The Jobless Trap

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ABSTRACT

Three recent audit studies on nonemployment discrimination report results consistent with the long-term jobless having significantly lower chances of being invited to job interviews. Given the design of previous studies unfavorable treatment can be due to a marginal preference among employers for hiring applicants with shorter spells or to stronger negative beliefs about the long-term nonemployed. Using a résumé audit study, I explore the extent to which employers become forgiving of longer nonemployment spells when other merits appear on an applicant's résumé: in this case relevant work experience. Responses indicate a strong distaste for applicants with long spells of nonemployment—even in a situation characterized by observationally superior résumés in comparison to applicants with short nonemployment spells. The findings reveal a sharp drop-off in the number of interview requests for those whose nonemployment spell topped six months, implying that those experiencing long jobless spells might become trapped in nonemployment, regardless of their prior experience. To interpret the findings, a nonstationary job search model under duration-dependent unemployment benefits and endogenous job search intensity is constructed. It is shown that in the spirit of Lockwood (1991), the model can generate a unique equilibrium for plausible parameter values, with unemployment benefits expiration date becoming a focal point around which job search intensifies and employer screening becomes optimal.

JEL CLASSIFICATION: J64
KEYWORDS: LONG-TERM UNEMPLOYMENT, EMPLOYER SCREENING, FIELD EXPERIMENTS, NONSTATIONARY JOB SEARCH.

1 INTRODUCTION

Although the unemployment rate in the U.S. declined slowly since the trough of the Great Recession, the duration of unemployment has continued to rise. In 2012, the duration of unemployment in the U.S. averaged around nine months-a 140 percent increase from its pre-recession average. This continued high level of long-term unemployment is especially puzzling in light of the fact that, during the same period, firms were posting substantially more vacancies. The mystery is not how this high fraction of long-term unemployed arose, but rather it's why long-term unemployment has far outlived its original causes. While it has proven difficult to credibly establish that jobseekers' re-employment prospects decline with the length of time out of work, a number of recent audit studies make it seem that long-term unemployment can mark jobseekers as undesirable, making it harder for them to compete against other job applicants; applicants with long nonemployment spells were less likely to be invited to job interviews than observationally similar workers with shorter spells. In one study, the authors report that at eight months of unemployment, callbacks are about 45 percent lower than at one month of unemployment, Kroft et al. (2013) . This worrisome pattern raises serious concerns about the social and macroeconomic dysfunctions that such chronic joblessness might cause.

Employers invest a good deal in screening applicants, but no screening process is perfect so hiring is commonly an investment made under uncertainty. Part of the hiring decision may thus be influenced by employers' beliefs about the average characteristics of different groups (statistical discrimination) and differential treatment may reflect these beliefs. Are employers' screening decisions based solely on easily observable characteristics such as the length of a nonemployment spell? When other productivity-related merits are revealed, do they rely less on this variable in screening applicants? These questions are directly relevant for economic policy making, however, as implications for labor market policy are likely to be different based on what factors explain the documented pattern. If the effect reflects stigma, then active short-term macroeconomic policies may not be necessary to lower aggregate unemployment rates in the long run because stigma effects are likely to be weaker in good times than when nonemployment is experienced in severe recessions. In contrast, if the effect reflects human capital depreciation, then short-term macroeconomic policies to alleviate unemployment and traditional job training programs to help the unemployed restore lost skills are appropriate.

Previous résumé audit studies on nonemployment discrimination have focused exclusively on measuring callback differentials across observationally similar workers who differ only in their nonemployment spell.[1] While these studies consistently find discrimination against individuals with long spells of nonemployment, the reported callback gaps across groups do not reveal the intensity of employer beliefs. If job seekers with short nonemployment spells are only marginally preferred, it implies that firms, all else equal, favor applicants with short jobless spells. An individual who had been without a job for a long time would only suffer from discrimination when there is a nearly identical applicant but with a shorter nonemployment spell competing for the same vacancy. This is very different from the case when the long-term nonemployed are believed to be significantly less productive on average than those with shorter durations. In this case applicants with long nonemployment spells would suffer from discrimination also in a situation characterized by superior résumés in comparison to the favored group (the short-term nonemployed).

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[1]Kroft et al., (2013); Eriksson and Rooth (2011); Oberholder-Gee (2008)

This study explores the extent to which employers become forgiving of longer nonemployment spells when other merits appear on an applicant's résumé: in this case, having worked in the same type of firm as the prospective employer.[2] While worker characteristics such as education may be thought to index more general skills of worker trainability into and adaptability at a new job position (Thurow, 1975), work experience might be more indicative of the accumulation of specific skills that are not readily transferred to all other employers or labor market sectors. If that is the case, then employers still have strong incentives to hire those with appropriate specific skills in order to minimize the incidence and costs of unproductive training. As a result, the probability to be matched to an employer in sector j will crucially depend on whether the applicant's own skills acquired through previous training and work experiences matches or at least functionally relates to those skills required in sector j.

While several studies have explored the importance of skills which are either specific to a given employer or completely general, many others have looked at industry-specific skills as an important component of the typical worker's human capital stock.[3] These studies conclude that workers are valued not only based on skills that are completely general and/or firm-specific, but rather on some skills that are specific to their industry or line of work. For example, all employers in the banking industry may value a common set of skills that are vital to the working conditions in that industry. However, these same skills may not be valued by employers looking to fill similar vacancies in closely related or different industries. In this audit study, I manipulate the length of time out of work and "relevancy" of prior industry experience to highlight the interaction between the higher returns to industry-relevant experience and the duration of nonemployment. I submit roughly 3360 fictitious résumés to 600 job ads divided among a specific set of firms in four targeted industries (Financial Activities, Wholesale and retail trade, Professional and Business Services, as well as Education and Health Services). Jobs ads were distributed among multiple occupations in different areas of the U.S. and applicants' credentials on résumés were randomly manipulated to uncover how different résumé characteristics affect firms' decisions on whether to interview an applicant. The résumés were constructed to plausibly represent relatively young applicants with six years of work experience out of college. Employment status and the duration of the current nonemployment spell were randomized across résumés and appeared as an end date for the applicant's most recent job. In addition, I randomized whether applicants worked previously (or are currently employed) in the same type of firm as the prospective employer by randomly assigning half of the résumés jobs with the same type of firm as the prospective employer and the other half jobs from different (no relevant experience) industries. This setup allows me to examine the strength of negative beliefs about those with long spells of nonemployment and the extent to which relevant industry experience compensates for any unfavorable treatment.

The reported results for my entire sample reveal that applicants with long nonemployment spells are less likely to be invited for job interviews. A graphical examination of the data (Figure I) reveals a sharp drop off in average interview requests after six months of nonemployment. Applicants with one month of nonemployment need to send about 10 résumés to get one interview request whereas applicants with seven months of nonemployment need to send about 35.

Results from comparing applicants with relevant industry experience to others with no relevant experience reveal a large and significant premium for applicants from the same type of

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[2]I refer to work experience that is transferable between the same type of firms in an industry as industry-specific human capital

[3]Neal (1995) and Kletzer (1993). Also, see Willis (1986) for a review of empirical work on human capital. Neal (1995)

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firm as the prospective employer. The probability of receiving an interview request is higher for jobseekers with skills specific to firms that produce similar products and services. However, this is only true for those with short nonemployment spells. After six months of nonemployment, the return to industry-relevant experience declines dramatically and the response gap between applicants with specific experience and those with no relevant experience becomes statistically insignificant. Between one and six months of nonemployment, the average interview requests for applicants who apply to job openings with similar type of firms is 8 percent higher than that of applicants without relevant industry experience.

I then explore how the gap in interview requests between short-term and long-term nonemployed varies with an applicant's work experience. The results indicate that recently nonemployed applicants with no relevant experience are more likely to be invited for an interview than those with experience who have been nonemployed for more than six months.

The experiment reveals direct evidence on how the length of time out of work affects reemployment prospects of heterogeneous workers by emphasizing the employer's role in generating negative duration dependence. In particular, it identifies the casual effect of nonemployment spells on the probability of receiving an interview request that arises either from employers' beliefs about the quality of the long-term unemployed or because employers prefer to hire those with the shortest duration of nonemployment. In the former case, employers may then engage in statistical discrimination when the productivity of workers is only imperfectly observed or they may associate long nonemployment spells with a loss in human capital. While there is a broad agreement that human capital may atrophy with long nonemployment spells, there is little, if any, evidence on how that differs between general and industry-specific human capital. The distinction between workers (résumés) with skills specific to the same type of firms and those with no industry-specific skills will shed light on the implications of long spells of nonemployment on the different types of human capital.

The second contribution of this paper is to provide a theoretical framework that explains the drop in the interview requests after six months of nonemployment. The theory nests a specific class of screening models, such as Lockwood (1991), where employers use the duration of nonemployment as a signal of applicants' productivity. Employers experience with the long-term nonemployed is that they are probably not very productive and therefore they are typically reluctant to interview them. The point where employers stop interviewing becomes something of a focal point when workers, realizing that being unemployed for long periods of time will hurt their chances of employment, intensify their search as that date grows near. This reinforces the focal point as good workers leave the workforce in large numbers during the frenzy of job hunting just before the cut off. In the U.S., I believe that this happens at six months when unemployment insurance normally expires.

The remainder of the paper is organized as follows. Section 2 provides an overview on the literature of duration dependence and adverse selection. Section 3 describes the resume experiment, with sub-section (3.1) presenting my study's experimental design; and (3.2) describing the measurement of firms' responses. Sections 4 and 5 present results and alternative theoretical explanations respectively. Section 6 extends Lockwood's (1991) model by allowing for nonstationarity in job search and unemployment benefits, while Section 7 concludes.

2 WHAT EXPLAINS NEGATIVE DURATION DEPENDENCE?

A common finding is that among unemployed workers, for the most part, those with the short spells are more likely to find a job than those with longer spells (Layard *et* al., 1991; van der Berg van Ours, 1996). This is referred to as negative duration dependence. A important question in the study of unemployment has been whether otherwise similar people with different lengths of unemployment have different probabilities of exiting unemployment (true duration dependence) or whether unobserved heterogeneity of the unemployed gives rise to spurious duration dependence. If unemployed workers have constant but different hazard rates, then the better workers (those with higher hazard rates) tend to exit unemployment earlier, leaving a pool of less-qualified workers as the ones who disproportionately make it to long-term unemployment. True duration dependence instead arises when the outflow rate at any point in time depends on the amount of time that has already passed. Intuitively, anyone entering unemployment will experience negative time dependence in the arrival rate of job opportunities.

This genuine (true) effect has been justified using several demand and supply side explanations. On the supply side, Devine and Kiefer (1991) summarize a number of studies which report a negative relationship between workers' search intensity and unemployment duration. This may be primarily due to workers becoming discouraged (and as a result search passively for vacancies as their jobless spells increase), or because skills and work training atrophy during unemployment (Sinfield, 1981). Furthermore, Heckman and Borjas (1980) document that there is a negative duration dependence in the arrival of job opportunities during unemployment. Individuals with long jobless spells find it more difficult to know about the existence of jobs, either due to the loss of networks and social contacts (Calvo-Armengol, 2000), or because the long-term unemployed become stigmatized by other workers in the market (Gregg and Wadsworth, 1996). Finally, Coles and Smith (1994) and Gregg and Petrongolo (1997) provide another supply side explanation revealing that the number of vacancies sampled by the unemployed fall rapidly as unemployment lengthens leading to negative duration dependence.

Alternatively, a lot of attention has been recently been devoted to the demand side explanations for duration dependence. The underlying factor behind the decline in outflow rate with duration of unemployment in this case is focused on firms screening and ranking strategies when evaluating job applicants (Kroft et al, 2013; Vishwanath, 1989; Lockwood, 1991; Blanchard and Diamond (1994)).

This paper attempts to study the nature of unemployment discrimination rather than its mere presence by providing direct evidence on how employers react to different signals on an applicant's résumé when a job candidates' productivity is not directly observable. I explore whether the weight that employers place on the recent gap in work experience when making hiring decisions is influenced by other merits that appears on an applicant's résumé. To be precise, I study whether employers adjust their beliefs about the productivity of long-term nonemployed applicants, as opposed to unemployed ones, when their résumés indicate experience in a similar type of firm. Since employers cannot distinguish whether the worker is actively looking for employment when not employed, the reported nonemployment spell continues to be the best available information about an applicant's labor market status.

If employers place great weight on the duration of an applicant's nonemployment spell when choosing whom to hire, then signaling other attributes may help overcome this unfavorable treatment. The findings posit that in situations when heterogeneity is unobserved by the em-

ployer they may then engage in statistical discrimination against the long-term nonemployed. If firms find it costly to test workers they may rely on nonemployment duration as a measure on which to base their hiring decisions. The basic insight is that nonemployment duration may be a useful signal of applicants' productivity, provided that productivity is imperfectly observable and correlated with group identity. This behavior will hurt applicants whose productivity is not low as much as those who are believed to be low-productivity workers. In a situation like this, unobserved heterogeneity will itself generate duration dependence.

2.1 Employer Beliefs and Nonemployment Duration

In this section, I describe how firms' hiring behavior may reveal information about their beliefs in favor or against certain types of workers. Job seekers present their characteristics to employers by sending résumés with detailed information on experience, education, etc. Firms evaluate these characteristics but may also have certain beliefs about certain unobservable aspects that correlate with productivity. When faced with incomplete information on the actual productivity of workers, employers may proxy for unobservable characteristics using the observed signals. One such variable that correlates with productivity is the length of a jobless spell. Individuals with long nonemployment spells may have their skills atrophy and as a result become relatively less productive. For this reason, previous résumé audits have experimentally varied nonemployment duration to quantify callback gaps between otherwise identical applicants. This study contributes to the literature on duration dependence by experimentally manipulating industry experience and nonemployment duration to examine whether the former can compensate for negative impacts of the latter.

Can relevant industry experience compensate for long spells of nonemployment? From a worker's perspective, in an environment where applicants with short-term spells are favored over others with long nonemployment spells, jobseekers from the disfavored group might be able to increase their likelihood of finding employment by applying to jobs at similar type of firms. These applicants (who are assumed to be more productive and to require less training) appeal more to employers than do others without relevant industry experience. Bishop (1998) provides compelling evidence that job-specific skills are essential to firms looking to fill job openings. He argues that in most jobs, productivity derives directly from skills specific to the job, the occupation, and the occupation-cluster. Bishop reports on a series of meta-analyses of empirical studies which all concluded that in almost all jobs, productivity derives directly from generic and cognitive skills specific to the industry or occupation.

The following section describes the experimental design – in which two easily observable characteristics are experimentally varied – to formally test the degree to which industry specific human capital can compensate for the stigma of long-term nonemployment.

3 FIELD EXPERIMENTS

Unequal treatment and discrimination in hiring practices have proven hard to document using survey data due to the lack of all the characteristics that employers observe when making a hiring decision. Aggregate data using household and employer surveys may bias any measured differences in outcomes for two groups due to the presence of factors observed by employers but not by the researcher. Thus observed labor market gaps between groups could be due to employer discrimination, to differences in productivity characteristics not observable in data, or to both. As a result, researchers began to employ a wide variety of experimental and quasi-

experimental techniques in an attempt to measure differential preferences for one group over another. Studying discrimination using experimental audit studies was first implemented by sending pairs of trained "auditors", matched in all respects that might affect productivity in employers' eyes except for the variable of interest, job interviews. However, despite matching auditors on numerous characteristics and training them for several days to coordinate interview styles, these experiments were very costly to implement and hardly accounted for the many differences that exist between auditors in a pair. Researchers have later developed audit studies by replacing real auditors with fictitious résumés allowing the generation of a large number of data points at a much small cost than a conventional audit. These résumé audits consist of sending fictional job applications that are carefully matched on all aspects except for the variable of interest, to real job openings and tracking the subsequent callback. This methodology insures that any differences in measured outcomes can be solely due to the manipulation of the variable of interest, and allows the researcher to isolate any demand effects that may affect results. Moreover, this approach allows disentangling employer discrimination from other factors that affect the job finding rate of unemployed applicants such as unemployment insurance or network effects.

Although experiments using fictitious résumés only allows the researcher to explore only the interviewing stage of the hiring process, they permit much more control over the experimental variables. Of equal importance is the fact that résumé audit experiments allow the generation of a large sample at a much lower cost than do conventional audits.

3.1 Experimental Design

The experimental design differs from conventional audit studies, in which comparable participants are sent in for actual interviews, but closely follows the methodology used in Bertrand and Mullainathan (2004) and Kroft, et al. (2013) to generate fictitious résumés, locate job ads according to a predetermined model, and measure interview request rates.[4]

Using a major online job board, résumés were sent in response to job ads across different regions of the United States between August and December 2012.[5] Work histories and other résumé characteristics were randomly selected and assigned to different templates using a résumé generator program adopted from Lahey and Beasley (2007). The program mixed and matched different characteristics based on real résumés (available on the web) to randomly create new ones for specified positions.[6] When randomly combined, every part of the résumé becomes a potential control variable that can be interacted with the variable of interest, independently from other variables. This allowed me to randomize characteristics across thousands of résumés, leaving room for testing different interactions of characteristics with group status.[7]

The sample of jobs applied to generally required five to six years of work experience and an

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[4]All of the experimental protocols were approved by the Institutional Review Board (IRB) at Northeastern University.

[5]My sample includes a fixed number of jobs across the largest 25 metropolitan statistical areas of the U.S

[6]The program was adjusted to fit the protocols of the experiment and is available from the author by request or at http://www.nber.org/data/ (under "Other"). The web program creates .rtf files that can be opened from résumé-randomizer-framemaster.exe, which then creates .doc résumés, .sav information files, and .txt tab delimited data. After all résumés in a session have been created, filegather.exe collects data information from .txt files into a tab delimited .dat file that can be opened in a spreadsheet program.

[7]In ongoing work, I explore the impact of short-term employment relationships on the probability of receiving an interview request by varying the number of job transitions on a subsample of the generated résumés. Preliminary results show that applicants who repeatedly switch jobs are less favored than others with long employment relationships.

undergraduate degree. Within each MSA, job openings were selected from four major industries and three different occupation categories. Following the occupational and industry classification system used in the Current Population Survey, job postings were grouped into four broad industry categories: Finance, Wholesale and Retail Trade, Professional and Business Services, and Healthcare Services. Furthermore, in each industry, job ads were chosen to be administrative occupations, sales occupations, and professional occupations. A unique set of e-mail addresses was used to track employer responses on a rolling basis.

Once a job opening was identified, résumés were randomly sampled without replacement from a bank of résumés and sent to each firm in random order over a two day period. The treatment groups differed on whether an applicant is currently employed or not, the length of his nonemployment spell, and whether he had worked in the same of firm as the prospective employer. (Appendix A.13 provides an example of two résumés used to apply for an administrative position at a bank in New Jersey. Sample 1 is a fictitious résumé for a long-term unemployed applicant with experience in the same type of firm as the prospective employer. Sample 2 is for a short-term unemployed with no industry specific).

All profiles were males with names that are considered minimally informative about an applicant's race.[8] While, age was not explicitly listed on the résumés, it was indirectly conveyed to employers through the number of years an individual has worked since graduation. In particular, all résumés were assigned a total of six working years with no nonemployment gaps in between. The focus on this younger cohort of the population is particularly important due to the long-term adverse labor market outcomes that may result from discrimination at the first stage of the career (Arulampalam, 2001; Gregg, 2001; Gregg and Tominey, 2004).

Each résumé was assigned two different jobs with three years of tenure at each. The job title and job description were determined according to the job posting's industry and occupation categories. For example, résumés generated for a financial analyst vacancy at a bank would either be assigned previous jobs at similar type of firms as that of the advertised vacancy (other banks) or experience in an industry other than finance (e.g. financial analyst with a retail chain such as Walgreens). Half of the generated templates were assigned experience with similar type of firms whereas the other half were randomly assigned experience in industries different from that of the prospective employer. Few job ads (four percent of my sample) required specific credentials (such as knowledge of SAS). For these job ads, the required experience was listed on each of the résumés sent.

Educational history was chosen to match the requirements of the advertised jobs and institutions were randomly selected from a sample of schools that belong to the same tier.[9] Each type of résumé was assigned the minimum qualifications required for the job to ensure a reasonably high response rate. Residential addresses were randomly assigned to each résumé to match each employer's metropolitan area. Additionally, each résumé's layout was randomized to ensure that no two résumés that were sent to the same employer looked the same.

Résumés indicating that the applicant is currently nonemployed were randomly assigned a nonem-

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[8]Though the same names are used repeatedly in the experiment, the design was constructed such that no job ad received multiple résumés with the same name.

[9]I used an online survey through which companies were asked to rank universities based on the employability of their graduates.

ployment spell (in months) according to a discrete uniform distribution on the interval [1,12].[10] Nonemployment duration appeared on the résumé in the form of an end date for the applicant's most recent job.

3.2 Measuring Responses

The study does not allow the observation of firms' hiring decisions, but rather whether applicants received a request for an interview (via e-mail).[11] Interview requests were recorded by matching employer IDs with the original submitted résumés using a job number assigned to each position considered.[12] Since residential addresses assigned to each résumé included nonexistent street numbers, interview requests via regular mail could not be measured.[13] To minimize inconvenience to firms, invitations were immediately declined and firms were notified about the objective of the study. Those that never replied were informed about the study six months after the applications were sent.

4 RESULTS

4.1 Nonparametric Evidence

Figure I displays the fraction of applications that received interview requests as a function of nonemployment duration. The dots correspond to interview request rates at each month of nonemployment. The pattern in the figure provides clear evidence of declining interview requests as the length of nonemployment spells increase. The rate of decline in interview requests appears to drop sharply after six months of nonemployment and stabilizes afterwards.

In Table A.5, I group my data into three bins to facilitate comparisons among different treatment groups. Résumés assigned a nonemployment duration between [1, 3] were grouped under short-term nonemployed; résumés assigned a duration between [4, 6] were grouped as medium term nonemployed; and finally those assigned a duration between [7, 12] were grouped under long-term nonemployed. The table reports interview request rates for the full sample and each treatment group. Included in brackets under each rate is the number of applications submitted in that cell.

Table A.6 reports for the entire sample and different subsamples of sent résumés, the interview request rate for applicants with experience in the same type of firm (column 1) and different industry experience (column 2), as well as the difference (column 3) between these interview request rates. Column 1 of Table A.5 presents the results for all occupations, while columns 2-4 break down the full sample across the different occupations considered. In sum, 279 of the résumés sent (8.3 percent) received requests for interviews. Résumés for employed applicants (row 2 of Table A.5) have a 10.25 percent chance of receiving an interview request, while the

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[10] Most of the real resumes collected online show that current unemployed applicants list both the year and months of when they last worked.

[11] Résumés were only assigned e-mail addresses (no telephone numbers). The main reason for this design is to minimize the inconvenience to firms. Since none of the résumés that were sent to a given firm had a telephone number, any effect such a signal could have on interview requests will therefore be equally distributed across all applicants.

[12] A few employers requested a telephone number to conduct a phone interview. Those employers were debriefed about the objective of the experiment and their requests were recorded as interview requests.

[13] Several human resource specialists informed me that employers rarely, if ever, reach out to job candidates for interview using regular mail.

Figure I
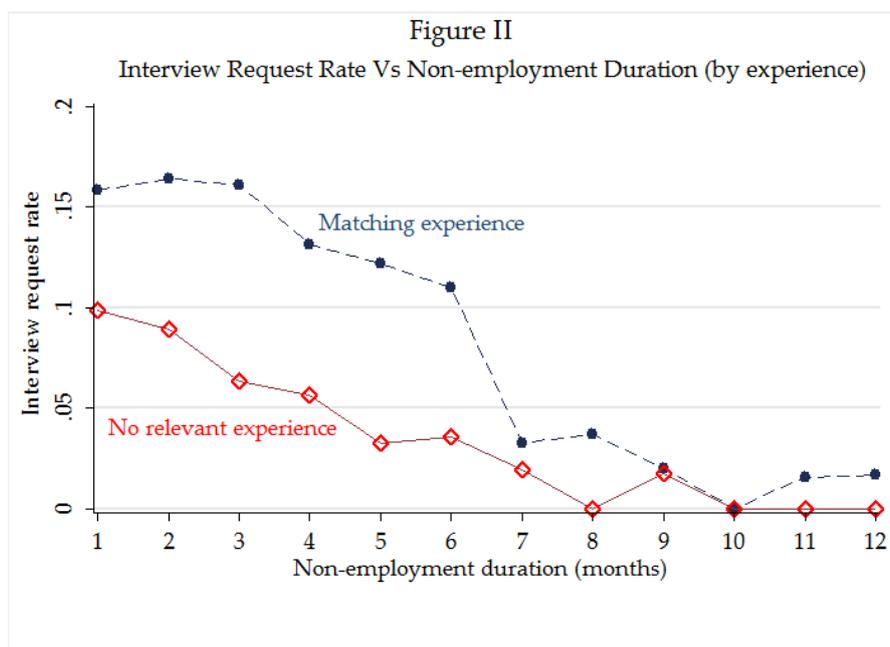Interview Request Rate Vs. Non-employment Duration
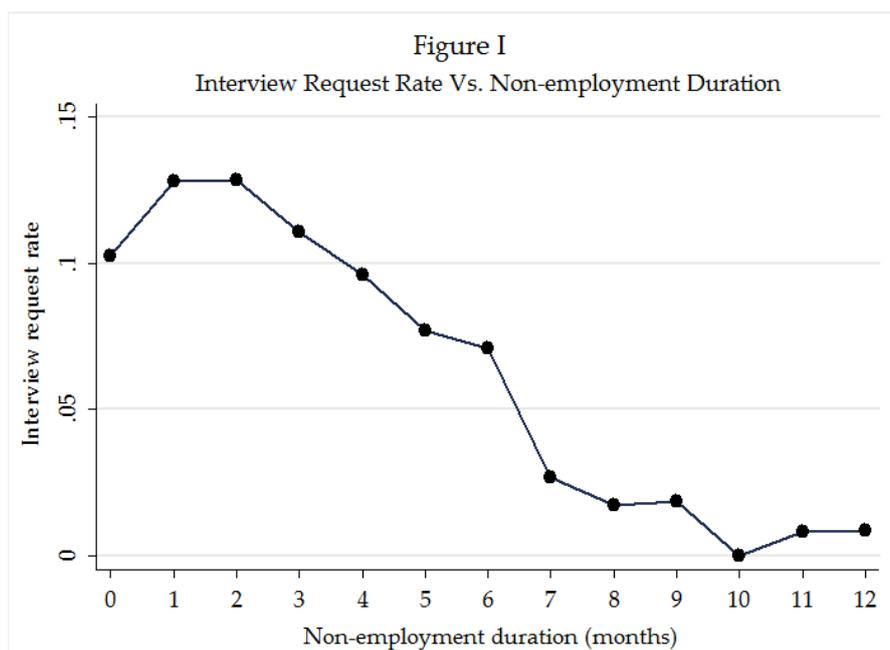
Notes: The figure reports the interview request rate by length of nonemployment spell (months). Résumés where the individual is currently employed are assigned a nonemployment duration of zero.

interview request rate for otherwise identical nonemployed applicants (row 3 of Table A.5) averaged 7.2 percent. The gap in interview requests between employed and nonemployed applicants varied between occupations and was highest in sales jobs, with employed candidates having twice the chance of nonemployed applicants of receiving a request for an interview. Rows 6-7 display results for nonemployed applicants with a spell of three months or less, while rows 8-9 report results for nonemployed candidates with jobless spells greater than three and less than or equal to six. Finally, the last two rowss of Table A.5 report results for nonemployed applicants who have been out of work for seven months or more (up to 12 months).

4.2 Nonemployment Duration and Industry Experience

Figure II provides disaggregated evidence on the relationship between average interview requests and nonemployment duration by dividing the sample depending on whether résumés were assigned experience in the same type of firm as the prospective employer or not. The dots (in blue) report average interview requests for applicants with experience in a similar firm, while the diamonds (in red) report average response rates for applicants with no relevant experience. The pattern reveals a sharp drop in the fraction of applications receiving an interview request after six months of nonemployment for those with experience in a similar firm as the prospective employer. The rate for those with no relevant experience declines steadily before six months and hits zero for résumés with 8, 10, 11, and 12 months of nonemployment.

Table A.6 presents interview request rates that are consistent with the graphical analysis in Figure II. Overall, 109 of the 1080 résumés (10.09 percent) of nonemployed applicants that were assigned similar firm experience as that of the prospective employer received an invite for an interview, while only 47 of the 1080 (4.35 percent) résumés of nonemployed applicants that had

Figure II

Interview Request Rate Vs Non-employment Duration (by experience)

Notes: Figure II reports the response rate by nonemployment duration (months) for applicants with experience in a same type of firm (dots) and others with no relevant industry experience (diamonds). Résumés where the individual is currently employed are assigned a duration of zero.

no relevant experience received interview requests. The industry premium is calculated as the difference between the interview requests rate of each group (column 3). A standard test for the hypothesis that the two proportions are equal is rejected at the one percent level. The table also reports the same descriptive statistics for each nonemployment spell and tests whether the difference at each month is significant. As shown in column 3, nonemployed from the same type of firm as the prospective employer are greatly favored over those without similar experience. However, this is only true for applicants who have been out of work for six months or less. The industry premium at long nonemployment durations declines dramatically and becomes not statistically different from zero.

4.3   Regression Results

Table A.7 reports results from estimating a linear probability model [14] where the dependent variable is an indicator that equals to 1 if applicant i receives an interview request and 0 otherwise.

The regression includes eight variables with no constant term. Four of these are: a dummy for those with experience in the same type of firm ($SAME_i$), a dummy for those with no relevant experience ($DIFF_i$), a dummy for those with similar firm experience who have not been employed for more than six months ($LTsame_i$) and one for those without industry experience who have not been employed for more than six months ($LTdifferent_i$). I also define four trend variables; two for those with similar firm experience and two for those without it. For those with similar firm experience I define a variable equal to the number of months not employed up to six ($Trend\_1\_6\_Same_i$). Those who have not been employed for more than six months

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[14]Results from estimating the model using probit and logit specifications are quantitatively similar.

have a value of six on this variable. The second trend for those with similar firm experience ($Trend\_7\_12\_Same_i$) counts the number of months not employed beyond 6 months and is equal to zero for those with spells less than seven months. Two similar trends are defined for those without industry experience: ($Trend\_0\_6\_Diff_i$) and ($Trend\_7\_12\_Diff_i$) respectively.

With this specification the first coefficient of the first trend variable is the rate of decline of interview requests with each month of nonemployment up to six months and the coefficient on the second trend gives the rate of decline after six months. The coefficient on the dummy interacting experience group with more than six months of nonemployment is an estimate of the decline in the rate of interview requests moving from six to seven months.

The results in column 1 of Table A.7 reveal that the rate of interview requests for résumés with similar firm experience drops 1.13 percentage points for each additional month of nonemployment up to six months. Interestingly, the rate of interview requests drops by 8 percentage points as the nonemployment spell listed on these résumés tops six months. After six months of nonemployment, the decline in the rate of interview requests slows down and becomes insignificant with each additional month of nonemployment. Similarly, the results indicate that the interview request rate for résumés that listed no relevant experience drops 1.41 percentage points with each month of nonemployment up to six months. For each nonemployment month beyond six, the decline in the rate of interview becomes small and not statistically significant.

Columns 2-4 of Table A.7 show that the estimates are robust to adding baseline characteristics (different occupations considered in the experiment), city fixed effects, and controls for résumé layout.

Table A.8 shows interview requests separated by the three different occupation categories. Résumés that were assigned experience from a similar type of firm as the prospective employer received significantly higher interview requests across all occupations. Results from comparing rows 1 and 2 of Table A.8 indicate that firm experience matters more in professional occupations than the other two job categories. In general, the table indicates that the overall results are not driven by one occupation in particular. The finding that the rate of interview requests drops sharply after six months of nonemployment is statistically significant in both professional and administrative occupations while it is not for sales occupations.

Figures A.9 - A.11 in the appendix provide graphical evidence for the differences in interview requests across occupations. In the bottom panel of each figure, the data are grouped into bins of two months. The pattern in each graph suggests that recently nonemployed applicants with no relevant experience are more likely to receive interview requests than those with similar firm experience who have been out of work for more than six months.

5   DISCUSSION

Section II provided a number of prominent explanations as to why individual re-employment prospects decline with the length of time out of work. The main evidence of negative duration dependence as presented in Figure I is consistent with predictions of Blanchard and Diamond's (1994) ranking model, Vishwanath (1989) and Lockwood's (1991) screening models, as well as with the view that long nonemployment spells may cause loss of human capital (Sinfield, 1981) which reduce individuals' job finding rate. Blanchard and Diamond (1994) argue that the fall in the exit probability with the duration of the unemployment spell can be due to firms ranking

behavior where each vacancy can get more than one applicant, and as a result, firms choose the one with the shortest duration of unemployment. Although, the model is consistent with the full sample, it is not clear how duration dependence due to ranking varies with industry experience.

The experiment reveals higher "returns" to industry-relevant experience for interview requests at low durations of nonemployment and greater negative duration dependence in the interview request rate for those with industry-relevant experience. We can therefore reject the hypothesis that the increase in long-term unemployment over the recent recession is entirely due to an increase in skills mismatch between the nonemployed and employers demand. To the extent that a mismatch between workers' skills and the demand of available jobs is generating prolonged spells of nonemployment, then one would expect those with relevant skills to have better job market prospects than others with no relevant experience. However, evidence from Figure II calls the mismatch hypothesis into question by the fact that job seekers with long nonemployment spells received far less interview requests on average than inexperienced short term jobless workers–even when they applied to jobs at similar type of firms.

One reason why negative duration dependence is stronger among those with specific industry experience is the possibility that human capital specific to firms of the same type depreciates very fast with the duration of nonemployment (according to Figure II, one could conclude that it takes nine months for six years of industry-specific human capital to depreciate completely), and thus after nine months the long-term nonemployed with and without industry-specific work experience are viewed the same by employers in that sector. However, the sharp drop in the rate of interview requests after six months of non-employment suggests that human capital depreciation is unlikely the sole mechanism behind the results; for what the gap is actually measuring, is the return to relevant industry skills and there is no reason to see that dropping sharply between six and seven months of nonemployment.

One prominent explanation for the pattern is related to the literature of statistical discrimination as pioneered by Arrow (1973) and Phelps (1972). In this literature, productivity is not perfectly observed, and thus the observable characteristics of workers are used to determine their expected productivity. In this case, firms may statistically discriminate against the long-term unemployed because they are negatively selected towards the less able. The empirical results presented in the paper show that the negative slope of the interview request function (with respect to nonemployment duration) for those with same type of experience as the prospective employer increases sharply after six months of nonemployment. Thus, the fact that employers discriminate more against the long-term nonemployed with industry-specific work experience than the short-term nonemployed without industry-specific work experience shows the extent of statistical discrimination against the long-term unemployed in general. If employers infer the unobserved components of the workers' quality from the length of their nonemployment spell and use this information to make their hiring decisions, the question arises why are they screening at six months. One prominent factor that may be driving this result is the design of the unemployment benefit system in the U.S. The relationship between unemployment benefits and search intensity has been well documented in the literature with a major consensus that the search behavior of an unemployed (characterized by either the choice of a reservation wage or the time per period allocated to job search) reacts directly to a change in the generosity of the benefit system. Krueger and Mueller (2010) study how the job search behavior of individuals varies at different points during an unemployment spell. They find increases in job search activities prior to benefit exhaustion, while those ineligible for unemployment benefits see no such increase. Therefore, the search behavior of an unemployed individual depends significantly on

how far in time he or she is from the benefit expiration date. In addition, employers experience with the long-term nonemployed is that they are probably not very productive and therefore they are typically reluctant to interview them. The point where employers stop interviewing may become a focal point when workers, realizing that being nonemployed for long periods of time will hurt their chances of employment, intensify their search as that date grows near. This reinforces the focal point as good workers leave the workforce in large numbers during the frenzy job hunting just before the cut off. In the U.S., the focal point is likely to be at six months when regular unemployment benefits are set to expire. In what follows, I set up a model in the spirit of Lockwood (1991) and allow workers' search intensity to differ depending on how far in time they are from the date when benefits will be reduced. For a given range of parameter values, the model provides support for the results from this experiment as well as replicates other empirical findings on the Beveridge curve by unemployment duration.

6   THEORETICAL MODEL

A common feature of unemployment insurance systems in many OECD countries is that benefits are only offered for a limited time. Indeed, it is not surprising that the duration of unemployment benefits would influence employment search decisions. These decisions are often characterized in the standard job search theory by a fall in the reservation wage or to a rise in search intensity—the time/effort allocated to job search activities. As the time to benefit expiration date shortens, unemployed workers increase their search intensity as they can not afford to remain unemployed anymore. This result was identified by Katz and Meyer (1990) who documented a spike in hazard rates when unemployment benefits expire. This is typically viewed as evidence that unemployment insurance distorts search behavior, as it suggests that people time their unemployment exits to coincide with the expiry of social welfare programs. A spike in unemployment exit hazards in the weeks prior to benefit exhaustion is now a well-documented empirical regularity. (see Card et. *al* (2007a) for a review of this literature.) This creates heterogeneity among workers as the better applicants (those with higher hazard rates) tend to exit unemployment before benefits expire, leaving a pool of less-qualified workers as the ones who disproportionately make it to long-term unemployment. Consequently, firms adjust their beliefs on worker types by duration of unemployment and establish screening thresholds to lower their chances of meeting a low productivity worker. The question therefore arises whether the sharp drop in the callback rate in the U.S. after six months of nonemployment can be explained by the structure of the unemployment insurance system which drives firms' beliefs and recruitment strategies.

I provide answers by using a two-sided search model which combines various strands of the literature and adds some new and essential features. The model features a structural non-stationary framework of job search in the fashion of Van den Berg (1990) that allows for duration-dependent unemployment benefits and job offer arrival rates. I depart from Van den Ber's model by allowing job searchers to optimize their behavior over an unemployment spell by choosing to search with low or high intensity rather than varying their reservation wage. On the employer side, I closely follow Lockwood (1991) by allowing firms to imperfectly test workers prior to hiring them and condition their hiring decisions on duration—hiring those whose duration is less than a critical value. In particular, job searchers may influence their job finding rate by varying the intensity of search. In this environment, agents have to select unemployment duration-contingent strategies that are mutually consistent in equilibrium. Employers set their hiring policy, while workers set the pace of their search effort. The model shows that for a given set of parameter values, search intensity will increase prior to unemployment benefit expiration when the marginal

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returns to search equal the marginal cost of search. This behavior will shape employers' beliefs about the composition of the unemployment pool it becomes optimal for them to set a duration threshold around that time. In the U.S., I believe that this happens at six months when regular unemployment insurance normally expires.

6.1 The Model

Consider a continuous time environment with a continuum of workers and employers. The labor market is described by a structural nonstationary model of job search. Nonstationarity originates from the variation of unemployment benefits and job finding rate over time. Individuals differ ex-ante by their productivity, but all firms are the same. Each firm can employ one worker. Let τ denote the elapsed duration of an individuals' unemployment spell. At each instant, a new cohort (I) of new workers flow into the pool of unemployed. Job seekers have private information about their types. π_0 of I are high productivity workers, while the rest are low-productivity. All these workers are initially entitled to unemployment benefits b_{UI} for the length T. When matched with an employer a high-productivity worker (type h) can produce y_h units of output and the low-productivity worker produce y_l, with $y_l < y_h$. I assume that both types of applicants are equally risk-neutral, discount the future at rate $r > 0$ and enjoy the same utility u(.) from consumption. I let

$$\pi_i(\tau) = \frac{u_i(\tau)}{u_h(\tau) + u_l(\tau)} \tag{1}$$

be the proportion of unemployed individuals that are of type i which will vary over time as workers of different qualities leave the pool at different rates.The reservation wages of low and high-productivity workers are the same and do not change with duration of unemployment. Workers can be in any of three states: unemployed, employed or retired. I assume an exogenous exit rate n_1 from unemployment into retirement, which is the same for both types of workers.

Unemployed agents receive unemployment benefits $b_{UI} < w$ for a fixed amount of time T, after which benefits are reduced to b_{UA}. Hence, unemployment insurance payments $b(\tau)$ are given by:

Assumption 1: Duration-dependent Benefits

$$b(\tau) = \begin{cases} b_{UI} > 0; & \tau \leq T \\ b_{UA} < b_{UI} & otherwise \end{cases}$$

Given the benefit scheme $[b_{UI}, b_{UA}]$, the unemployed agent chooses to search with either low intensity $s_L(\tau)$ or with high intensity $s_H(\tau)_H$. $s_i(\tau)$ is assumed to be endogenous in the model, i.e. the effort devoted to the search activity is controlled by the worker (see, e.g. Burdett and Mortensen 1978, Benhabib and Bull 1983, Mortensen 1986). While models in these studies are of "one-sided" search, they inform my analysis of job search behavior. In Burdett and Mortensen (1978) and Mortensen (1986) search intensity is endogenized by allowing an increase in the time spent on search to increase the average number of job offers arriving in a given interval of time. In the present model, the level of search intensity affects the speed at which an individual exits unemployment: a higher intensity of search increases the job finding rate. In his decision to increase his search intensity, the job seeker faces a tradeoff between increasing search costs on the one hand and an increasing probability of reemployment on the other. Let c be marginal cost of searching with high intensity. The total lifetime utility an individual expects when remaining unemployed is the key variable determining this decision.

In addition, I assume that once an individual starts work, he will keep his job with a fixed wage w that is between y_l and y_h. We can thus calculate an employed worker's total expected lifetime utility in period τ as:

$$E(\tau) = \frac{u(w)}{\rho} \tag{2}$$

where $\rho = r + n_1$ is the effective discount rate. As a result of this wage, hiring low-productivity workers will generate a loss to firms.

Since firms cannot perfectly observe the type of workers, they conduct a pass/fail test (in the spirit of Lockwood, 1991) to learn about the workers type. By testing applicants, the employer acquire better information about the productivity of its own workers. By choosing to condition their hiring decisions on the results of the test (interview), the higher productivity workers will exit at a faster rate from nonemployment, and so the period of nonemployment of a worker test by a particular employer will convery information to other employers about his productivity. In this case, employers may choose to condition their hiring decisions on the nonemployment duration of a worker. Hence, they may wish to only hire an applicant if his period of nonemployment is below some cutoff point x. According to this policy, high productivity workers will always pass the test $(H_h) = 1$ if and only if their nonemployment duration is less than a threshold (x) that is determined optimally by the employer. Low productivity workers, on the other hand, will be hired with some probability $H_l < 1$ if and only if their nonemployment duration is below x.

I assume that there is no monetary cost to taking the test.[15]

6.2   Jobseekers' Behavior

Any of the unemployed workers of type i flow from unemployment to employment with some probability $\mu(.)$ that depends on the match rate m, their intensity of job search s, and the employer's screening strategy H_i, such that:

$$\mu_i(s_i(\tau), m, H_i(\tau)) = m * s_i(\tau) * H_i(\tau) \tag{3}$$

Consider the search behavior of a single individual facing a stepwise unemployment benefit system and a cutoff point that is symmetrically set by firms.
The probability of staying in unemployment up to τ conditional on being unemployed at t_0 (the survival function at τ)and is given by:

$$P_i(\tau, t) = e^{-\int_{t_0}^{\tau} \mu_i(x)dx} \tag{4}$$

Given the employer's hiring (screening) strategy, the expected lifetime utility of an unemployed worker at t_0, $U_i(t_0)$, is the discounted sum of three terms: (i) the sum from t_0 to τ of the instantaneous monetary equivalent utility in unemployment $(u(b(\tau)) - c[s_i(\tau)])$ weighted by the probability of still being unemployed at each moment τ $(P_i(\tau, t_0))$; (ii) the sum from t_0 to τ of the expected utility of employment $E(\tau)$ weighted by the density of unemployment duration

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[15]Guasch and Weiss (1980) show that allowing for a test fee can induce workers to self-select. Lockwood (1991) argues that even with self-selection, fully efficient hiring is not feasible for the firm and so even with testing, unemployment duration may convey information. Therefore, a zero cost for testing is not so much a restrictive assumption as a simplifying assumption.

at τ, $\mu(\tau)P_i(\tau, t_0)$; (iii) the expected lifetime utility at x ($U_i(x)$) weighted by the probability of surviving in unemployment up to x ($P_i(\tau, t_0)$):

$$U_i(t_0) = \int_{t_0}^{x} [u(b(\tau)) - c(s_i(\tau)) + \mu(\tau)E_i(\tau)]P(\tau, t_0)e^{-\rho(\tau - t_0)}d\tau + U_i(x)P_i(x, t_0)e^{-\rho(x - t_0)} \quad (5)$$

where $U_i(x)$ denotes the stationary expected lifetime utility after x. In the context of the model, $U_i(x)$ will be equal to the utility from receiving b_{UA}. In Appendix A.1, it is shown that $U_i(t_0)$ can be stated recursively using a differential equation with an initial condition similar to that given by Mortensen (1986).[16] The worker's optimization problem can therefore be written as:

$$\frac{dU_i(\tau)}{d\tau} = \rho U_i(\tau) - u(b(\tau)) - \mu_i(.)[E_i - U_i(\tau)] + cs(\tau) \quad (6)$$

where the intial condition is given by $U_i(x) = u(b_{UA})/\rho$.
In order to get an intuitive feeling for equation (6) we can re-write it in terms of the optimal present value of search $U_i(\tau)$ at time τ.

$$\rho U_i(\tau) = u(b(\tau)) + \frac{dU_i(\tau)}{d\tau} - cs(\tau) + \mu(s(\tau), m, H_i(\tau))[E - U_{1i}(\tau)] \quad (7)$$

The instantaneous utility flow of being unemployed, $\rho U_i(\tau)$, is given by four components. The first component shows the instantaneous utility resulting from consumption of $b(\tau)$ The second component is a deterministic change of $U_i(\tau)$ as the value of being unemployed changes over time. It matters for the unemployed how long unemployment benefits are paid. This time (spell) derivative of $U_i(\tau)$ reflects the change in the value of being unemployed as the individual becomes closer to the point where benefits will be reduced. The third component is the cost of search with high intensity. Finally, the fourth component is a stochastic change that occurs with a probability $\mu(.)$, the job finding rate. When a job is found, an unemployed worker gains the difference between the value of being employed E and $U_i(\tau)$. To better interpret equation (7), suppose that the optimal value U is an asset which can be traded in a perfect capital market with an interest rate that equals the discount rate ρ. In equilibrium, the return from the asset value in a small time interval [t,t+dt], which is $\rho U_i(\tau)$, must equal what one expects to get from holding the asset in that period. The latter consists of four parts: first, the benefits flow in the interval; second, the appreciation of the asset value in that period; third, the disutility in that state; and fourth, the expected gain of selling the asset in the period (see Pissarides (1985) and Van Den Berg, (1990) for other examples of such an interpretation).
The optimal behavior of the unemployed over the time interval $[t_0, x]$ can be derived from equation (7) such that $s(\tau) = s_H$ if and only if $H_i m[E - U_i(\tau)] \geq c$
This implies that $s(\tau) = s_L$, or there exists a unique duration $z_i \epsilon[0, x]$ such that $s(\tau) = s_H$ iff $\tau \geq z_i$.
In a nonstationarity environment, the unemployed individual's perception of the future depends on time or unemployment duration. In this case, the optimal strategy is nonconstant during the spell of unemployment unlike the optimal behavior in the case of stationarity. Since unemployment benefit payments are discontinuous at T and the job finding depends on τ, another way of looking at equation (7) is by splitting the time horizon into three intervals and characterizing the time path of the optimal strategy by a search intensity function, $s(\tau)$, that satisfies a differential equation for every point in time at which $b(\tau)$ and $\mu(\tau)$ are continuous in time (see Appendix A.2).

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[16]In Mortensen's model the optimal strategy of a job search is characterized by a reservation wage function rather than a level of search intensity.

A differential equation similar to (6) can be used in order to solve for the optimal behavior of a job searcher in every interval that is continuous in time. First, we solve for $s(\tau)$ at the point x after which all exogenous variables are constant (this is given by $U(x) = \frac{b_{UA}}{\rho}$); representing the stationary expected lifetime utility of unemployment after x). $U_i(\tau)$ is a continuous function of τ. Therefore, U(x) serves as an initial condition for the differential equation in the time interval ending at x. Similarly, $s(\tau)$ can be solved for every τ in this interval. Backward induction leads to the solution $s(\tau)$ for every $\tau \geq 0$ (see Appendix A.2). The resulting solution denotes the worker reaction function which depends positively on the employer cutoff threshold, x.

Jobseeker Reaction Function

$$z = T + \frac{1}{\rho + m * s_H} ln \left[\frac{u(b_{UI}) + c\frac{\rho+m}{m} - u(w)}{u(b_{UI}) - u(b_{UA}) + \frac{\left(m*s_H \frac{u(w)-u(b_{UA})}{\rho} - c*s_H\right)}{e^{(\rho+m*s_H)(x-T)}}} \right] \tag{8}$$

Inspection of this equation shows that as employers extend their screening threshold x, z will increase. This means that when the duration of employability increases, workers will postpone the time at which they start searching with high intensity.

6.3 The Optimal Stopping Rule

The aim of this section is to derive an optimal stopping rule for interviewing workers. In what follows, I show that the optimal rule can be expressed in terms of the variable z and the other parameters defined in the model. Intuitively, the point at which employers stop interviewing will be driven primarily by the evolution of high-productivity workers in the applicants pool. When the ratio of high-productivity workers to low-productivity ones shrinks considerably, employers may wish to stop interviewing in an attempt to reduce their likelihood of hiring a low-productivity worker.

Let J be the expected present value of profit to the employer from a vacant job, and $F_i(\tau)$ be the corresponding value from a type-i worker of unemployment duration τ. The value of a job F_i to a firm is given by the instantaneous profits $y_i - w$, which is expected revenue from the worker, conditional on the fact that he has passed the test, net of the wage. Therefore, the Bellman equation for a filled position is:

$$\rho F_i(\tau) = y_i(\tau) - w \tag{9}$$

Given the assumption that workers are matched for life, there is no expected loss from a breaking up of the match. The interest rate is denoted by $\rho > 0$, which is identical to the discount rate of households.

The Bellman equation for a vacancy is:

$$rJ = m(\theta)^{-1} \int_0^\infty f(\tau) max\{[p_h(\tau)(F_h - J) + (1 - p_h(\tau)) * H * (F_l - J)], 0\} d\tau \tag{10}$$

where $p_i(\tau)$ is the probability of contacting a type-i worker conditional on contacting a worker whose unemployment duration is τ, and $f(\tau) = \frac{u(\tau)}{U}$ is the pdf distribution of the unemployment spell; where $u(\tau)$ is the number of unemployed with duration τ, and U is the total number of unemployed.

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The size of the cohort of high and low productivity workers whose unemployment duration is τ as of time t, $u_i(\tau, t)$, is evolving according to the following differential equation:

$$\frac{\partial u_i(\tau, t)}{\partial \tau} + \frac{\partial u_i(\tau, t)}{\partial t} = -[\mu(.) + n_1] u_i(\tau, t) \tag{11}$$

$$u_i(0, t) = I * \pi_i(0) \tag{12}$$

The solution to this differential equation with initial condition defined in (12) can be written as:

$$u_i(\tau) = I * \pi_i(0) * exp^{-\int_0^\tau [H_i(q)*m*s_i(q)+n_1]dq} \tag{13}$$

Therefore, $u(\tau)$, the total number of high and low productivity workers is equal to:

$$u(\tau) = \sum_{i=h,l} I * \pi_i(0)e^{-\int_0^\tau [H_i(q)*m*s_i(q)+n_1]dq} \tag{14}$$

And the total number of unemployed, U, is equal to

$$U = \int_0^\infty \sum_{(i=h,l)} I * \pi_i(0)e^{-\int_0^\tau [H_i(q)*m*s_i(q)+n_1]dq} dj \tag{15}$$

Therefore, the pdf distribution of the unemployment spell, $f(\tau)$, can be written as:

$$f(\tau) = \frac{u(\tau)}{U} = \frac{\sum_{(i=h,l)} I * \pi_i(0)e^{-\int_0^\tau [H_i(q)*m*s_i(q)+n_1]dq}}{\int_0^\infty \sum_{(i=h,l)} I * \pi_i(0)e^{-\int_0^\tau [H_i(q)*m*s_i(q)+n_1]dq} dj} \tag{16}$$

I define the the probability of contacting an unemployed worker of type-i conditional on contacting a worker whose unemployment duration is τ, as:

$$p_i(\tau) = \frac{m * s_i(\tau) * u_i(\tau)}{m * s_h(\tau) * u_h(\tau) + m * s_l(\tau) * u_l(\tau)} \tag{17}$$

Free entry condition implies that the value of a vacancy J=0. Given the Bellman equation for a vacant position (defined in equation 6), employers hiring decision, $H_i(\tau)$, will depend on whether:

$$p_h(\tau)(F_{\{h\}} - J) + [1 - p_h(\tau)]H(F_l - J) \geq 0 \tag{18}$$

where H is the probability that a bad worker will pass the test. Hence, a duration- τ type-i worker is hired with probability H_i if:

$$p_h(\tau) \geq -H * \frac{(F_l - J)}{(F_h - H * F_l - (1 - H)J)} \tag{19}$$

In equilibrium, the free entry condition implies that J=0. As a result, employers will set their cutoff points when:

$$p_h(x) \geq -H * \frac{F_l}{F_h - H * F_l} \tag{20}$$

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In Appendix A.3, I show that the function $p_h(\tau)$ is differentiable and strictly decreasing on [z,x] Therefore, there exists an inverse p_h^{-1}, such that:

$$x = p_h^{-1}(-H * \frac{F_l}{F_h - HF_l})$$

(21)

Solving for x (Appendix A.3), yields the employer's optimal cutoff time defined explicitly in the equation below:

Employer's Reaction Function x(z)

$$x = \frac{s_H}{(s_H - H)}z + ln\left[\frac{(y_h - w)\pi_0 s_H]}{H(w - y_l)(1 - \pi_0)}\right]^{m(s_H - H)}$$

(22)

While the employer's strategy, defined in (22) does not depend on any of the unemployment insurance system components, it is directly proportional to workers' search behavior. As workers increase their search intensity, the number of high productivity workers left among the pool of unemployed will drop. This informs employers' hiring behavior who update their beliefs accordingly. For a range of parameter values, the nonstationarity in the unemployment benefit system that initiates an increase in the intensity of search will drive employers to set a cutoff time closer to the benefits expiry date.

6.4 Equilibrium

The equilibrium involves finding a vector (z,x) such that

$$\begin{cases} z = T + \frac{1}{\rho + m*s_H}ln\left[\frac{u(b_{UI}) + c\frac{\rho+m}{m} - u(w)}{u(b_{UI}) - u(b_{UA}) + \frac{\left(m*s_H\frac{u(w) - u(b_{UA})}{\rho} - c*s_H\right)}{e^{(\rho + m*s_H)(x - T)}}}\right] \\ \\ x = \frac{s_H}{(s_H - H)}z + ln\left[\frac{(y_h - w)\pi_0 s_H]}{H(w - y_l)(1 - \pi_0)}\right]^{m(s_H - H)} \end{cases}$$

(23)

For a range of parameter values, I show that there exists an equilibrium where high productivity worker will intensify their search as the time left to benefit expiration date comes close. This will happen at some time $0 < z < T$ when the marginal return to high search effort becomes greater than the search cost. This will increase an employer's chances to meet with a high productivity worker after z. This causes the fraction of good workers among the unemployed to fall hence driving the optimal cutoff point x down.

Equation (23) shows that the optimal behavior of both jobseekers and employers, denoted by a vector (z,x), depends on the value of s. For a given collection of fixed values for the other parameters of the model, it is clear that z will converge to T when s becomes sufficiently large. To know which parameter configurations imply z=T, I simulate values for z when s increases arbitrary. It is shown in figure III.a. below that the gap between z and T shrinks considerably
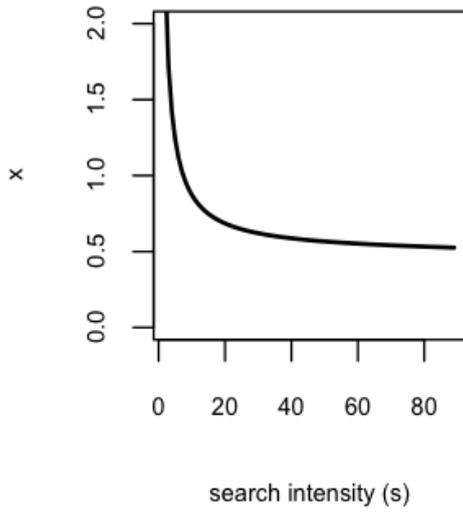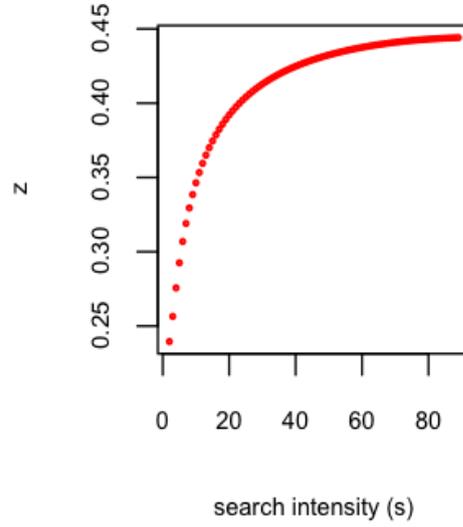
Figure III.a. Employer Optimal Cutoff

Figure III.b. Jobseeker Optimal Behavior

as s grows. Figure III.b. presents the simulated values of x as s grows from low to high. As s increases further, it becomes worthwhile for employers to set their cutoff point, x, closer to T. To simulate the model, I chose parameter values for T, b_{UI} and b_{UA} that broadly replicates the U.S. unemployment benefits system. Second, the other parameter values in the model were chosen to be as reasonable as possible such that T=0.5, $b_{UI} = 0.6$, $b_{UA} = 0.2$, w=1, $\pi_0 = 0.55$, m=1, $\rho = 0.1$, n=0.029, H=0.27, $y_1 = 1.4$, $y_2 = 0.9$ and c=0.49.

7 CONCLUSION

The paper attempts to measure the intensity of discrimination against the long-term unemployed by exploring the extent to which employers become forgiving of longer nonemployment spells when other merits appear on an applicant's résumé: in this case, having worked in the same type of firm as the prospective employer. The evidence suggests that discrimination is an important factor to why individuals with long nonemployment spells are doing poorly in the labor market. Results from tracking employer responses to job applications which differed in experience and nonemployment duration reveal a sharp drop off in the probability of receiving an interview request after six months of nonemployment. Additionally, I find that nonemployed jobseekers who have worked in the same type of firm for which the employer is hiring are greatly favored over those without similar experience. However, this is only true for those who have been nonemployed for less than six months. Most importantly, the data reveals that recently nonemployed applicants with no relevant industry experience are more likely to be invited for an interview than those with experience who have been out of work for more than six months.

The finding that recently employed workers are more likely to receive interview requests than those who are currently unemployed is inconsistent with the predictions from theories that emphasize the signaling attributes of unemployment (Greenwald, 1986). Greenwald's work as well as work by Gibbens and Katz (1991), show that employed workers tend to be of higher quality than unemployed ones. However, one reason why employed jobseekers may not be as attractive to firms as those who are recently unemployed is the concern that employed workers are not serious job seekers and might be intrinsically less loyal and especially prone to job hopping (Kroft et al., 2013). Kroft et al. (2013) shed light on other reasons for this pattern including the possibility of easier wage negotiations with unemployed workers (those with no other options) relative to employed ones.

While results from this study speak mostly directly to younger job seekers with relatively little work experience, evidence from disaggregating the vacancy and unemployment relationship by different age groups reveals an increase in vacancies for a given level of unemployment across all categories (Ghayad and Dickens, 2012). This suggests that similar forces are likely to be at work among older age groups.

All together, the results shed light on an important labor market phenomenon which is the dependence of re-employment probabilities on the length of a jobless spell. The evidence in this paper suggests that some of this duration dependence may be due to employer's hiring behavior. The model discussed in this paper provides an explanation for this negative duration dependence, and so provides a framework within which one can discuss the use of measures to control. In a situation when employers cannot perfectly observe the productivity of job seekers, they may then engage in statistical discrimination against the long-term nonemployed by using nonemployment duration as a measure on which to base their hiring decisions. This is in accordance with Lockwood (1991) who shows that firm imperfectly test workers prior to hiring them to learn about their productivity. If (some) firms hire only applicants who pass the test, there is an informational externality; unemployment duration is a signal of productivity. In equilibrium, if it is profitable for a firm to test, it is also profitable for it to condition its hiring decision on duration, hiring those whose duration is less than a critical value. This behavior will hurt job seekers with long jobless spells whose productivity is not low as much as those who are. In this case, it becomes increasingly harder for job seekers to find work as their nonemployment duration increases. Using a non-stationary structural matching model in the spirit of Lockwood

(1991) and allowing for duration-dependent unemployment benefits and hazard rates, I show that for a plausible range of parameters, the firms' cutoff point becomes a focal point when workers, realizing that being unemployed for long periods of time will hurt their chances of employment, intensify their search as that date grows near. This reinforces the focal point as good workers leave the workforce in large numbers just before the cutoff. In the U.S, this happens at six months when unemployment benefits normally expires and before which job search intensifies.

One question that may arise is whether the recent increase in the availability of unemployment insurance to unemployed jobseekers can generate a new equilibrium at some time above six months. While this is possible in an environment of perfect information, it is not true when agents have little information to use to form beliefs about the behavior of their counterparts. It may take quiet some time for employers to learn about the composition of the unemployment pool beyond six months of unemployment which postulates a coordination problem that may reinforce the six months focal point.

In an extension to the experimental study, I am evaluating the impact on hiring decisions in New York City after the recently enacted anti-discrimination bill protecting the unemployed. The law which has been effective since June 11, 2013, prohibits employers and employment agencies from basing hiring decisions on an applicant's unemployment history. Moreover, there are some straightforward extensions to the theoretical model and directions for further research. First, the present model assumes that the matching rate is constant. In ongoing work, we relax this assumption by allowing the matching rate to depend on the labor market tightness and explore the implications on the vacancy and unemployment relationship—the Beveridge curve (Dickens and Ghayad, 2013). Both the decision by employers to test and the choice of an "acceptable" period if unemployment affect the position of the Beveridge curve. In particular, we conjecture that the outward shift in the Beveridge curve can be fully explained by the screening decisions of firms. Another task for future research would be to depart from assuming that unemployed individuals have perfect forsight with respect to the future time paths of $b(\tau)$, H, and $\mu(.)$, and instead allow for stochastic changes in these variables. These may be due to such things as unforeseen changes in aggregate macroeconomic conditions or changes in personal circumstances. It then seems reasonable to assume that agents are aware of uncertainty and derive their optimal strategies given some (subjective) assessment of the probabilities that such changes occur.

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A   Appendices

A.1   The Bellman Equation: Continuous Time

Here I present the derivation of the first order differential equation for an unemployed individual (Bellman equation) from equation (5) in the text. The Bellman equation can effectively reduce the multi-period optimization to a two-stage problem.

$$U(t_0) = \int_{t_0}^{x} [u(b(\tau)) - c(s(\tau)) + \mu(\tau)E(\tau)]P(\tau, t_0)e^{-\rho(\tau - t_0)}d\tau + U(\tau)P(x, t_0)e^{-\rho(x - t_0)} \tag{A.1.1}$$

This can be written as

$$U(\tau)P(\tau, t)e^{-\rho(\tau - t)}d\tau - U(t) = \int_{t}^{x} [u(b(\tau) - cs(\tau)) + \mu(\tau)E(\tau)]$$
$$* P(\tau, t)e^{-\rho(\tau - t)}d\tau \tag{A.1.2}$$

Finding the derivative of the expression in (20) with respect to τ we get

$$\frac{d}{d\tau}\left(U(\tau)P(\tau, t)e^{-\rho(\tau - t)}d\tau\right) = -[u(b(\tau) - cs(\tau)) + \mu(\tau)E(\tau)]$$
$$* P(\tau, t)e^{-\rho(\tau - t)}$$
$$\Leftrightarrow$$
$$P(\tau, t)e^{-\rho(\tau - t)}\left[U'(\tau) - [\rho + \mu(\tau)]U(\tau)\right] =$$
$$- [u(b(\tau) - cs(\tau)) + \mu(\tau)E(\tau)]$$
$$* P(\tau, t)e^{-\rho(\tau - t)} \tag{A.1.3}$$

And, dividing both sides by $P(\tau, t)e^{-\rho(\tau - t)}$,

$$U'(\tau) - [\rho + \mu(\tau)]U(\tau) = -[u(b(\tau) - cs(\tau)) + \mu(\tau)E(\tau)] \tag{A.1.4}$$

Which can be rearranged to get

$$\rho U(\tau) = u(b(\tau) - cs(\tau)) + U'(\tau) + \mu(\tau)[E(\tau) - U(\tau)] \tag{A.1.5}$$

which is the maximized Bellman equation at the optimal solution for control variables (a first order differential equation). The solution to this first-order differential, subject to the appropriate boundary condition, is the value function for the problem.

26

Maximum duration of UI benefits

Employer cutoff point
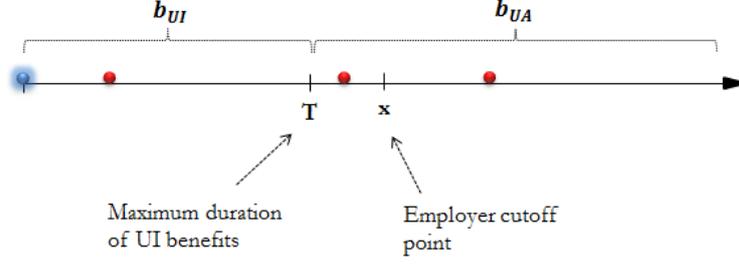
A.2 Properties of the Optimal Strategy

For a derivation of the properties of the optimal strategy it is necessary to examine in detail the expected present value of income when unemployed. Individuals who are unemployed for τ units of time are assumed to maximize the following expression:

$$U(t_0) = \int_{t_0}^{x} [u(b(\tau)) - c(s_i(\tau)) + \mu(\tau)E(\tau)]P(\tau,t_0)e^{-\rho(\tau-t_0)}d\tau + U(\tau)P(x,t_0)e^{-\rho(x-t_0)} \tag{A.2.1}$$

in which $u(b(\tau))$ denotes the income flow at τ, $c*s(\tau)$ is the cost of searching with high intensity, $\mu(.)$ is the job finding rate, and $P_i(\tau, t)$ is the probability of staying in unemployment up to τ conditional on being unemployed at t. Let $U(\tau)$ denote the expected present value of income at time τ when following the optimal strategy. Then $U(\tau)$ is the supremum of expression (A.2.1) over all admissible policies (see Van Den Berg (1990) for more information of least upper bounds). For nonstationary decision processes, a recursive equation in terms of the optimal value generally does not follow trivially from some optimality principle. To solve for the equilibrium outcome in this paper, the recursive relation is stated using a differential equation with an initial condition at each point where the exogenous variables governing the unemployed lifetime utility change value.

The worker's optimization problem can be written as:

$$\frac{dU_i}{d\tau} = \rho U_i(\tau) - u(b(\tau)) + cs_i(\tau) - (m*(s_i(\tau))*H_i)[E - U_i(\tau)] \tag{A.2.2}$$

where $U_i(x) = u(b_{UA})/\rho$ is the continuation value after x. Therefore, an individual will find it optimal to search with high intensity iff $H_i m[E-U_i(\tau)] > c$

This implies that that either $s(\tau) = s_L$ for all $\tau \geq 0$ or there exists a unique duration $0 \leq z_i \leq x$ such that $s(t) = s_H$ iff $\tau \geq z_i$

First, if $H_i m[u(w) - u(b_{UA})] < \rho c$, then the optimal behavior of an unemployed is to search with low intensity for all $\tau \geq 0$. Otherwise, to solve for the optimal duration at which a jobseeker switches from searching with low intensity to high intensity, I split the time axis into a finite number of intervals, within which all exogenous variables are continuous functions of time and then work backwards. As unemployment benefits are discontinuous at T, the question arises what happens to the value of being unemployed at this point. Value functions measure overall utility from optimal behavior between now and the end of the planning horizon. The value of being unemployed depends on unemployment benefits and unemployment duration only and is continuous in τ. Hence, it holds that the value of being unemployed at T, where b_{UI} are still paid, equals the value an instant thereafter where b_{UA} are paid (Launov and Walde, 2012).

Formally,

$$U(b_{UI}, T) = U(b_{UA}, T)$$

First, we solve the jobseeker's problem for $\tau \leq x$:
The stationary expected lifetime utility at x (when all exogenous variables are constant) is

$$U_1(x) = P(x,t)*e^{-\rho(x-t)}*\hat{U}(b_{UA}) \tag{A.2.3}$$

and the value of being unemployed at any time less than x,

$$U_{1i}(t_0) = \int_{t}^{x} \left\{ [u(b_{UA} - c*s(\tau)) + \mu(s(\tau),m,H_i(\tau))*E]*P(\tau,t)*e^{-\rho(\tau-t)} \right\} d\tau \tag{A.2.4}$$

Following the steps in Appendix A1, equation (A.2.4) can be written as a first order differential equation such that:

$$\frac{dU_{1i}(\tau)}{d\tau} = \rho U_{1i}(\tau) + c * s_H - u(b_{UA}) - (m * (s_H) * H_i)[E - U_{1i}(\tau)] \tag{A.2.5}$$

where $U_{1i}(x) = \frac{u(b_{UA})}{\rho}$ is the continuation value at x representing the initial solution for the differential equation. The solution for this first order differential equation can therefore be written as:

$$U_{1i}(\tau) = \frac{u(b_{UA}) + (m * (s_H) * H_i) E - ch}{\rho + m * (s_H) * H_i} \left[1 - e^{-(\rho + (m*(s_H)*H_i))(x-\tau)}\right]$$
$$+ \frac{u(b_{UA})}{\rho} e^{-(\rho + (m*(s_H)*H_i))(x-\tau)} \tag{A.2.6}$$

If $H_i m[E-U_{1i}(T)] < c$, then z_i is such that $H_i m[E-U_{1i}(z_i)] = c$. Otherwise, move backwards to the time interval [0,T]
Next, we solve the jobseeker's problem for all $\tau \leq T$:

$$U_{2i}(t_0) = \int_t^T \left\{ [u(b_{UI} - c * s(\tau)) + \mu(s(\tau), m, H_i(\tau)) * W] \right.$$
$$\left. * P(\tau, t) * e^{-\rho(\tau - t)} \right\} d\tau \tag{A.2.7}$$
$$U_{2i}(T) = U_{1i}(T) \tag{A.2.8}$$

Following Appendix A.1, the continuous time Bellman equation for (A.2.7 & A.2.8) can be written as:

$$\frac{dU_{2i}(\tau)}{d\tau} = \rho U_{2i}(\tau) - u(b_{UI}) + c * s_H - (m * (s_H) * H_i)[E - U_{2i}(\tau)] \tag{A.2.9}$$

with $U_{2i}(T) = U_{1i}(T)$ being the continuation value at T (or the initial solution for the differential equation). The solution for this first-order differential equation can therefore be written as:

$$U_{2i}(\tau) = \frac{u(b_{UI}) + (m * (s_H) * H_i) E - c * s_H}{\rho + (m * (s_H) * H_i)} \left[1 - e^{-(\rho + (m*(s_H)*H_i))(T-\tau)}\right]$$
$$+ U_{1i}(T) e^{-(\rho + (m*(s_H)*H_i))(T-\tau)} \tag{A.2.10}$$

If $H_i m[E-U_{2i}(0)] < c$, then z_i is such that $H_i m[E-U_{2i}(z_i)] = c$. If not, $s(\tau) > 0$ for all $\tau \leq x$. We can substitute backwards in the value functions to solve for z:

$$U_{2i}(z) = \frac{u(b_{UI}) + (m * (s_H) * H_i) E - c * s_H}{\rho + (m * (s_H) * H_i)} \left[1 - e^{-(\rho + (m*(s_H)*H_i))(T-z)}\right]$$
$$+ U_{1i}(T) e^{-(\rho + (m*(s_H)*H_i))(T-z)} \tag{A.2.11}$$

but

$$U_{1i}(T) = \frac{u(b_{UA}) + (m * (s_H) * H_i) E - c * s_H}{\rho + (m * (s_H) * H_i)} \left[1 - e^{-(\rho + (m*(s_H)*H_i))(x-T)}\right]$$
$$+ \frac{u(b_{uA})}{\rho} e^{-(\rho + (m*(s_H)*H_i))(x-T)} \tag{A.2.12}$$

substituting $U_{1i}(T)$ in $U_{21}(z_i)$ and solving for z we get

$$z = T + \frac{1}{\rho + m * s_H} ln \left[\frac{u(b_{UI}) + c\frac{\rho+m}{m} - u(w)}{u(b_{UI}) - u(b_{UA}) + \frac{\left(m*s_H \frac{u(w)-u(b_{UA})}{\rho} - c*s_H\right)}{e^{(\rho+m*s_H)(x-T)}}} \right] \tag{A.2.13}$$

A.3 Solving for the Optimal Cut-off Time

Using equations (13) and (17) from the text, the probability that an employer meets a high-productivity applicant with duration τ can be written as:

$$p_h(\tau) = \frac{(s_H)\pi_0}{(s_H)\pi_0 + (1-\pi_0)e^{-m*s_H*z+m(s_H-H)\tau}} \tag{A.3.1}$$

$p_h(\tau)$ is strictly decreasing in τ:

$$\frac{dp_h(\tau)}{d\tau} = \frac{-(s_H)\pi_0(1-\pi_0)m(s_H-H)e^{-mhz+m(s_H-H)\tau}}{\left[(s_H)\pi_0 + (1-\pi_0)e^{-ms_Hz+m(s_H-H)\tau}\right]^2} < 0 \tag{A.3.2}$$

Given the definitions of π_0 and H, both (1 - π_0) and ($s_H - H$) are positive. The exponentiation term is positive as is m given its definition. Consequently, the numerator is always negative given its leading negative sign. Since the denominator, being a squared term, is always positive, the first derivative is always negative. Consequently, $p_h(\tau)$ is strictly decreasing in τ.

To solve for the optimal cut-off x, isolate τ and denote it x

$$x = \frac{\ln\left(\left[\frac{(s_H)\pi_0}{p_h(\tau)} - (h+1)\pi_0\right]\left(\frac{1}{1-\pi_0}\right)\right) + ms_Hz}{m(s_H-H)} \tag{A.3.3}$$

Separate terms and substitute the expression for $p_h(\tau)$

$$x = \frac{s_Hz}{(s_H-H)}$$
$$+ \frac{1}{m(s_H-H)}\ln\left(\left[\frac{(s_H)\pi_0}{\frac{-H\pi_1}{\pi_h-H\pi_1}} - (s_H)\pi_0\right]\left(\frac{1}{1-\pi_0}\right)\right) \tag{A.3.4}$$

Eliminate the compound fraction in the first term of the log product

$$x = \frac{s_Hz}{(s_H-H)}$$
$$+ \frac{1}{m(s_H-H)}\ln\left(\left[\frac{(s_H)\pi_0(\pi_h-H\pi_1)}{-H\pi_1} - (s_H)\pi_0\right]\right.$$
$$\left.* \left(\frac{1}{1-\pi_0}\right)\right) \tag{A.3.5}$$

Combine the first term in the log product into one fraction over a common denominator

$$x = \frac{s_Hz}{(s_H-H)} + \frac{1}{m(s_H-H)}\ln\left(\left[\frac{(s_H)\pi_0(\pi_h)}{-H\pi_1}\right]\left(\frac{1}{1-\pi_0}\right)\right) \tag{A.3.6}$$

Substitute in the expressions for π_h and π_l

$$x = \frac{s_Hz}{(s_H-H)} + \frac{1}{m(s_H-H)}\ln\left(\left[\frac{\frac{y_h-w}{\rho}}{H\left[\frac{w-y_l}{\rho}\right]}\right]\left(\frac{(s_H)\pi_0}{1-\pi_0}\right)\right) \tag{A.3.7}$$

Eliminate ρ

$$x = \frac{s_Hz}{(s_H-H)} + \frac{1}{m(s_H-H)}\ln\left(\left[\frac{y_h-w}{H[w-y_l]}\right]\left(\frac{(s_H)\pi_0}{1-\pi_0}\right)\right) \tag{A.3.8}$$

A.4 Solving for Equilibrium Candidate z

$$z = T + \frac{1}{\rho + m * s_H} ln \left[\frac{u(b_{UI}) + c\frac{\rho+m}{m} - u(w)}{u(b_{UI}) - u(b_{UA}) + \frac{\left(m*s_H \frac{u(w)-u(b_{UA})}{\rho} - c*s_H\right)}{e^{(\rho+m*s_H)(x-T)}}} \right] \tag{A.4.1}$$

$$x = \frac{s_H}{(s_H - H)}z + ln \left[\frac{(y_h - w)\pi_0 s_H]}{H(w - y_l)(1 - \pi_0)} \right]^{m(s_H - H)} \tag{A.4.2}$$

Substituting (A.4.2) into (A.4.1) and setting the resulting equation equal to zero will solve for an equilibrium candidate z. For a given set of parameters, z will be between 0 and T.

Table A.5: Response Rates

			Full Sample	Professional	Sales	Administrative
(1)	All Resumes		8.30%	8.84%	8.30%	7.77%
			[3360]	[1120]	[1120]	[1120]
(2)	Employed		10.25%	9.00%	12.75%	9.00%
			[1200]	[400]	[400]	[400]
(3)	Nonemployed		7.18%	8.75%	5.83%	7.08%
			[2160]	[720]	[720]	[720]
(4)	Employed	Same Industry	14.67%	13.00%	17.50%	13.50%
			[600]	[200]	[200]	[200]
(5)		Diff Industry	5.83%	5.00%	8.00%	4.50%
			[600]	[200]	[200]	[200]
(6)	ST Nonemployed	Same Industry	16.11%	21.67%	15.00%	11.67%
			[360]	[120]	[120]	[120]
(7)		Diff Industry	8.33%	5.83%	8.33%	10.83%
			[360]	[120]	[120]	[120]
(8)	Med Nonemployed	Same Industry	12.22%	17.50%	7.50%	11.67%
			[360]	[120]	[120]	[120]
(9)		Diff Industry	4.17%	3.33%	1.67%	7.50%
			[360]	[120]	[120]	[120]
(10)	LT Nonemployed	Same Industry	1.94%	3.33%	1.67%	0.83%
			[360]	[120]	[120]	[120]
(11)		Diff Industry	0.56%	0.83%	0.83%	0.00%
			[360]	[120]	[120]	[120]

Interview Requests Rate

Notes: The table reports response rates across subsamples of the experimental data. In brackets in each cell is the number of resumes sent in that cell. Resumes with a spell between [1, 3] are grouped under ST Nonemployed; resumes with a spell between [4, 6] are grouped under Med Nonemployed; and those with a spell greater than 6 months are grouped under LT Nonemployed.

Table A.6: Mean Response Rates By Industry Experience

	Matching Experience *Mean Response*	No Relevant Experience *Mean Response*	Percent difference *(p-value)*
Employed	14.66% [600]	5.83% [600]	8.83% (0.0000)
Nonemployed	10.09% [1080]	4.35% [1080]	5.74% (0.0000)
duration=1	15.83% [120]	9.84% [122]	6.00% (0.0821)
duration=2	16.39% [122]	8.93% [112]	7.46% (0.0443)
duration=3	16.10% [118]	6.35% [126]	9.75% (0.0076)
duration=4	13.13% [137]	5.64% [124]	7.49% (0.0200)
duration=5	12.19% [123]	3.22% [124]	8.97% (0.0040)
duration=6	11.00% [100]	3.57% [112]	7.43% (0.0177)
duration=7	3.27% [61]	1.96% [51]	1.31% (0.3301)
duration=8	3.70% [54]	0.00% [62]	3.70% (0.0661)
duration=9	2.00% [50]	1.72% [58]	0.28% (0.4583)
duration=10	0.00% [71]	0.00% [68]	0.00% (.)
duration=11	1.56% [64]	0.00% [61]	1.56% (0.165)
duration=12	1.66% [60]	0.00% [60]	1.66% (0.1597)

(Left vertical label for the duration rows: Nonemployed Applicants)

Notes: The table reports, for the entire sample and different subsamples of sent resumes, the interview response rates for applicants with matching industry experience (column 1) and different industry experience (column 2), as well as the difference (column 3) of these response rates. In brackets in each cell is the number of resumes sent in that cell. Column 3 also reports the p-value for a test of proportion testing the null hypothesis that the response rates are equal across groups with matching or no relevant experience.

Table A.7: The Effects of Nonemployment and Industry Experience
Dependent variable: Received a request for interview
Sample: Unemployed Only

	(1)	(2)	(3)	(4)
$SAME_i$	0.180***	0.179***	0.176***	0.183***
	(0.022)	(0.023)	(0.039)	(0.035)
$DIFF_i$	0.112***	0.111***	0.110***	0.111*
	(0.022)	(0.023)	(0.032)	(0.035)
$LTsame_i$	-0.0798**	-0.0799**	-0.0788**	-0.0768*
	(0.030)	(0.030)	(0.030)	(0.036)
$LTdifferent_i$	-0.010	-0.010	-0.011	-0.006
	(0.019)	(0.019)	(0.019)	(0.036)
$TREND\_0\_6\_SAME_i$	-0.0113*	-0.0113*	-0.0114*	-0.0122
	(0.006)	(0.006)	(0.006)	(0.006)
$TREND\_7\_12\_SAME_i$	-0.005	-0.005	-0.004	-0.0053
	(0.004)	(0.004)	(0.004)	(0.008)
$TREND\_0\_6\_DIFF_i$	-0.0141**	-0.0141**	-0.0145**	-0.0143**
	(0.005)	(0.005)	(0.006)	(0.005)
$TREND\_7\_12\_DIFF_i$	-0.003	-0.003	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Baseline Characteristics		X	X	X
MSA Fixed Effects			X	X
Resume Template				X
Average response rate	0.072	0.072	0.072	0.072
N	2160	2160	2160	2160
adj. R-sq	0.113	0.114	0.111	0.113

Standard errors in parentheses
* $p<0.05$. **$p<0.01$. *** $p<0.001$

Note: Data are resume submissions matched to employer responses. The baseline controls are indicators for the three job categories (administrative. sales. and professional). Standard errors (in parentheses) are clustered at the firm level to address the non-independence of errors within firms.

Table A.8: Regression Results by Occupation
Dependent variable: Received a request for interview
Sample: Unemployed Only

	Overall (1)	Professional (2)	Sales (3)	Administrative (4)
$SAME_i$	0.180***	0.235***	0.183***	0.121*
	(0.022)	(0.058)	(0.050)	(0.050)
$DIFF_i$	0.112***	0.0959**	0.126**	0.115**
	(0.022)	(0.038)	(0.042)	(0.042)
$LTsame_i$	-0.0798**	-0.131*	0.0112	-0.104*
	(0.030)	(0.057)	(0.060)	(0.041)
$LTdifferent_i$	-0.010	0.0302	0.0171	-0.0744*
	(0.019)	(0.045)	(0.021)	(0.030)
$TREND\_0\_6\_SAME_i$	-0.0113*	-0.0116	-0.0205	-0.00115
	(0.006)	(0.015)	(0.012)	(0.013)
$TREND\_7\_12\_SAME_i$	-0.005	0.001	-0.0148	-0.00101
	(0.004)	(0.009)	(0.011)	(0.001)
$TREND\_0\_6\_DIFF_i$	-0.0141**	-0.0143	-0.0216*	-0.00679
	(0.005)	(0.009)	(0.009)	(0.010)
$TREND\_7\_12\_DIFF_i$	-0.003	-0.00881	-0.00145	-2.71e-17***
	(0.003)	(0.009)	(0.002)	(0.000)
Average response rate	0.072	0.086	0.058	0.071
N	2160	720	720	720
adj. R-sq	0.113	0.153	0.093	0.1044

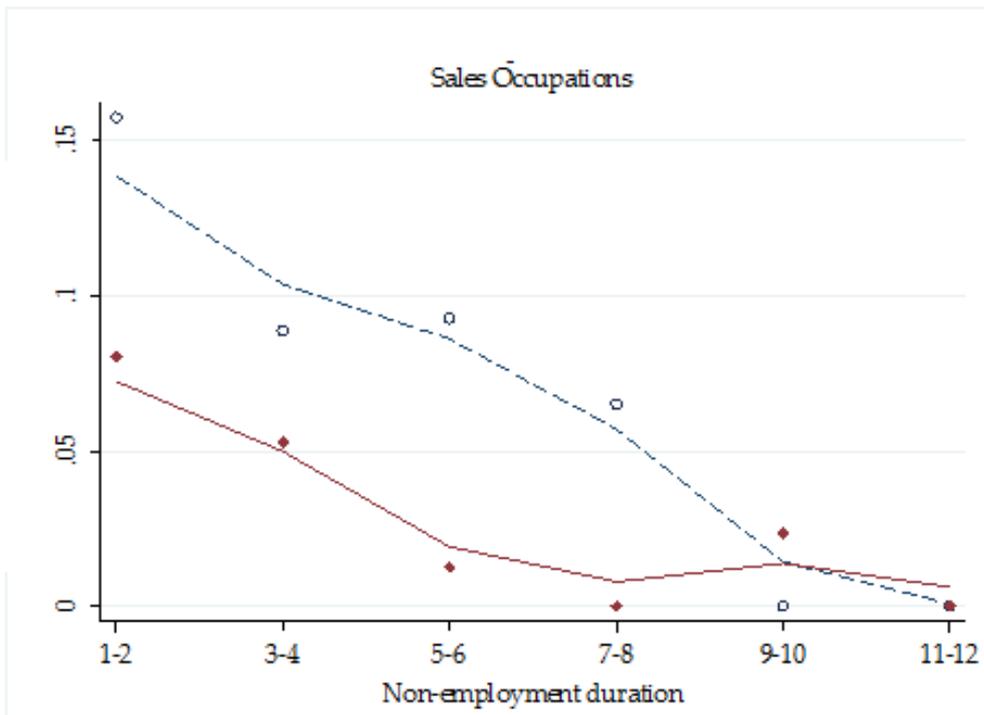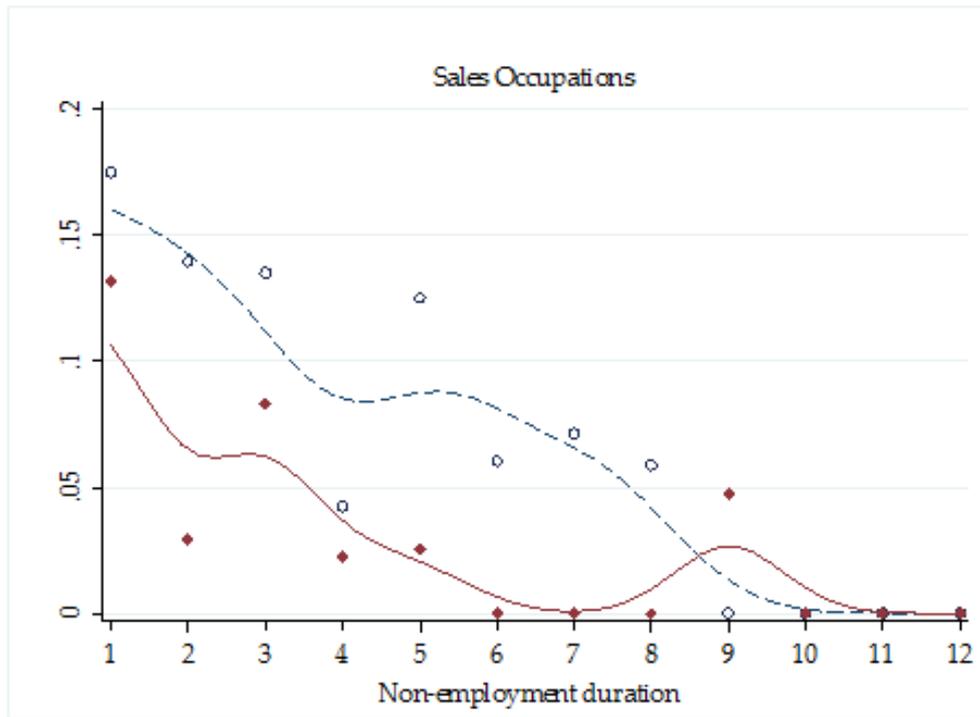Standard errors in parentheses
* p<0.05. **p<0.01. *** p<0.001

Note: Data are resume submissions matched to employer responses. The baseline controls are indicators for the three job categories (administrative, sales and professional). Standard errors (in parentheses) are clustered at the firm level to address the non-independence of errors within firms.

Figure A.9: Response Rate by Industry-Specific Experience | Professional Occupations
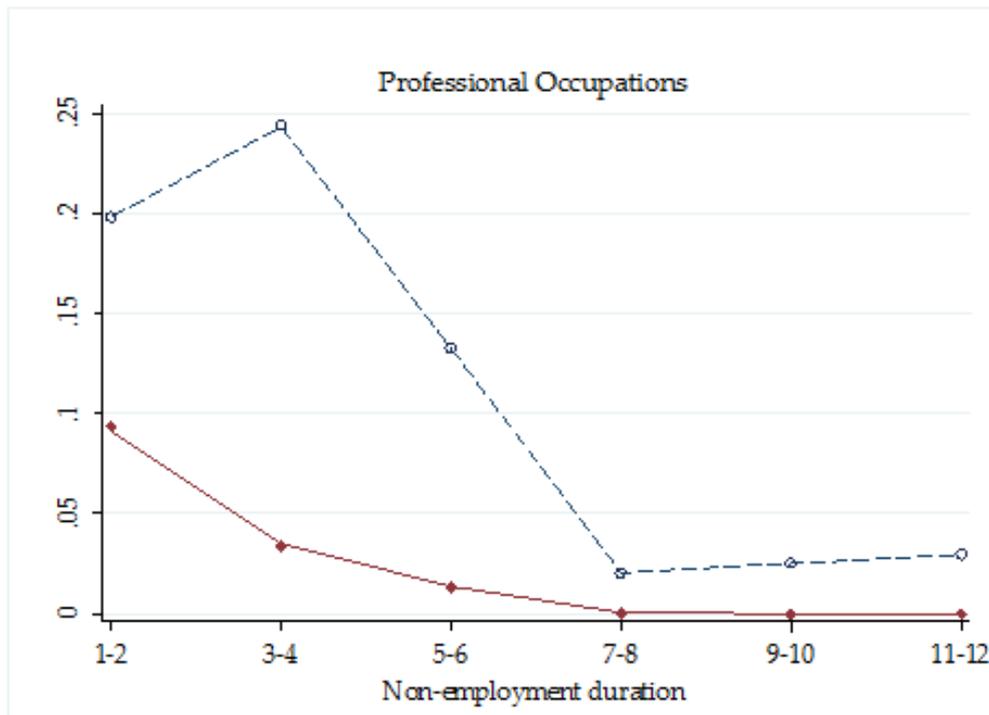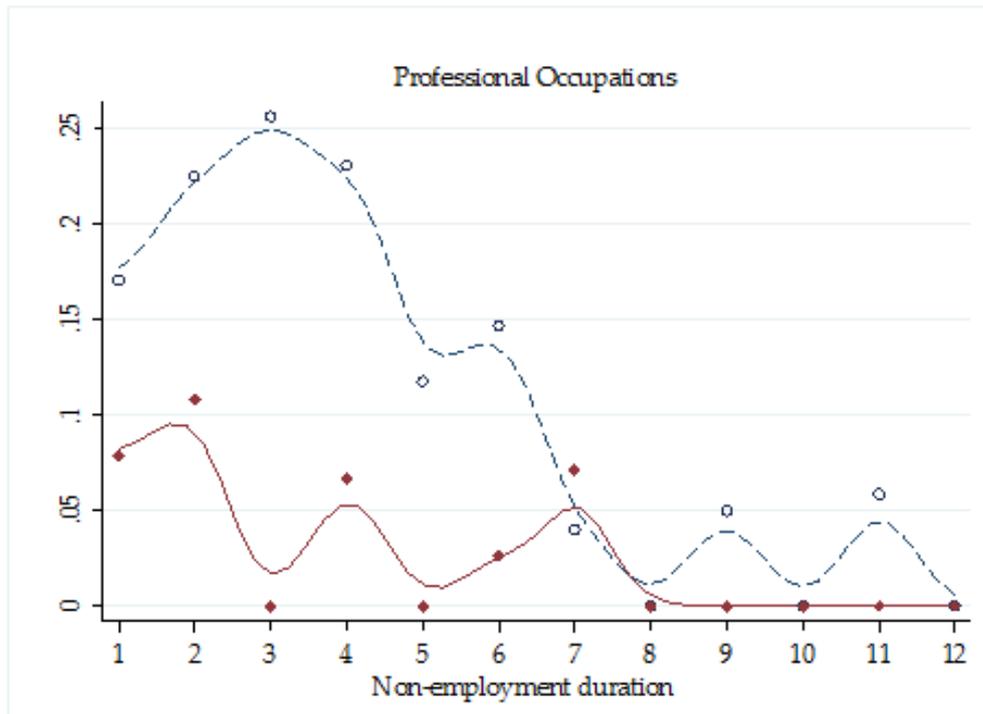
Professional Occupations

Non-employment duration

Professional Occupations

Non-employment duration

[a]

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[a]Notes: The top figure reports the interview request rate by length of nonemployment spell (months) for applicants with experience in the same type of firm (blue dots) and others with no relevant industry experience (red diamonds) using the sample of professional résumés. In the bottom figure, the data are grouped into 1-2 month bins before computing the response rate. In both figures, the curves connecting the data points are (smoothed) local means generated using a Guassian kernel and a bandwidth of 0.5.

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Figure A.10: Response Rate by Industry-Specific Experience | Sales Occupations

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Figure A.11: Response Rate by Industry-Specific Experience | Administrative Occupations
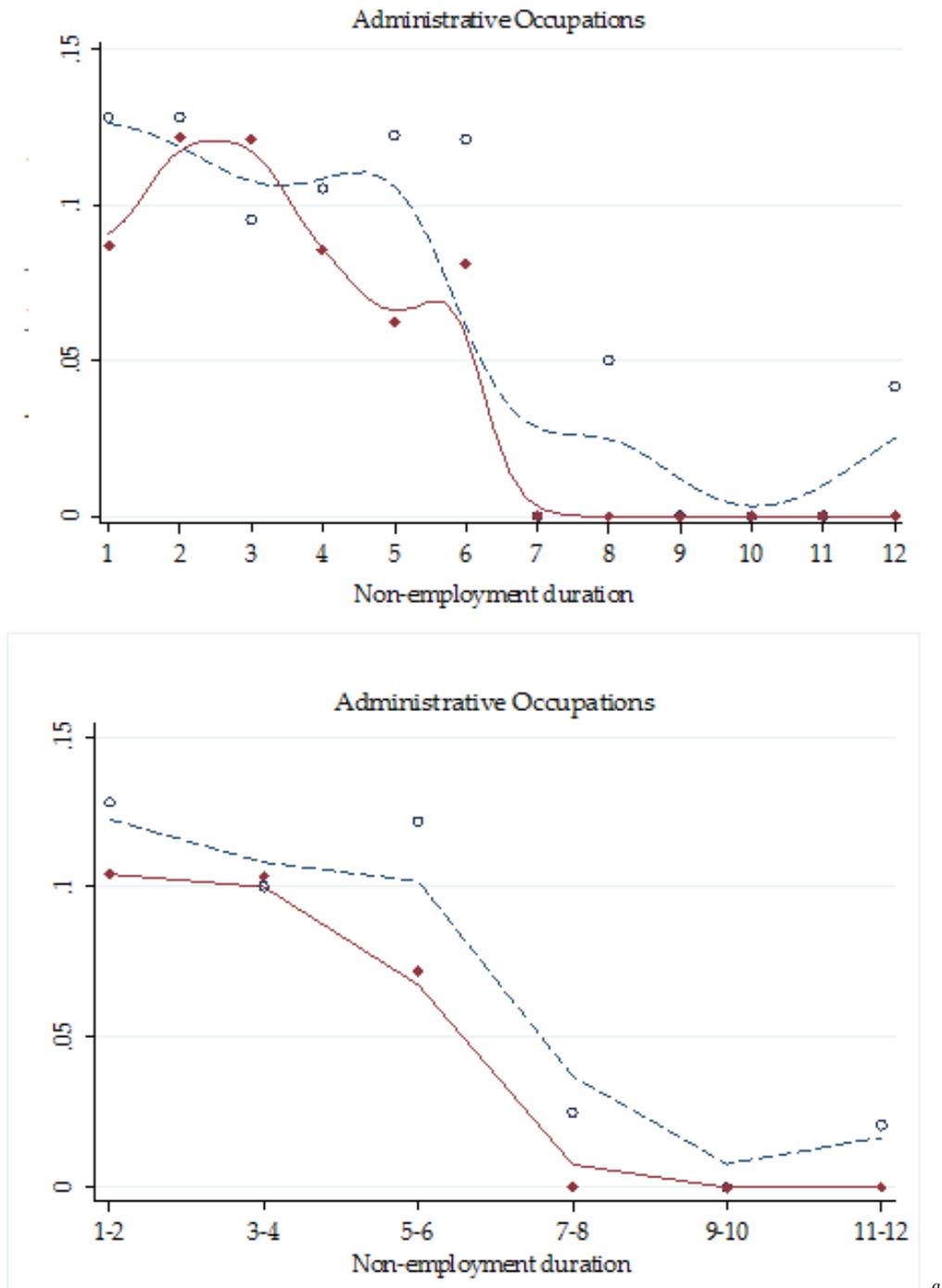
[a]Notes: The top figure reports the interview request rate by length of nonemployment spell (months) for applicants with experience in the same type of firm (blue diamonds) and others with no relevant industry experience (red dots) using the sample of administrative résumés. In the bottom figure, the data are grouped into 1-2 month bins before computing the average callback. In both figures, the curves connecting the data points are (smoothed) local means generated using a Guassian kernel and a bandwidth of 0.5.

SAMPLE 1

Jake Courtney

100 Warren St

Jersey City, NJ 07302-6406

jakecourtney2013@gmail.com

Employment History:

January 2012- January 2009
Administrative Assistant,
Bank of America, Pennington, NJ

- ❖ Processed loan applications and other administrative duties
- ❖ Processed check requests/invoices; prepared travel/expense reports
- ❖ Supported the recruiting process by performing all administrative aspects of the new hire and onboarding life cycle, including background checks, new hire paperwork, and onboarding.
- ❖ Input and retrieved data utilizing knowledge of various computer software packages

December 2008- December 2005
Administrative Assistant,
First Commerce Bank, Lakewood, NJ

- ❖ Provided general lending information to clients; prepared loan applications for credit approval; disbursed approved loans; provided client services related to the lender's consumer, commercial and real estate loan clients and potential clients.
- ❖ Processed and filed loan documentation within bank standards.
- ❖ Collected and analyzed data to produce weekly and monthly specialized reports.

Education:

- Monmouth University,   West Long Branch, NJ
  B.S. in Business Administration, 2005
- James J Ferris High School, 2002,   Jersey City, NJ

Victor Manove
787 Ocean Ave
Jersey City, NJ 07304-2753
Vmanove13@gmail.com

SAMPLE 2

Employment History:

June 2012- June 2009   **Rutgers University**, New Brunswick, NJ
Administrative Assistant

- Maintained and updated databases, spreadsheets, and official records, and implements administrative policies.
- Provided support to Dean's staff (scheduled meetings, managed calendars, and researched and prepared documents).
- Performed administrative duties, such as answering telephone calls, filing, faxing, copying, sorting incoming mail, and preparing correspondence.
- Drafted correspondence, memoranda, speeches, position papers, program/grant proposals and other written documentation.

May 2009- May 2006   **Trinitas Regional Medical Center**, Elizabeth, NJ
Administrative Assistant

- Provided routine administrative support such as: typing memos and letters, answering telephones, and taking and distributing messages.
- Performed general office duties, including mailings, photocopies, and filing.
- Proofread and edited manuscripts, performed library and literature searches, and helped create and edit presentation materials.
- analyzed data into reports and presentations; coordinated and monitored budget preparation;

Education:

2006   BS in Business Administration
       Bloomfield College, Bloomfield, NJ
2001   *St Mary High School*, Jersey City, NJ