apply to fewer jobs as search continues. Using the same data set as here, Faberman and Kudlyak (2014) find that the latter is the case, i.e., a job seeker sends fewer applications as the search continues.[7] Finally, the documented pattern cannot be explained by a stock-flow matching model whereby job seekers apply for lower-type jobs as search continues because they have already exhausted the stock of the preferable higher-type jobs. In particular, in the analysis, we control for the distribution of the types of available jobs in the job seeker's metropolitan statistical area in every period of his search. We find that job seekers apply for lower-type jobs even though higher-type jobs are available.

Our findings are consistent with the empirical literature that finds a declining reservation wage over the course of the job search (Kasper (1967), Kiefer and Neumann (1979), Brown, Flinn, and Schotter (2011)) and with the empirical literature that argues that the reservation wage is not binding but rather that a job seeker faces a lower wage-offer distribution with search tenure (Schmieder, von Wachter, and Bender (2012)). An advantage of our study is that our data contain records of actual individual behavior while most of the existing studies use data from a laboratory experiment or indirect evidence from unemployment duration and subsequent employment wages.

The paper contributes to a few different literatures. First, it contributes to the literature that seeks to explain a negative relationship between search duration and reemployment wages. We add to this literature by showing that the lower wage-offer distribution with search tenure does not necessarily arise only because firms offer lower wages to workers who have been unemployed for a long time.[8] Rather, there is an adjustment on the job seekers' part: Negative search outcomes lead to applying for lower-wage jobs. In our work, we characterize a job by an educational index, which encompasses job seekers' information about wages as well as the probability of being hired. Our findings thus suggest that not

[7]It should be noted that the commonly used search effort variables such as the number of search methods in the Current Population Survey or the time spent on job search in American Time Use Survey (Shimer (2004), Aguiar, Hurst, and Karabarbounis (2013), Mukoyama, Patterson, and Sahin (2014), Gomme and Lkhagavsuren (2014)) do not allow for the kind of analysis contained in Kudlyak and Faberman (2014) or in the current paper because these datasets are limited to cross-sectional data and thus do not allow following job seekers' behavior over time.

[8]Kroft, Lange, and Notowidigdo (2013), using data from a field experiment, find that firms are less likely to call back applicants with longer unemployment durations.

only wages but also the probability of getting hired play an important role in which jobs to apply for. Second, the paper also contributes to the literature that seeks to explain the cross-sectional dispersion of wages that exists after conditioning for observable worker characteristics (see, for example, Hornstein, Krusell, and Violante (2011)). Our findings suggest that the duration of search is an additional factor that contributes to different wages of otherwise observationally equivalent workers. Third, the finding that job seekers direct their search to different types of jobs as they continue their search suggests that the observed firm-worker matches are mismatched compared to the frictionless world. This, in turn, serves as an identification assumption for the literature that tests for assortative matching in matched firm-worker data.[9]

Finally, this paper is among the first papers that use data from an online job board to study job search. Autor (2001) foresees the emergence of the data from online job boards as a valuable source of information about the functioning of the labor market. Kuhn (2014) provides an excellent overview of the most recent literature. In particular, using data from online job boards, Brencic (2012) studies wage posting, Kuhn and Shen (2013) study gender discrimination in job ads, and Brown and Matsa (2013) study job applications to distressed firms. Baker and Fradkin (2011) use Google search data and Marinescu (2014) uses the aggregated application data from an online job board to study the impact of the unemployment benefits extensions on job search.

The rest of the paper is organized as follows. Section 2 describes the data and the sample. Section 3 presents results on sorting by education at the beginning of search. Section 4 presents results on the direction of applications with search tenure. Section 5 concludes.

2 Data and Sample Description

This section describes the data used in the analysis and basic facts about job search on the website.

[9] To obtain identification, Eeckhout and Kircher (2011) employ the idea that workers "tremble" to off-the-equilibrium firms. Gautier and Teulings (2006) explicitly assume that there are search costs.

2.1 Data Description

We use proprietary data from SnagAJob, an online private job search engine (hereafter, website). Anyone can browse the jobs available through the website at no cost. To apply for a job, a job seeker is required to register. Registration entails providing information about one's age, gender, ethnicity, education, and location (zip code). There is no fee to apply for a job and no limit on how many jobs a job seeker can apply for. Firms contract with the website to post vacancies. One important feature that characterizes jobs posted on the website is that the jobs are hourly jobs.

The data set contains application-level, matched job applicant-job posting data. On the job seekers' side, it is a panel of individual daily records on each application sent to the job postings available on the website. Each application is characterized by the date and the identification number of the job for which it is sent. We have information on job seeker's age, gender, ethnicity, education, and location (zip code) submitted at the time of registration on the website.[10] On the job postings' side, the data set contains information about all applications received by a job posting on each date during the sample period. The data set made available to us contains industry affiliation and location information only for a subset of job postings.[11] The data set in this paper covers all applications sent by registered job seekers to job postings on the website between September 2010 and April 2012.

When a job seeker stops applying for jobs on the website, there can be a few explanations: The job seeker has accepted a job offer that resulted from an application on the website, the job seeker finds a job elsewhere, the job seeker stops searching on the website and keeps searching elsewhere, or the job seeker stops searching and drops out of the labor force. The data do not contain information to distinguish between these alternatives, nor do they contain information on whether a job seeker's search results in hiring. However, for the purposes of our analysis it is sufficient to maintain the assumption that if a job seeker keeps applying for jobs, he has not yet received a desired job offer or has not received an offer at all.

[10] Currently, the data set made available to us does not contain information on whether a job seeker is employed at the time of search.

[11] The subset covers all job postings that received applications between September 2010 and September 2011. Faberman and Kudlyak (2014) use the subsample in their study of search intensity.

2.2 Sample Description

We restrict the sample to 25- to 64-year-old individuals to focus on the search experiences of the prime working-age population. This restriction reduces the sample of applications by approximately half. Individuals who report their education level as "Unknown" or "Ph.D." are also excluded. The resulting sample consists of more than 19.5 million applications.[12]

Table 1 describes the sample. The table contains the summary statistics for the full sample and separately for the subsample of job seekers registered after September 2010 (i.e., after the beginning of our sample period). In the latter subsample, we can track individuals' application activity from the first day of their job search on the website. Further examination of the subsample of job seekers registered after the beginning of our sample period reveals that some job seekers send applications only on the registration day and never send applications again. To understand whether there is a difference between applicants who apply only on the registration day and applicants who apply also on non-registration days, we further split the subsample of job seekers registered after September 2010 into two groups: registration-day-only applicants and other applicants. These two groups are described in columns 2 and 3 of Table 1, respectively.

As can be seen from the table, the characteristics of the full sample (column 1) and the two subsamples (columns 2 and 3) are very similar in terms of the distribution of applicants by gender, age, and education. Females constitute 57.6% of the applicants in the full sample. Job seekers between 25 and 34 years old constitute 46.4% of the sample; job seekers between 35 and 44 years old constitute 23.8% of the sample; and the remaining 29.8% are job seekers 45 to 64 years old. The fact that the jobs posted on the website are predominantly hourly jobs influences who searches on the website: 50.8% of the sample has a high school or lower level of education, 16.0% of the sample has a bachelor's degree, and 2.7% of the sample has a master's degree. The share of applicants with a master's degree in the subsample of job seekers who apply on a non-registration day is somewhat smaller compared to the share in the subsample of job seekers who apply on a registration day only, 2.6% and 3.3%, respectively.

Table 2 shows statistics by age and education in the subsample of applicants registered

[12] In some instances, we observe more than one application sent from a job seeker to the same job posting on the same date. We cap the number of applications from a job seeker to a particular job posting on each day at 1.

after September 2010. It contains the average number of applications per day per job seeker, conditional on the days when at least one application is sent, and the average number of days from registration to the last application sent by an applicant during the sample period.

As can be seen from Table 2, on average, older job seekers send fewer applications per day, and the standard deviation of the statistic is lower. In particular, a 25- to 34-year-old job seeker on average sends 1.75 applications, while a 55- to 64-year-old job seeker sends 1.38 applications, with standard deviations of 1.50 and 0.92, respectively. The period between the registration day and the last day we observe application activity for a 25- to 34-year-old job seeker is 47 days, while for a 55- to 64-year-old job seeker it is 70 days, with standard deviations of 97 and 115, respectively. To the extent that the duration during which we observe a job seeker in the sample proxies for the duration of unemployment, this observation is consistent with the existing fact that older workers typically experience longer unemployment spells. Table 2 shows that there is no monotonic relationship between the average number of applications and education or the average duration and education.

Table A.1 in the appendix contains the distribution of job postings and applications by industry affiliation when available. The majority of job postings are in retail, food, and restaurant and customer service. There are also jobs in accounting, finance, and health care.

2.3 Definition of Search Tenure

2.3.1 A Period in Job Search

In the analysis, we define the duration of a period in a job search as a unit of time that is long enough for a job seeker to apply for a job and receive some signal about the outcome of the search. If the outcome is negative (i.e., the job seeker receives a rejection notice or simply does not hear back from the firm), the job seeker continues his search in the next period. To understand what the appropriate length of the period for studying search activity on the website is, we analyze the periodicity with which job seekers send applications. Our data are daily. However, a closer look at the daily records of application activity reveals that a week rather than a day better describes a period in the job search on the website. In particular, we find that there is substantial volatility in application activity within a week and that there is a 7-day periodicity in application behavior. An additional reason for using a week rather than a day as a period in a job search is that if geographical labor markets are sampled at a daily frequency, then some markets have few observations.

Figure 1 shows the mean and the standard deviation of the number of applications sent by an applicant each day. The figure is constructed using information from the sample of applicants registered after the beginning of our sample. The blue scatterplots show the mean and the standard deviation calculated from the information on all job seekers in the sample, independently of whether or not the job seeker sends an application on a particular day, as long as the job seeker sends an application on a later date (i.e., is still in the sample). The figure shows that both the mean and the standard deviation exhibit a 7-day periodicity. For comparison, the figure also shows the statistics calculated conditionally on at least 1 application sent per day (green scatterplots). These statistics do not exhibit the periodicity evident from the unconditional statistic.

2.3.2 Search Tenure

Let the day on which a job seeker registers on the website be day 1 of his job search. For each job seeker we define week 1 of his search on the website as the period from day 1 to day 7 of his search and define the subsequent weeks accordingly. Thus, the start and the end of a week in search tenure might differ from job seeker to job seeker. For example, a week in search tenure might start on Tuesday or Thursday. Note that our data do not contain information about the duration of the period between the date when a job seeker lost his job and the date when the job seeker starts to search on the website. Thus, we interpret our analysis as evidence of the dynamics of search in a new labor market (i.e., the website) rather than the dynamics of search from the date of job loss.

Figure 2 shows the mean and the standard deviation of the number of applications sent by an applicant each week during the first 14 weeks from the start of the search, conditional on the job seeker still being in the sample (i.e., sending an application on a later date).

3 Sorting by Education at the Beginning of Search

Our main interest is in the question of whether job seekers with different levels of education apply for different jobs and how the sorting by education changes with search tenure. We start the analysis by examining the sorting at the beginning of search on the wesbite.

At the beginning of a search, do job seekers with different educational levels direct their searches to different jobs? That is, is education an important determinant of which job a job seeker applies for? To answer this question, we estimate the following regression for all applications sent from job seekers in their first week of search on the website:

$$e^i = \sum \mu^j I(j \in J^{1,i}) + \varepsilon^{ij}, \forall (i,j) : j \in J^{1,i}, \tag{1}$$

where e^i is the educational level of job seeker i in years of schooling, $e^i = \{12, 13, 14, 16, 18\}$[13], $J^{\tau,i}$ is the set of all jobs that job seeker i applies for in week τ of his search, and $I(\cdot)$ is the indicator function. That is, each observation in equation (1) represents an application from job seeker i to job j in job seeker i's first week of search.

The test of sorting by education at the beginning of search consists of estimating to what extent the variation in education among job seekers can be explained by the set of dummies that represent all jobs that receive applications from job seekers in their *first* week of search, as opposed to by the variation in the random term, ε^{ij}. Note that the estimate of μ^j is the average education of all such first-week applicants for job j. Thus, we use an F-test to examine the joint significance of the indicator dummies, $\{I(j \in J^{1,i})\}$, i.e.,

$$H_0 : \mu^j = \mu^{j'}, \forall (j, j'), \tag{2}$$

against the two-sided alternative.

As a robustness check, we also estimate equation (1) using an indicator function for a particular educational level, $e^* = \{12, 13, 14, 16, 18\}$, as the dependent variable, i.e.,

$$I(e^i = e^*) = \sum \phi^j I(j \in J^{1,i}) + \varepsilon^{ij}, \forall (i,j) : j \in J^{1,i}. \tag{3}$$

We estimate equation (3) separately for each educational level and perform the same test as in equation (2), i.e., we test $\phi^j = \phi^{j'} \forall (j, j')$. In doing so, we test whether the proportion of job seekers with education e^* among applicants for a job is the same across all jobs.

Table 3 contains the results of the tests. The F-statistics of the hypothesis in (2) is 1.839 and the p-value is 0.000. Therefore, the null hypothesis that the distribution of applicants by education at the beginning of search is the same for all jobs is rejected. The test indicates that the average education of first-week applicants for different jobs differs. Table 3 also reports

[13] Without loss of generality, assume that during a job search, a job seeker's educational level remains constant. See Table A.2 in the appendix for the correspondence between educational levels and years of schooling.

the p-values of the test statistics from estimating equation (3). The results in the table show that for each educational level, the null hypothesis that the proportion of applicants of a particular educational level at the beginning of search is the same across all jobs is rejected.

To control for location fixed effects, we also estimate equations (1) and (3) separately for each metropolitan statistical area (hereafter, MSA) using information on job seekers' zip codes available in our data set. The p-values of the statistics of the tests in equation (2) are 0.000 for each MSA. Thus, the hypothesis that the distribution of applicants by education at the beginning of search is the same for all jobs in the MSA is rejected for each MSA.

Tables 3 also reports the coefficients of determination from regressions (1) and (3) and the distribution of the coefficients of determination from regressions by MSA. The coefficient of determination from estimating regression (1) is 0.33, indicating that, for an average first-week applicant, the correlation between the applicant's education and the education of other first-week applicants who apply for the same job is 0.33.[14]

These results suggest that education is an important determinant of which jobs job seekers apply for at the beginning of search.

[14] An alternative way of measuring the sorting of applicants across job postings is to examine the correlation between the educational level of job seeker i, e^i, and the average educational level of all job seekers who apply for the same job as job seeker i (including the job seeker's own education) in their first week of search, ρ, i.e.,

$$\rho \equiv \frac{\sum_{j \in J^1} \sum_{i \in J^{1,i}} \left(e^i - \overline{e}\right) \sum_{k \in J^{1,i}} \left(e^k - \overline{e}\right) / |J^{1,i}|}{\sum_{j \in J^1} \sum_{i \in J^{1,i}} \left(e^k - \overline{e}\right)^2}, \tag{4}$$

where $\overline{e}$ is the average educational level in the sample, i.e., $\overline{e} = \sum_{j \in J^1} \sum_{i \in J^{1,i}} e^i / N$, and N is the total number of job seekers in the sample of first-week applicants. A correlation of zero indicates that all jobs have the same skill-mix of applicants, and a correlation of one indicates complete sorting, in which all applicants for a job have the same e. Kremer and Maskin (1996) show that ρ in equation (4) is equivalent to one minus the variance of education within jobs divided by the overall variance of education and, thus, to the R^2 from estimating regression (1).

4 Framework for Estimating the Direction of Applications

As search continues, how do job seekers direct their applications? Do they continue sorting by education as at the beginning of search? In this section, we propose a framework for estimating the direction of applications and how it changes with search tenure.

4.1 Application Rule

Let K^j denote the time-invariant index that characterizes the type of job j (the details of which we defer to the next subsection). Let K^i_τ be the index of the job for which job seeker i applies in week τ of his search on the website. Suppose each job seeker targets specific types of jobs according to some rule $f(\cdot)$ that depends on his individual characteristics, Ω^i, and his search tenure at the time of application, τ, i.e., the application rule is

$$K^i_\tau = f(\Omega^i, \tau).$$

Since we explicitly observe a job seeker's educational level, e^i, let $\Omega^i = \{e^i, \alpha^i\}$, where α^i is the composite effect of individual characteristics other than education that affect the decision of which job to apply for (i.e., individual fixed effect).[15] Assume that $f(\cdot)$ is linear in parameters. Then, job seeker i with education level e^i and fixed effect α^i in period of his search τ applies for jobs characterized by index K^i_τ according to

$$K^i_\tau = \eta_\tau + \gamma_\tau e^i + \alpha^i + u^i_\tau, \tag{5}$$

where η_τ and γ_τ are the parameters of the search rule $f(\cdot)$, and u^i_τ is the error term that reflects a measurement error in K^i_τ and/or some unobserved factors (other than e^i and α^i) that affect application decision.

The coefficient η_τ shows the average job type in week τ for job seekers of all educational levels. The coefficient γ_τ shows how much the direction of applications in period τ is determined by the job seeker's level of education. Finally, heteroskedasticity in u^i_τ by τ indicates how well education and other time-invariant job seeker's characteristics explain where the job seeker applies. The higher the variance of u^i_τ, the less the job seekers direct their search based on their education and other individual-specific characteristics.

[15] For simplicity, we assume that Ω^i is time-invariant.

4.2 Characterization of Jobs

4.2.1 The Educational Index of Jobs

To characterize jobs, we would like to have information about job requirements, wages, nonpecuniary benefits and other attributes of jobs. Unfortunately, the data set available to us does not contain such information. For each job, however, we have information about all job seekers who apply for it. This information is important because the job seeker's decision to apply for a particular job summarizes the decision to apply based on the job seeker's ex ante information about the job and the labor market, i.e., wage, job requirements, and the probability of being hired.

In Section 3, we find that the educational level of a job seeker is an important determinant of which jobs he applies for at the beginning of search. It implies that education of first-week applicant proxies for job characteristics that are relevant to the job seeker's application decision (but not available to researchers). We use this information to develop a new index to characterize jobs.

We define the educational index of job j, K^j, as the average educational level of all job seekers who apply for the job in the first week of their search on the website, i.e.,

$$K^j \equiv \frac{1}{|W^{1,j}|} \sum_{i \in W^{1,j}} e^i, \tag{6}$$

where $W^{\tau,j}$ is the set of all job seekers who apply for job j in week τ of their search, and $|X|$ is the number of job seekers in set X.

An underlying assumption behind using first-week applicants for calculating the educational index of a job is that the jobs that job seekers apply for at the beginning of search represent their first-order choice, i.e., the most preferred jobs in the pool of available jobs. Another assumption underlying the characterization of jobs by the educational index in (6) is that the job seeker's education is an important determinant of the job that the job seeker chooses to apply for (which is shown in Section 3).

A job with a higher educational index is one that, on average, receives applications from more highly educated job seekers in their first week of search. In what follows, we refer to the jobs with higher educational indices as higher-type jobs. Without additional information about the jobs, however, we cannot infer whether the higher type jobs are necessarily high wage jobs. The statement that, conditional on being hired, a job seeker prefers a job with a higher educational index (for example, because of a higher wage) requires the assumption that the sorting at the beginning of search is positive. Positive sorting is defined as more highly educated job seekers attempting to match with jobs with higher requirements, where the requirements are positively correlated with education. For example, these jobs might have an explicit educational requirement or a requirement of some specific set of skills that is positively correlated with education. Testing of whether the estimated sorting at the beginning of search is positive or negative requires additional data on, for example, skill requirements of the jobs.[16] Note, however, that the assumption that the sorting is positive is not needed to obtain the results in the paper; however, it is useful in interpreting the findings.

Consider two hypotheses about applicants' sorting by education across job postings. Under the null hypothesis, sorting by education does not change with search tenure. Under the alternative hypothesis, job seekers change the direction of their applications with search tenure by applying for different types of jobs than the jobs they apply for in their first week of a search. These hypotheses essentially describe the test we perform in this paper.

Under the null hypothesis, the educational index of a job calculated from the average educational level of the applicants in their first week of a search is asymptotically equal to the index calculated from the average education of the applicants in, for example, their second or third week of search or from the average education of all applicants for the job, independently of the week of the search tenure in which they apply for the job. Under the alternative hypothesis these indices differ. Thus, the educational index constructed from the average education of the applicants in the first week of their search tenure as described in equation (6) is a consistent measure of the type of job both under the hypothesis of no change in the direction of applications with search tenure and the hypothesis of a change in the direction of applications with search tenure.

4.2.2 Empirical Implementation of the Educational Index of Jobs

The index described in equation (6) assumes that each job receives at least one application from job seekers during their first period of search. In the data, 93% of jobs receive an

[16] The inability to empirically identify assortative matching (i.e., better quality workers match with better quality firms) without additional information on firms is a well-known issue in the literature (for example, Eeckhout and Kircher (2011)).

application from a first-week job seeker while the remaining 7% of jobs show up later in job seekers' searches.[17] To capture this possibility, for each job we calculate the earliest week in job seekers' searches when the job receives an application, $\tau_j^{\min} \equiv \min\{\tau : j \in J^{\tau,i}, \forall i\}$.

We then generalize the index in equation (6) to include those jobs for which the earliest week does not equal 1. For these jobs, we calculate the educational index from the types of job seekers who apply for the job in the week of their search that corresponds to the job's earliest week in the search. The generalized educational index is

$$K^j \equiv \frac{1}{\left|W^{\tau_j^{\min},j}\right|} \sum_{i \in W^{\tau_j^{\min},j}} e^i. \tag{7}$$

Figure 3 shows the distribution of jobs by the generalized educational index calculated using equation (7).[18] Thus, in addition to the educational index, K^j, each job is characterized by the earliest week in which the job appears in the job seekers' searches, $\tau_j^{\min}$. We conjecture that the latter describes the general attractiveness of a job to all types of job seekers (i.e., the later a job seeker applies for the job during his search, the lower the job is on his list of choices).[19]

4.3 The Labor Market of a Job Seeker

The available jobs and the competition for these jobs are relevant factors in the application decision. Job seekers in different geographical areas face different job prospects and different competition for these prospects because moving cost considerations often exclude some jobs from a job seeker's decision set. In addition, even within a geographic area, the job prospects and the competition for jobs may change over the course of job seeker's search. To address these issues, we define a labor market for each job seeker and control for the distribution of

[17]Table A.3 in the appendix summarizes the distribution of jobs by the earliest week in job seekers' search tenure.

[18]Figure A.1 shows the distribution of jobs by the average educational level of all job seekers who applied for the job during the entire sample period, regardless of the week in their search tenure. As can be seen, the shapes of the distributions in Figures A.1 and 3 differ. The difference between the distributions suggests that as search continues, job seekers of different educational levels direct their applications to different jobs than in the first week of their search.

[19]The underlying assumption is that in every period when a new job posting appears on the website, there are new job seekers registering on the website.

job seekers and the distribution of available jobs in the job seeker's market at the time of application.

We define the labor market of job seeker i by the MSA of i's location. Thus, for each job seeker i, the labor market in week τ of his search is a pair (U_τ^i, V_τ^i), where U_τ^i is the set of all job seekers in the MSA who send at least one application in the calendar week that corresponds to period τ and V_τ^i is the set of all jobs that receive applications from U_τ^i in the calendar week that corresponds to period τ. Labor market (V_τ^i, U_τ^i) is characterized by the average educational level of a job seeker, $\overline{e_\tau^i}$, and by the average educational index of jobs in the market, $\overline{K_\tau^i}$.[20]

A simple way to control for the distribution of jobs and the distribution of job seekers in the market is to redefine the type of job seeker and the type of job relative to their market averages, $\Delta e_\tau^i = e^i - \overline{e_\tau^i}$ and $\Delta k_\tau^{i,j} = K^j - \overline{K_\tau^i}$, respectively. A positive value of Δe_τ^i implies that job seeker i has more years of schooling than the average job seeker in job seeker i's labor market (i.e., MSA) in period τ. A positive value of $\Delta k_\tau^{i,j}$ implies that job j has a higher educational index than the average job in market (V_τ^i, U_τ^i). In the data, a job seeker may apply for multiple jobs within a period of job search. To focus on the change with search tenure, for each job seeker for each week τ in his search tenure, we construct the weekly average of the relative job indices of all jobs he applies for in week τ, $\Delta k_\tau^i \equiv \sum_{j \in J^{\tau,i}} \Delta k_\tau^{i,j} / \left|J^{\tau,i}\right|$.[21]

5 The Direction of Applications with Search Tenure

To estimate the parameters of the application rule in equation (5), we estimate the following specification

$$\Delta k_\tau^i = c + \sum_{d=2}^{T} \eta^d I^{i,d} + \gamma^1 \Delta e_\tau^i + \sum_{d=2}^{T} \gamma^d \Delta e_\tau^i I^{i,d} + \alpha^i + \varepsilon_\tau^i, \tag{8}$$

where Δk_τ^i is the average relative index of jobs that job seeker i applies to in week τ of his search on the website, τ^i is the search tenure of job seeker i, α^i is the individual fixed effect, $I^{i,d} \equiv I(\tau^i = d)$ (where $I(\cdot)$ is the indicator function), and we set $T = 26$.[22]

[20] That is, $\overline{e_\tau^i} = \frac{1}{|U_\tau^i|} \sum_{n \in U_\tau^i} e^n$ and $\overline{K_\tau^i} = \frac{1}{|V_\tau^i|} \sum_{j \in V_\tau^i} K^j$.

[21] The weekly average of Δe_τ^i equals Δe_τ^i.

[22] That is, for each job seeker, we use information from the first 26 weeks of search tenure on the website. The data are not suitable to test, for example, for a possible discrete change in search behavior around week

In equation (8), the coefficients on the search tenure indicators, η^d, show the change in the types of jobs for which an average job seeker (i.e., $\Delta e^i_\tau = 0$) applies in week d relative to week 1. Coefficient γ^1 shows how the educational level of a job seeker is associated with the type of job that the job seeker applies for in week 1 of his search, controlling for the job seeker's labor market. Coefficient γ^d shows the change in the strength of sorting between the educational level of a job seeker and the type of job he applies for between week 1 and week d of his search tenure.[23]

In the estimation of equation (8), we restrict the sample to job seekers who reside in the metropolitan statistical areas so that we can control for job seekers labor markets as described in the section above.[24] Since our focus is on the changes in search behavior with search duration, we restrict the analysis to job seekers with at least two weeks of search tenure on the website.

5.1 Main Results

We first examine the unconditional correlations between the type of job seeker and the type of jobs the job seeker applies for at different search tenures, $corr(K^i_\tau, e^i)$. Figure 4 shows the correlations. The correlation between a job seeker's education and the type of job that he applies for is 0.626 in the first week and then sharply decreases to 0.3658 in the second week. Then it drops to 0.3049 in week 5 and to 0.2450 in week 26. Thus, the correlation drops by 33 percent from week 2 to week 26 of search, with half of the drop happening by week 5. While the correlation between the job seeker's education and the type of job he applies for in

26 due to the unemployment benefits exhaustions primarily because we do not know at what period after job loss a job seeker starts searching on the website and whether a job seeker is employed or unemployed.

[23]The underlying assumption is monotonicity of the relationship between the job seeker's type and the job type.

[24]To characterize the labor market faced by job seeker i in week τ of his search tenure, we first aggregate daily records in each MSA into calendar weeks and calculate the market weekly averages of e^i and K^j, we then choose the market averages of the calendar week that overlaps with week τ of the job seeker's search tenure. Note that there can be two calendar weeks partially overlapping with the week in a job seeker's search tenure on the website (because a week in search tenure starts from the registration day, which can fall on any day of the week - Monday, Tuesday, and so on). We choose the labor market averages from the earliest one.

the first week of search is positive by construction,[25] the change in the correlations after the first week of search is informative about the change of sorting of applicants across jobs. The correlations, however, do not allow discerning the change in the direction of applications, nor do they allow controlling for the job seeker fixed effects. We thus proceed to the regression analysis.

Table 4 shows the results from estimating a few specifications based on equation (8). Column 1 contains the results from the specification with only a set of duration dummies (i.e., no controls for Δe^i_τ). Column 2 contains the results from the specification with duration dummies and the controls for Δe^i_τ. Column 3 adds the controls for the monthly unemployment rate in job seeker's MSA and monthly calendar dummies. This is our benchmark specification. All regressions control for the average $\tau_j^{\min}$ of the jobs the job seeker applies for in week τ of his search and are estimated controlling for heteroscedasticity in the error term.[26] The results from the three specifications are similar, and thus below we discuss the estimates from the benchmark one.

As can be seen from the table, the estimate of the coefficient on Δe^i is positive, $\widehat{\gamma^1} > 0$. While the correlation between the job seeker's educational level and the type of job he applies for in the first week of search is positive by construction, the sign and the absolute value of the coefficients after the first week of search informs about the pattern and the strength of sorting of applicants across jobs relative to week 1. The estimates of the coefficients on the interaction terms between Δe^i and the indicators for search tenure are statistically significantly negative, smaller in absolute value than the estimate of γ^1, and weakly increasing in absolute value with the increase of search tenure. Thus, the results show that as search continues, sorting by education follows the same pattern as at the beginning of search (i.e., $\widehat{\gamma^1} > 0$ and $\widehat{\gamma^1} + \widehat{\gamma^d} > 0 \ \forall d > 1$), i.e., on average, more highly educated job seekers apply for higher type jobs. The decline in the absolute value of $(\widehat{\gamma^1} + \widehat{\gamma^d})$ with search tenure indicates the change in the strength of sorting, i.e., as search continues, the educational level of a job seeker is a weaker predictor of the type of job that he applies for. Importantly, most of the

[25] The job index K^j is constructed from the average educational level of the job seekers who apply for the job during their first week of search, and in the previous section we find evidence in favor of sorting by education at the beginning of search.

[26] For robustness, we also employ the Driscoll and Kraay (1998) procedure to correct for possible spatial correlation in the errors. All our conclusions carry through. These results are contained in the appendix available from the authors.

decline takes place in the first few weeks of search. This pattern can be seen in Figure 5, which shows the estimated coefficients $\{\widehat{\gamma^d}\}_{d=2}^{26}$.

The estimates of the coefficients on search tenure dummies, η^d, show the expected change in the type of jobs that an average job seeker (i.e., a job seeker with $\Delta e^i = 0$) applies for as he continues his search relative to the types of jobs he applies for in the first week of the search. The estimates are statistically significantly negative for all values of search tenure and increase in absolute value with search tenure (estimated coefficients $\{\widehat{\eta^d}\}_{d=2}^{26}$ are shown in Figure 6). For example, the estimate is -0.021 in week 2 and -0.033 in week 10. Thus, as the search continues, an average job seeker applies for lower-type jobs.

Figure 8 shows the estimated application rule (equation (5)) by education, i.e.,

$$\widehat{\Delta k^i_\tau} = \widehat{c} + \widehat{\eta^\tau} + (\widehat{\gamma^1} + \widehat{\gamma^\tau})(e^i - \overline{e^i_\tau}), \text{ for } e^i = \{12, 13, 14, 16, 18\}, \tag{9}$$

where we set $\overline{e^i_\tau} = \overline{e^i}\ \forall\tau$ (where $\overline{e^i}$ is the average education in the sample) and the estimates are from equation (8).

The figure demonstrates the decline of sorting by education with search tenure. It shows that at the beginning of a search, job seekers sort themselves by education; as the search continues, there is less sorting by education, and most of the decline in the strength of sorting takes place in the first few weeks of the search.

As discussed earlier, the variance of the residual, u^i_τ, in the application rule (5) shows the extent to which the direction of an individual application in week τ deviates from the rule described by the individual's education, search tenure, and the individual-specific fixed effect. To examine the heteroscedasticity in u^i_τ with search tenure, we estimate a specification similar to the one described by our benchmark specification in equation (8). In contrast to the benchmark specification, we use individual applications as a unit of observation rather than the weekly average of the individual applications. To focus on the developments after the first week of a search, we estimate the regression using the data from weeks $2 - 26$ of search. We then obtain the predicted residuals, not corrected for heteroscedasticity. Figure 7 plots the average squared residual by week of search tenure. As the figure shows, the variance of the estimated residuals increases with search tenure. The Breusch–Pagan test rejects the homoscedasticity of the residuals. Thus, we conclude that, as the search continues, the direction of an individual application is to a lesser degree governed by the application rule described by $f_\tau(e^i, \alpha^i)$.

5.2 Results Without Controls for Labor Market

Our benchmark specification in equation (8) estimates the change in the direction of applications with search tenure controlling for the change in labor supply and labor demand in the job seeker's labor market. Such estimation is an empirical counterpart of the theoretical rule in equation (8). It is of interest, however, to also examine the absolute change in the direction without controls for the labor market.

To examine the change in the direction of applications without controls for labor market, we estimate the following specification

$$K_\tau^i = c + \sum_{d=2}^{T} \chi^d I^{i,d} + \psi^1 \left(e^i - \overline{e^i}\right) + \sum_{d=2}^{T} \psi^d \left(e^i - \overline{e^i}\right) I^{i,d} + \alpha^i + \upsilon_\tau^i, \tag{10}$$

where K_τ^i is the average index of jobs that job seeker i applies for in week τ of his search on the website, and $\overline{e^i}$ is the average education in the sample (which is used for normalization).

Figure 9 shows the estimates of coefficients γ^d from the equation with controls for labor market (equation (8)) and from the equation without controls for labor market (equation (10)).[27] As can be seen from the figure, the estimates from the two specifications are almost indistinguishable.

Figure 10 shows the estimates of coefficients η^d from the equation with controls for labor market and from the equation without controls for labor market. The results from the specification without controls for the labor market show a steeper profile of decline in the type of jobs for which an average job seeker applies as he continues his search. In particular, the decline between week 1 and week 10 is -0.040 without controls for the job seeker's labor market and -0.032 with controls for the labor market. The profiles are statistically significantly different.

5.3 Results by Total Duration of Job Search

The estimates in Table 4 control for individual heterogeneity (i.e., individual-specific effect). It is possible, however, that the job seekers observed at longer search durations are different from those who end their searches earlier. We thus split the sample into three mutually exclusive subsamples by the total duration of their search on the website: the job seekers whom we observe sending applications on the website for at most 10 weeks, the job seekers

[27] Table A.4 in the appendix shows the coefficients from estimating equation (10).

whom we observe sending the last application in weeks $11-20$, and the job seekers whom we observe sending the last application in weeks $21-26$ during their first 26 weeks of search on the website.[28] The results from estimating equation (8) separately for each of the three subsamples are presented in Table 5. Figure 11 shows the estimates of coefficients γ^d, and Figure 12 shows the estimates of coefficients η^d for the three subsamples.

The results from the full sample carry through to the subsamples. The strength of sorting by education decreases with the duration of search and, as can be seen from Figure 11, the estimates of the change in the strength of sorting with search tenure (γ^d) are not statistically significantly different across three subsamples.

In the three subsamples, we find that an average job seeker applies for lower type jobs as search continues. The magnitude of the decline in the types of jobs, however, differs across the three subsamples. The job seekers who search for at most 10 weeks on the website have a much steeper profile of decline in job types than the job seekers who search longer. For example, among the job seekers who search for at most 10 weeks, the change in the type of jobs between week 1 and week 7 is -0.045, while among the job seekers who search for more than 20 weeks, the drop between week 1 and week 7 is -0.026. Thus, the declining profile estimated in the full sample is not due to the differences in the composition of job seekers observed at different durations of the search (i.e., not due to the selection on duration), instead the job seekers who lower the types of jobs they apply for faster are also the ones who exit the search sooner.

Since our data do not contain information about, for example, whether an application results in hiring, we do not know why an individual stops searching on the website. If we assume that the job seekers who stop searching on the website have found a job, then these results indicate that job seekers who find jobs sooner are the ones who tend to more quickly lower the type of jobs they apply for.

5.4 Results with Controls for the Unemployment Rate in the MSA

Column 4 of Table 4 shows the specification, where in addition to the benchmark application rule described in equation (8), we allow the coefficients η_τ and γ_τ to depend on the unemployment rate in the job seeker's MSA. The coefficient estimates are shown in Figures 13 and

[28] Note that we focus on the first 26 weeks of search on the website.

14 for three different values of the unemployment rate in the MSA, 5, 8.4 and 10%.[29] For constructing the figure, we keep the unemployment rate constant throughout the duration of search.

As can be seen from Figure 13, conditionally on the unemployment rate remaining constant throughout the search, the profiles of sorting by education with search tenure in the MSAs with higher unemployment rates represent a vertical shift downward from the profile of sorting in the MSAs with lower unemployment rates. This suggests that there is more sorting by education in markets with lower unemployment rate. The differences, however, are only marginally statistically significant. Figure 13 also shows that the change in the unemployment rate in the MSA is negatively associated with the change in the strength of sorting with search tenure (i.e., if between week d and $d+1$ of search tenure the unemployment rate increases, the strength of sorting declines more than when the unemployment rate remains constant). These results suggest that in markets with low unemployment, education is a stronger predictor of which job a job seeker will apply for.

Figure 14 shows that, if from one period to another the unemployment rate decreases, there is some evidence that an average job seeker applies for lower-type jobs than when the unemployment rate remains constant. To the extent that the areas with lower unemployment rates are the areas with higher probability of finding a job, we can explain these findings through the learning model of Gonzalez and Shi (2010). Gonazalez and Shi show that a negative search outcome in the market characterized by a high job finding rate delivers a more informative signal for a job seeker about his (unknown) ability than a negative search outcome in the market characterized by a low job finding rate. Thus, in a market characterized by a high job finding rate, job seeker will be more willing to apply for lower-wage jobs after a negative search outcome.

5.5 What Economic Model Can Explain the Results?

A higher-type job in the analysis is the job for which more highly educated job seekers apply in their first week of search on the website. With the additional assumption that sorting at the beginning of a search is positive, i.e., that more highly educated job seekers apply for jobs with higher educational requirements (see the discussion of the job index in Section 4.2.1),

[29] Figure A.2 shows the distribution of the monthly unemployment rate across MSAs during September 2010 – April 2012.

a higher-type job can be interpreted as follows. First, a higher-type job likely pays higher wages; and, second, the lower the job type compared to the job seeker's own educational level (conditional on the job type being not greater than the job seeker's educational level), the higher the job seeker's probability of satisfying the job requirements (and, thus, of being hired).[30]

Our findings thus uncover a systematic pattern of search in a new labor market: A job seeker samples high-wage opportunities first (conditional on his belief about the probability of meeting the job requirements) and lower-wage opportunities later. What economic models can explain the documented systematic search pattern? The pattern is consistent with a learning model whereby a negative search outcome leads a job seeker to reevaluate his job prospects and lower the types of jobs to apply for. It also appears potentially consistent with the standard non-stationary job search models or some stock-flow matching mechanisms. The detailed look at the results, however, points toward learning-driven explanation of our findings.

In the standard non-stationary job search models (Mortensen (1977), van den Berg (1990)) the reservation wage declines because job seekers exhaust their savings or unemployment insurance benefits. While the data do not contain information on job seekers assets and thus preclude a detailed investigation, the evidence points against such liquidity constraints being the main driver of the documented pattern. First, we find that most of the adjustment takes place during the first four to five weeks of search, which is consistent with a job seeker's learning (and suggests that learning happens relatively fast) instead of with a job seeker's exhausting the assets, which happens later in the search process. Second, in the standard model, if the reservation wage falls over time, job seekers should apply to more jobs, while in a learning model job seekers might apply to fewer jobs as the search continues. Using the same data set as here, Faberman and Kudlyak (2014) find that the latter is the case, i.e., a job seeker sends fewer applications as search continues. Third, the results in Section 5.4 show that if from one period to another the unemployment rate decreases, an average job seeker applies for lower-type jobs than when the unemployment rate remains constant. This evidence is consistent with a learning model, whereby the signal is more informative if the average job finding rate in the market is high; while it appears at odds

[30] Corroborating the initial *positive* sorting requires data on the skill requirements of the jobs, which, unfortunately, we do not have.

with the standard non-stationary model.

Under a stock-flow matching mechanism, job seekers might apply for lower-type jobs as their searches continue because they have already exhausted the stock of the preferable higher-type jobs. However, in the analysis, we control for the distribution of the types of available jobs in the job seeker's metropolitan statistical area in every period of his search, and find that job seekers apply for lower-type jobs even though higher-type jobs are available. Thus a stock-flow matching mechanism cannot fully rationalize the documented search pattern.

Our results hence point toward a learning model (in which a job seeker learns about the labor market or about his own ability) as a main driving mechanism behind the decline in the strength of sorting by education with search tenure and the decline in the type of jobs that an average job seeker applies for as the search continues. An example, of such a model is a directed search model of Gonzalez and Shi (2010), who study an environment in which a job seeker has imperfect information about his ability, which is positively associated with the job seeker's productivity.[31] Firms are heterogeneous and the firms that offer higher wages require higher productivity. Job seeker's productivity is revealed when the job seeker and a firm meet. In such an environment, a job seeker applies to the highest-wage firm conditional on his initial belief about his ability. A negative search outcome serves as a signal about the job seeker's ability. As search continues, job seekers on average apply to lower-wage firms.[32]

One can extend the model of Gonzalez and Shi (2010) to a setting with different educational groups by postulating that the job seeker's productivity is positively associated with his educational level. In such an environment, an optimizing job seeker first applies to the firms that offer the highest wages conditional on the job seeker's prior belief about his probability of meeting the job requirements. Having experienced a negative search outcome, a job seeker updates his belief about his ability and applies for jobs that offer lower wages but for which he is more likely to get hired. Thus, at the beginning of a search, there is sorting of applicants across job postings by education. As the search continues, there is less sorting by education, and an average job seeker applies for jobs that are the first-period choice of

[31] Salop (1973) provides an alternative model in which job seekers search systematically, sampling better opportunities first and the poorer ones later. In contrast to the model of Gonzalez and Shi (2010), in Salop's model job seekers do not have a choice to keep sampling the same opportunities throughout their search because there is only one opportunity of each type and there is no resampling.

[32] We refer an interested reader to Gonzalez and Shi (2010) for details.

less-educated job seekers.

The model of Gonzalez and Shi (2010) can be extended to a setting with different educational groups by postulating that the job seeker's productivity is positively associated with his educational level.[33] In such an environment, an optimizing job seeker first applies to the firms that offer the highest wages conditional on the job seeker's prior belief about his probability of meeting the job requirements. Having experienced a negative search outcome, a job seeker updates his belief about his ability and applies for jobs that offer lower wages but for which he is more likely to get hired. Thus, at the beginning of the search, there is a sorting of applicants across job postings by education. As the search continues, there is less sorting by education, and an average job seeker applies for jobs that are the first-period choice of less-educated job seekers.

6 Conclusion

We use a novel data set to study how job seekers direct their applications over the course of a job search. The data contain information about the daily applications of job seekers for jobs posted on a job posting website and, thus, are uniquely suited to studying the search behavior over the course of a job search.

We characterize the job seeker's rule of which job to apply for as a function of the job seeker's educational level, search tenure, and individual-specific fixed effect that captures characteristics other than educational level. Our results show that at the beginning of a search in a new labor market, job seekers sort across job postings by education.

To characterize the change in the direction of applications with search tenure, we develop an educational index for each job. The educational index of a job is the average educational level of the job seekers who apply for the job during their first week of searching on the website. Our estimation framework controls for the distribution of available jobs and the distribution of job seekers in the job seeker's MSA in every period of his search. We argue that a week rather than a day better describes a search period on the website.

We find that, as search continues, there is less sorting by education and an average job seeker applies for jobs with a relatively lower index than at the beginning of a search

[33] In the appendix, we construct an example of such a model, which illustrates the ideas by considering key elements of the model of Gonzalez and Shi (2010) in a simplified, partial equilibrium setting.

even though the jobs with a relatively higher index are available in the job seeker's MSA. Importantly, most of the decline in the strength of sorting by education takes place in the first few weeks of a search. We also find evidence that the job seekers who exit the search on the website sooner have a steeper profile of decline in job type with search tenure. In addition, if, from period to period, the unemployment rate in the MSA falls, the downward change in the type of jobs the job seekers apply for is greater than when the unemployment rate remains unchanged.

With an additional assumption that the sorting of applicants across job postings at the beginning of a search is positive (in the sense that more highly educated job seekers apply for jobs with higher educational requirements), the higher-type job is likely a job that pays higher wages but is harder to get because of higher educational requirements. We can then interpret our findings as follows. At the beginning of a search on the website, job seekers apply for the highest-wage jobs conditional on the probability of being hired. A negative search outcome leads an average job seeker to reevaluate his job prospects and apply for a job that offers lower wages but is likely easier to get. We argue that our findings can be rationalized in a search model with learning.

Our findings have a few important implications. First, the results suggest that the labor market is rather flexible: Job seekers learn from the search process and adjust their search behavior over the course of search. Second, our findings suggest that different durations of job searches might contribute to different wages for observationally equivalent workers. Third, knowing the actual search pattern in the labor market allows for testing of different economic models that predict distinct search and matching equilibrium patterns.

In terms of the question of a job seeker adjusting his search over the search tenure, our work is related to the empirical literature that examines the behavior of reservation wages over the course of job search. An advantage of our study is that our data set contains records of actual individual behavior. Most of the existing work relies on survey data or data from a laboratory experiment, or employs particular identifying assumptions about the wage-offer distribution to estimate reservation wages from the data on unemployment duration and subsequent employment wages. Our findings are consistent with the literature that finds that reservation wages decline with search tenure (for example, Kasper (1967), Kiefer and Neumann (1979), Brown, Flinn, and Schotter (2011)). Krueger and Mueller (2011) use data from a survey and find that the reservation wage is "remarkably stable over the course of unemployment for most workers, with the notable exception of workers who are over age 50 and those who had nontrivial savings at the start of the study." These estimates, however, might suffer from the self-reporting bias. For example, Krueger and Mueller (2011) report that only 23.6% of their survey respondents reject a wage offer that is below the reported reservation wage.

In terms of the magnitudes of our estimates of the decline of the type of jobs for an average job seeker, we find that the (relative) job index declines by -0.0288 after 5 weeks of searching (by -0.008 between week 2 and week 5), and the (relative) job index declines by -0.0327 after 10 weeks of searching (by -0.012 between week 2 and week 10). The declines are larger if we do not control for the job seeker's labor market: -0.010 between week 2 and 5, and -0.017 between week 2 and week 10. These magnitudes are expressed in terms of a hypothetical index, which is expressed in years of schooling, and thus are not directly comparable with estimates in the studies of reservation wages. It is, however, of interest to summarize the estimates found in these studies. Kasper (1967) uses data from the survey of unemployed persons from the Minnesota Department of Employment Security during April 1961 to September 1961 and finds that the reservation wage declines by 0.3 percent per month. Kiefer and Neumann (1979) find a decline of 2.5 percent per month. Schmieder, von Wachter, and Bender (2012) use data from the German unemployment insurance system and find that each month out of work reduces wage offers by 0.9 percent.

The jobs in the analysis are hourly jobs. Remarkably, even in the sample of these relatively homogeneous jobs we find evidence of sorting by education. Hourly jobs attract workers with lower levels of education as well as younger workers. Precisely, these workers constitute a large part of aggregate unemployment. Thus, studying the search behavior of workers using the labor market of hourly jobs provides important insights into the functioning of the segment of the aggregate labor market relevant to unemployment-reduction policies.

The data set available to us does not contain information on whether a job seeker is unemployed or employed. The labor status of a job seeker determines his outside option and, thus, contributes to how low a job the job seeker is willing to apply for. This bias likely works against our results. Our data set also does not contain information about the time elapsed between the period when a job seeker lost his job and the period when the job seeker starts his search on the website. Thus, we interpret our results as evidence about a search pattern in a new labor market rather than a search pattern from the period of job loss. It is possible that job seekers who start searching on the website in different periods since their job loss might have different slopes of the decline in the types of jobs they apply for. These questions remain interesting avenues for future research.

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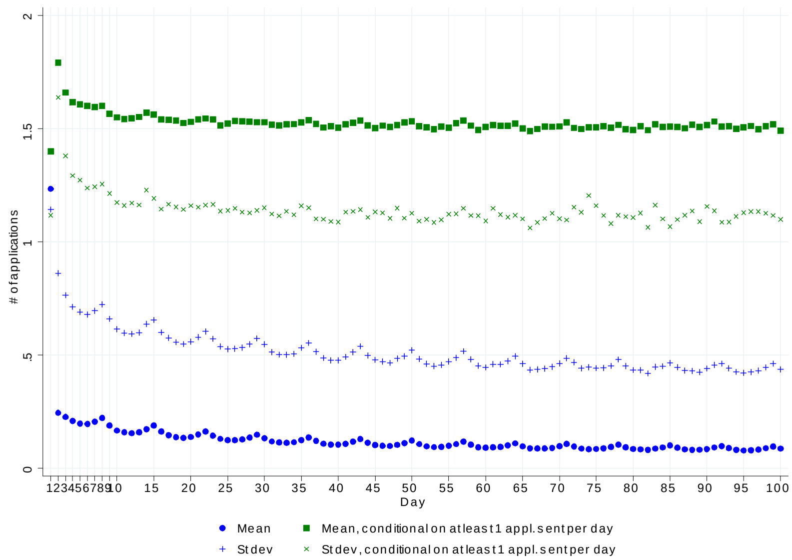
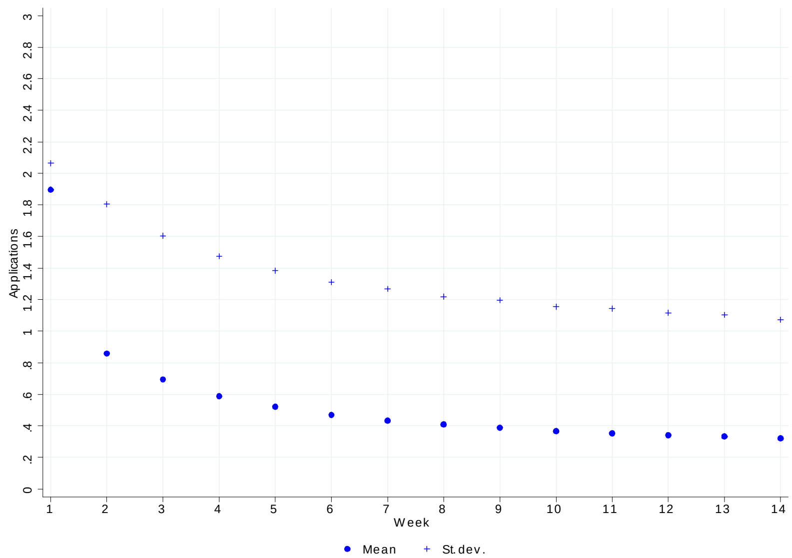
Figure 1: The Number of Applications per Job Seeker per Day



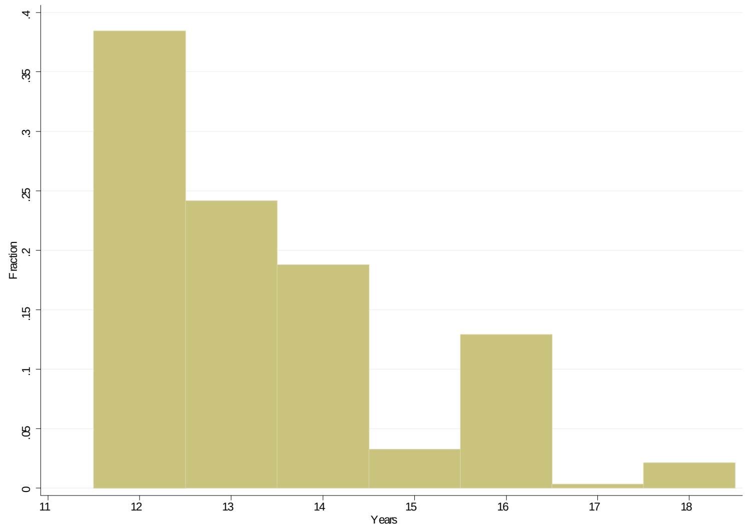
Note: The statistics are from the sample of applicants (MSA and non-MSA locations) registered after August 2010. Day 1 is the day of registration on the website. The figure shows the mean and the standard deviation of the number of applications sent by an applicant daily, starting from the registration day. The blue dots show the mean and the standard deviation calculated from the information on all job seekers in the sample, independently of whether or not the job seeker sends an application on a particular day, as long as the job seeker sends an application on a later date (i.e., is still in the sample). The green dots show the statistics conditional on at least one application sent per day.

Figure 2: The Number of Applications per Job Seeker per Week



Note: The statistics are from the sample of applicants registered after August 2010. Week 1 is the week of registration on the website. Week 1 starts on Day 1, the day of registration on the website. The statistics are calculated from the information on all job seekers in the sample, independently of whether or not the job seeker sends an application in a particular week, as long as the job seeker sends an application on a later date (i.e., is still in the sample).

Figure 3: The Distribution of Jobs by the Educational Index



Note: The educational index of a job is the average years of schooling of the first-week applicants for the job.

Figure 4: Correlation between Job Seeker's Education and Job Index

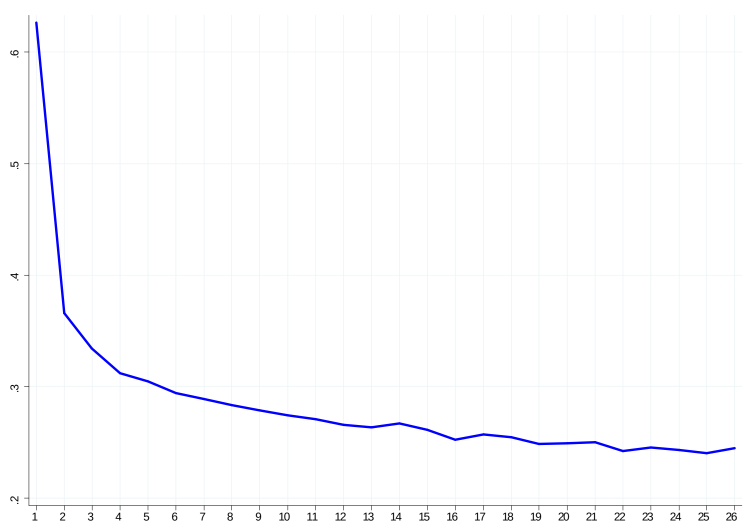
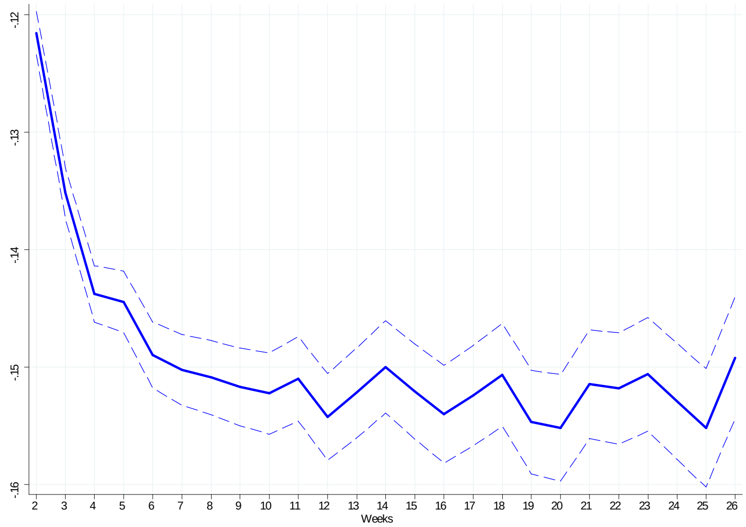
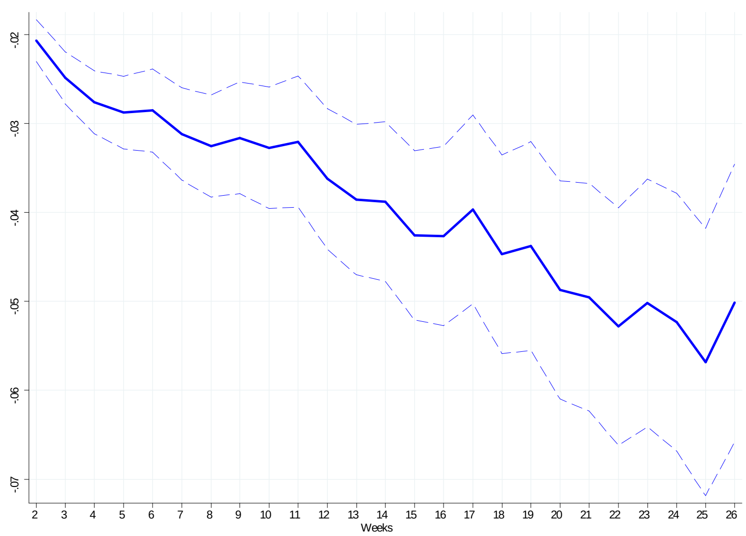


Figure 5: The Estimated Change in the Strength of Sorting by Education



Note: The figure shows the estimates of the coefficients on the interactions of the tenure dummies with the relative education of the job seeker from the benchmark regression. The dashed lines denote the 95% confidence interval based on the heteroscedasticity robust standard errors.

Figure 6: The Estimated Change in the Index of Jobs



Note: The figure shows the estimates of the coefficients on the tenure dummies from the benchmark regression. The dashed lines denote the 95% confidence interval based on the heteroscedasticity robust standard errors.

Figure 7: The Average Squared Residual, by Search Tenure

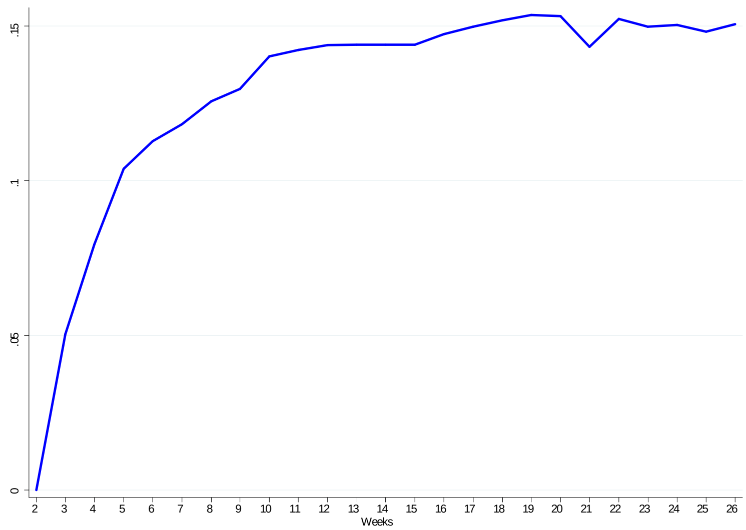


Figure 8: The Estimated Change in the Direction of Applications, by Education

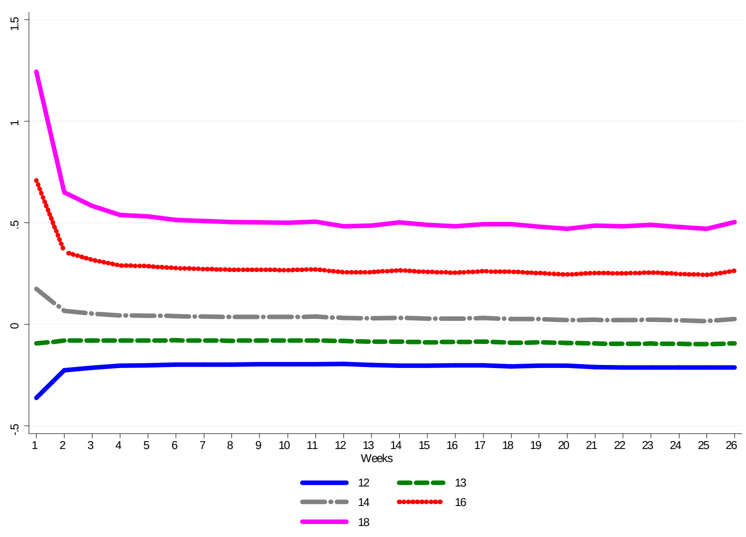
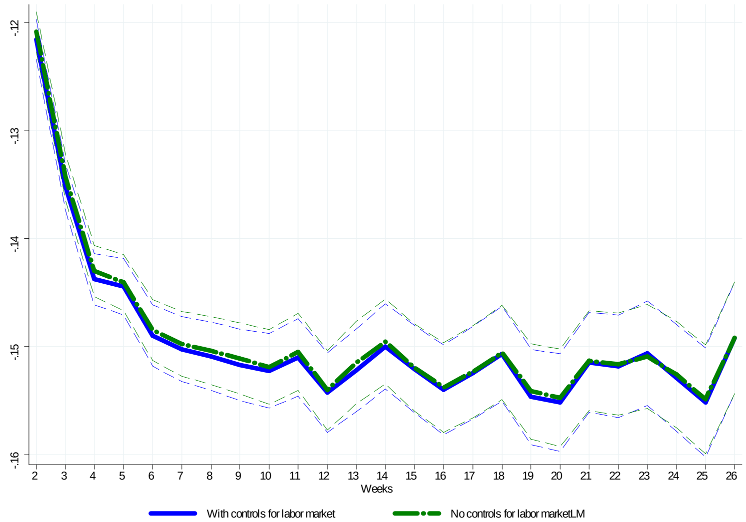
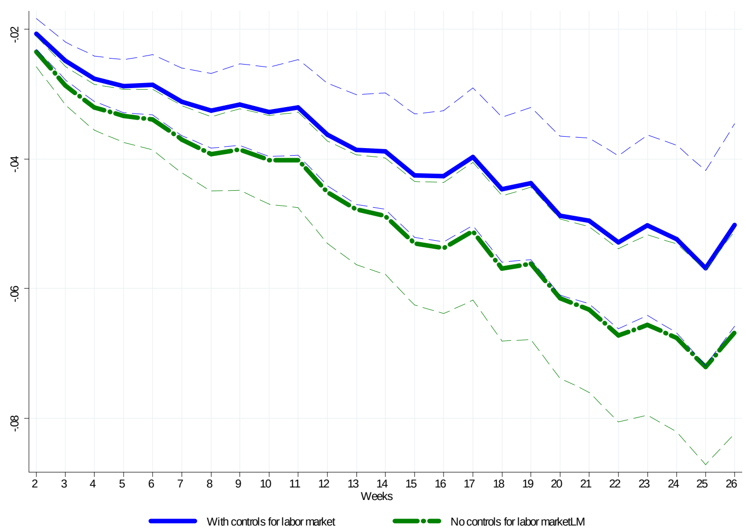


Figure 9: The Estimated Change in the Strength of Sorting by Education, with and w/o Controls for Labor Market



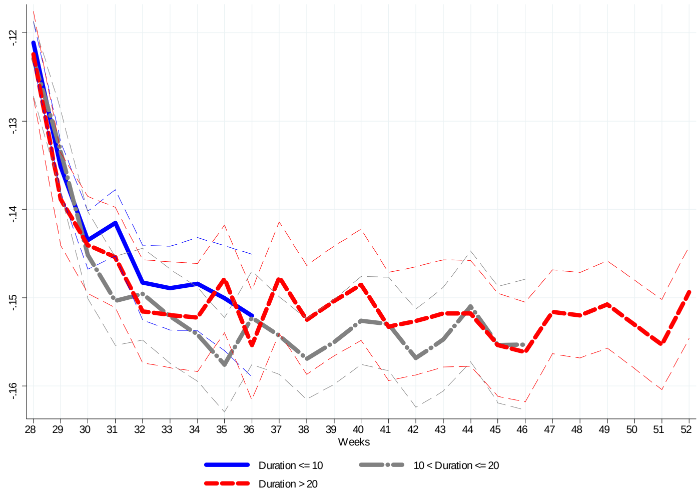
Note: The figure shows the estimates of the coefficients on the interactions of the tenure dummies from regressions (8) and (10). The dashed lines denote the 95% confidence interval.

Figure 10: The Estimated Change in the Index of Jobs, with and w/o Controls for Labor Market



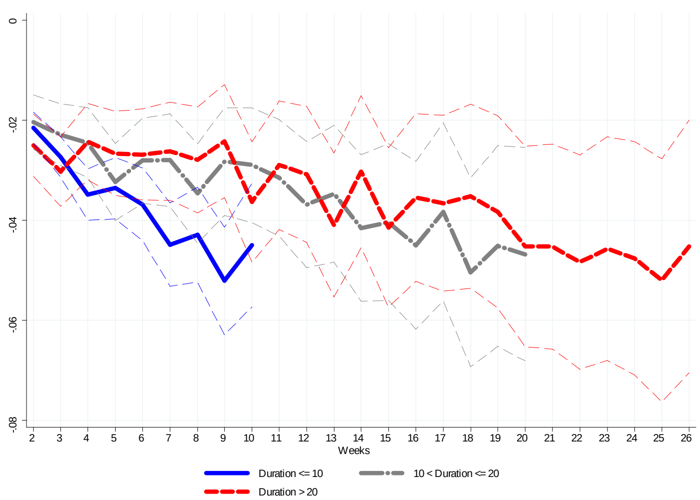
Note: The figure shows the estimates of the coefficients on the tenure dummies from regressions (8) and (10). The dashed lines denote the 95% confidence interval.

Figure 11: The Estimated Change in the Strength of Sorting by Education, by Max Duration of Search



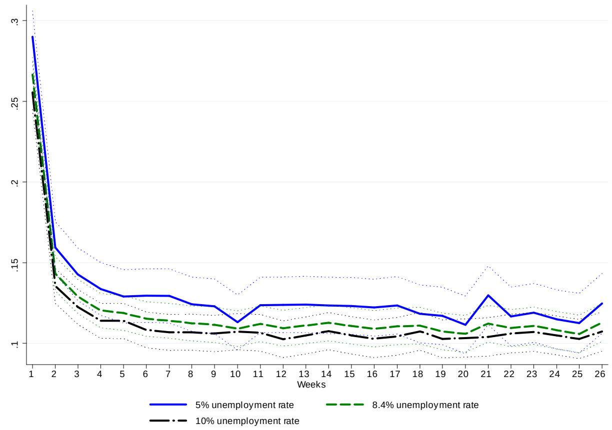
Note: The figure shows the estimates of the coefficients on the interactions of the tenure dummies with the relative education of the job seeker from regression (8) estimated separately for each of the three subsamples. The dashed lines denote the 95% confidence interval.

Figure 12: The Estimated Change in the Index of Jobs, by Max Duration of Search



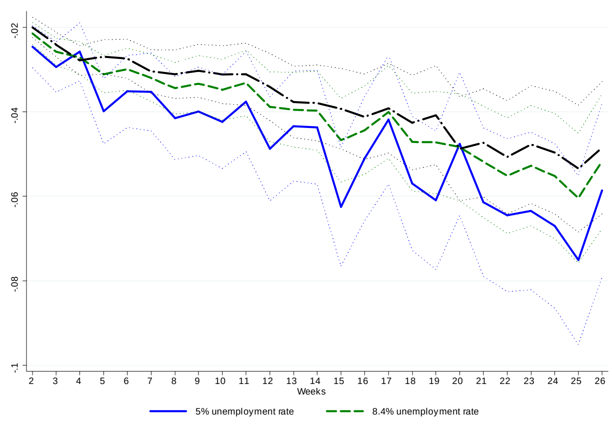
Note: The figure shows the estimates of the coefficients on the tenure dummies from regression (8) estimated separately for each of the three subsamples. The dashed lines denote the 95% confidence interval based on the heteroscedasticity robust standard errors.

Figure 13: The Estimated Change in the Strength of Sorting, Conditional on the Unemployment Rate in the MSA



Note: The figure shows the estimates of the coefficients on the interactions of the tenure dummies, the relative education of the job seeker, and the unemployment rate in the job seeker's MSA (column 4 in Table 4). The plotted lines correspond to three different scenarios for the unemployment rate: 5, 8.4 and 10%. The thin lines denote the 95% confidence interval based on the heteroscedasticity consistent standard errors.

Figure 14: The Estimated Change in the Index of Jobs, Conditional on the Unemployment Rate in the MSA



Note: The figure shows the estimates of the coefficients on the tenure dummies and the interactions of the tenure dummies with the unemployment rate in the job seeker's MSA (column 4 in Table 4). See note to Figure 13. The change is calculated under the assumption that the unemployment rate remains constant between week x and week 1.

Table 1: Sample Description

	Full Sample	Subsample of job seekers registered during the sample period	
		Registration day applicants only	At least one application on non-registration day
	1	2	3
Job seekers:			
Total	5,614,548	2,062,730	2,059,095
By Gender, %:	100.0	100.0	100.0
Female	57.6	56.3	58.0
Male	41.2	43.7	42.0
Not reported	1.3	0.0	0.0
By Age, %:	100.0	100.0	100.0
25-34	46.4	49.3	42.7
35-44	23.8	24.6	24.4
45-54	19.6	17.8	21.4
55-64	10.2	8.4	11.5
By Education, %:	100.0	100.0	100.0
Master's Degree Program	2.7	3.3	2.6
Bachelor's Degree Program	16.0	15.3	16.0
Associate's Degree Program	15.3	13.6	16.0
Vocational/Trade School	7.0	6.9	7.2
Professional or Training School	4.2	4.1	3.9
Certification Program	3.8	3.5	3.9
High School	42.4	43.3	41.9
GED Program	8.4	10.1	8.6
Applications:			
Total	19,451,136	2,872,374	16,973,705
Per applicant per day, conditional on days when at least 1 appl is sent:			
Mean	1.61	1.39	1.63
St. dev.	1.32	1.02	1.34
Median	1	1	1
75th percentile	2	1	2
Duration on the website,days:			
Mean		1	106.5
St. dev.		0	125.28
Min		1	2
25th percentile		1	14
Median		1	52
75th percentile		1	158
Max		1	600

Note: The sample period is from September 2010 to April 2012. The duration on the website is defined as the number of days between the registration day and the day when the last application is sent during the sample period.

Table 2: Sample Statistics by Age and Education, for the Subsample of Job Seekers registered after 9/1/2010

	# of applications per day, conditional on days when at least 1 appl is sent		# of days between the registration day and the last day observed in the sample	
	Mean	St. dev.	Mean	St. dev.
All	1.59	1.29	53.70	103.07
By Age				
25-34	1.75	1.50	47.04	97.19
35-44	1.57	1.26	52.57	101.68
45-54	1.45	1.06	62.47	109.96
55-64	1.38	0.92	70.12	115.11
By Education				
Master's Degree Program	1.47	1.15	45.44	94.73
Bachelor's Degree Program	1.56	1.26	55.65	104.51
Associate's Degree Program	1.61	1.32	61.19	109.20
Vocational/Trade School	1.57	1.29	54.82	104.08
Professional or Training School	1.53	1.20	53.74	103.83
Certification Program	1.59	1.29	59.74	108.39
High School	1.60	1.30	52.11	101.70
GED Program	1.64	1.37	42.27	94.70

Note: The sample period is from September 2010 to April 2012. The duration on the website is defined as the number of days between the registration day and the day when the last application is sent during the sample period.

Table 3: Sorting by Education at the Beginning of Search

	Full Sample		R sq, By MSA	
Skill measure	value)	R sq	Mean	St. dev.
Continuous (years of schooling)	1.839 (0.000)	0.33	0.39	0.08
Bivariate				
- High school or GED	1.489 (0.000)	0.29	0.36	0.08
- Vocational School, Professional/Trade School, or	1.183 (0.000)	0.24	0.34	0.09
- Associate's degree	1.146 (0.000)	0.24	0.33	0.09
- Bachelor's degree	1.563 (0.000)	0.30	0.37	0.08
- Master's degree	1.515 (0.000)	0.29	0.38	0.11

Table 4: The Estimated Change in the Direction of Applications, with Controls for Labor Market

	(1)	(2)	(3)	(4)
I(week=2)	-0.0201***	-0.0200***	-0.0207***	-0.0292***
	(0.00114)	(0.00113)	(0.00121)	(0.00483)
I(week=3)	-0.0240***	-0.0235***	-0.0249***	-0.0347***
	(0.00134)	(0.00133)	(0.00150)	(0.00571)
I(week=4)	-0.0267***	-0.0256***	-0.0276***	-0.0237***
	(0.00152)	(0.00150)	(0.00180)	(0.00657)
I(week=5)	-0.0274***	-0.0263***	-0.0288***	-0.0528***
	(0.00167)	(0.00165)	(0.00208)	(0.00730)
I(week=6)	-0.0274***	-0.0262***	-0.0286***	-0.0429***
	(0.00182)	(0.00180)	(0.00237)	(0.00792)
I(week=7)	-0.0290***	-0.0280***	-0.0312***	-0.0402***
	(0.00194)	(0.00192)	(0.00265)	(0.00847)
I(week=8)	-0.0296***	-0.0289***	-0.0326***	-0.0519***
	(0.00204)	(0.00203)	(0.00293)	(0.00892)
I(week=9)	-0.0284***	-0.0276***	-0.0316***	-0.0495***
	(0.00215)	(0.00213)	(0.00320)	(0.00948)
I(week=10)	-0.0293***	-0.0283***	-0.0327***	-0.0536***
	(0.00226)	(0.00224)	(0.00349)	(0.00987)
I(week=11)	-0.0285***	-0.0274***	-0.0321***	-0.0441***
	(0.00234)	(0.00233)	(0.00376)	(0.0106)
I(week=12)	-0.0324***	-0.0311***	-0.0362***	-0.0634***
	(0.00242)	(0.00240)	(0.00403)	(0.0108)
I(week=13)	-0.0349***	-0.0341***	-0.0386***	-0.0491***
	(0.00251)	(0.00249)	(0.00432)	(0.0113)
I(week=14)	-0.0339***	-0.0331***	-0.0388***	-0.0494***
	(0.00257)	(0.00256)	(0.00458)	(0.0116)
I(week=15)	-0.0371***	-0.0365***	-0.0426***	-0.0857***
	(0.00266)	(0.00264)	(0.00486)	(0.0121)
I(week=16)	-0.0364***	-0.0358***	-0.0427***	-0.0609***
	(0.00274)	(0.00273)	(0.00515)	(0.0125)
I(week=17)	-0.0340***	-0.0333***	-0.0397***	-0.0445***
	(0.00281)	(0.00279)	(0.00543)	(0.0128)
I(week=18)	-0.0389***	-0.0386***	-0.0447***	-0.0714***
	(0.00288)	(0.00286)	(0.00571)	(0.0133)
I(week=19)	-0.0376***	-0.0372***	-0.0438***	-0.0811***
	(0.00294)	(0.00293)	(0.00598)	(0.0136)
I(week=20)	-0.0407***	-0.0406***	-0.0487***	-0.0464***
	(0.00301)	(0.00300)	(0.00626)	(0.0139)
I(week=21)	-0.0421***	-0.0423***	-0.0496***	-0.0754***
	(0.00304)	(0.00303)	(0.00653)	(0.0144)
I(week=22)	-0.0434***	-0.0439***	-0.0528***	-0.0782***
	(0.00313)	(0.00312)	(0.00682)	(0.0147)
I(week=23)	-0.0422***	-0.0424***	-0.0502***	-0.0791***
	(0.00320)	(0.00319)	(0.00710)	(0.0151)
I(week=24)	-0.0442***	-0.0444***	-0.0524***	-0.0844***
	(0.00330)	(0.00328)	(0.00739)	(0.0157)
I(week=25)	-0.0458***	-0.0466***	-0.0568***	-0.0968***
	(0.00336)	(0.00334)	(0.00767)	(0.0160)
I(week=26)	-0.0397***	-0.0405***	-0.0502***	-0.0687***
	(0.00346)	(0.00345)	(0.00797)	(0.0162)
Earliest week of j	0.00913***	0.00993***	0.00983***	0.00987***
	(0.000300)	(0.000306)	(0.000315)	(0.000316)
U rate (msa)			0.00233	0.00356
			(0.00365)	(0.00368)

	(1)	(2)	(3)	(4)
		Table continued		
I(week=2)*d_e		-0.121***	-0.122***	-0.142***
		(0.000917)	(0.000946)	(0.00412)
I(week=3)*d_e		-0.135***	-0.135***	-0.162***
		(0.00106)	(0.00109)	(0.00478)
I(week=4)*d_e		-0.144***	-0.144***	-0.171***
		(0.00118)	(0.00122)	(0.00540)
I(week=5)*d_e		-0.145***	-0.144***	-0.180***
		(0.00128)	(0.00133)	(0.00587)
I(week=6)*d_e		-0.149***	-0.149***	-0.174***
		(0.00140)	(0.00144)	(0.00635)
I(week=7)*d_e		-0.150***	-0.150***	-0.173***
		(0.00149)	(0.00154)	(0.00682)
I(week=8)*d_e		-0.151***	-0.151***	-0.183***
		(0.00157)	(0.00161)	(0.00696)
I(week=9)*d_e		-0.151***	-0.152***	-0.185***
		(0.00164)	(0.00169)	(0.00735)
I(week=10)*d_e		-0.152***	-0.152***	-0.206***
		(0.00172)	(0.00177)	(0.00753)
I(week=11)*d_e		-0.151***	-0.151***	-0.184***
		(0.00178)	(0.00183)	(0.00811)
I(week=12)*d_e		-0.154***	-0.154***	-0.179***
		(0.00182)	(0.00188)	(0.00821)
I(week=13)*d_e		-0.153***	-0.152***	-0.181***
		(0.00189)	(0.00196)	(0.00867)
I(week=14)*d_e		-0.150***	-0.150***	-0.185***
		(0.00195)	(0.00201)	(0.00875)
I(week=15)*d_e		-0.152***	-0.152***	-0.183***
		(0.00200)	(0.00206)	(0.00905)
I(week=16)*d_e		-0.153***	-0.154***	-0.183***
		(0.00206)	(0.00212)	(0.00931)
I(week=17)*d_e		-0.152***	-0.152***	-0.182***
		(0.00211)	(0.00218)	(0.00963)
I(week=18)*d_e		-0.151***	-0.151***	-0.195***
		(0.00217)	(0.00224)	(0.00998)
I(week=19)*d_e		-0.154***	-0.155***	-0.193***
		(0.00219)	(0.00225)	(0.00969)
I(week=20)*d_e		-0.155***	-0.155***	-0.205***
		(0.00224)	(0.00231)	(0.0101)
I(week=21)*d_e		-0.151***	-0.151***	-0.169***
		(0.00229)	(0.00236)	(0.0104)
I(week=22)*d_e		-0.152***	-0.152***	-0.197***
		(0.00235)	(0.00242)	(0.0109)
I(week=23)*d_e		-0.151***	-0.151***	-0.194***
		(0.00239)	(0.00247)	(0.0106)
I(week=24)*d_e		-0.152***	-0.153***	-0.200***
		(0.00245)	(0.00252)	(0.0108)
I(week=25)*d_e		-0.154***	-0.155***	-0.202***
		(0.00250)	(0.00258)	(0.0113)
I(week=26)*d_e		-0.148***	-0.149***	-0.182***
		(0.00257)	(0.00264)	(0.0114)
d_e		0.267***	0.262***	0.325***
		(0.00499)	(0.00527)	(0.0147)
d_e*U rate (msa)				-0.00691***
				(0.00151)

	(1)	(2)	(3)	(4)
	Table continued			
I(week=2)*U rate (msa)				0.000922*
				(0.000488)
I(week=3)*U rate (msa)				0.00106*
				(0.000574)
I(week=4)*U rate (msa)				-0.000414
				(0.000657)
I(week=5)*U rate (msa)				0.00258***
				(0.000729)
I(week=6)*U rate (msa)				0.00155**
				(0.000785)
I(week=7)*U rate (msa)				0.000968
				(0.000833)
I(week=8)*U rate (msa)				0.00208**
				(0.000874)
I(week=9)*U rate (msa)				0.00192**
				(0.000928)
I(week=10)*U rate (msa)				0.00224**
				(0.000961)
I(week=11)*U rate (msa)				0.00130
				(0.00103)
I(week=12)*U rate (msa)				0.00293***
				(0.00104)
I(week=13)*U rate (msa)				0.00114
				(0.00109)
I(week=14)*U rate (msa)				0.00115
				(0.00111)
I(week=15)*U rate (msa)				0.00464***
				(0.00115)
I(week=16)*U rate (msa)				0.00197*
				(0.00118)
I(week=17)*U rate (msa)				0.000534
				(0.00120)
I(week=18)*U rate (msa)				0.00288**
				(0.00124)
I(week=19)*U rate (msa)				0.00403***
				(0.00127)
I(week=20)*U rate (msa)				-0.000232
				(0.00129)
I(week=21)*U rate (msa)				0.00280**
				(0.00134)
I(week=22)*U rate (msa)				0.00275**
				(0.00137)
I(week=23)*U rate (msa)				0.00314**
				(0.00138)
I(week=24)*U rate (msa)				0.00348**
				(0.00145)
I(week=25)*U rate (msa)				0.00433***
				(0.00147)
I(week=26)*U rate (msa)				0.00203
				(0.00146)

	(1)	(2)	(3)	(4)
	Table continued			
I(week=2)*d_e*U rate (msa)				-0.00691***
				(0.00151)
I(week=3)*d_e*U rate (msa)				0.00217***
				(0.000425)
I(week=4)*d_e*U rate (msa)				0.00286***
				(0.000492)
I(week=5)*d_e*U rate (msa)				0.00296***
				(0.000556)
I(week=6)*d_e*U rate (msa)				0.00387***
				(0.000607)
I(week=7)*d_e*U rate (msa)				0.00265***
				(0.000654)
I(week=8)*d_e*U rate (msa)				0.00238***
				(0.000701)
I(week=9)*d_e*U rate (msa)				0.00342***
				(0.000710)
I(week=10)*d_e*U rate (msa)				0.00354***
				(0.000756)
I(week=11)*d_e*U rate (msa)				0.00575***
				(0.000773)
I(week=12)*d_e*U rate (msa)				0.00345***
				(0.000830)
I(week=13)*d_e*U rate (msa)				0.00265***
				(0.000841)
I(week=14)*d_e*U rate (msa)				0.00307***
				(0.000887)
I(week=15)*d_e*U rate (msa)				0.00371***
				(0.000892)
I(week=16)*d_e*U rate (msa)				0.00324***
				(0.000929)
I(week=17)*d_e*U rate (msa)				0.00304***
				(0.000956)
I(week=18)*d_e*U rate (msa)				0.00306***
				(0.000988)
I(week=19)*d_e*U rate (msa)				0.00472***
				(0.00103)
I(week=20)*d_e*U rate (msa)				0.00406***
				(0.000995)
I(week=21)*d_e*U rate (msa)				0.00527***
				(0.00104)
I(week=22)*d_e*U rate (msa)				0.00175
				(0.00107)
I(week=23)*d_e*U rate (msa)				0.00480***
				(0.00113)
I(week=24)*d_e*U rate (msa)				0.00453***
				(0.00109)
I(week=25)*d_e*U rate (msa)				0.00491***
				(0.00112)
I(week=26)*d_e*U rate (msa)				0.00493***
				(0.00117)
Monthly time dummies	no	no	yes	yes
Constant	-0.0266***	-0.0285***	-0.0564	-0.0680*
	(0.000691)	(0.000669)	(0.0369)	(0.0372)
Observations	5,672,155	5,672,155	5,350,236	5,350,236
R-squared	0.454	0.465	0.465	0.465

Note: The dependent variable is the average index of jobs a job seeker applies for during week x of his search tenure. The regressions are estimated using OLS with individual-specific fixed effects. Dummies show the difference between week x and week 1. The heteroscedasticity-robust standard errors are in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: THE ESTIMATED CHANGE IN THE DIRECTION OF APPLICATIONS WITH CONTROLS FOR LABOR MARKET, BY TOTAL DURATION OF SEARCH

	(1)	(2)	(3)
I(week=2)	-0.0216***	-0.0204***	-0.0250***
	(0.00158)	(0.00275)	(0.00317)
I(week=3)	-0.0274***	-0.0229***	-0.0303***
	(0.00208)	(0.00316)	(0.00354)
I(week=4)	-0.0349***	-0.0245***	-0.0243***
	(0.00261)	(0.00357)	(0.00391)
I(week=5)	-0.0336***	-0.0324***	-0.0267***
	(0.00314)	(0.00393)	(0.00429)
I(week=6)	-0.0369***	-0.0281***	-0.0269***
	(0.00369)	(0.00436)	(0.00465)
I(week=7)	-0.0449***	-0.0280***	-0.0262***
	(0.00426)	(0.00472)	(0.00501)
I(week=8)	-0.0429***	-0.0347***	-0.0280***
	(0.00484)	(0.00508)	(0.00539)
I(week=9)	-0.0521***	-0.0283***	-0.0242***
	(0.00549)	(0.00548)	(0.00575)
I(week=10)	-0.0450***	-0.0290***	-0.0364***
	(0.00630)	(0.00585)	(0.00615)
I(week=11)		-0.0316***	-0.0290***
		(0.00594)	(0.00655)
I(week=12)		-0.0369***	-0.0309***
		(0.00644)	(0.00693)
I(week=13)		-0.0347***	-0.0410***
		(0.00698)	(0.00734)
I(week=14)		-0.0416***	-0.0303***
		(0.00747)	(0.00774)
I(week=15)		-0.0404***	-0.0414***
		(0.00800)	(0.00813)
I(week=16)		-0.0450***	-0.0355***
		(0.00855)	(0.00856)
I(week=17)		-0.0384***	-0.0366***
		(0.00909)	(0.00897)
I(week=18)		-0.0505***	-0.0352***
		(0.00965)	(0.00940)
I(week=19)		-0.0451***	-0.0384***
		(0.0102)	(0.00981)
I(week=20)		-0.0468***	-0.0453***
		(0.0109)	(0.0102)
I(week=21)			-0.0452***
			(0.0105)
I(week=22)			-0.0484***
			(0.0109)
I(week=23)			-0.0457***
			(0.0114)
I(week=24)			-0.0476***
			(0.0119)
I(week=25)			-0.0520***
			(0.0124)
I(week=26)			-0.0453***
			(0.0129)
Earliest week of j	0.0267***	0.0125***	0.00721***
	(0.00126)	(0.000540)	(0.000381)
U rate (msa)	0.0108	0.00477	-0.000792
	(0.0104)	(0.00599)	(0.00483)
d_e	0.258***	0.271***	0.260***
	(0.00888)	(0.00915)	(0.00914)

	(1)	(2)	(3)
		Table continued	
I(week=2)*d_e	-0.121***	-0.123***	-0.122***
	(0.00121)	(0.00216)	(0.00250)
I(week=3)*d_e	-0.135***	-0.133***	-0.139***
	(0.00145)	(0.00236)	(0.00266)
I(week=4)*d_e	-0.143***	-0.145***	-0.144***
	(0.00168)	(0.00250)	(0.00280)
I(week=5)*d_e	-0.142***	-0.150***	-0.145***
	(0.00191)	(0.00255)	(0.00290)
I(week=6)*d_e	-0.148***	-0.150***	-0.152***
	(0.00217)	(0.00265)	(0.00298)
I(week=7)*d_e	-0.149***	-0.152***	-0.152***
	(0.00242)	(0.00272)	(0.00306)
I(week=8)*d_e	-0.148***	-0.154***	-0.152***
	(0.00269)	(0.00272)	(0.00312)
I(week=9)*d_e	-0.150***	-0.158***	-0.148***
	(0.00304)	(0.00273)	(0.00311)
I(week=10)*d_e	-0.152***	-0.152***	-0.155***
	(0.00354)	(0.00270)	(0.00317)
I(week=11)*d_e		-0.154***	-0.148***
		(0.00224)	(0.00322)
I(week=12)*d_e		-0.157***	-0.153***
		(0.00234)	(0.00314)
I(week=13)*d_e		-0.155***	-0.150***
		(0.00246)	(0.00318)
I(week=14)*d_e		-0.153***	-0.149***
		(0.00254)	(0.00321)
I(week=15)*d_e		-0.153***	-0.153***
		(0.00270)	(0.00312)
I(week=16)*d_e		-0.157***	-0.153***
		(0.00284)	(0.00312)
I(week=17)*d_e		-0.155***	-0.152***
		(0.00300)	(0.00310)
I(week=18)*d_e		-0.151***	-0.152***
		(0.00320)	(0.00305)
I(week=19)*d_e		-0.155***	-0.155***
		(0.00336)	(0.00297)
I(week=20)*d_e		-0.155***	-0.156***
		(0.00377)	(0.00288)
I(week=21)*d_e			-0.152***
			(0.00242)
I(week=22)*d_e			-0.152***
			(0.00247)
I(week=23)*d_e			-0.151***
			(0.00251)
I(week=24)*d_e			-0.153***
			(0.00256)
I(week=25)*d_e			-0.155***
			(0.00260)
I(week=26)*d_e			-0.149***
			(0.00266)
Monthly dummies	yes	yes	yes
Constant	-0.173*	-0.0789	-0.0224
	(0.103)	(0.0608)	(0.0491)
Observations	2,069,370	1,657,217	1,623,649
R-squared	0.579	0.428	0.348

Note: See notes to Table 4.

A Appendix Not for Publication

A.1 A Simple Learning Model

In this section, we illustrate the ideas by considering a simple model in which workers differ by their educational level and unobserved ability. We then demonstrate how unemployed workers learn their unobserved ability from job search.

A.1.1 Model's Environment

Time is discrete. An economy is populated by risk neutral workers and firms that discount future by the common discount factor, $\tilde{\beta}$, where $0 < \tilde{\beta} < 1$.

Workers differ by their educational level, e, and their unobserved ability, a. The educational level can take one of the two values, $e \in \{1, 2\}$. Worker's ability can also take one of the two values, $a \in \{0, 1\}$. Workers know their educational level but do not know their ability. A worker's educational level and ability are his permanent characteristics and are determined at the time the worker enters the labor market. Worker's productivity, θ, is determined by his educational level and unobserved ability as follows

$$\theta = e + a.$$

A worker in the economy is either employed or unemployed. Employed workers produce. Unemployed workers search for jobs. There is no on-the-job search. Each period, a worker dies exogenously with probability δ, while a fixed number of unemployed workers enter the economy. The distribution of the new entrants by education and ability remains the same over time.

Let z denote a type of a job. There are three types of jobs: $z = \{1, 2, 3\}$. A z-type job pays per-period wage $w(z) > 0$, where $w(\cdot)$ is a strictly increasing function. The flow utility of an unemployed worker is zero; once employed, the worker enjoys flow utility of $w(z)$. Each period an unemployed worker can apply for at most one job.

Let p_t denote a worker's expectation of a at the beginning of period t. We refer to p_t as the worker's belief about his ability. The initial belief of a new entrant about his unobserved ability is uniformly distributed on $[0, 1]$.

Suppose that a worker with productivity θ applies for a job of type z. Given the application, the probability that the worker is hired is[34]

$$g(\theta, z) = \begin{cases} 0 & \text{if } \theta < z, \\ 1 & \text{if } \theta \geq z. \end{cases} \tag{11}$$

For example, if a more educated, high ability worker (i.e., $e = 2$ and $a = 1$) applies for type 3 job, his probability of being hired is 1. However, if a more educated, lower ability worker (i.e., $e = 2$ and $a = 0$) applies for the same job, the probability of being hired is 0.

A.1.2 Model's Implications

We assume, for simplicity, that employment is an absorbing state. Consider an unemployed worker in period t whose educational level is 2 and belief is p_t. If the worker applies for a type 2 or type 1 job, his expected lifetime utility is

$$U(p_t|e = 2, z = k) = \frac{\beta}{1-\beta} w(k), \; k = \{1, 2\}, \tag{12}$$

where $\beta = \tilde{\beta}(1 - \delta)$.

If the worker applies for a type 3 job, his expected utility is

$$U(p_t|e = 2, z = 3) = p_t \frac{\beta}{1-\beta} w(3) + (1 - p_t) \frac{\beta^2}{1-\beta} w(2). \tag{13}$$

Then, it can be shown that $U(p_t|e = 2, z = 1) < U(p_t|e = 2, z = 2)$ and $U(p_t|e = 2, z = 1) < U(p_t|e = 2, z = 3)$ and

$$U(p_t|e = 2, z = 3) \geq U(p_t|e = 2, z = 2) \; \forall p_t > p_A,$$

where $p_A = \frac{1-\beta}{w(3)/w(2)-\beta}$.

Analogously,

$$U(p_t|e = 1, z = 2) \geq U(p_t|e = 1, z = 1) \; \forall p_t > p_B,$$

where $p_B = \frac{1-\beta}{w(2)/w(1)-\beta}$. Note that since $w(1) < w(2) < w(3)$, $0 < p_A < 1$ and $0 < p_B < 1$.

Consequently, in the first period of search, depending on the distribution of wages in the economy, unemployed workers of different educational levels may apply for different types of jobs or for jobs of the same type - type 2.

[34] The model can be modified to allow for stochastic realization of productivity conditional on a or e. Such a modification, however, does not alter the model's implications that we demonstrate here.

If an unemployed worker with educational level 2 applies for a type 3 job in period t and does not get a job, the person's subsequent belief about his ability becomes $p_{t+1} = 0$. This worker then applies for a type 2 job in period $t + 1$. Similarly, if an unemployed worker with educational level 1 applies for a type 2 job in period t and does not get a job, the worker's updated belief is $p_{t+1} = 0$. This worker then applies for a type 1 job in period $t + 1$.

Finally, let $\psi(e|z)$ denote the probability mass function of the educational level of the first-period applicants for a type z job. Then, the mean educational level of the first-period applicants for the job is given by

$$E_z(e) = \psi(1|z) + 2\psi(2|z), \tag{14}$$

for each z. Clearly,

$$1 = E_1(e) \leq E_2(e) \leq E_3(e) = 2. \tag{15}$$

We posit that $E_z(z)$ is the model's counterpart of the job type index that we construct in the empirical analysis.

The model has the following implications that are consistent with our empirical findings. First, the model can generate sorting by education at the beginning of search. Second, as an unemployed worker continues his search, he applies for jobs that are the first-period choice of less educated job seekers.

Figure A.1: The Distribution of Jobs by the Average Education of All Applicants for the Job

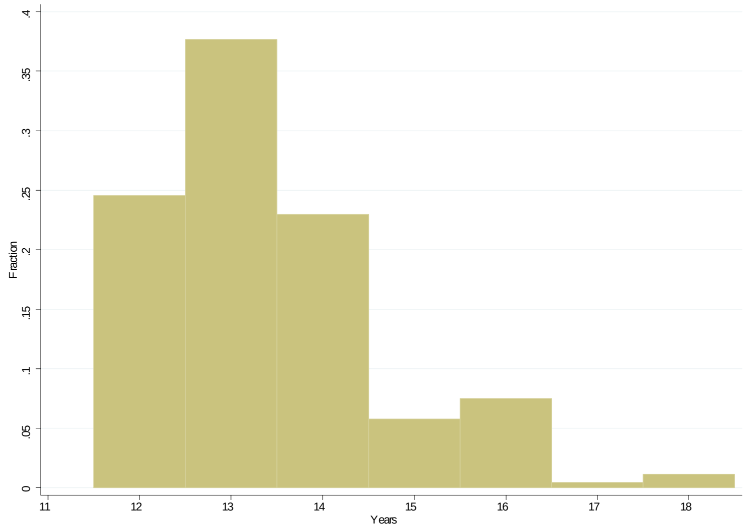


Figure A.2: The Distribution of the Monthly Unemployment Rate across MSAs, September 2010 - April 2012

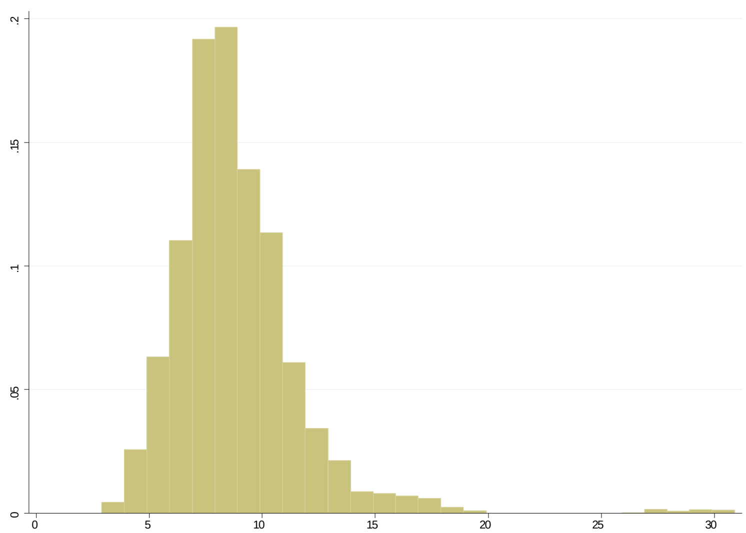


Table A.1: The Distribution of Jobs and the Distribution of Applications by Industry (in the Subsample with Available Industry Affiliation)

Industry	By job posting, %	By # of applications, %
	1	2
Accounting & Finance	4.03	1.67
Administration & Office Support	1.48	0.95
Agriculture & Environment	0.09	0.02
Automotive	2.77	2.83
Computers & Technology	0.39	0.32
Construction	0.68	0.15
Customer Service	9.14	5.73
Education	0.68	1.28
Food & Restaurant	15.69	16.69
Government & Military	0.07	0.05
Healthcare	4.86	2.57
Hotel & Hospitality	2.1	2.75
Installation & Repair	1	1.19
Law Enforcement & Security	0.22	1.38
Legal	0.02	0.01
Maintenance & Janitorial	0.43	0.71
Management	2.17	2.07
Media & Entertainment	0.4	0.52
Other	0	0.01
Personal Care & Services	1.73	1.09
Retail	43.57	51.07
Sales & Marketing	3.65	1.63
Salon/Spa/Fitness	0.28	0.11
Social Services	0.18	0.12
Transportation	1.35	1.85
Unknown	0.01	0.01
Warehouse & Production	2.95	1.72
Wellness	0.04	0.01
Work at Home	0	1.52
Total with industry affilation available	1,615,168	23,633,910
Percent of the full sample	58.5	75.6

Table A.2: Crosswalk between Educational Levels and Years of Schooling

Education	Years of Schooling
Master's Degree Program	18
Bachelor's Degree Program	16
Associate's Degree Program	14
Vocational/Trade School	13
Other Professional or Training School	13
Certification Program	13
High School	12
GED Program	12

Table A.3: The Distribution of Job Postings by the Earliest Week in Job Seekers' Search

Week	%
1	93.02
2	2.43
3	1.33
4	0.86
5	0.63
6	0.49
7	0.39
8	0.33
9	0.28
>=10	0.24

Note: The statistics are calculated for the sample used in the regression analysis. See text for details.

Table A.4: The Estimated Change in the Direction of Applications, without Controls for Labor Market

	(1)	(2)	(3)	(4)
I(week=2)	-0.0214***	-0.0210***	-0.0234***	-0.0149***
	(0.00114)	(0.00113)	(0.00122)	(0.00492)
I(week=3)	-0.0267***	-0.0257***	-0.0287***	-0.0196***
	(0.00134)	(0.00133)	(0.00150)	(0.00582)
I(week=4)	-0.0303***	-0.0286***	-0.0320***	-0.00902
	(0.00152)	(0.00151)	(0.00180)	(0.00668)
I(week=5)	-0.0314***	-0.0296***	-0.0333***	-0.0382***
	(0.00167)	(0.00165)	(0.00208)	(0.00742)
I(week=6)	-0.0322***	-0.0302***	-0.0339***	-0.0276***
	(0.00182)	(0.00180)	(0.00238)	(0.00805)
I(week=7)	-0.0343***	-0.0324***	-0.0370***	-0.0245***
	(0.00194)	(0.00192)	(0.00266)	(0.00861)
I(week=8)	-0.0360***	-0.0343***	-0.0392***	-0.0378***
	(0.00205)	(0.00203)	(0.00293)	(0.00904)
I(week=9)	-0.0353***	-0.0335***	-0.0385***	-0.0352***
	(0.00215)	(0.00213)	(0.00321)	(0.00962)
I(week=10)	-0.0369***	-0.0348***	-0.0401***	-0.0411***
	(0.00226)	(0.00224)	(0.00349)	(0.0100)
I(week=11)	-0.0370***	-0.0347***	-0.0402***	-0.0319***
	(0.00234)	(0.00233)	(0.00376)	(0.0107)
I(week=12)	-0.0419***	-0.0394***	-0.0451***	-0.0509***
	(0.00242)	(0.00240)	(0.00403)	(0.0109)
I(week=13)	-0.0450***	-0.0430***	-0.0478***	-0.0363***
	(0.00251)	(0.00250)	(0.00433)	(0.0115)
I(week=14)	-0.0452***	-0.0430***	-0.0488***	-0.0372***
	(0.00257)	(0.00256)	(0.00459)	(0.0118)
I(week=15)	-0.0490***	-0.0469***	-0.0530***	-0.0741***
	(0.00266)	(0.00265)	(0.00486)	(0.0122)
I(week=16)	-0.0492***	-0.0471***	-0.0538***	-0.0493***
	(0.00275)	(0.00273)	(0.00515)	(0.0127)
I(week=17)	-0.0476***	-0.0453***	-0.0512***	-0.0320**
	(0.00281)	(0.00279)	(0.00543)	(0.0130)
I(week=18)	-0.0533***	-0.0513***	-0.0569***	-0.0629***
	(0.00288)	(0.00286)	(0.00571)	(0.0134)
I(week=19)	-0.0527***	-0.0505***	-0.0561***	-0.0711***
	(0.00295)	(0.00293)	(0.00599)	(0.0138)
I(week=20)	-0.0564***	-0.0544***	-0.0615***	-0.0356**
	(0.00302)	(0.00300)	(0.00627)	(0.0141)
I(week=21)	-0.0587***	-0.0570***	-0.0632***	-0.0652***
	(0.00305)	(0.00303)	(0.00653)	(0.0146)
I(week=22)	-0.0609***	-0.0594***	-0.0672***	-0.0685***
	(0.00313)	(0.00312)	(0.00682)	(0.0149)
I(week=23)	-0.0606***	-0.0587***	-0.0656***	-0.0710***
	(0.00321)	(0.00319)	(0.00710)	(0.0152)
I(week=24)	-0.0623***	-0.0603***	-0.0676***	-0.0769***
	(0.00330)	(0.00328)	(0.00740)	(0.0159)
I(week=25)	-0.0638***	-0.0623***	-0.0721***	-0.0872***
	(0.00336)	(0.00335)	(0.00768)	(0.0163)
I(week=26)	-0.0591***	-0.0575***	-0.0668***	-0.0580***
	(0.00347)	(0.00345)	(0.00798)	(0.0164)
Earliest week of j	0.00889***	0.00972***	0.00987***	0.00988***
	(0.000300)	(0.000307)	(0.000316)	(0.000316)
U rate (msa)			0.0104***	0.0111***
			(0.00365)	(0.00368)

	(1)	(2)	(3)	(4)
		Table continued		
I(week=2)*d_e		-0.120***	-0.121***	-0.140***
		(0.000911)	(0.000942)	(0.00410)
I(week=3)*d_e		-0.134***	-0.134***	-0.161***
		(0.00105)	(0.00109)	(0.00478)
I(week=4)*d_e		-0.143***	-0.143***	-0.171***
		(0.00118)	(0.00122)	(0.00539)
I(week=5)*d_e		-0.144***	-0.144***	-0.180***
		(0.00128)	(0.00132)	(0.00586)
I(week=6)*d_e		-0.148***	-0.148***	-0.173***
		(0.00139)	(0.00143)	(0.00633)
I(week=7)*d_e		-0.149***	-0.150***	-0.173***
		(0.00148)	(0.00153)	(0.00679)
I(week=8)*d_e		-0.150***	-0.150***	-0.183***
		(0.00156)	(0.00161)	(0.00696)
I(week=9)*d_e		-0.150***	-0.151***	-0.183***
		(0.00163)	(0.00168)	(0.00735)
I(week=10)*d_e		-0.151***	-0.152***	-0.204***
		(0.00171)	(0.00176)	(0.00751)
I(week=11)*d_e		-0.150***	-0.150***	-0.182***
		(0.00177)	(0.00183)	(0.00813)
I(week=12)*d_e		-0.154***	-0.154***	-0.179***
		(0.00181)	(0.00187)	(0.00820)
I(week=13)*d_e		-0.152***	-0.151***	-0.180***
		(0.00188)	(0.00195)	(0.00861)
I(week=14)*d_e		-0.149***	-0.150***	-0.184***
		(0.00194)	(0.00200)	(0.00873)
I(week=15)*d_e		-0.151***	-0.152***	-0.184***
		(0.00199)	(0.00206)	(0.00902)
I(week=16)*d_e		-0.152***	-0.154***	-0.184***
		(0.00205)	(0.00212)	(0.00930)
I(week=17)*d_e		-0.151***	-0.152***	-0.179***
		(0.00210)	(0.00217)	(0.00960)
I(week=18)*d_e		-0.150***	-0.151***	-0.196***
		(0.00216)	(0.00223)	(0.00997)
I(week=19)*d_e		-0.152***	-0.154***	-0.191***
		(0.00218)	(0.00225)	(0.00971)
I(week=20)*d_e		-0.154***	-0.155***	-0.204***
		(0.00223)	(0.00230)	(0.0101)
I(week=21)*d_e		-0.150***	-0.151***	-0.169***
		(0.00228)	(0.00235)	(0.0104)
I(week=22)*d_e		-0.151***	-0.152***	-0.197***
		(0.00234)	(0.00241)	(0.0108)
I(week=23)*d_e		-0.150***	-0.151***	-0.193***
		(0.00237)	(0.00246)	(0.0106)
I(week=24)*d_e		-0.151***	-0.153***	-0.198***
		(0.00244)	(0.00251)	(0.0108)
I(week=25)*d_e		-0.153***	-0.155***	-0.198***
		(0.00249)	(0.00257)	(0.0113)
I(week=26)*d_e		-0.147***	-0.149***	-0.179***
		(0.00256)	(0.00264)	(0.0114)
d_e		0.267***	0.262***	0.325***
		(0.00499)	(0.00527)	(0.0147)
d_e*U rate (msa)				-0.00498**
				(0.00230)

	(1)	(2)	(3)	(4)
		Table continued		
I(week=2)*U rate (msa)				-0.000893*
				(0.000501)
I(week=3)*U rate (msa)				-0.000948
				(0.000589)
I(week=4)*U rate (msa)				-0.00244***
				(0.000673)
I(week=5)*U rate (msa)				0.000555
				(0.000745)
I(week=6)*U rate (msa)				-0.000650
				(0.000803)
I(week=7)*U rate (msa)				-0.00132
				(0.000852)
I(week=8)*U rate (msa)				-0.000116
				(0.000891)
I(week=9)*U rate (msa)				-0.000328
				(0.000947)
I(week=10)*U rate (msa)				0.000154
				(0.000980)
I(week=11)*U rate (msa)				-0.000851
				(0.00105)
I(week=12)*U rate (msa)				0.000644
				(0.00106)
I(week=13)*U rate (msa)				-0.00120
				(0.00111)
I(week=14)*U rate (msa)				-0.00121
				(0.00113)
I(week=15)*U rate (msa)				0.00230**
				(0.00117)
I(week=16)*U rate (msa)				-0.000449
				(0.00121)
I(week=17)*U rate (msa)				-0.00203*
				(0.00123)
I(week=18)*U rate (msa)				0.000696
				(0.00127)
I(week=19)*U rate (msa)				0.00165
				(0.00129)
I(week=20)*U rate (msa)				-0.00274**
				(0.00132)
I(week=21)*U rate (msa)				0.000245
				(0.00136)
I(week=22)*U rate (msa)				0.000185
				(0.00139)
I(week=23)*U rate (msa)				0.000632
				(0.00141)
I(week=24)*U rate (msa)				0.00105
				(0.00147)
I(week=25)*U rate (msa)				0.00168
				(0.00151)
I(week=26)*U rate (msa)				-0.000898
				(0.00149)

	(1)	(2)	(3)	(4)
		Table continued		
I(week=2)*d_e*U rate (msa)				0.00209***
				(0.000423)
I(week=3)*d_e*U rate (msa)				0.00288***
				(0.000492)
I(week=4)*d_e*U rate (msa)				0.00303***
				(0.000555)
I(week=5)*d_e*U rate (msa)				0.00389***
				(0.000605)
I(week=6)*d_e*U rate (msa)				0.00264***
				(0.000653)
I(week=7)*d_e*U rate (msa)				0.00245***
				(0.000698)
I(week=8)*d_e*U rate (msa)				0.00352***
				(0.000711)
I(week=9)*d_e*U rate (msa)				0.00347***
				(0.000755)
I(week=10)*d_e*U rate (msa)				0.00567***
				(0.000771)
I(week=11)*d_e*U rate (msa)				0.00341***
				(0.000834)
I(week=12)*d_e*U rate (msa)				0.00263***
				(0.000839)
I(week=13)*d_e*U rate (msa)				0.00303***
				(0.000880)
I(week=14)*d_e*U rate (msa)				0.00365***
				(0.000890)
I(week=15)*d_e*U rate (msa)				0.00342***
				(0.000925)
I(week=16)*d_e*U rate (msa)				0.00321***
				(0.000954)
I(week=17)*d_e*U rate (msa)				0.00282***
				(0.000984)
I(week=18)*d_e*U rate (msa)				0.00489***
				(0.00102)
I(week=19)*d_e*U rate (msa)				0.00393***
				(0.000996)
I(week=20)*d_e*U rate (msa)				0.00525***
				(0.00104)
I(week=21)*d_e*U rate (msa)				0.00180*
				(0.00106)
I(week=22)*d_e*U rate (msa)				0.00483***
				(0.00112)
I(week=23)*d_e*U rate (msa)				0.00450***
				(0.00109)
I(week=24)*d_e*U rate (msa)				0.00479***
				(0.00112)
I(week=25)*d_e*U rate (msa)				0.00458***
				(0.00117)
I(week=26)*d_e*U rate (msa)				0.00312***
				(0.00117)
Monthly time dummies	no	no	yes	yes
Constant	13.26***	13.26***	13.11***	13.10***
	(0.000691)	(0.000669)	(0.0369)	(0.0371)
Observations	5,672,155	5,672,155	5,350,236	5,350,236
R-squared	0.474	0.484	0.480	0.480

Note: The dependent variable is the average index of jobs a job seeker applies for during week x of his search tenure. The regressions are estimated using OLS with individual-specific fixed effects. Dummies show the difference between week x and week 1. The heteroscedasticity-robust standard errors are in parentheses: *** p<0.01, ** p<0.05, * p<0.1.