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Sorting by Skill over the Course of Job Search*

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Abstract

We use novel high-frequency panel data on individuals' job applications from an online job posting engine to study (1) whether at the beginning of search job seekers with different levels of education (skill) apply to different jobs, and (2) how search behavior changes as search continues. First, we find that there is sorting by skill at the beginning of search. Second, as search continues, job seekers apply to different types of jobs than at the beginning of search. In particular, assuming that sorting at the beginning of search is positive, as search continues there is less sorting by education and job seekers, on average, apply to lower quality jobs.

Keywords: Job Application, Search, Heterogenous Agents, Sorting, Directed Search.

JEL Codes: J31, J24, E24 .

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1 Introduction

Is education an important predictor of a job seeker's decision of what jobs to apply to? How does the type of jobs applied to change with search tenure? We use novel high-frequency panel data on individuals' job applications from an online job posting engine to study these questions. First, we investigate whether, at the beginning of their search, job seekers with different levels of education apply to different jobs, i.e., whether there is sorting by education across jobs. Second, we investigate whether job seekers direct their search to different types of jobs as their search continues. To our knowledge, this is the first paper that examines the dynamics of search behavior using search data on job seekers' actual applications.

Our first question speaks to a paramount issue in equilibrium search theory, i.e., whether search is random or directed.[1] Job seekers make a choice of where to apply, taking into consideration their own characteristics and information about the labor market. For modeling purposes, it is important to know whether the resulting application decision delivers a detectable pattern of sorting across jobs or whether search can be considered random. In this paper, we investigate whether education is an important factor in directing the search decision.

Our second question relates to an important issue in job search theory, which is how individual search behavior changes over the course of search tenure. Related literature allows a job seeker some ex ante information about the labor market and/or relaxes the assumption of stationarity of the labor market environment. In such models, a job seeker samples jobs in a systematic manner, and is often willing to accept less attractive jobs later during search than at the beginning of search. Example models include models with finite work-life of a job seeker (Gronau (1971)), liquidity constraints (Danforth (1979)), imperfect knowledge of the distribution of the prevailing wages and learning (Salop (1973), Rothschild (1974), Burdett and Vishwanath (1988), Gonzalez and Shi (2010)), limited unemployment benefits (Mortensen (1977), Burdett (1978)), time-varying unemployment benefits (Albrecht and Axell (1984), Albrecht and Vroman (2005)), and a trade-off between individual incentives and macroeconomic conditions (Moscarini (2001)). However, empirical evidence on search behavior over the duration of search is scarce. Most of the existing empirical literature focuses on change in reservation wages and, since reservation wages are not observable, relies on strong identifying assumptions or uses data from small-scale self-reporting surveys. The novel data set used in our analysis allows us to observe individuals' application decisions directly.

The application-level, matched job applicant-job posting data set in the analysis is

[1] See Rogerson, Shimer and Wright (2005) for a survey of search theory literature.

uniquely suited to studying search behavior over the course of job search. On the job seekers' side, it is a panel data set that consists of daily individual records on each application sent for the job postings available on the engine. Each application is characterized by the date and the identification number of the job for which it is sent. On the job postings side, the data set contains information about all applications received for each job posting (hereafter, job) on the engine. The raw data set is unprecedentedly large: it contains information on the applications of 8,000,174 job seekers who sent applications on the engine between September 2010 and September 2011 and on 1,810,610 unique job postings spread out across all U.S. states.

In the analysis, we use the job seeker's level of education as a measure of his general skill. First, we test whether at the beginning of search job seekers of different skill sort randomly across jobs (or sorting, if present, is not sufficiently pronounced) or each direct their search to a distinct subset of jobs. We reject the hypothesis that the distribution of applicants by skill at the beginning of search is the same across all jobs, i.e., we find that the average skill level of applicants differs by jobs.

We then proceed to test how sorting by skill changes with search tenure. For each job, we construct a skill index as the mean value of skill of all applicants who apply to the job during the first week of their search tenure on the engine. The index is revealed by each job seeker's choice of which jobs to apply to 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.[2] We use the index to characterize the job's type. Then we examine two aspects of the change in search behavior with search tenure. The first aspect is the change in the strength of sorting between the type of a job seeker and the type of the job that he applies to. The second aspect is the change in the types of jobs a job seeker applies to as he continues his search. In the analysis, we control for the distribution of the types of available jobs and the skills of job seekers in the job seeker's labor market in every period of his search.

We find that, as search continues, job seekers apply to different types of jobs than at the beginning of search. First, as search continues, there is less sorting by education. Second, on average, a job seeker applies to jobs of a lower type than the jobs he applies to at the beginning of search. A low type job is defined as one that on average receives applications from lower educated job seekers in their first week of search. With an additional assumption that sorting at the beginning of search is "positive", i.e., higher educated job seekers apply to higher quality jobs, we can interpret a low type job as a low quality job.

Our findings show that job seekers' ex ante information about the labor market translates into a detectable sorting pattern by education across jobs at the beginning of search. The

[2]Note that the data do not contain information on any of these attributes.

finding that, with search tenure, job seekers, on average, apply to lower type jobs than at the beginning of search has a few important implications. First, knowing the actual search pattern in the labor market allows for testing of different economic models that predict distinct search and matching equilibrium patterns. Second, it helps in understanding the job seeker's behavior and the allocation of resources in the labor market. Third, it is relevant for policy that affects job search behavior (for example, duration and generosity of unemployment benefits). In particular, with the assumption of positive sorting at the beginning of search, the finding suggests that, on average, the longer the duration of job search, the more likely a job seeker will be hired at a job with a lower skill requirement than his own skill. On the other hand, the finding suggests that the labor market is rather flexible and job seekers adjust their search as search continues.

Our work contributes to a few strands in the search literature. First, we contribute to the empirical literature that examines the behavior of reservation wages over the course of search tenure. This literature has proceeded in two directions. One direction is to estimate the behavior of reservation wages using answers to questions like, "What wage are you currently seeking?", from the cross-section of unemployed workers at different durations of their respective search tenures. For example, Kasper (1967) estimates that reservation wage declines by 0.4 percent per month. Most recently, Krueger and Mueller (2011a) 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 selection bias, as job seekers who revise their reservation wage downward are likely to find employment and thus exit the search earlier.[3] Another direction is to estimate the reservation wage from the data on unemployment durations and subsequent employment wages. While these studies take into account the selection of the search process, they require strong identifying assumptions about the wage offer distribution (see, for example, Kiefer and Neumann (1979)). A departure from these approaches is a recent work by Brown, Flinn, and Schotter (2011), who, in a series of controlled laboratory experiments in the stationary search environment, find that reservation wages decrease over time.

In our work, we characterize a job by a skill index rather than by wage. The skill index encompasses job seekers' information about wage as well as other attributes of the job and the probability of being hired. Our data set differs from the data sets used in the existing studies in that it contains records of actual individual behavior rather than self-reporting records. In this sense, our work is closely related to Brown, Flinn, and Schotter

[3] Brown, Flinn, and Schotter (2011) report dynamic selection in their laboratory experiment study, i.e., they find that unemployed workers who exit earlier have lower reservation wages.

(2011). However, in contrast to Brown, Flinn, and Schotter (2011), who examine data from a laboratory experiment, we examine a large data set where the job seekers' decisions influence their life time utility. Our findings are consistent with the literature that finds reservation wages decline with search tenure. In contrast with the results in, for example, Krueger and Mueller (2011a) from self-reporting data on reservation wages, we find that there is some adjustment of search behavior over the course of search.[4]

Our findings also contribute to the literature that tests for the presence of assortative matching between workers and firms. The result that job seekers apply to different types of jobs as search continues suggests that the observed firm-worker matches are mismatched as compared to the frictionless world. Such mismatch serves as an identification assumption for tests of assortative matching in the matched firm-worker data (see, for example, Eeckhout and Kircher (2011) and Gautier and Teulings (2006)[5]). In addition, the finding that job seekers direct their search to jobs conditional on their skill is evidence in favor of assortative matching.

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

2 Data and Sample Description

2.1 Data Description

The data in the analysis are from a private online job search engine. To apply for a job, a job seeker is required to register. Any job seeker can browse the jobs available through the engine at no cost without registration. Registration entails providing information about one's age, gender, ethnicity, education, and zip code. There is no fee to apply for a job. Also, there is no limit to how many jobs a job seeker can apply to. Firms contract with the engine to post vacancies (job postings). One important feature that characterizes jobs posted on the engine is that the jobs are hourly jobs.

The data set covers the period from September 1, 2010, to September 1, 2011. It contains information about each application sent by a registered job seeker to a job posting on the engine.[6]

[4] See a brief discussion by Robert E. Hall in Krueger and Mueller (2011b).

[5] 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.

[6] The original data set contains records of 46,125,797 applications. In some instances we observe more than one application sent from a job seeker to the same job posting on the same date. A contact person from

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 engine. Each application is characterized by the date and the identification number of the job to which it is sent. Applications match the job seekers' information to the job postings' information. 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. In the analysis we focus on jobs that receive at least one application.

When we observe that a job seeker stops applying for jobs on the engine, there can be a few explanations: 1) the applicant has accepted a job offer from a job on the engine; 2) the applicant finds a job elsewhere; 3) the applicant stops searching on the engine and keeps searching elsewhere; 4) the applicant stops searching and drops out from the labor force. We cannot distinguish between these alternatives. In addition, the search records at the end of the sample are truncated. However, for the purposes of our analysis it is sufficient to maintain the assumption that if an applicant keeps applying for jobs, this implies that he has not yet received an acceptable job offer or has not received an offer at all.[7]

2.2 Sample Description

We restrict the sample to 25-64-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." and who report gender as "Unknown" are also excluded. The resulting sample consists of 17,913,532 applications from 3,614,379 registered job seekers to 1,513,081 job postings. Note that the sample, which we refer to as the "full" sample, consists of applications sent from job seekers registered prior to September 1, 2010, (the beginning of our sample period) as well as from job seekers registered after September 1, 2010. In the analysis that follows, we sometimes focus on the sub-sample of job seekers who registered after the beginning of the sample. Such a restriction allows us to track individuals from the first period of their job search. The resulting sub-sample consists of 10,486,187 applications from 2,496,819 job seekers to 1,307,962 unique job postings. We refer to this sub-sample as the "core" sample.

Table 1 describes the full sample and the core sample. The table shows that the characteristics of the full sample (Panel A) and the core sample (Panel B) are very similar, thus,

the job postings engine has explained to us that such behavior is due to "applicants applying multiple times with the hope 'to be noticed' among applications". Thus, we cap the number of applications from a job seeker to a particular job posting on each day at 1. The resulting sample contains 40,836,592 applications.

[7] The data set does not have information on employment histories of job seekers or on wages. In addition, it does not contain information on whether the search results in hiring or not.

we focus on the description of the core sample. The core sample consists of 1,419,341 females and 1,077,478 males. Job seekers between 25 and 34 years old constitute 45% of the sample, job seekers between 35 and 44 years old constitute 25% of the sample, and the remaining 30% are 45-64-year-old job seekers. Inevitably, the types of jobs posted on the engine influence who searches on the engine. 51.7% of the sample has a high school or lower level of education, 15.5% of the sample has a bachelor's degree, and 3% of the sample has a master's degree.

Panel B of Table 1 shows that, on average, a job seeker sends 1.5 applications per day on the days that he applies. More than 50% of the job seekers in the core sample send one application. On average, we observe the last application sent by an applicant 34 days after his registration day.[8]

Further examination of the data 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 this sub-sample and the sub-sample of applicants who apply on non-registration days, we split the core sample into two sub-samples: a sub-sample of registration-day applicants only and a sub-sample of non-registration-day applicants. Panels C and D of Table 1 contain the associated summary statistics. The results indicate that the two sub-samples are similar in terms of the distribution of applicants by gender, age, and education. The share of applicants with a master's degree in the sub-sample of job seekers who apply on a non-registration day is somewhat smaller compared to the share in the sub-sample of job seekers who apply on a registration day only, 2.7% and 3.4%, respectively.

Table 2 presents statistics by age and education. 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 since registration when we observe the last application sent by an applicant in the core sample.

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 25-34-year-old job seeker on average sends 1.69 applications, while a 55-64-year-old job seeker sends 1.34 applications, with standard deviations of 1.44 and 0.87, respectively. On the other hand, the period during which we observe an older job seeker in the sample is, on average, longer than the period during which we observe a younger job seeker. In particular, the period between the registration day and the last day we observe application activity for a 25-34-year-old job seeker is 30.67 days, while for a 55-64-year-old job seeker it is 46.51 days, with standard deviations of 62.34 and 74.77, respectively. To the extent that the duration during which we observe a job seeker in the sample proxies for the duration of unemployment, this

[8] This number should be interpreted with caution because of the right-hand side truncation of the sample.

observation is consistent with the existing finding 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.

2.3 Definition of Search Tenure

2.3.1 A Period in Job Search

To understand what the appropriate length of the period to study search activity is, we analyze the periodicity with which job seekers send applications. A closer look at the daily records of application activity suggests that a week rather than a day better describes a period in the job search. 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 job search is that if labor markets are sampled at daily frequency, then some geographical labor markets have no observations.

Figure 1 shows the mean and the standard deviation of the number of applications sent by an applicant each day, conditional on the applicant still being in the sample, i.e., sending an application on a later date. The figure is constructed using information from the core sample. The statistics for each day of search tenure are calculated from the information on all job seekers in the sample, independent of whether or not the job seeker sends an application on a particular day, as long as the job seeker is still in the sample.[9] The figure shows that both the mean and the standard deviation exhibit a 7-day periodicity.

2.3.2 Search Tenure

Denote the day when a job seeker registers on the engine as day 1 of his job search. For each job seeker we define week 1 of his search as the period from day 1 to day 7 of his search, and define the subsequent weeks accordingly. Note that the start and the end of a week in search tenure differ from job seeker to job seeker. For example, a week in search tenure might start on Tuesday or Thursday.

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. Figure 3 shows the distribution of the number of applications sent in week 1 of search tenure.

[9] Thus, if a job seeker sends no applications on a particular day of his search tenure, he contributes zero applications towards calculating the statistics.

3 Sorting by Skill at the Beginning of Search

Our main questions are: Do job seekers with different skills send their applications to different jobs, and how does the sorting by skill change with search tenure? We start the analysis by examining the sorting at the beginning of search.

Let $\mathbf{U}$ denote the set of all registered job seekers and $\mathbf{V}$ denote the set of all active job postings on the engine during the sample period. We use index i to denote job seekers, $i \in \mathbf{U}$, and index j, $j \in \mathbf{V}$, to denote jobs. Let $J^{\tau,i}$ denote the set of all jobs which job seeker i applies to in week τ of his search. Let $W^{\tau,j}$ denote the set of job seekers who apply to job j in week τ of their search. Let $|\cdot|$ denote cardinality of the set.

Let e^i denote the skill level of job seeker i. We use job seeker's education as a measure of job seeker's skill and convert education levels reported by job seekers into a continuous variable that measures years of schooling and takes four values, 12, 14, 16 and 18.[10] Without loss of generality, assume that during job search, the job seeker's skill remains constant.

At the beginning of job search, do job seekers of different skills direct their searches to different jobs? Intuitively, we would like to test if sorting of job seekers across job postings is explained by skill. To answer this question, we estimate the following regression

$$e^i = \sum_{j \in \bigcup_{i \in \mathbf{U}} J^{1,i}} \alpha^j I(j \in J^{1,i}) + \varepsilon^{ij}, \forall (i,j) : j \in J^{1,i} \tag{1}$$

where each observation represents an application from job seeker i to job j in job seeker i's first week of search, and $I(\cdot)$ is the indicator function.

The test of sorting by skill at the beginning of search consists of testing

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

against the two-sided alternative. We use an F-test to test (2).

The F-statistics is 1.797 and the p-value is 0.000. Therefore, we reject the null hypothesis that the distribution of applicants by skill at the beginning of search is the same for all jobs. In particular, the results of the test indicate that the average skill level of applicants to different jobs differs.

As a robustness check, we also estimate equation (1) using an indicator function for a particular skill level, e^*, where $e^* = \{12, 14, 16, 18\}$, as a dependent variable. Thereby, we test whether the proportion of job seekers of that skill level among applicants to a job is the same across all jobs. The regression is

$$I(e^i = e^*) = \sum_{j \in \bigcup_{i \in \mathbf{U}} J^{1,i}} \alpha^j I(j \in J^{1,i}) + \varepsilon^{ij}, \forall (i,j) : j \in J^{1,i}. \tag{3}$$

[10] See Table 3 for the correspondence between educational levels and years of schooling.

We perform the same test as in equation (2), i.e., we test $\alpha^j = \alpha^{j'} \forall (j, j')$. Table 4 reports the p-values of the test statistics and the coefficients of determination from estimating equations (1) and (3) in the entire sample. The results in the table show that for each educational level, we reject the null hypothesis that the shares of applicants of a particular educational level at the beginning of search are the same across all jobs.

To control for location fixed effects, we also estimate equations (1) and (3) separately by state of residence of a job seeker. We use U.S. Census relationship files to translate zip code information into state information.[11] The p-values of the statistics of the tests for each state are 0.000.[12] For all states, we reject the hypothesis that the distribution of applicants by skill at the beginning of search is the same for all jobs.

These results suggest that at the beginning of search, job seekers direct their applications to jobs conditional on skill.

4 Change in Sorting by Skill with Search Tenure

As search continues, how do job seekers change their search? Do they continue sorting by skill as at the beginning of search? In this section we examine whether search behavior changes and how it changes with search tenure.

To answer these questions, we first characterize job seekers and the jobs they apply to. We then characterize the labor market that a job seeker faces in every period of his search tenure. Finally, we characterize the change in search behavior with search tenure.

4.1 Characterization of Jobs

4.1.1 Skill Index of Job

In the analysis, we characterize a job seeker's type by his level of education, e^i, expressed in years of schooling. We develop a new index to characterize jobs. For each job, we have information about all job seekers who apply to it. This information is important because the job seeker's decision to apply to a particular job summarizes the choice 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.

[11] The relationship between zip codes and states is obtained from http://www.census.gov/epcd/www/zipstats.html. If a zip code corresponds to more than one state, the area where the majority of the zip code population resided in 2010 is used.

[12] Table 5 reports the distribution of the coefficients of determination from regressions (1) and (3) by state.

In the previous section we find that education of a job seeker is an important determinant of which jobs he applies to at the beginning of search. It implies that education can proxy for job characteristics that are relevant for the job seeker's application decision (but not available to the researchers). Therefore, we characterize a job by the average level of skill of the job seekers who apply to the job in the first week of their job search. The skill index of job j, K^j, is defined as

$$K^j \equiv \frac{1}{|W^{1,j}|} \sum_{i \in W^{1,j}} e^i, \tag{4}$$

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

An underlying assumption behind using first-week applicants for calculating the skill index of a job is that the jobs that job seekers apply to 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 skill index in (4) is that the job seeker's skill is an important determinant of the job to which the job seeker chooses to apply. Our finding on sorting by skill at the beginning of search provides support for this assumption.

4.1.2 Discussion

A job with a higher skill index is one that, on average, receives applications from higher educated job seekers in their first week of search. In what follows, we refer to the jobs with higher skill indices as higher type jobs. The statement that, conditional on being hired, a job seeker prefers a job with a higher skill index (for example, because of higher wage), requires the assumption that the sorting uncovered at the beginning of search is, in fact, positive. Positive sorting is defined as higher educated job seekers attempting to match with higher quality firms. Without additional information about the quality of jobs associated with a particular K^j, we cannot infer whether the uncovered sorting is positive or negative.[13] Testing the assumption requires additional data on, for example, skill requirements of the jobs. Note that the assumption that the uncovered sorting at the beginning of search is positive is not needed to obtain the results in Sections 3 or 4; however, it is important for interpretations of the results in Section 4.

[13] The conditions for the existence of assortative matching, i.e., whereas better quality workers match with better quality firms is studied by Becker (1973) and in follow-up literature. The inability to empirically identify assortative matching without additional information on firms is a well-known issue in the assortative matching literature (for example, see Lopes de Melo (2009) and Eeckhout and Kircher (2011)).

Consider two hypotheses about sorting by skill with search tenure. Under the null hypothesis, sorting by skill does not change with search tenure. Under the alternative hypothesis, job seekers change their behavior with search tenure by applying to different types of jobs than the jobs they apply to in their first week of search. These hypotheses essentially describe the test that we perform in this paper. Under the null, the skill index of a job calculated from the average skill of the applicants in their first week of search tenure should be asymptotically equal to the skill index calculated from the average skill of the applicants in, for example, their second or third week of search tenure or from the average skill of all applicants to the job, independent of the week of their search tenure in which they apply. However, under the alternative hypothesis these indices differ. Thus, the skill index constructed from the average skill of the applicants in the first week of their search tenure as described in equation (4) is a consistent measure of the type of a job under both the hypothesis of no change in search behavior and the hypothesis of changing search behavior with search tenure.

The examination of how search behavior changes with search tenure consists of examining the change in the types of jobs (K^j) a job seeker applies to as he continues his search.

4.2 The Labor Market Faced by a Job Seeker

Different job seekers face different job prospects and different competition for these prospects over the course of their job search. The available jobs and the competition for these jobs are relevant factors in the application decision. In addition, moving cost considerations exclude some jobs from a job seeker's decision set. To address these issues, we define a labor market for each job seeker and control for the distribution of job seekers and available jobs in the market at the time of application.

For each job seeker i we define the labor market in calendar week t as a pair (U_t^i, V_t^i), where U_t^i denotes the set of all job seekers in the labor market and V_t^i denotes the set of all jobs in the labor market. Note that, in principle, the labor market can be defined on an individual basis. In the paper, we define the labor market of job seeker i by state of residence, $s(i)$. Thus, the set of job seekers, U_t^i, in labor market (V_t^i, U_t^i) is given by all job seekers in $s(i)$ who send at least one application in period t. The set of jobs, V_t^i, in labor market (V_t^i, U_t^i) is given by all jobs to which the job seekers from $s(i)$ apply in calendar week t, i.e., all jobs that receive applications from U_t^i.

Labor market (V_t^i, U_t^i) can be characterized by the average education of a job seeker, $\overline{e_t^i}$, and the average skill index of job in the market, $\overline{K_t^i}$, i.e.,

$$\overline{e_t^i} \equiv \frac{1}{|U_t^i|} \sum_{n \in U_t^i} e^n,$$

where $|U_t^i|$ is the number of job seekers in set U_t^i, and

$$\overline{K_t^i} \equiv \frac{1}{|V_t^i|} \sum_{j \in V_t^i} K^j,$$

where $|V_t^i|$ is the number of jobs in set V_t^i.

A simple way to control for the distribution of jobs and of job seekers is to work with their types relative to the averages in their respective markets. The type of job seeker i relative to the type of job seekers in market (V_t^i, U_t^i) is given by

$$\Delta e_t^i = e^i - \overline{e_t^i}.$$

A positive value of Δe_t^i implies that job seeker i has more years of schooling than the average job seeker in job seeker i's labor market.

The type of job j relative to the types of jobs in market (V_t^i, U_t^i) is given by

$$\Delta k_t^{i,j} = K^j - \overline{K_t^i}.$$

A positive value of $\Delta k_t^{i,j}$ implies that job j has a higher skill index than the average job in market (V_t^i, U_t^i).

4.3 A Framework for Measuring Change in Search Behavior with Search Tenure

In this subsection we develop a simple framework that allows for the estimation of the two aspects of the change in search behavior with search tenure. The first aspect is the change in the strength of sorting between the relative type of a job seeker, Δe_t^i, and the relative type of the job that he applies to, $\Delta k_t^{i,j}$, (i.e., the change in the variance of $\Delta k_t^{i,j}$ conditional on Δe_t^i). The second aspect is the average change of the relative type of jobs, $\Delta k_t^{i,j}$, that a job seeker applies to as his search continues (the change in the mean of $\Delta k_t^{i,j}$ conditional on Δe_t^i).

We start with the first aspect. Consider the correlation between the relative type of a job seeker, Δe_t^i, and the relative type of the job that he applies to, $\Delta k_t^{i,j}$, at different durations of search tenure.[14] The correlation between Δe_t^i and $\Delta k_t^{i,j}$ in the first week of search is positive

[14] Note that $corr\left(e^i - \overline{e_t^i}, K^j - \overline{K_t^i}\right)$ resembles the segregation index proposed by Kremer and Maskin (1996) for the measurement of segregation of workers by skill. However, there is an important difference: the Kremer and Maskin (1996) index would require calculating K^j from skills of all applicants who submit applications to job j, independenty of the week of their search tenure. In our paper, calculating K^j from the skills of the applicants in their first week of search is crucial for the analysis.

because (1) the job index K^j is constructed from the average education of the job seekers who apply to the job during their first week of search, and (2) in the previous section we find evidence in favor of sorting by skill at the beginning of search. To examine the change in sorting with search tenure, we examine the change in the correlation between the type of a job seeker and the type of job that he applies to as he continues his search, controlling for the distribution of available jobs and of job seekers in a labor market. Our focus on examining the correlation to study the change in sorting relies on the assumption of monotonicity of the relationship between the job seeker type (e^i) and the job type (K^j). Given the assumption of monotonicity, we proceed with interpreting the change in the correlation.

One can distinguish between the change in the sign of the correlation (the change in the pattern) and the change in the absolute value conditional on no change in the sign (the change in the strength). The sign of the correlation calculated from the applications submitted after week 1, $corr\left(\Delta e_t^i, \Delta k_t^{i,j}\right) \ \forall \ (i,t) : \tau_t^i > 1$, informs about the sorting pattern of applicants relative to the pattern at the beginning of job search. In particular, a positive correlation indicates that sorting follows the same pattern as at the beginning of search, i.e., a job seeker of a relatively higher type applies to relatively higher type jobs.

A change in the absolute value of the positive correlation between Δe_t^i and $\Delta k_t^{i,j}$ with search tenure implies a change in the strength of sorting from the beginning of search. In particular, if the correlation remains positive but decreases in absolute value, this implies that the relative education of a job seeker is a weaker predictor of the relative type of a job that he applies to.

We now turn to the second aspect of the change in search behavior with search tenure. In addition to examining the change in sorting by skill with search tenure, i.e., the change in the variance of $\Delta k_t^{i,j}$ conditional on Δe_t^i, we examine the change in the mean of $\Delta k_t^{i,j}$ conditional on Δe_t^i. The change in $\Delta k_t^{i,j}$ shows the change in the relative type of jobs that a job seeker applies to as he continues his search. If $\Delta k_t^{i,j}$ decreases with search tenure, it implies that a job seeker applies to lower type jobs as compared to the types of jobs he applies at the beginning of his search. By our definition of the type of job, a low type job means a job to which lower educated job seekers apply in their first week of search. The interpretation that a decrease in $\Delta k_t^{i,j}$ implies that a job seeker applies to lower *quality* jobs requires an additional assumption that the sorting at the beginning of search is positive (as discussed in Section 4.1.2).

To capture the change in the strength of sorting by skill with search tenure and the average change in the type of jobs a job seeker applies to, i.e., the change in the direction of applications, we estimate the following regression:

$$\Delta k_t^{i,j} = const + \gamma^1 \Delta e_t^i + \sum_{d=2}^{T} \gamma^d \Delta e_t^i I(\tau_t^i = d) + \sum_{d=2}^{T} \eta^d I(\tau_t^i = d) + \alpha^i + \varepsilon_t^i, \tag{5}$$

where τ_t^i is the search tenure of job seeker i in period t, $I(\cdot)$ is the indicator function, α^i is the individual fixed effect, and T is the total duration of search.

In equation (5), the coefficient γ^1 reflects the conditional correlation between the relative type of a job seeker and the relative type of the job that he applies to in week 1 of his search tenure. As explained above, by construction of $\Delta k_t^{i,j}$ and Δe_t^i, we expect $\gamma^1 > 0$. The coefficients on the interaction terms between Δe_t^i and $I(\tau_t^i = d)$, γ^d, show the change in the strength of sorting between the relative type of a job seeker and the relative type of the job between week 1 and week d of search tenure. The coefficients on the search tenure indicators, η^d, show the change in the average relative type of jobs a job seeker applies to between week 1 and week d of search tenure.

4.4 Empirical Results on the Skill Index of a Job

4.4.1 Empirical Implementation

The index described in equation (4) assumes that each job receives at least one application from a job seeker during his first period of search. However, this might not be the case. Some jobs might receive applications only in the second or later periods of applicants' search. To capture this possibility, for each job we calculate the earliest week in job seekers' search tenure when they apply to the job, $\tau_j^{\min}$:

$$\tau_j^{\min} \equiv \min\{\tau : j \in J^{\tau,i}, \forall i\}. \tag{6}$$

The job index in equation (4) can be generalized to include those jobs for which the earliest week does not equal 1. For these jobs, we calculate the job index from the types of job seekers who apply to the job in the week of their search that corresponds to the job's earliest week in the search. The generalized skill job index is

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

4.4.2 Results

Table 6 summarizes the distribution of the skill job index, K^j, calculated using equation (7). The average skill job index is 13.44, and the standard deviation is 1.52. For comparison,

Table 7 also contains a summary of the distribution of an alternative job index calculated using the education of all job seekers who sent applications to the job during the entire sample period. As can be seen from the table, the distributions of job indices calculated from the earliest week and from the entire sample of applicants share the same mean; however, the shapes of the distributions differ. These differences can also be seen from the two panels of Figure 4 that shows the two distributions. The difference between the distributions suggests that as search continues, job seekers of different skills direct their applications to different jobs than in their first week of job search.

4.5 Main Empirical Results

4.5.1 Empirical Implementation

In the data, a job seeker may apply to multiple jobs within a period of job search. Figure 1 shows that search intensity varies with search tenure. In addition, Table 2 indicates that there are some differences in search intensity by educational level. In the empirical implementation we ensure that the search intensity of job seekers is treated symmetrically in calculating job types and job seeker types.

The calculation of the skill index of a job takes into account search intensity because each application is counted as a separate observation. In particular, if a job seeker sends applications to multiple jobs in the first week of his search tenure, his education contributes to the calculations of the job indices of all the jobs to which he applies. Consistent with the calculation of the job indices, in calculating of the average education of job seekers in a particular market we weight each job seeker by the number of applications he sends.[15]

Since the focus of this paper is investigating the change of sorting with search tenure, we estimate equation (5) using individual weekly averages rather than individual applications. In particular, for each job seeker we calculate the average $\Delta k_t^{i,j}$ and Δe_t^i in each week of his search tenure, i.e., $\overline{\Delta k_\tau^i}$ and $\overline{\Delta e_\tau^i}$, respectively. In the estimation, each applicant-week observation is weighted by the number of applications included in the calculation of that week's average.

Regression (5) is estimated using individual fixed effects and controlling for heteroscedasticity in the error term. To identify individual fixed effects, the regressions are estimated on the sample restricted to job seekers with at least two weeks of search tenure. The sample includes all applicants who satisfy this criterion, independent of whether they were registered before or after the start of the sample period (September 1, 2010). In all regressions

[15] Note that the results do not change qualitatively if each job seeker is weighted equally, independent of how many applications he sends per period.

we control for calendar time (business cycle) effects by using a set of 12 calendar monthly dummies, from September 2010 to August 2011. We restrict the analysis to the first 10 weeks of search tenure, i.e., $T = 10$.

4.5.2 Results

Unconditional Correlations by Duration Table 8 shows the unconditional correlations between $\overline{\Delta k^i_\tau}$ and $\overline{\Delta e^i_\tau}$ at different search tenures.[16] The results in Table 8 show that the correlation between the relative type of a job seeker and the relative type of a job is positive and statistically significant in all 10 weeks of search tenure. The correlation is 0.622 in the first week and then sharply decreases to 0.342 in the second week. After the second week, the correlation gradually decreases to 0.252 in week 10. The positive correlation indicates that relatively higher educated job seekers apply to relatively higher type jobs and vice versa at all durations of search tenure, where the type of a job is identified from the types of job seekers in their first week of search. The decrease in the absolute value of the correlation with search tenure suggests that the strength of sorting of job seekers by education decreases with search tenure.

Main Regression Results The correlations at different durations of search tenure reported in Table 8 do not control for the calendar time effects or individual fixed effects. Thus, we proceed to estimate equation (5), which allows us to control for these effects and also to identify the expected average change in the relative type of jobs applied to over the course of search tenure. Column 1 of Table 9 shows the results from estimating equation (5) using the sample of job seekers with at least two weeks of search tenure and up to 10 weeks of search from the registration date on the engine.

The estimate of the coefficient on $\overline{\Delta e^i_\tau}$, γ^1, is 0.238 with a standard deviation of 0.013. The estimates of the coefficients on the interaction terms between $\overline{\Delta e^i_\tau}$ and the indicators for different durations of search tenure, γ^d, are (1) statistically significantly negative at all durations, (2) smaller in absolute value than the estimate of γ^1 at all durations, and (3) increase in absolute value with an increase of the duration. These results indicate that the correlation between the relative type of a job seeker and the relative type of a job that he applies to is positive at all durations. The negative coefficients on the interaction terms indicate that the association between $\overline{\Delta k^i_\tau}$ and $\overline{\Delta e^i_\tau}$ is statistically significantly smaller after the first week of search and becomes smaller at longer durations. Thus, the strength of sorting by education is lower at longer durations of search.

[16] In calculation of the correlations we do not restrict the sample to at least two weeks of search tenure per job seeker.

The estimates of the coefficients on the indicators that represent the duration of search, η^d, show the expected average change in the relative type of jobs, $\overline{\Delta k^i_\tau}$, that job seekers apply to at different durations of search relative to the types of jobs they apply to in the first week. The estimates are statistically significantly negative at all durations and decrease in absolute value at longer durations, albeit non-monotonically. The estimate is -0.012 in the second week and it is -0.017 in the tenth week of search tenure. These results indicate that, on average, the expected relative type of jobs that a job seeker applies to decreases with his search tenure.[17]

Column 2 of Table 9 contains estimates of equation (5) with two additional controls, the relative earliest week the job appears in a job seeker's search and the relative age of a job seeker in his labor market. Recall that in addition to the skill index, each job can be characterized by the earliest week it appears in a job seeker's search, $\tau_j^{\min}$. We can hypothesize that $\tau_j^{\min}$ describes the general appeal of a job to all types of job seekers (i.e., the later they apply to the job during their job search, the lower the job is on their list of choices). Consistent with the relative skill index, we define the relative earliest week as $\Delta\tau_j^{\min,i} = \tau_j^{\min} - \overline{\tau_j^{\min,i}}$, where $\overline{\tau_j^{\min,i}}$ is the average of $\tau_j^{\min}$ for jobs in market (U_t^i, V_t^i). The relative age is calculated by analogy with the relative skill of a job seeker, i.e., $\Delta a_t^i = a^i - \overline{a_t^i}$, where $\overline{a_t^i}$ is the average age of job seekers in market (U_t^i, V_t^i).

The results in Column 2 of Table 9 show that the estimate of the coefficient on $\Delta\tau_j^{\min,i}$ is 0.20 and the standard deviation is 0.001. The coefficient on the relative age of a job seeker is -0.002 and is not statistically significant. The estimates of the coefficients on the tenure dummies and the interaction terms are similar to the estimates in Column 1. In particular, the estimate of γ^1 is 0.256 with a standard deviation of 0.015. The estimates of the coefficients on the interaction terms between Δe_t^i and the indicators for different durations of search tenure, γ^d, are identical to those in Column 1. The notable differences are in the absolute values of the coefficient estimates on the tenure dummies, η^d. The coefficients are larger in absolute value and show a steeper increase with search tenure compared to the results in Column 1. In particular, the estimate is -0.014 for week 2 and -0.029 for week 10. The results show that if we take into account the earliest week when the job appears in job seekers' search, the average expected decline in the skill type of jobs is larger. Intuitively,

[17] The estimates show the change in the *average* direction of applications of job seekers in the economy. The direction of the change for job seekers with the lowest and the highest educational levels in the sample is restricted by construction. However, the educational composition of the sample in the study does not influence the results. The results are very similar quantitatively if we alter the educational composition of the original sample by, for example, excluding a random 90% sample of job seekers with 12 years of education (the largest education group in the sample).

there is a trade-off between the general appeal of a job and its appeal for job seekers of a particular skill.

Regression Results by Duration The estimates in Table 9 control for within individual heterogeneity; however, it is possible that the job seekers observed at longer search durations are different from those who end search earlier. To examine whether our findings are entirely a reflection of some self-selection rather than the change in search behavior with search tenure, we estimate equation (5) separately by maximum duration of search. This allows us to control for the behavior differences caused by longer-term job search. Thus, we split the sample used for the estimation of the results in Table 9 into nine sub-samples. In particular, the first sub-sample consists of all job seekers for whom we observe the last application sent in week 2 during their first ten weeks of search on the engine. The ninth sub-sample consists of all job seekers for whom we observe the last application sent in week 10 during their first ten weeks of search on the engine. The results of the estimation of equation (5) for the nine sub-samples are presented in Table 10. The results of the estimation of equation (5) with additional controls $\Delta\tau_j^{\min,i}$ and Δa_t^i for all nine sub-samples are presented in Table 11.

The results from the sample of pooled durations carry through to the sub-samples by duration. As the estimates in Table 10 indicate, the correlation between $\overline{\Delta e_\tau^i}$ and $\overline{\Delta k_\tau^i}$ decreases with the duration of the search; however, it remains positive at all durations. In all nine sub-samples, the coefficient estimates on the interaction terms between $\overline{\Delta e_\tau^i}$ and search tenure dummies are very similar. In all sub-samples, except for the sub-sample of job seekers who search for five weeks, we find that, on average, job seekers apply to lower type jobs as search continues. This is indicated by the coefficient estimates on search tenure dummies that are negative and increasing in absolute value.

The results in Table 11, which control for $\Delta\tau_j^{\min,i}$ and Δa_t^i, are similar to those observed in Table 10. By analogy with Columns 1 and 2 of Table 9, we observe that controlling for the earliest week of a job causes an increase in the absolute value of the coefficient estimates on the tenure dummies by a factor of two.

5 Conclusion

In this paper we use a novel data set to study sorting by education during job search. Essentially, sorting is a projection of the choice of where to apply on education.

The results in the paper indicate that at the beginning of job search, job seekers sort across jobs by education. As search continues, search behavior of a job seeker changes: job seekers apply to different types of jobs than at the beginning of search.

To characterize the change in search behavior with search tenure, we develop a skill index for each job. The skill index of a job is the average educational level of job seekers who apply to the job during their first week of search. The estimation framework developed in the paper controls for the distribution of available jobs and the distribution of job seekers in the labor market faced by the job seeker in every period of his search.

We find that as search continues there is less sorting by education. In addition, we find that as a job seeker continues his search, he, on average, applies to jobs with a relatively lower index than at the beginning of search. With an additional assumption that sorting at the beginning of search is positive (i.e., higher educated job seekers apply to higher quality jobs), we can interpret our finding that, on average, a job seeker applies to lower quality jobs as search continues. To corroborate the initial positive sorting one needs data on the skill requirements of the jobs.

The results have a few important implications for the theoretical job search literature. First, the results could be interpreted as indicating that private cost of job search (unemployment) increases with search tenure.[18] Second, the results provide some evidence in favor of assortative matching in the sense that job seekers of different educational levels send applications to different jobs, at least at the beginning of their job search. Finally, our finding that job seekers direct their search to lower type 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.

As stated earlier, the jobs in the analysis are hourly jobs. Remarkably, even in the sample of these relatively homogenous jobs we find evidence of sorting by education. With salaried jobs, the cost of mismatch is likely higher than with hourly jobs because, for example, hourly jobs have higher turnover than salaried jobs. Thus, with salaried jobs the sorting at the beginning of search is likely stronger. However, the speed of the change of the direction of search might be slower. More data are needed to examine these questions.

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 for unemployment-reduction policies.

[18] We do not have information on whether a job seeker is unemployed or employed: presumably, for employed job seekers the reservation wage does not need to decline below their current wage. This bias works against our results.

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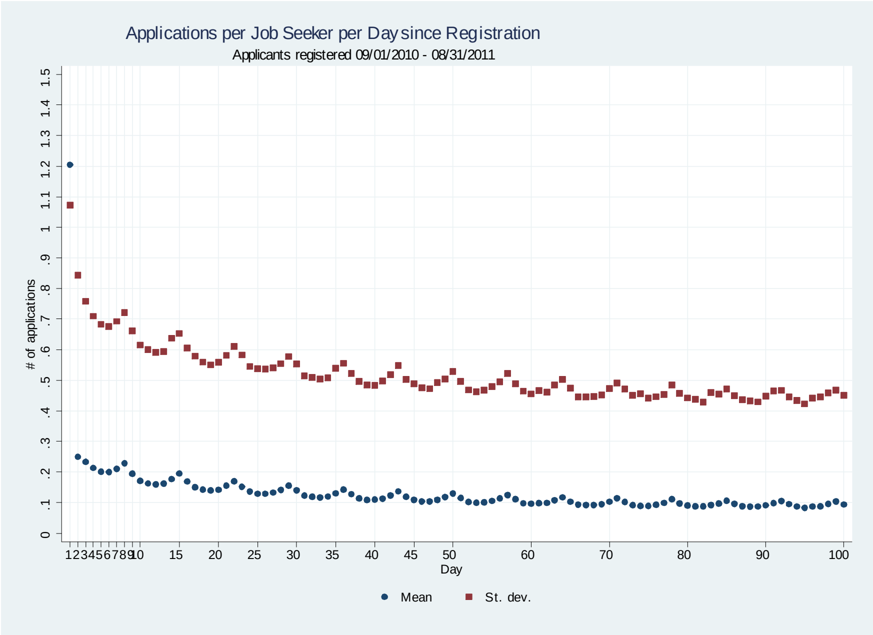
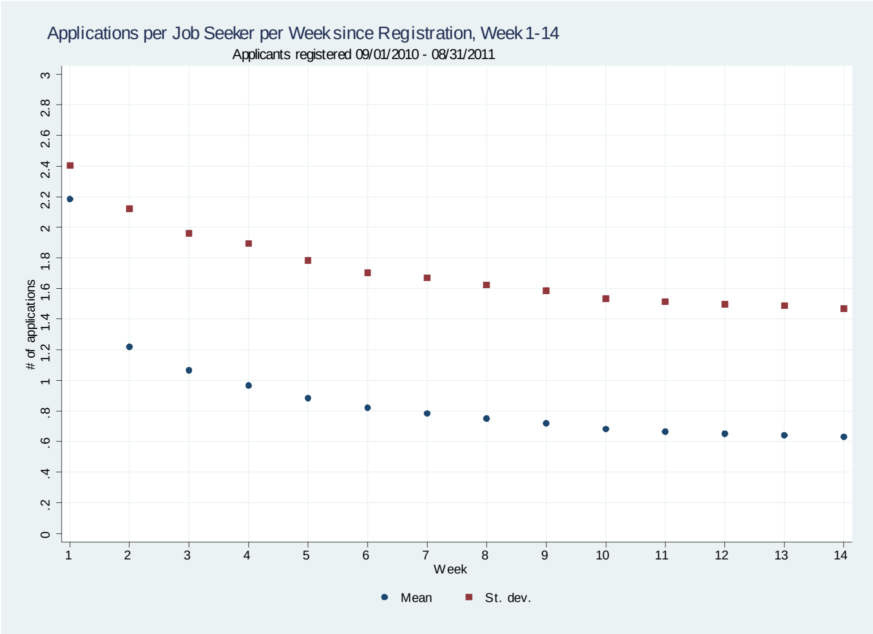
Figure 1:



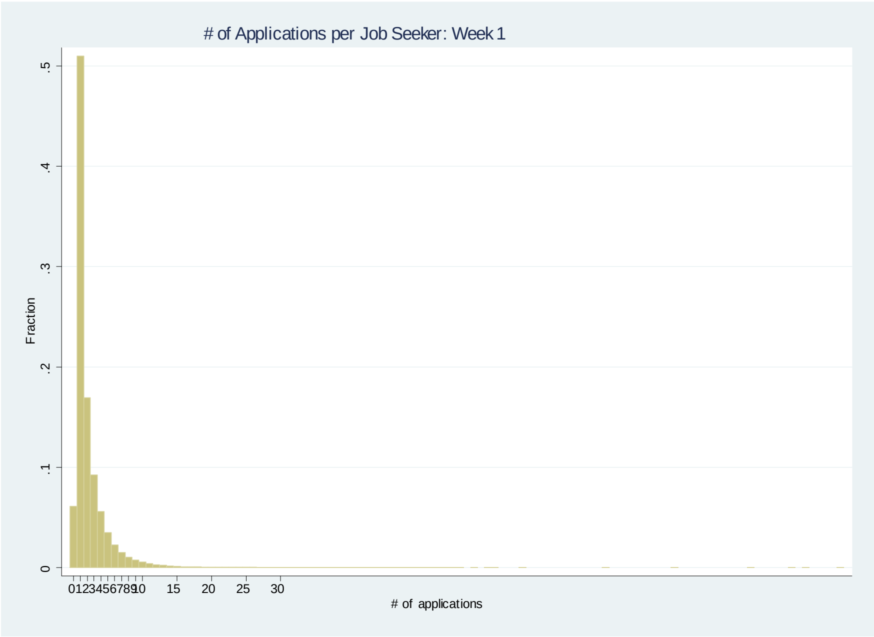
Notes: The statistics are from the core sample, i.e., the sample of applicants registered between September 1 2010 and September 1 2011.

Figure 2:



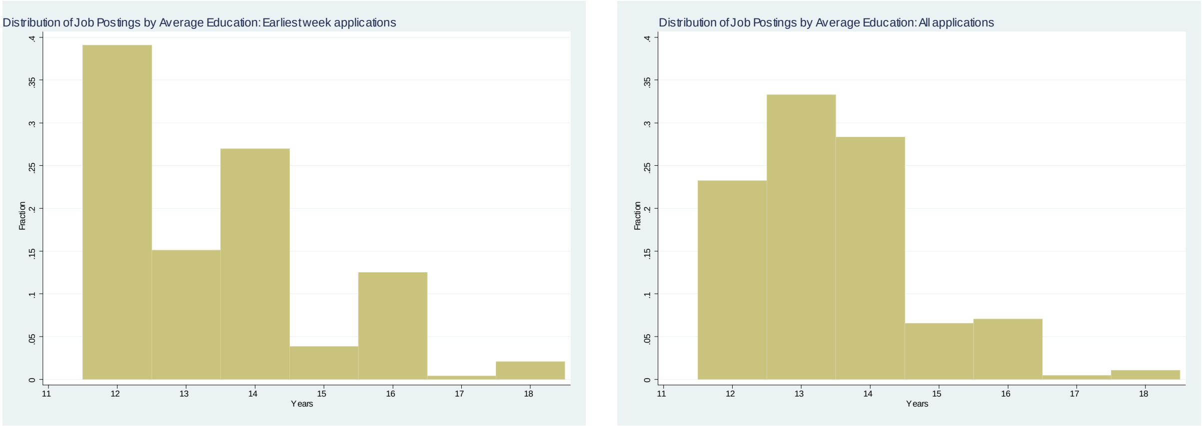
Notes: The statistics are from the core sample, i.e., the sample of applicants registered between September 1 2010 and September 1 2011.

Figure 3:



Note: The bin width is 1.

Figure 4:



Notes: Bin width is 1.

Table 1: Sample Description

	Sample							
	Full		Core (a subsample of job seekers registered 9/1/2010-9/1/2011)					
			Core sample, all		Registration day applicants only		At least one application on non-registration day	
	Panel A		Panel B		Panel C		Panel D	
	#	%	#	%	#	%	#	%
Job seekers								
Total	3,614,379	100.0	2,496,819	100.0	1,321,964	100.0	1,174,855	100.0
By Gender								
Female	2,100,670	58.1	1,419,341	56.9	744,305	56.3	675,036	57.5
Male	1,513,709	41.9	1,077,478	43.2	577,659	43.7	499,819	42.5
By Age								
25-34	1,626,724	45.0	1,126,625	45.1	635,822	48.1	490,803	41.8
35-44	895,410	24.8	633,547	25.4	336,886	25.5	296,661	25.3
45-54	739,398	20.5	503,372	20.2	243,484	18.4	259,888	22.1
55-64	352,847	9.8	233,275	9.3	105,772	8.0	127,503	10.9
By Education								
Masters Degree Program	100,788	2.8	76,010	3.0	44,711	3.4	31,299	2.7
Bachelors Degree Program	570,564	15.8	386,859	15.5	201,582	15.3	185,277	15.8
Associate Degree Program	554,148	15.3	366,202	14.7	181,189	13.7	185,013	15.8
Vocational/Trade School	259,826	7.2	180,316	7.2	94,808	7.2	85,508	7.3
Professional or Training School	153,616	4.3	103,851	4.2	56,680	4.3	47,171	4.0
Certification Program	137,474	3.8	91,991	3.7	46,972	3.6	45,019	3.8
High School	1,535,324	42.5	1,062,245	42.5	566,348	42.8	495,897	42.2
GED Program	302,639	8.4	229,345	9.2	129,674	9.8	99,671	8.5
Applications								
Total	17,913,532		10,486,187		1,792,820		8,693,367	
Per applicant per day, conditional on days when at least 1 appl is sent								
Mean	1.6		1.5		1.4		1.6	
St. dev.	1.3		1.2		1.0		1.3	
Min	1		1		1		1	
Median	1		1		1		1	
75th percentile	2		2		1		2	
Max	142		94		71		94	
Period between the registration day and the last day observed in the sample								
Mean	219.5		35.4		1.0		74.1	
St. dev.	363.1		66.7		0.0		81.4	
Min	1		1		1		2	
Median	26		1		1		40	
75th percentile	295		35		1		113	
Max	4062		365		1		320	

Table 2: Sample Statistics by Age and Education, for the Subsample of Job Seekers Registered 9/1/2010-9/1/2011

	# of applications per day, conditional on days when at least 1 appl is sent		Period between the registration day and the last day observed in the sample	
	Mean	St. dev.	Mean	St. dev.
All				
	1.55	1.23	35.41	66.70
By Age				
25-34	1.69	1.44	30.67	62.34
35-44	1.53	1.20	34.92	66.33
45-54	1.42	1.01	41.50	71.40
55-64	1.35	0.87	46.51	74.77
By Education				
Masters Degree Program	1.45	1.13	30.09	62.10
Bachelors Degree Program	1.52	1.21	36.81	67.99
Associate Degree Program	1.57	1.26	39.71	70.36
Vocational/Trade School	1.54	1.23	35.69	66.85
Professional or Training School	1.49	1.14	34.44	66.06
Certification Program	1.55	1.24	38.42	69.46
High School	1.55	1.24	34.77	66.08
GED Program	1.58	1.28	29.94	61.07

Notes: The statistics are from the core sample, i.e., the sample of applicants registered between September 1 2010 and September 1 2011.

Table 3: Educational Levels Expressed in Years of Schooling

Education	Years of Schooling
Masters Degree Program	18
Bachelors Degree Program	16
Associate Degree Program	14
Vocational/Trade School	14
Other Professional or Training School	14
Certification Program	12
High School	12
GED Program	12

Table 4: Sorting by Education at the Beginning of Search

Skill measure	F-stat (p-value)	R sq
Continuous		
Education (years of schooling)	1.797 (0.000)	0.32
Bivariate		
High school, GED or Certificate	1.491 (0.000)	0.28
Associate Degree, Vocational School or Professional/Trade School	1.163 (0.000)	0.23
Bachelor degree	1.527 (0.000)	0.29
Master degree	1.572 (0.000)	0.29

Table 5: Regression Results from Estimating Sorting by Education at the Beginning of Search, by State

Skill measure	R sq	
	Mean	St. dev.
	1	2
Continuous		
Education (years of schooling)	0.366	0.062
Bivariate		
High school, GED or Certificate	0.332	0.063
Associate Degree, Vocational School or Professional/Trade School	0.296	0.067
Bachelor degree	0.342	0.066
Master degree	0.353	0.081

Table 6: Distribution of Jobs by the Skill Index

	Percentiles	Smallest		
1%	12.00	12		
5%	12.00	12		
10%	12.00	12	Obs	1513081
25%	12.00	12	Sum of Wgt.	1513081
50%	13.11		Mean	13.44
		Largest	Std. Dev.	1.52
75%	14.00	18		
90%	16.00	18	Variance	2.30
95%	16.00	18	Skewness	0.93
99%	18.00	18	Kurtosis	3.17

Table 7: Distribution of Jobs by the Average Education of All Applicants to the Job

	Percentiles	Smallest		
1%	12.00	12		
5%	12.00	12		
10%	12.00	12	Obs	1513081
25%	12.55	12	Sum of Wgt.	1513081
50%	13.30		Mean	13.44
		Largest	Std. Dev.	1.50
75%	14.00	18		
90%	15.00	18	Variance	1.50
95%	16.00	18	Skewness	1.05
99%	18.00	18	Kurtosis	4.28

Table 8: Correlation between the Relative Type of Job Seeker and the Relative Type of Job, by Search Tenure

Week 1	0.622
	0.000
Week 2	0.342
	0.000
Week 3	0.314
	0.000
Week 4	0.293
	0.000
Week 5	0.286
	0.000
Week 6	0.272
	0.000
Week 7	0.270
	0.000
Week 8	0.262
	0.000
Week 9	0.260
	0.000
Week 10	0.252
	0.000

Notes: The standard errors are in small font.

Table 9: THE CHANGE IN SORTING BY SKILL WITH SEARCH TENURE, POOLED DURATIONS SAMPLE

	1	2
delta_e	**0.238**	**0.256**
	0.013	0.015
I(week=2)*delta_e	**-0.116**	**-0.116**
	0.001	0.001
I(week=3)*delta_e	**-0.127**	**-0.127**
	0.001	0.001
I(week=4)*delta_e	**-0.136**	**-0.136**
	0.001	0.001
I(week=5)*delta_e	**-0.139**	**-0.139**
	0.001	0.001
I(week=6)*delta_e	**-0.142**	**-0.143**
	0.002	0.002
I(week=7)*delta_e	**-0.142**	**-0.143**
	0.002	0.002
I(week=8)*delta_e	**-0.143**	**-0.143**
	0.002	0.002
I(week=9)*delta_e	**-0.145**	**-0.145**
	0.002	0.002
I(week=10)*delta_e	**-0.143**	**-0.143**
	0.002	0.002
I(week=2)	**-0.012**	**-0.014**
	0.001	0.001
I(week=3)	**-0.012**	**-0.016**
	0.002	0.002
I(week=4)	**-0.014**	**-0.019**
	0.002	0.002
I(week=5)	**-0.012**	**-0.018**
	0.002	0.002
I(week=6)	**-0.012**	**-0.020**
	0.003	0.003
I(week=7)	**-0.015**	**-0.023**
	0.003	0.003
I(week=8)	**-0.015**	**-0.025**
	0.004	0.004
I(week=9)	**-0.018**	**-0.029**
	0.004	0.004
I(week=10)	**-0.017**	**-0.029**
	0.004	0.004
Relative age of i	x	-0.002
		0.002
Relative min week of j	x	**0.020**
		0.001
Const	**-0.047**	**-0.063**
	0.002	0.003
Monthly time effects	yes	yes
Fixed effects	yes	yes
Adj. Rsq.	0.386	0.386
N obs.	2,438,129	2,438,129
N ind.	791,057	791,057

Note: The sample is restricted to job seekers with at least two weeks of job search. Dummies show the difference between week x and week 1. The variables in bold are statistically significant at a 5% significance level. The standard errors are in small font.

Table 10: Sorting by Skill with Search Tenure, by Duration of Search

	Total Duration of Job Search, weeks								
	2	3	4	5	6	7	8	9	10
delta_e	**0.219**	**0.271**	**0.294**	**0.265**	**0.234**	**0.159**	**0.257**	**0.240**	**0.242**
	0.051	0.047	0.045	0.045	0.045	0.042	0.040	0.035	0.027
I(week=2)*delta_e	**-0.113**	**-0.115**	**-0.123**	**-0.113**	**-0.111**	**-0.119**	**-0.128**	**-0.113**	**-0.120**
	0.002	0.003	0.003	0.003	0.004	0.004	0.004	0.003	0.003
I(week=3)*delta_e	x	**-0.123**	**-0.130**	**-0.123**	**-0.125**	**-0.125**	**-0.137**	**-0.132**	**-0.129**
		0.002	0.004	0.004	0.004	0.004	0.004	0.004	0.003
I(week=4)*delta_e	x	x	**-0.137**	**-0.137**	**-0.140**	**-0.135**	**-0.140**	**-0.135**	**-0.135**
			0.002	0.004	0.004	0.004	0.004	0.004	0.003
I(week=5)*delta_e	x	x	x	**-0.136**	**-0.136**	**-0.144**	**-0.140**	**-0.141**	**-0.143**
				0.003	0.004	0.004	0.004	0.004	0.003
I(week=6)*delta_e	x	x	x	x	**-0.136**	**-0.146**	**-0.150**	**-0.147**	**-0.144**
					0.003	0.004	0.004	0.004	0.003
I(week=7)*delta_e	x	x	x	x	x	**-0.141**	**-0.143**	**-0.148**	**-0.145**
						0.003	0.004	0.004	0.003
I(week=8)*delta_e	x	x	x	x	x	x	**-0.144**	**-0.145**	**-0.146**
							0.003	0.004	0.003
I(week=9)*delta_e	x	x	x	x	x	x	x	**-0.142**	**-0.152**
								0.003	0.003
I(week=10)*delta_e	x	x	x	x	x	x	x	x	**-0.145**
									0.002
I(week=2)	**-0.011**	**-0.008**	**-0.013**	-0.004	**-0.012**	**-0.018**	**-0.017**	**-0.016**	**-0.010**
	0.003	0.004	0.005	0.005	0.005	0.005	0.005	0.005	0.004
I(week=3)	x	**-0.011**	**-0.011**	-0.003	**-0.014**	**-0.017**	**-0.018**	**-0.018**	**-0.009**
		0.004	0.005	0.006	0.006	0.006	0.006	0.006	0.004
I(week=4)	x	x	**-0.012**	-0.012	**-0.020**	**-0.019**	**-0.021**	**-0.023**	-0.006
			0.005	0.007	0.007	0.007	0.007	0.006	0.005
I(week=5)	x	x	x	-0.007	-0.015	**-0.015**	**-0.015**	**-0.021**	-0.008
				0.006	0.008	0.007	0.007	0.007	0.005
I(week=6)	x	x	x	x	**-0.016**	-0.013	**-0.020**	**-0.015**	**-0.014**
					0.008	0.008	0.008	0.008	0.006
I(week=7)	x	x	x	x	x	-0.012	**-0.033**	**-0.013**	**-0.013**
						0.008	0.009	0.008	0.006
I(week=8)	x	x	x	x	x	x	**-0.030**	**-0.017**	**-0.012**
							0.009	0.009	0.007
I(week=9)	x	x	x	x	x	x	x	**-0.019**	**-0.019**
								0.009	0.007
I(week=10)	x	x	x	x	x	x	x	x	**-0.017**
									0.008
Const	**-0.086**	**-0.083**	**-0.076**	**-0.060**	**-0.045**	**-0.039**	**-0.029**	**-0.033**	**-0.045**
	0.018	0.014	0.012	0.010	0.009	0.007	0.007	0.006	0.004
Monthly time effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. Rsq.	0.501	0.453	0.424	0.402	0.382	0.373	0.357	0.338	0.327
N obs.	277,492	251,053	231,542	221,946	215,971	223,478	250,394	301,349	464,904
N ind.	138,746	106,522	86,815	75,876	68,345	65,818	68,826	76,514	103,595

Note: Each regression is estimated on the sub-sample restricted to the job seekers with the stated maximum duration of search (the period from the registration date to the date of last observed application). Each sample is restricted to job seekers with at least two weeks of job search. Dummies show the difference between week x and week 1. The variables in bold are statistically significant at a 5% significance level. The standard errors are in small font.

Table 11: Sorting by Skill with Search Tenure (Regressions with Additional Controls), by Duration of Search

	Total Duration of Job Search, weeks								
	2	3	4	5	6	7	8	9	10
delta_e	**0.212**	**0.260**	**0.284**	**0.268**	**0.239**	**0.154**	**0.258**	**0.241**	**0.244**
	0.052	0.047	0.045	0.045	0.045	0.042	0.040	0.035	0.027
I(week=2)*delta_e	**-0.113**	**-0.116**	**-0.124**	**-0.113**	**-0.111**	**-0.119**	**-0.128**	**-0.113**	**-0.120**
	0.002	0.003	0.003	0.003	0.004	0.004	0.004	0.003	0.003
I(week=3)*delta_e	x	**-0.124**	**-0.130**	**-0.124**	**-0.125**	**-0.125**	**-0.137**	**-0.132**	**-0.130**
		0.002	0.004	0.004	0.004	0.004	0.004	0.004	0.003
I(week=4)*delta_e	x	x	**-0.138**	**-0.137**	**-0.140**	**-0.135**	**-0.140**	**-0.135**	**-0.135**
			0.002	0.004	0.004	0.004	0.004	0.004	0.003
I(week=5)*delta_e	x	x	x	**-0.137**	**-0.137**	**-0.144**	**-0.140**	**-0.141**	**-0.143**
				0.002	0.004	0.004	0.004	0.004	0.003
I(week=6)*delta_e	x	x	x	x	**-0.137**	**-0.147**	**-0.150**	**-0.148**	**-0.145**
					0.003	0.004	0.004	0.004	0.003
I(week=7)*delta_e	x	x	x	x	x	**-0.142**	**-0.143**	**-0.148**	**-0.145**
						0.003	0.004	0.004	0.003
I(week=8)*delta_e	x	x	x	x	x	x	**-0.145**	**-0.146**	**-0.147**
							0.003	0.004	0.003
I(week=9)*delta_e	x	x	x	x	x	x	x	**-0.143**	**-0.152**
								0.003	0.003
I(week=10)*delta_e	x	x	x	x	x	x	x	x	**-0.146**
									0.002
I(week=2)	**-0.021**	**-0.014**	**-0.016**	-0.007	**-0.015**	**-0.020**	**-0.018**	**-0.017**	**-0.011**
	0.003	0.004	0.005	0.005	0.005	0.005	0.005	0.005	0.004
I(week=3)	x	**-0.022**	**-0.018**	-0.010	**-0.020**	**-0.021**	**-0.021**	**-0.020**	**-0.011**
		0.004	0.005	0.006	0.006	0.006	0.006	0.005	0.004
I(week=4)	x	x	**-0.022**	**-0.022**	**-0.028**	**-0.024**	**-0.026**	**-0.027**	**-0.009**
			0.005	0.007	0.007	0.007	0.007	0.006	0.005
I(week=5)	x	x	x	**-0.021**	**-0.025**	**-0.021**	**-0.021**	**-0.026**	**-0.012**
				0.007	0.008	0.008	0.007	0.007	0.005
I(week=6)	x	x	x	x	**-0.029**	**-0.020**	**-0.027**	**-0.021**	**-0.019**
					0.008	0.008	0.008	0.008	0.006
I(week=7)	x	x	x	x	x	**-0.021**	**-0.041**	**-0.020**	**-0.018**
						0.008	0.009	0.008	0.006
I(week=8)	x	x	x	x	x	x	**-0.039**	**-0.025**	**-0.019**
							0.009	0.009	0.007
I(week=9)	x	x	x	x	x	x	x	**-0.028**	**-0.026**
								0.009	0.007
I(week=10)	x	x	x	x	x	x	x	x	x
Relative age of i	0.001	0.002	0.008	**-0.010**	-0.009	0.005	-0.004	-0.002	-0.003
	0.006	0.006	0.005	0.005	0.005	0.005	0.005	0.004	0.003
Relative min week	**0.103**	**0.060**	**0.041**	**0.040**	**0.031**	**0.023**	**0.019**	**0.017**	**0.013**
of j	0.014	0.008	0.006	0.005	0.004	0.003	0.003	0.002	0.002
Const	**-0.179**	**-0.134**	**-0.108**	**-0.094**	**-0.069**	**-0.039**	**-0.042**	**-0.046**	**-0.050**
	0.023	0.016	0.013	0.011	0.009	0.007	0.008	0.008	0.008
Monthly time effect	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. Rsq.	0.502	0.454	0.424	0.403	0.383	0.373	0.357	0.338	0.327
N obs.	277,492	251,053	231,542	221,946	215,971	223,478	250,394	301,349	464,904
N ind.	138,746	106,522	86,815	75,876	68,345	65,818	68,826	76,514	103,595

Note: Each regression is estimated on the sample restricted to the job seekers with the stated maximum duration of search (the period from the registration date to the date of last observed application). Each sample is restricted to job seekers with at least two weeks of job search. Dummies show the difference between week x and week 1. The variables in bold are statistically significant at a 5% significance level. The standard errors are in small font.