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Unemployment, Underemployment, and Employment Opportunities: Results from a Correspondence Audit

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The Effects of Unemployment and Underemployment on Employment Opportunities: Results from a Correspondence Audit of the Labor Market for College Graduates

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Abstract

We use data from a résumé audit to estimate the impact of unemployment and underemployment on the employment prospects facing recent college graduates. We find no statistical evidence of negative duration dependence associated with unemployment spells for recent college graduates. Alternatively, college graduates who are underemployed have callback rates that are 30 percent lower than that for applicants who are adequately employed. The adverse effects of underemployment are robust across cities with different labor-market conditions. Internship experience obtained while completing one's degree reduces the negative effects of underemployment substantially. We conclude that underemployment serves as a strong, negative signal to prospective employers.

JEL categories: J23, J24, J64, J70

Key words: unemployment, underemployment, duration dependence, labor demand, employment, internships, field experiments, correspondence studies, résumé audits

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1 Introduction

The unemployment and underutilization of human capital suffered by college graduates who began their careers during and following the Great Recession is unprecedented.[1] Throughout this period, the unemployment rate of newly-minted college graduates was significantly higher than the national unemployment rate (Spreen 2013). In addition, many recent college graduates who were able to find work took jobs that were below their skill level (Abel, Dietz and Su 2014).

It is important to understand how recessions harm new entrants to the labor market, as the largest increases in pay and promotions typically occur during the initial career phase (Murphy and Welch 1990). Research shows that college graduates who enter the labor force during recessions have lower life-time earnings and diminished career advancement (Kahn 2010; Oeropoulos, von Wachter and Heisz 2012). While the effect of unemployment duration on re-employment probabilities has been studied extensively (Imbens and Lynch 2006; Oberholzer-Gee 2008; Shimer 2008; Kroft, Lange and Notowidigdo 2013; Eriksson and Rooth 2014; Baert, Cockx, Gheyle, and Vandamme 2014; Baert and Verhaest 2014; Demmer et al. 2014), less emphasis has been placed on the subsequent labor-market consequences associated with underemployment.

We conduct a résumé audit of the labor market for recent college graduates. We simulate the labor-market experiences of college graduates affected by the Great Recession with randomly assigned spells of unemployment and underemployment to fictive work histories. For a seven-month period during 2013, over 2300 online help-wanted advertisements were answered with a randomized set of fictitious résumés from recent college graduates who completed their degrees in May 2010.[2] Differences in callback rates across a variety of perceived

[1] The severity of the employment crisis experienced by this cohort of "unlucky" young people has led to such undesirable monikers as the "New 'Lost' Generation" (See Casselman and Walker 2013).

[2] With the same experimental data set, Nunley, Pugh, Romero and Seals (2015a) examine the effects of different college majors and internship experience on employment prospects and Nunley, Pugh, Romero and Seals (2015b) test for racial discrimination. In the former paper, we find that business degrees do not increase the probability of receiving a callback for jobs specific to business degrees (e.g., having a degree in finance or economics does not increase the probability of interview request from a bank or financial firm). However,

productivity characteristics, which are signaled on the résumés, constitute the outcomes of interest. Job seekers in our sample are either unemployed at the time of application, have an initial spell of unemployment after graduation but are employed at the time of application, or have no gaps in their work histories. In an effort to estimate the impact of underemployment on subsequent job opportunities, applicants are randomly assigned work experience that either requires no college education or requires a college education and is relevant to the industry of the prospective employer.

We applied to job openings in seven large U.S. cities across the following industries: banking, finance, insurance, management, marketing and sales. A key feature of our experimental design is the incorporation of variation in premarket productivity characteristics that closely match the skill-sets specific to these industries. First, we randomly assign traditional business degrees in accounting, economics, finance, management, and marketing and degrees from arts and sciences in biology, english, history, and psychology. Second, applicants could have an industry-specific internship, which occurs the summer before graduation, assigned independent of the undergraduate major.

We find no statistical evidence of negative duration dependence associated with unemployment spells for recent college graduates, regardless of the labor-market conditions present in the city/metropolitan area. By contrast, we find strong evidence that subsequent employment prospects are harmed by becoming underemployed after graduation. Applicants who are underemployed at the time of application are about 30 percent less likely to receive a callback than applicants who are adequately employed at the time of application.[3] The harm caused by underemployment is large in both relatively "tight" and "loose" labor markets, although the adverse impact is larger in labor markets with relatively more slack.

internship experience significantly increases, both statistically and economically, the chances of an interview request. In the latter paper, we find that employers discriminate against candidates with black-sounding names, but the racial gap in employment opportunities does not depend on employment status. Overall, the racial differences detected are driven by greater discrimination in jobs that require substantial customer interaction (e.g., sales agent, loan officer, customer-service representative).

[3] Throughout the manuscript, we use the terms "adequate employment" to reflect employment in a job that requires a college degree and is specific to the industry of the prospective employer.

Our data suggest that prospective employers view underemployment as a signal. We reach this conclusion because of the following patterns in the data. First, it is likely that unemployment and underemployment would have similar effects on the decline in applicants' skill-sets. However, we find no evidence that unemployment spells negatively affect callback rates. By contrast, the effect of underemployment is strong and negative. Second, the unemployed who were underemployed in the past are *favored* over their contemporaneously underemployed counterparts. Third, industry-relevant internship experience obtained while completing one's degree mitigates the effect of underemployment significantly. As an example, consider applicants who are underemployed at the time of application. The callback rate for underemployed applicants who worked as interns while completing their degrees is about 17 percent higher than underemployed applicants who did not obtain internship experience.

The strong, mitigating effect of internship experience in our sample likely represents a lower bound, as the internships last only three months and occurred approximately four years prior to the date of application (Nunley, Pugh, Romero and Seals 2015a). This finding is both surprising and encouraging, as incentivizing firms to take on interns could be a relatively low-cost option for policymakers interested in reducing the adverse effects of recessions on young workers. However, more research is needed to determine whether industry-specific experience early in one's career enhances productivity and/or serves as a signal.[4]

Our study is part of a growing literature in which résumé audits are used to study employment variables other than demographic indicators (e.g., race/ethnicity, gender and age). Studies by Oberholzer-Gee (2008), Eriksson and Rooth (2014) and Kroft, Lange and Notowidigdo (2013) document the negative effects of unemployment spells on firms' perceptions of job candidates. However, Erikkson and Rooth (2014) find no evidence (a) of

[4]Nunley, Pugh, Romero and Seals (2015a) contend that industry-relevant internship experience signals unobservables valued by prospective employers in the initial phase of the hiring process. However, the skills gained via internship experience may be more relevant in later stages of the hiring process. As a result, Nunely, Pugh, Romero and Seals (2015a) argue that a full assessment of mechanism(s) through which internships affect employment outcomes is not possible with a resume-audit study. However, the signaling interpretation is supported by Saniter and Siedler (2014), who argue that internship experience for workers in Germany is a "door opener" to the labor market.

negative duration dependence for high-skilled applicants (those with a college degree) or (b) that past unemployment spells affect employment opportunities. Oberholzer-Gee (2008) and Kroft, Lange and Notowidigdo (2013) also find that the newly unemployed are more likely to receive a positive response from employers than the currently employed. While our results are roughly consistent with Eriksson and Rooth's (2014) findings for high-skilled workers, the existing audit literature has not generated robust estimates with respect to employers' perceptions of job applicants' work histories.

2 Background

Entry and re-entry to the workforce involve complicated dynamics that are not yet well understood by economists. Theoretical research emphasizes the loss of skill (Acemoglu 1995; Ljungqvist and Sargent 1998), signaling (Lockwood 1991; Vishwanath 1989), ranking (Blanchard and Diamond 1994) and search behavior (e.g., Rogerson, Shimer, and Wright 2005) as mechanisms through which re-employment probabilities are affected by unemployment duration. A voluminous empirical literature on the relationship between unemployment spells and re-employment probabilities exists. Machin and Manning (1999) conduct a review of the literature on the relationship between unemployment spells and re-employment probabilities in Europe, concluding that the empirical evidence does not strongly support negative duration dependence. Using data from the U.S., Imbens and Lynch (2006) find evidence of negative duration dependence. In addition, the importance of duration dependence appears to vary between countries (van den Berg and van Ours 1994) and races within a country (van den Berg and van Ours 1996).[5]

[5] The aforementioned studies focus on labor-market consequences of contemporaneous unemployment. An empirical literature also exists on the impact of past unemployment spells on employment (Arulampalam, Booth and Taylor 2001; Burgess et al. 2003; Heckman and Borjas 1980; Gregg 2001; Ruhm 1991). The findings from this literature are mixed. However, most European studies generally find negative effects of past unemployment on current (un)employment probabilities, while U.S. studies tend to find little empirical support for such effects. In addition, there are a number of studies that examine the "scarring" effects of unemployment on future earnings (Arulampalam 2001; Gregory and Jukes 2001; Jacobson, LaLonde and Sullivan 1993; Mroz and Savage 2006; Ruhm 2001; Stevens 1997). For the most part, these studies report that past unemployment/displacement results in reductions in long-term earnings.

Because the majority of studies in the duration-dependence literature rely on administrative or survey data, it is difficult to know whether the results reflect a causal relationship or unobserved heterogeneity.[6] The existing literature is also primarily concerned with supply-side behavior, as the demand-side of the market is a reflection only of the sample of workers who have accepted wage offers from firms and, as a result, the full distribution of wage offers is unobserved. The lack of information in existing survey and administrative data regarding the pool of workers from which firms choose also limits our ability to understand the micro-foundations of the process through which firms match with workers (Petrongolo and Pissarides 2001).

To circumvent some of these identification issues, researchers have conducted résumé audits to examine the effects of job applicants' unemployment spells on firms' hiring decisions. Kroft, Lange and Notowidigdo (2013) randomly assign unemployment spells of 1-36 months to fictitious résumés to study duration dependence in over 100 labor markets in the U.S. Although the authors find large, negative effects on call backs for applicants with long spells of unemployment, they also find the short-term unemployed are more likely to receive a call back than the currently employed. Eriksson and Rooth (2014) study the Swedish labor market with a sample of fictitious job seekers who apply for work in occupations roughly representative of the job openings in both Sweden and the U.S. They find some evidence of duration dependence for unemployment spells over nine months in length for low- and medium-skilled job applicants. However, they find no evidence that employers condition callbacks on periods of unemployment when job seekers apply to high-skilled jobs (defined as occupations which require a university degree).[7] Both Kroft, Lange and Notowidigdo (2013) and Eriksson and Rooth (2014) document negative duration dependence for low-

[6]Heckman (1991) and Machin and Manning (1999) provide detailed information on the empirical issues related to identifying the causal effect of unemployment duration on re-employment probabilities.

[7]Eriksson and Rooth (2014) also examine the impact of past unemployment spells on employment prospects. Their experimental data indicate that employers do not use past unemployment spells to inform current hiring decisions. These findings could indicate that the subsequent work experience obtained after a past unemployment spell mitigates the prospective "scarring" effect.

and middle-skilled workers.[8] Oberholzer-Gee (2008) recruits two job seekers and conducts a job search on their behalf. The experiment manipulates the duration of unemployment by assigning spells of 6, 12, 18, 24 and 30 months to the recruited job seekers. He finds strong evidence of duration dependence in the labor market for administrative assistants with unemployment spells of 24 and 30 months. However, unemployment spells of up to two years have positive effects on interview requests.

During the Great Recession, college graduates were more likely to accept jobs below their skill level (i.e. underemployment) than in the past (Abel, Deitz and Su 2014).[9] Although rates of underemployment had begun to increase in response to the 2001 recession, the 2007-2009 recession led to even higher rates of underemployment among college graduates entering the labor force (Abel, Deitz and Su 2014). Oeropoulos, von Wachter, and Heisz (2012) study the effect of recessions on life-cycle earnings with a matched data set of Canadian college graduates and their employers. They find long-term earnings losses associated with recessions are primarily a consequence of the quality of the employer with whom graduates initially find work. Moreover, the time required to recover from poor initial labor-market conditions depends on the quality of the job candidate, with the less able college graduates suffering the effects of recessions longer. Similarly, Baert, Cockx and Verhaest (2013) find that young workers in North Belgium who accept jobs below their educational attainment experience difficulties transitioning to employment that matches the worker's educational level.

Spells of underemployment or unemployment could cause skills to depreciate and/or serve as a signal of lower expected productivity. McCormick (1990) develops a model of job search in which firms use employment in a secondary market (i.e. underemployment) as a negative signal of future productivity because more productive potential employees face higher costs to work outside their respective trades. In McCormick's model, high-quality workers reveal their productivity to employers via job-search effort and are better off not taking an interim

[8] Riach and Rich (2002) and Pager (2007) provide discussions on the correspondence methodology and its alternatives.

[9] See Leuven and Oosterbeek (2011) for a review of the literature on overeducation.

job that is beneath their skill-set. Baert and Verhaest (2014) conduct a correspondence audit of the Belgian labor market in which they examined the differential treatment between school leavers, the previously unemployed, and the previously "overeducated".[10] Although they find some evidence that underemployment spells are deleterious to employment prospects, Baert and Verhaest (2014) conclude the stigma associated with unemployment is greater than that of underemployment. We return to this issue in section 4.5 when we discuss the findings of Baert and Verhaest (2014) in greater detail and review some of literature on the effect of gaining relevant experience early in a job seeker's career.

3 The Experiment

3.1 Design

We submitted 9396 résumés to job openings that were posted online in the following large cities: Atlanta, GA, Baltimore, MD, Boston, MA, Dallas, TX, Los Angeles, CA, Minneapolis, MN and Portland, OR. The cities chosen for our experiment span the midwestern, northeastern, northwestern, southeastern, and southwestern regions of the U.S. We applied to job openings in banking, financial services, insurance, management, marketing and sales. The experiment began in January 2013 and lasted until the end of July 2013 – a seven-month period. Four résumés were submitted to each job opening.[11]

The credentials listed on the resumes were randomly assigned to the fictive applicants via the résumé-randomizer program developed by Lahey and Beasley (2009). The resume-randomizer program allows one to create thousands of randomly-generated resumes, which eliminates the prospect of experimenter effects. Each applicant is randomly assigned a name,

[10]In Baert and Verhaest (2014), overeducation refers to having work experience that does not require a college degree post-graduation, which we refer to as underemployment. See figure 1 in Baert and Verhaest (2014).

[11]The Institutional Review Boards at both University of Wisconsin-La Crosse and Auburn Unversity ruled that our experiment did not consitute human subjects research. The only requirements were that we would not reveal the identities of any names of the universities or firms used in our experiment.

a street address, a university where they completed their Bachelor's degree, an academic major, (un)employment status, whether they report a high grade point average (GPA), whether the applicant completed their Bachelor's degree with an Honors distinction, the type of work experience the applicant obtained after completing their degrees, and whether the applicant obtained internship experience while completing their Bachelor's degree.

Certain aspects of the experiment are held constant. First, all applicants have Bachelor's degrees, which were completed in May 2010. Our focus on recent college graduates stems from the difficulties associated with finding employment in general (Spreen 2013) and employment commensurate with their schooling (Abel, Deitz and Su 2014) for young people. The experiment is designed to simulate the actual experiences that recent college graduates encountered when they first entered the job market after graduation in May 2010. Second, the fictive applicants obtain only one job after graduating from college; hence, after graduation, the job seekers either become adequately employed or underemployed. The assignment of a simplified work history allows us to make each applicant's work experience more salient.[12] Third, resumes are submitted exclusively to job openings in business-related fields. The submission of resumes to business-related jobs is due to our interest in testing whether particular college majors (business and nonbusiness) and business-related internships improve employment prospects (See Nunley, Pugh, Romero and Seals 2015a). Fourth, we applied to jobs which did not (a) require a certificate or specific training, (b) require the submission of a detailed firm-specific application, and (c) require materials other than a résumé to be considered for the job. We chose to apply to jobs that meet these criteria to avoid introducing unwanted variation into the experiment and to generate the largest amount of data points at the lowest possible cost.

In the interest of brevity, we describe the aspects of the experiment that are the focus of this study. The details of the other résumé characteristics are either discussed when they

[12] As a part of our experimental design, we incorporated racially-distinct names into our design, which permits a test for racial discrimination. Short and simplified work histories also make it easier to pin down whether discrimination stems from prejudice or imperfect/incomplete information (See Nunley, Pugh, Romero and Seals 2015b).

are used in our empirical models in Section 4 or in Appendix Section A1.[13] The key résumé characteristics are the (un)employment statuses and the types of work experience applicants accumulate after completing their Bachelor's degrees. For the (un)employment statuses, there are seven possibilities for the applicants at the time of application, and applicants are either employed or unemployed at the time of application. For those who are employed at the time of application, they can be (a) employed with no gaps in work history, (b) employed but were unemployed for three months after completing their Bachelor's degree, (c) employed but were unemployed for six months after completing their Bachelor's degree, or (d) employed but were unemployed for 12 months after completing their Bachelor's degree. For the applicants who were unemployed at the time of application, they can be (a) unemployed for three months, (b) unemployed for six months; or (c) unemployed for 12 months. Twenty-five percent of our applicants are assigned no gaps in their work histories, while the remaining 75 percent of applicants have either a "front-end" (after graduation) or "back-end" (at the time of application) unemployment spell. Applicants with some type of unemployment spell in their work history are assigned one of the six possible work-history gaps with equal probability (i.e. 12.5 percent).

In an effort to examine the impact of underemployment on employment prospects, applicants are randomly assigned two types of work experience. The first type is what we consider underemployment, which is employment for which a Bachelor's degree is not required. In our experiment, underemployment is working at national retail stores with the title of "Retail Associate" or "Sales Associate".[14] Fifty percent of the fictitious applicants are randomly assigned work histories that indicate that they are currently underemployed or were previously underemployed but unemployed at the time of application. The remaining 50 percent of applicants are randomly assigned work experience that requires a college degree and is specific to job category for which they are applying. Specifically, in-field work experi-

[13] Appendix Section A1.1 provides detailed information on each of the résumé characteristics; Section A1.2 provides sample résumés used in the experiment; and Section A1.3 describes the application process.

[14] When applying to job advertisements in the sales job category, we use "Retail Associate" exclusively. For the other job categories, applicants are randomly assigned "Retail Associate" or "Sales Associate".

ence is working either previously or currently as a "Bank Branch Assistant Manager" in the banking job category; "Accounts Payable" or "Financial Advisor" in the finance job category; "Insurance Sales Agent" in the insurance job category; "Distribution Assistant Manager" or "Administrative Associate" in the management job category; "Marketing Specialist" in the marketing job category; and "Sales Representative" or "Sales Consultant" in the sales job category.[15] Our fictitious applicants obtain only one job after graduation. As a result, it is *not* possible for an applicant to have been underemployed and then adequately employed or vice versa.[16]

3.2 Analysis of Observational Data

We examine publicly-available observational data from the March Current Population Survey (CPS) and the American Community Survey (ACS) to (a) compute the share of labor-market participants who are unemployed in general and unemployed for different durations and (b) compute the share of workers employed and the average earnings of workers in occupations that are similar to the ones used in our experiment. The purpose of the analysis is to ascertain whether the features of our experiment match the actual experiences of recent college graduates in the labor market.

Using data from the 2013-2014 March CPS, we calculate the percentage of labor-market participants who are unemployed overall and unemployed for different durations. Calcula-

[15]The use of "Sales Associate" and "Sales Representative" might seem like an arbitrary way of signaling underemployment and adequate employment. However, workers with the title of "Sales Associate" tend to work in retail shops/stores, while a sales representative typically sells their company's product/service to its customers (e.g., wholesalers, retailers, and end-users) in different ways (door-to-door sales, phone calls, etc.). Due to the somewhat nebulous nature of the words "associate" and "representative", we conduct two sensitivity checks. First, we exclude the sales job category from our analysis. Second, we implement our analysis separately using data only from the sales job category. The patterns in the data are similar when using these subsamples (See columns 1 and 2 of Appendix Table A1).

[16]Applicants who are underemployed or adequately employed at the time of application could either have an initial spell of unemployment after graduation or no gap in their work histories. By contrast, applicants who are unemployed at the time of application but were previously underemployed or adequately employed would not experience an initial spell of unemployment after graduation; thus, such applicants would have no gap in their work history until the current spell of unemployment takes place.

tions are provided separately for three education groups: those with less than a Bachelor's degree, those with a Bachelor's degree, and those with more than a Bachelor's degree. From Table 1, labor-market participants with Bachelor's degrees make-up a nontrivial share of the unemployed, as the share of this group who is unemployed is in excess of 10 percent overall and for short (11-18 weeks), medium (23-34 weeks) and long (43-52 weeks) durations. Thus, the observational data support the design of our experiment, as unemployment as well as lengthy unemployment spells are common among recent college graduates.

We use data from the 2010-2013 American Community Survey (ACS) to calculate the percentage employed, average earnings and average hours worked in occupations that are similar to those used in our experiment for banking, finance, insurance, management, marketing, sales and the occupations that are treated as "underemployment". The ACS provides a detailed list of occupations, and we are able to match, albeit imperfectly, these occupations to those assigned to our fictive applicants.[17]

From Panel A of Table 2, workers with Bachelor's degrees comprise the majority of workers in occupations similar to those used in our experiment for banking, finance, management and marketing (i.e. over 50 percent). For the insurance and sales occupations, the share of workers with less than a Bachelor's degree outweigh the share with a Bachelor's degree.[18] In regards to the underemployment occupations used in our experiment, workers with Bachelor's degree make-up about 19 percent of workers in occupations similar to "Retail Associate"

[17] A brief explanation regarding how the occupation variable available from the ACS is used to match the occupations assigned to our fictitious applicants is provided in Appendix Section A2. In addition, Appendix Table A2 presents the occupation codes from the ACS used to match the occupations randomly assigned to the fictive applicants in our experiment. In addition to the occupation groupings provided in Table 2, we also created broader measures that included more occupations. The statistics from these broader definitions reveal the similar patterns. We also replicated our analysis with data from the March CPS, finding similar patterns in the data.

[18] In Appendix Table A1, we estimate models that exclude observations in which applicants applied to sales jobs (column 1), include only observations in which applicants applied to sales jobs (column 2), exclude observations in which applicants applied to insurance jobs (column 3), include only observations in which applicants applied to insurance jobs (column 4), exclude observations in which applicants applied to sales and insurance jobs (column 5), and include only observations in which applicants applied to sales or insurance jobs (column 6). Overall, the estimates indicate similar patterns in the data when we omit observations from the sales and/or insurance job categories and examine observations exclusively from the sales and/or insurance job categories. However, the magnitude of underemployment's impact on callback rates varies for different subsamples.

and "Sales Associate". Although it is less common (relative to the adequate-employment occupations), college graduates represent a nontrivial portion of workers in jobs that are traditionally done by workers with lower levels of educational attainment.

In Panel B of Table 2, we present average earnings and average hours worked in occupations similar to those used in our experiment for workers with Bachelor's degrees. It is apparent that the occupations in "adequate-employment" category earn significantly more than those in the "underemployment" category. Average hours worked for all occupations is above 35 hours, which is the cutoff used by the Bureau of Labor Statistics for full-time work. Because the ACS data do not provide exact matches to the occupations used in our experiment, we cross-check the annual earnings estimates presented in Table 2 by using the salary-search engine provided by indeed.com.[19] The search engine provided by indeed.com allows one to search the salary for a specific job title. Overall, the cross-check between the ACS and the indeed.com's salary database are consistent with one another, except for the "Accounts Payable" occupation used in our experiment: indeed.com's salary database indicates that workers with this job title earn about $30,000 per year.[20]

The descriptive statistics presented in Tables 1 and 2 provide support for our experimental design. It is common for recent college graduates to be unemployed during the time-frame of our experiment. Recent college graduate make-up a nontrivial share of the long-term unemployed (i.e. six months of more). A sizable portion of recent college graduates work in jobs traditionally occupied by workers with less than a Bachelor's degree. The earnings of college graduates in menial jobs are substantially less than those of college graduate who become adequately employed. Thus, our experiment provides a way to evaluate the subsequent employment consequences of college graduates who completed their degrees in

[19] The salaries for the job titles randomly assigned to our fictive applicants is presented in Appendix Table A3. The salary database search engine is accessible at the following web address: http://www.indeed.com/salary?q1=&l1=.

[20] Because of the discrepancy in earnings between the other banking job (i.e. Bank Branch Assistant Manager), we check the sensitivity of the estimated impact of underemployment on callback rates by treating the "Accounts Payable" occupation as a form of underemployment as well. The reclassification of the "Accounts Payable" occupation as underemployment has a minimal impact on the estimates. These estimates are presented in Appendix Table A4.

the aftermath of a severe economic downturn, which resulted in high rates of unemployment and underemployment.

3.3 Data

In Table 3, we present randomization probabilities for each resume credential, sample means for these credentials, and estimates from linear regressions implemented to test whether the (a) unemployed and employed and (b) underemployed and adequately employed are equally likely to be randomly assigned the other resume credentials. The comparison of columns 1 and 2 from Table 3 indicates that the sample means are similar to the randomization probabilities chosen for the creation of the resumes. The estimates in columns 3 and 4 indicate that the unemployed and ever-underemployed are not more or less likely than their employed and ever-adequately-employed counterparts to be assigned the other resume credentials, an indication that the covariates are balanced across the treatment and comparison groups.

Job opportunities are measured by callbacks from prospective employers. The use of callbacks follows other studies that rely on the correspondence methodology to study labor-market opportunities (Baert et al. 2013; Bertrand and Mullainathan 2004; Carlsson and Rooth 2007; Eriksson and Rooth 2014; Kroft, Lange and Notowodigo 2013; Lahey 2008; Oreopolous 2011). When an employer calls or emails an applicant to set up an interview or to discuss the job opening in more detail, we treat such a response as a callback.[21]

[21] A small number of responses from prospective employers were difficult to classify. In particular, there were 17 callbacks that were difficult to code. Six employers asked if the applicant was interested in other positions. One employer asked for information on the applicant's salary requirements. Two employers asked if the applicants were interested in full- or part-time work. Eight employers asked if the applicants had location preferences. Our strategy to deal with each of these atypical employer inquiries is to (a) include observation-specific dummy variables for these types of employer responses, (b) code these employer responses as callbacks, and (c) code these employer responses as non-callbacks. Regardless of how these employer responses are treated, our findings are unaffected. Because our results are not sensitive to ways in which the questionable callbacks are coded, the estimates presented in the manuscript treat these employer responses as callbacks. In addition, 108 applicants were contacted to complete a detailed application through the employer's website. When this happened, all four applicants in a four-person pool received the same phone call or email, making it possible that the response was automated. However, such responses could be non-discriminatory. It is important to point out that there is no variation in callbacks that received these types of employer responses within a four-applicant pool. Because our specifications are based on within-job-advertisement variation, these types of employer responses do not materially affect our estimates.

Table 4 provides descriptive statistics on callback rates for all applicants (column 1), applicants who are unemployed at the time of application (column 2), applicants who were employed at the time of application (column 3), applicants who became underemployed at some point after graduation (column 4) and applicants who became adequately employed at some point after graduation (column 5).[22] Table 4 presents the callback rates for each (un)employment-status group (a) overall, (b) by city and (c) by the industry of the job opening for which applications were submitted. Rather than comment on each statistic presented, we note some general patterns. The city of Baltimore and jobs in the insurance, marketing and sales job categories have the highest callback rates. The callback rates are similar between applicants who are unemployed and employed (compare columns 2 and 3), and the callback rates tend to be lower (substantially in some cases) for applicants who became underemployed relative to those who became adequately employed.

3.4 Regression Models of Interest

Because resume attributes are randomly assigned to the fictive applicants, the estimated parameters from our regression models have a causal interpretation. Despite the reliability of the estimated differentials, the regression models presented in this section do not provide a definitive way of isolating the channel through which periods of unemployment and underemployment affect employment prospects. As a result, we use a variety of different empirical specifications to establish patterns in the data to shed light on these important questions.

In the next section, the estimates presented in Tables 5, 6, 7 and 9 are derived from regression models that are reformulated to produce the desired estimates and empirical tests. In lieu of presenting each of these regression models, we present the two primary regression models that form the basis of our analysis in Sections 4.1-4.4.

Nevertheless, we used the strategy described above to examine the influence of these 108 observations, finding that the ways in which these employer responses are treated does not affect our estimates.

[22]Note that applicants who became underemployed or adequately employed could be employed or unemployed at the time of application.

The first regression model of interest is

$$callback_{imcfj} = \beta_0 + \beta_1 unemp_i + \beta_2 under_i + \mathbf{X}_i'\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \qquad (1)$$

The subscripts i, m, c, f and j index applicants, the month the application was submitted, the city where the application was submitted, the job category of the the job opening and the job advertisement, respectively.[23] The variable *callback* is a dummy variable that equals one when an applicant receives a callback, which consists of an interview request or an invitation to discuss the job opening or other openings in more detail, from an employer and zero otherwise;[24] *unemp* is a zero-one indicator that equals one when an applicant is unemployed and zero otherwise; *under* is a zero-one indicator that equals one when an applicant is underemployed (either previously or at the time of application) and zero otherwise; $\mathbf{X}$ is vector of controls for the résumé characteristics (See Section 3, Table 3 and Appendix Section A1.1); ϕ_m, ϕ_c, ϕ_f and ϕ_j are sets of dummy variables for the month the application was submitted, the city where the application was submitted, the job category (i.e. banking, finance, insurance, management, marketing and sales), and the job advertisement, respectively; u represents unobserved factors that affect the callback rate that are not held constant. We are primarily interested in the estimates for β_1 and β_2. The parameter β_1 measures the average difference in the callback rate between applicants who are unemployed and employed at the time of applicant, and the parameter β_2 measures the average difference in the callback rate between applicants who became underemployed and adequately employed at some point after graduating with their Bachelors degrees.

Our second specification incorporates an interaction between unemployment (*unemp*)

[23] All regression models are estimated as linear probability models. However, we check the robustness of the estimated marginal effects by using the logit/probit specifications, and we find that the estimates are similar. As a result, the estimates presented in the tables are based on linear probability models. In addition, standard errors are clustered at the job-advertisement level in all specifications.

[24] While not presented, we checked the sensitivity of our estimates to a more restrictive version of the *callback* variable, which includes only employer responses that can be conclusively treated as interview requests. Using this more restrictive definition, our findings are unaffected. As a result, we focus exclusively on callback rates instead of interview-request rates.

and underemployment (*under*). We include this interaction term so that we are able to test whether underemployment at the time of application and underemployment in the past have different effects on employment opportunities. Formally,

$$\begin{aligned} callback_{imcfj} = \beta_0 + \beta_1 unemp_i + \beta_2 under_i + \beta_3 unemp_i \times under_i \\ + \mathbf{X}_i'\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{2}$$

All variables in equation 2 are defined above. We use equation 2 to test for differences in callback rates between (a) unemployed applicants who were underemployed in the past and underemployed applicants and (b) unemployed applicants who were adequately employed in the past and adequately-employed applicants.

We augment equations 1 and 2 by substituting a set of dummy variables for different unemployment durations for the *unemp* variable. As a part of our design, applicants who are unemployed at the time of application could be unemployed for a period of three, six or 12 months. The augmented versions of equations 1 and 2 allow us to test for duration dependence, which has been the subject of recent field experiments (Eriksson and Rooth 2014; Kroft, Lange and Notowidigdo 2013; Oberholzer-Gee 2008).

4 Results

4.1 Effects of Unemployment and Underemployment

We begin our analysis by focusing on the effects of contemporaneous unemployment spells and being ever-underemployed[25] on job opportunities.[26] In particular, we present the estimates from equation 1 as well as the augmented version of equation 1 that replaces the

[25] Note that "ever-underemployed" means that the applicant could be underemployed at the time of applicant or unemployed at the time of application but underemployed in the past.

[26] As a part of our experimental design, we also randomly assigned unemployment spells that occur immediately after graduation, similar to Eriksson and Rooth (2014). Ultimately, our data indicate that such gaps in work history have no impact on callback rates, which is also consistent with what Eriksson and Rooth (2014) find. In the interest of brevity, we relegate these estimates to Appendix Tables A5 and A6.

unemployment variable (*unemp*) with the set of indicators for different unemployment durations in Table 5. We present the effects of being unemployed of any duration and ever-underemployed on callback rates in Panel A, and the effects of being unemployed for three-, six- and 12-month durations and ever-underemployed on callback rates in Panel B. In both panels, the estimated effects of unemployment in general or unemployment for specific durations and being ever-underemployed are stable as right-hand-side controls are successively added to the regression models.

From Panel A, contemporaneous unemployment has a positive but statistically and economically insignificant impact on callback rates. However, we find strong statistical evidence that underemployment, whether at the time of application or in the past, negatively affects callback rates. Applicants who became underemployed have a callback rate about 25 percent lower than applicants who became adequately employed.

In Panel B, applicants who have been unemployed for a period of three months are 1.2 percentage points *more* likely to receive a callback than applicants who are employed at the time of application. We also find a positive effect of an unemployment duration of six months, but the magnitude of the effect is small (less than one percentage point). For applicants who are contemporaneously unemployed for a period of 12 months, they experience a lower callback rate than applicants who are employed at the time of application but the effect is small in a practical sense. However, none of these estimated callback differentials between the unemployed and employed are statistically significant at conventional levels. Moreover, the results from an F-test for the joint exclusion of the unemployment duration variables also indicate that different unemployment durations have no effect on callback rates. Similar to the estimates presented in Panel A, we find a robust, negative effect of underemployment on callback rates. The ever-underemployed, again, are about 25 percent less likely to receive a callback than the ever-adequately-employed.

4.2 Past Employment versus Contemporaneous Employment

In this subsection, we present estimates from equation 2, which interacts the unemployment and underemployment variables. Equation 2 and the reformulation of it that substitutes the set of unemployment-duration indicator variables allows us to examine differences in callback rates between (a) unemployed applicants who were underemployed in the past and underemployed applicants and (b) unemployed applicants who were adequately employed in the past and adequately-employed applicants. These estimates are presented in Table 6.[27] In Table 6, there are four columns of estimates for the two sets of comparisons, which differ based on the length of the unemployment spell. We examine unemployment durations of (a) three, six or 12 months in column 1, (b) three months in column 2, (c) six months in column 3, and (d) 12 months in column 4.

Among applicants who are or were underemployed in the past, the callback rate for applicants who are unemployed at the time of application is 12 percent (or 1.7 percentage points) higher than that for applicants who are underemployed at the time of application (row 1, column 1). The higher callback rate for the unemployed is driven, in large part, by the 17 percent (or 2.5 percentage point) and 12 (or 1.7 percentage point) higher callback rates for applicants who have been unemployed for three and six months, respectively (row 1, columns 2 and 3). The impact of a 12-month unemployment spell is positive, but it is small economically and statistically indistinguishable from zero (row 1, column 4). Overall, the unemployed who were underemployed are favored (in terms of interview requests) over those who are unemployed at the time of application, but the effects dissipate with the length of the unemployment spell. For applicants who are or were adequately employed in the past, each of the estimated callback differentials between the unemployed and the employed is negative but small in magnitude. In addition, none of the estimated callback differentials

[27] The estimates presented in Table 6 are based on the parameters and linear combinations of parameters from equation 2. Appendix Section A4.1 provides details on the how the estimates presented in Table 6 are obtained. For interested readers, we present the estimates for the main effects with interaction terms in Appendix Table A7.

is statistically different from zero. These findings contest the presence of negative duration dependence.

4.3 Internship Experience as a Mitigating Factor

As a part of our experiment, a portion of the fictive applicants are randomly assigned internship experience that took place during Summer 2009, the year before the applicants graduated with their Bachelor's degree in May 2010. In particular, internship experience is a form of industry-relevant experience, as it is specific to the industry/job-category for which the applicant is applying. In particular, internship experience is working as a(n) "Equity Capital Markets Intern" in the banking job category; "Financial Analyst Intern" in the finance job category; "Insurance Intern" in the insurance job category; "Project Management Intern" or "Management Intern" in the management job category; "Marketing Business Analyst" in the marketing job category; and "Sales Intern" or "Sales Future Leader Intern" in the sales job category. In a companion paper (Nunley, Pugh, Romero and Seals 2015a), we find that internship experience has a large, positive impact on callback rates.

In this subsection, our goal is to explore the possibility internship experience obtained during the completion of the fictive applicants' Bachelors degrees mitigates the harm caused by underemployment.[28] Perhaps the underemployed are high-quality applicants but were unlucky and took a job that was below their skill level.[29] To investigate the possible mitigating effect of internship experience, we augment equation 2 such that an exhaustive set

[28] We exclude the analysis of interactions between the unemployment-spell indicators and internship experience, as we find no substantive evidence that unemployment spells of any length negatively affect employment prospects.

[29] It is also possible that applicants might accepts jobs that are below their skill level out of need. A measure of "need" might be applicants' socioeconomic statuses. We investigate this possibility by using the street addresses that are randomly assigned to applicants, which is a proxy for socioeconomic status. For each city, applicants are assigned one of four street addresses. Two of the street addresses are in neighborhoods where house prices exceed $750,000, while the remaining two street addresses are in neighborhoods where house prices are below $100,000. For the most part, these tests indicate little difference in the callback rates between the underemployed who live in high-socioeconomic-status areas and those who live in low-socioeconomic-status areas. The only exception is among the unemployed, in which case the previously underemployed who are assigned high-socioeconomic-status street addresses are affected less negatively than those with low-socioeconomic-status street addresses. These estimates are presented in Appendix Table A8.

of comparisons between the underemployed and adequately employed with and without internship experience can be made. These comparisons are presented in Table 7.[30] Column 1 presents the estimated callback gap between underemployed and adequately-employed applicants without internship experience; column 2 presents the estimated callback gap between underemployed applicants with internship experience and adequately-employed applicants without internship experience; column 3 presents the estimated callback gap between underemployed applicants without internship experience and adequately-employed applicants with internship experience and column 4 presents the estimated callback gap between underemployed and adequately-employed applicants with internship experience.

To investigate the mitigating effect of internship experience, comparisons between the estimates in columns 1 and 2, columns 3 and 4 and columns 1 and 4 are particularly informative. If the estimated effects of underemployment (relative to adequately employment) decline in magnitude (in absolute value) across columns 1 and 2, columns 3 and 4 and columns 1 and 4, such patterns in the data would be indicative of a mitigating effect. However, if the coefficient estimates remain similar in magnitude or increase (in absolute value), the data would not support the idea that internship experience mitigates the harm caused by underemployment.

Among applicants who did not work as interns while completing their degrees, the callback rate for the underemployed is about 31 percent (or 4.9 percentage points) lower than the callback rate for the adequately employed. When the underemployed worked as interns and the adequately employed did not work as interns, the callback differential is reduced by about 45 percent. The comparison between the underemployed who did not work as interns and the adequately employed who worked as interns yields a much larger callback differential (42 percent or 6.7 percentage points). Among applicants who worked as interns while completing their degrees, the callback rate for the underemployed is 23 percent (or 4.4 percentage points) lower than the callback rate for the adequately employed. Each of

[30] See Appendix Section A4.3 for details regarding how the estimates presented in Table 7 are obtained.

the estimated differentials presented in Table 7 are statistically significant at either the five- or one-percent levels. Although not presented in Table 7, we also examined the impact of internship experience on the callback differential between underemployed applicants who did and did not work as interns while completing their degrees. These estimates indicate that internship experience improves employment prospects among the underemployed by about 16 percent (relative to the underemployed who did not work as interns). Taken together, the estimates presented in Table 7 support the notion that internship experience mitigates the negative impact of underemployment.[31]

4.4 Effects of Unemployment and Underemployment in Tight and Loose Labor Markets

The existing literature has produced mixed evidence regarding the presence of negative duration dependence in labor markets with "tight" and "loose" conditions. For example, Imbens and Lynch (2006) find that duration dependence is stronger when the labor market is tight. By contrast, Dynarski and Sheffrin (1990) find the opposite. Abbring, van den Berg and van Ours (2001) find that the interaction effect varies with the duration of the unemployment spell. Using experimental data, Kroft, Lange and Notowididgo (2013) provide support for the conclusions of Imbens and Lynch (2006). In this subsection, we examine whether the lack of evidence supporting negative duration dependence in Section 4.1 and 4.2 is due to differential effects of unemployment in relatively tight and loose labor markets. We also examine whether callback differentials between the underemployed and adequately employed vary between labor markets with relatively tight and loose conditions.

In Table 8, we present the average unemployment rate as well as the minimum and

[31] We note that the coefficient estimates in columns 1 and 4 of Table 7 are not substantially different from one another, as the percentage point differences differ only by 0.05 percentage points. However, the predicted difference in the callback rate in terms of probability indicate a reasonably smaller callback gap between the underemployed and adequately employed with internship experience (column 4) than that between the underemployed and adequately employed without internship experience (column 1). It is important to point out the average callback rate among applicants without internship experience is 16.1%, and the callback rate among applicants with internship experience is 18.4%, which explains the 25% difference (computed as $1 - {}^{0.23}/_{0.31}$) in the predicted probabilities.

maximum values for the unemployment rates in the metropolitan areas in which the cities used in our experiment are found. The unemployment statistics presented in Table 8 pertain to the period in which our experiment took place: January 2013 through July 2013. The average unemployment rates in Boston, Dallas and Minneapolis are the lowest (ranging from 5.2% to 6.4%), and those in Atlanta and Los Angeles are the highest (ranging from 8.3% to 9.2%). The remaining cities (i.e. Baltimore and Portland) have average unemployment rates in between these extremes (between 7.3% and 7.8%). We treat cities with the lowest average unemployment rates as having relatively "tight" conditions (i.e. Boston, Dallas and Minneapolis), and we treat cities with the highest unemployment rates as having relatively "slack" or "loose" conditions (i.e. Atlanta and Los Angeles).[32]

In our sample, the overall callback rate in the relatively tight labor markets is about 16 percent, while it is slightly over 13 percent in the relatively loose labor markets. Table 9 presents the estimated effects of unemployment and underemployment on employment prospects in relatively "tight" and "loose" labor markets.[33] The estimates in row 3 allow us to test whether the callback gap between the unemployed and employed (column 1, 2, 3 and 4) and the callback gap between the underemployed and adequately employed (column 5) is larger or smaller in relatively loose versus relatively tight labor markets.

From row 1, the data indicate that unemployment spells of any length (column 1), three months (column 2) and six months (column 3) have positive but statistically-insignificant effects on callback rates. By contrast, unemployment spells of 12 months (column 4) have a negative effect on callback rates, but the estimated differential is small in an economic sense and is not statistically different from zero. For applicants who are underemployed at the time of application, their callback rates are 3.8 percentage points lower than applicants who are adequately employed at the time of application (column 5). This estimate translates into

[32]Because it is somewhat arbitrary to classify cities with unemployment rates in the 7% and 8% ranges as having fundamentally different labor-market conditions, we conduct a sensitivity check in which we treat cities with an average unemployment rate that is 7% or higher as having "loose" or "slack" conditions. Ultimately, the patterns in the data are the same. These estimates are presented in Appendix Table A8.

[33]We present the regression model used to produce the estimates in Appendix Section A4.4.

a 23 percent callback differential in terms of probability, and it is statistically significant at the one-percent level.

From row 2, applicants with an unemployment spell of any length are more likely to receive callbacks than applicants who are employed (column 1). The estimated impact of a three-month unemployment spell is statistically significant at the 10-percent level and is large in a economic sense (i.e. 19 percent in terms of probability or 2.6 percentage points). Unemployment spells of six and 12 months have negative effects on callback rates. However, these effects are small (in absolute value), and both estimated differentials are statistically indistinguishable from zero. Between the underemployed and adequately employed, the underemployed are about 6.7 percentage points less likely to receive callbacks. This estimated differential is statistically significant at the one-percent level, and it translates into a 41 percent lower callback rate for the underemployed relative to the adequately employed.

In row 3 of Table 9, we present the relative differences within each comparison (i.e. unemployed versus employed and underemployed versus adequately employed) between the relatively loose and relatively tight labor markets. For the unemployment statuses (columns 1-4), we find small relative differences, which are statistically indistinguishable from zero, across the relatively loose and tight labor markets. However, we find the estimated callback gap between the underemployed and the adequately employed is about 17 percent larger in relatively loose labor markets, but the estimated differential is not statistically significant.[34]

4.5 Discussion of Results

We find no statistical evidence in support of negative duration dependence for recent college graduates, which is, to some extent, at odds with other correspondence audits of the labor market. However, the results in Kroft, Lange and Notowidigdo (2013), Eriksson and Rooth (2014) and Oberholzer-Gee (2008) do not consistently show robust, negative duration dependence. In our study, the composition of the comparison group is critically im-

[34]The estimated differential is close to being statistically significant at the 10-percent level (the p-value is 0.113), and an estimated 17-percent callback gap is potentially significant in an economic sense.

portant, as we detect (a) a negative but not statistically significant relationship between unemployment and callback rates among the ever-adequately-employed and (b) a positive and statistically significant relationship between unemployment and callback rates among the ever-underemployed.[35]

Differences in experimental design, population of interest, sample period, and institutional structure of labor markets likely account for the variation in estimates of duration dependence from the existing audit literature. Our study focuses on recent college graduates, who have short work histories (maximum of three years of work experience) and the same educational attainment; thus, our applicants are fundamentally different from the fictive job seekers used in other correspondence-type studies. The data collection spans the period of January 2013 through the end of July 2013, while the data used in the other field experiments was collected in 1999 (Oberholzer-Gee 2008), 2011-2012 (Kroft, Lange and Notowidigdo 2013), and 2007 (Eriksson and Rooth 2013). Given that Kroft, Lange and Notowidigdo (2013) show that duration dependence is more pronounced in tight labor markets, it is possible that our lack of support for negative duration dependence reflects the slack conditions present in the labor markets examined in our experiment. However, when we examine the effects of unemployment in general and unemployment spells of different length in relatively tight and loose labor markets, we find no statistical evidence of negative duration dependence.

We find strong evidence underemployment harms the employment prospects facing recent college graduates, and these findings hold across labor markets with tight and slack conditions. These findings are not generally consistent with those of Baert and Verhaest (2014) who show unemployment spells are a stronger negative signal than underemployment. Their experimental design and sample differ from our study in several important ways. First, all

[35] We use three different unemployment-spell categories, while Kroft, Lange and Notowidigdo's (2013) experiment randomly assigns unemployment durations from one to 36 months. It is possible that our study misses some of the decline in callback rates in response to unemployment duration, as Kroft, Lange and Notowidigdo (2013) detect sharp declines in callback rates within the first few months of unemployment spells.

of their fictitious applicants are unemployed at the date of application, while our experiment involves both employed and unemployed applicants. Secondly, applicants are assigned three different levels of education (Secondary, Bachelors, and Masters degrees), whereas we assign different majors within the same education level (i.e. a Bachelors degree). Thirdly, they study the Belgian labor market, which has a different institutional structure than that of the U.S.

Our experiment is also designed to examine the effect of recessions on young workers. Oeropoulos, von Wachter, and Heisz (2012) show the quality of the first job is crucial for lifecycle earnings. Hence, our findings could indicate that employers perceive applicants who are underemployed as lower-quality employees, given that such applicants have not found employment that matches their skill-set three to four years after graduation. Such a conclusion is supported by our analysis of internship experience as a characteristic that could mitigate the harm caused by underemployment. While not conclusive, the mitigating effect of internship experience suggests that employers "forgive" bad luck.

Of the premarket factors incorporated in our study, internship experience has the largest positive effect for those who became underemployed following graduation. While internships have not received much attention in the literature,[36] there is a closely related literature that focuses on the effect of structured apprenticeship programs in European labor markets (Adda et al. 2013; Fersterer, Pischke, and Winter-Ebmer 2008; von Wachter and Bender 2006). Some have argued that apprenticeships, particularly in Germany where approximately 60 percent of youth apprentice, offer substantial labor-market returns for participants and reduce youth unemployment by structuring the school-to-work transition (Ryan 2001). The mechanisms through which apprenticeships affect employment outcomes and labor-market dynamics are, however, complex and likely vary based on the quality of the apprenticeship

[36] Knouse, Tanner and Harris (1999) and Saniter and Siedler (2014) are the only two studies (to our knowledge) that examine the effects of internships on labor-market outcomes. The former study finds business students who received internships had higher grade point averages and were also more likely to receive offers of employment. However, it is difficult to know whether their findings reflect a causal relationship. The latter study relies on a plausibly exogenous policy change regarding mandatory internships in Germany, and they find internships raise earnings by approximately six percent.

(Adda et al. 2013; Ryan 2001). The same is likely true of internships.[37]

5 Conclusions

The labor market college graduates entered in 2010 was particularly weak. We study labor market demand in the U.S. for college graduates from the class of 2010 with a large-scale résumé-audit study. Approximately 9400 résumés were submitted to prospective employers from fictitious job seekers who graduated in May 2010. The sample period runs from January 2013 through the end of July 2013. Unemployment spells of a year or less are randomly assigned to job seekers. Applicants are also randomly assigned industry-relevant work experience as well as job experience that did not require a college degree (i.e. underemployment). In our experimental design, we randomly assign a number of "premarket" characteristics, including whether the applicants worked as interns while completing their Bachelors degrees.

We find no evidence in support of negative duration dependence, as unemployment spells (of any length) have no statistically significant impact on callback rates. We should note the employers in our sample probably expected recent college graduates to have gaps in their work histories, given that they graduated at a time (May 2010) when the national unemployment rate was near 10 percent and the unemployment rate for recent college graduates was 13 percent (Abel, Dietz and Su 2014; Spreen 2013). Alternatively, underemployment has a strong, negative effect on callback rates: job seekers who are underemployed have callback

[37] With internship experience, young workers may accumulate industry-specific experience that is valued by employers. Neal (1995) finds that workers who are displaced from jobs are better able to recover wage losses if they find a job in the same pre-displacement industry. Our experiment does not allow a direct test of whether the observed return to internships occurs through industry-specific human capital, as internship experience was assigned specific to the industry of the observed firm. However, the results for internships suggest that the accumulation of industry-specific capital could be an important channel through which young workers increase their marketability. It could also be that an applicant with industry-relevant internship experience signals higher match quality with the firm. Our companion paper (Nunley, Pugh, Romero and Seals 2015a) and Saniter Siedler (2014) present evidence that supports signaling as the most likely channel through which internships affect labor-market outcomes.

rates that are 30 percent lower than adequately-employed applicants. The adverse effects of underemployment hold across labor markets with relatively tight and loose conditions, although the adverse effects are larger in labor markets with relatively more slack.

Our data suggest underemployment is substantially more harmful than unemployment in terms of subsequent job opportunities for recent college graduates. There are two theoretical predictions of particular relevance to this finding: (i) underemployment causes skill depreciation and (ii) underemployment signals lower ability and/or expected productivity. It is unlikely skill loss explains the patterns in our data. If skill loss is the mechanism through which subsequent employment prospects are reduced for the underemployed, the degree of skill loss would likely be similar for the unemployed and underemployed. Based on the results from different empirical specifications, we contend that underemployment operates as a strong, negative signal to potential employers. For example, applicants who are unemployed at the time of application, who were previously underemployed, fair better than the applicants who are underemployed at the time of application.

We also test whether internship experience obtained during one's undergraduate years reduces the differential treatment based on underemployment status. We find a three-month internship in Summer 2009 reduces the negative effect of underemployment substantially. The mitigating effect of internship experience may have important implications for policy, as incentivizing firms to hire college students as interns could alleviate the negative effects on their life-time earnings from entering the labor market during and following an economic downturn.

References

[1] Jaap H Abbring, Gerard J Van Den Berg, and Jan C Van Ours. Business cycles and compositional variation in u.s. unemployment. *Journal of Business and Economic Statistics*, 19(4):436–448, 2001.

[2] Jaison R Abel, Richard Deitz, and Yaqin Su. Are recent college graduates finding good

jobs? *Federal Reserve Bank of New York: Current Issues in Economics and Finance*, 20(1):1–8, 2014.

[3] Daron Acemoglu. Public policy in a model of long-term unemployment. *Economica*, 62(246):161–178, 1995.

[4] Jerome Adda, Christian Dustmann, Costas Meghir, and Jean-Marc Robin. Career progression, economic downturns, and skills. *National Bureau of Economic Research Working Paper Series No. 18832*, 2013.

[5] Ching Albert Ma and Andrew M Weiss. A signaling theory of unemployment. *European Economic Review*, 37(1):135–157, 1993.

[6] Wiji Arulampalam. Is unemployment really scarring? effects of unemployment experiences on wages. *The Economic Journal*, 111(475):585–606, 2001.

[7] Wiji Arulampalam, Alison L Booth, and Mark P Taylor. Unemployment persistence. *Oxford Economic Papers*, 52(1):24–50, 2000.

[8] Wiji Arulampalam, Paul Gregg, and Mary Gregory. Unemployment scarring. *The Economic Journal*, 111(475):577–584, 2001.

[9] Stijn Baert, Bart Cockx, Niels Gheyle, and Cora Vandamme. Is there less discrimination in occupations where recruitment is difficult? *Industrial and Labor Relations Review*, page forthcoming, 2014.

[10] Stijn Baert, Bart Cockx, and Dieter Verhaest. Overeducation at the start of the career: Stepping stone or trap? *Labour Economics*, 25:123–140, 2013.

[11] Stijn Baert and Dieter Verhaest. Unemployment or overeducation: Which is a worse signal to employers? *IZA Discussion Paper No. 8312*, 2014.

[12] Marianne Bertrand and Sendhil Mullainathan. Are emily and greg more employable than lakisha and jamal? a field experiment on labor market discrimination. *The American Economic Review*, 94(4):991–1013, 2004.

[13] Olivier Jean Blanchard and Peter Diamond. Ranking, unemployment duration, and wages. *The Review of Economic Studies*, 61(3):417–434, 1994.

[14] Simon Burgess, Carol Propper, Hedley Rees, and Arran Shearer. The class of 1981: The effects of early career unemployment on subsequent unemployment experiences. *Labour Economics*, 10(3):291–309, 2003.

[15] Magnus Carlsson and Dan-Olof Rooth. Evidence of ethnic discrimination in the swedish labor market using experimental data. *Labour Economics*, 14(4):716–729, 2007.

[16] Ben Casselman and Marcus Walker. Wanted: Jobs for the new lost generation. *Wall Street Journal, September 13th. : http://online. wsj. com/news/articles/SB10001424127887323893004579057063223739696*, 2013.

[17] David J Deming, Noam Yuchtman, Amira Abulafi, Claudia Goldin, and Lawrence F Katz. The value of postsecondary credentials in the labor market: An experimental study. *National Burea of Economic Research Working Paper Series No. 20528*, 2014.

[18] William C Dudley. Are recent college graduates finding good jobs? *Federal Reserve Bank of New York Speech*, (June 27), 2013.

[19] Marcus Eliason and Donald Storrie. Lasting or latent scars? swedish evidence on the long-term effects of job displacement. *Journal of Labor Economics*, 24(4):831–856, 2006.

[20] Stefan Eriksson and Dan-Olof Rooth. Do employers use unemployment as a sorting criterion when hiring? evidence from a field experiment. *The American Economic Review*, 104(3):1014–1039, 2014.

[21] Josef Fersterer, Jörn-Steffen Pischke, and Rudolf Winter-Ebmer. Returns to apprenticeship training in austria: Evidence from failed firms. *The Scandinavian Journal of Economics*, 110(4):733–753, 2008.

[22] Paul Gregg. The impact of youth unemployment on adult unemployment in the ncds. *The Economic Journal*, 111(475):626–653, 2001.

[23] James J Heckman. Identifying the hand of past: Distinguishing state dependence from heterogeneity. *The American Economic Review*, 81(2):75–79, 1991.

[24] Guido W Imbens and Lisa M Lynch. Re-employment probabilities over the business cycle. *Portuguese Economic Journal*, 5(2):111–134, 2006.

[25] Louis S Jacobson, Robert J LaLonde, and Daniel G Sullivan. Earnings losses of displaced workers. *The American Economic Review*, 83(4):685–709, 1993.

[26] Lisa B Kahn. The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics*, 17(2):303–316, 2010.

[27] Stephen B Knouse, John R Tanner, and Elizabeth W Harris. The relation of college internships, college performance, and subsequent job opportunity. *Journal of Employment Counseling*, 36(1):35–43, 1999.

[28] Kory Kroft, Fabian Lange, and Matthew J Notowidigdo. Duration dependence and labor market conditions: Evidence from a field experiment. *The Quarterly Journal of Economics*, 128(3):1123–1167, 2013.

[29] Joanna N Lahey. Age, women, and hiring: An experimental study. *Journal of Human Resources*, 43(1):30–56, 2008.

[30] Joanna N Lahey and Ryan A Beasley. Computerizing audit studies. *Journal of Economic Behavior and Organization*, 70(3):508–514, 2009.

[31] Edwin Leuven and Hessel Oosterbeek. Overeducation and mismatch in the labor market. In Eric A Hanushek, Stephen J Machin, and Ludger Woessmann, editors, *Handbook of the Economics of Education*, volume 4, pages 283–326. Elsevier, 2011.

[32] Lars Ljungqvist and Thomas J Sargent. The european unemployment dilemma. *Journal of Political Economy*, 106(3):514–550, 1998.

[33] Ben Lockwood. Information externalities in the labour market and the duration of unemployment. *The Review of Economic Studies*, 58(4):733–753, 1991.

[34] Stephen Machin and Alan Manning. The causes and consequences of long-term unemployment in europe. In *Handbook of Labor Economics*, volume 3, pages 3085–3139. Elsevier, 1999.

[35] Barry McCormick. A theory of signalling during job search, employment efficiency, and stigmatised jobs. *The Review of Economic Studies*, 57(2):299–313, 1990.

[36] Kevin M Murphy and Finis Welch. The structure of wages. *The Quarterly Journal of Economics*, 107(1):285–326, 1992.

[37] John M Nunley, Adam Pugh, Nicholas Romero, and R Alan Seals. College major, internship experience, and employment opportunities: Estimates from a résumé audit. *Auburn University Department of Economics Working Paper Series No. AUWP AUWP2015-08*, 2015(a).

[38] John M Nunley, Adam Pugh, Nicholas Romero, and R Alan Seals. Racial discrimination in the labor market for recent college graduates: Evidence from a field experiment. *The BE Journal of Economic Analysis & Policy*, 2015(b).

[39] Philip Oreopoulos. Why do skilled immigrants struggle in the labor market? a field experiment with thirteen thousand résumés. *American Economic Journal: Economic Policy*, 3(4):148–171, 2011.

[40] Philip Oreopoulos, Till von Wachter, and Andrew Heisz. The short-and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1):1–29, 2012.

[41] Devah Pager. The use of field experiments for studies of employment discrimination: Contributions, critiques, and directions for the future. *The Annals of the American Academy of Political and Social Science*, 609(1):104–133, 2007.

[42] Barbara Petrongolo and Christopher A Pissarides. Looking into the black box: A survey of the matching function. *Journal of Economic literature*, 39(2):390–431, 2001.

[43] Peter A Riach and Judith Rich. Field experiments of discrimination in the market place. *The Economic Journal*, 112(483):F480–F518, 2002.

[44] Richard Rogerson, Robert Shimer, and Randall Wright. Search-theoretic models of the labor market: A survey. *Journal of Economic Literature*, 43(4):959–988, 2005.

[45] Christopher J Ruhm. Are workers permanently scarred by job displacements? *The American Economic Review*, 81(1):319–324, 1991.

[46] Paul Ryan. The school-to-work transition: A cross-national perspective. *Journal of Economic Literature*, 39(1):34–92, 2001.

[47] Nils Saniter and Thomas Siedler. Door opener or waste of time? the effects of student internships on labor market outcomes. *IZA Discussion Paper No. 8141*, 2014.

[48] Robert Shimer. The probability of finding a job. *The American Economic Review*, 98(2):268–273, 2008.

[49] Thomas Luke Spreen. Recent college graduates in the u.s. labor force: Data from the current population survey. *Monthly Labor Review*, 136:3–13, 2013.

[50] Ann Huff Stevens. Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics*, 15(1):165–188, 1997.

[51] Gerard J Van den Berg and Jan C Van Ours. Unemployment dynamics and duration dependence in france, the netherlands and the united kingdom. *The Economic Journal*, 104(423):432–443, 1994.

[52] Gerard J Van den Berg and Jan C Van Ours. Unemployment dynamics and duration dependence. *Journal of Labor Economics*, 14(1):100–125, 1996.

[53] Tara Vishwanath. Job search, stigma effect, and escape rate from unemployment. *Journal of Labor Economics*, 7(4):487–502, 1989.

[54] Till Von Wachter and Stefan Bender. In the right place at the wrong time: The role of firms and luck in young workers' careers. *The American Economic Review*, 96(5):1679–1705, 2006.

Table 1: Percentage of Labor-Market Participants who are Unemployed by Education

	Unemployed	Unemployed 11-18 Weeks	Unemployed 23-34 Weeks	Unemployed 43-52 Weeks
	(1)	(2)	(3)	(4)
Less than Bachelors Degree	84.5%	81.3%	84.1%	85.9%
Bachelors Degrees	12.5%	15.0%	14.5%	10.8%
More than a Bachelors Degree	2.9%	3.7%	1.4%	3.4%

Notes: Data are from the March 2013-2014 Current Population Survey (CPS). The sample consists of respondents between the ages of 24 and 32 who are (a) eligible to work, (b) participants in the labor force and (c) unemployed. Thus, the statistics presented are the share of each education group that is unemployed in general (column 1) or unemployed for short (column 2), moderate (column 3) and long (column 4) durations. The short, moderate and long unemployment durations correspond to the 3-, 6- and 12-month durations chosen for our experiment.

Table 2: Percentage Employed, Earnings, and Hours Worked by Occupation

	Occupation Categories						
	Banking	Finance	Insurance	Management	Marketing	Sales	Under-Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Shares of Workers by Educational Attainment							
Less than Bachelors Degree	32.1%	28.1%	48.1%	38.0%	19.1%	59.7%	78.9%
Bachelors Degree	52.9%	52.3%	46.7%	47.2%	64.9%	36.0%	18.9%
More than a Bachelors Degree	15.0%	19.6%	5.2%	14.8%	16.0%	4.3%	2.2%
Observations	13,882	28,832	3,173	29,930	7,962	38,304	41,057
Panel B: Average Earnings and Hours Worked of Bachelors-Degree Holders							
Average Earnings	$60,875	$56,085	$49,653	$55,743	$55,436	$46,869	$28,023
Average Usual Hours Worked	43.8	42.6	42.6	44.6	43.94	41.7	35.5
Observations	7,348	15,079	1,482	14,112	5,168	13,787	7,765

Notes: Data are from the 2010-2013 American Community Surveys (ACS). The sample for the statistics presented in Panel A is comprised of respondents between the ages of 24 and 32 who are working. The sample for the statistics presented in Panel B is comprised of respondents between the ages of 24 and 32 who are working and have completed a Bachelor's degree, which excludes respondents with schooling levels below and above a Bachelors degree. The details of the occupation codes are provided in Appendix Section A2 and Appendix Table A2.

Table 3: Résumé Characteristics

Résumé Credential	Randomization Probability	Sample Mean	Linear Regression of Unemployed Variable on Other Résumé Credentials: Coeff.	Std. Error	Linear Regression of Underemployed Variable on Other Résumé Credentials: Coeff.	Std. Error
	(1)	(2)	(3)	(4)	(5)	(6)
Employment Statuses						
Unemployed	0.375	0.374	–	–	0.006	(0.010)
Underemployed	0.500	0.498	0.006	(0.010)	–	–
Premarket Characteristics						
Internship Experience	0.250	0.248	-0.014	(0.012)	-0.013	(0.014)
High Grade Point Average	0.250	0.249	0.017	(0.012)	0.004	(0.015)
Graduation with Honors	0.250	0.248	-0.005	(0.012)	-0.012	(0.015)
Business Major	0.555	0.552	-0.009	(0.010)	-0.001	(0.010)
Demographic and Economic Characteristics						
Black	0.500	0.497	0.006	(0.010)	0.004	(0.011)
Female	0.500	0.499	-0.004	(0.010)	-0.018	(0.011)
High Socioeconomic Status	0.500	0.499	0.000	(0.010)	0.019	(0.012)
Universities						
#1	0.250	0.251	-0.007	(0.017)	0.009	(0.017)
#2	0.250	0.250	0.005	(0.017)	-0.006	(0.017)
#3	0.250	0.249	-0.002	(0.017)	-0.011	(0.017)
p-value for F-test on Full Set of Résumé Controls			0.812		0.592	

Notes: Column 1 lists the randomization probability that we chose for each résumé credential; column 2 presents the sample means for each résumé credential; columns 3 and 4 present the coefficient estimates (labeled as 'Coeff.') and standard errors (labeled as 'Std. Error') from a linear regression of the unemployment indicator variable on each of the other résumé credentials; and columns 5 and 6 present the coefficient estimates (labeled as 'Coeff.') and standard errors (labeled as 'Std. Error') from a linear regression of the underemployment indicator variable on each of the other résumé credentials. See Section 3.1 and Appendix Section A1.1 for detailed descriptions of the unemployment and underemploymetn indicator variables as well as the other résumé credentials.

Table 4: Callback Rates

	All Applicants	Unemployed	Employed	Under-Employed	Adequately Employed
	(1)	(2)	(3)	(4)	(5)
Overall	0.166	0.168	0.166	0.146	0.187
By City:					
Atlanta	0.131	0.134	0.129	0.109	0.153
Baltimore	0.257	0.264	0.252	0.247	0.267
Boston	0.130	0.133	0.128	0.101	0.159
Dallas	0.180	0.165	0.189	0.160	0.200
Los Angeles	0.138	0.149	0.132	0.108	0.168
Minneapolis	0.181	0.196	0.172	0.161	0.201
Portland	0.160	0.148	0.168	0.150	0.171
By Industry/Job Category:					
Banking	0.090	0.074	0.100	0.065	0.115
Finance	0.102	0.108	0.099	0.092	0.112
Insurance	0.243	0.245	0.242	0.191	0.295
Management	0.103	0.106	0.101	0.108	0.098
Marketing	0.214	0.228	0.205	0.203	0.225
Sales	0.215	0.211	0.217	0.179	0.249

Notes: The callback rates for each (un)employment status are presented: all applicants (column 1), applicants who are unemployed at the time of application (column 2), applicants who are employed at the time of application (column 3), applicants who became underemployed at some point after graduation (column 4), and applicants who became adequately employed at some point after graduation. In Section 3.1 and Appendix Section A1.1, we describe in detail the different (un)employment statuses that the fictive applicants in our experiment are randomly assigned. The second and third parts of the table present separately the callback rates for each city and industry/job-category.

Table 5: The Effects of Unemployment and Underemployment

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Effects of Underemployment and Unemployment						
Unemployed	0.002	0.003	0.002	0.003	0.004	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Underemployed	-0.041***	-0.040***	-0.040***	-0.040***	-0.041***	-0.040***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Panel B: Effects of Unemployment Duration and Underemployment						
Unemployed 3 Months	0.012	0.012	0.012	0.013	0.017	0.012
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)
Unemployed 6 Months	-0.008	-0.008	-0.008	-0.007	-0.007	0.006
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)
Unemployed 12 Months	0.003	0.003	0.002	0.002	0.002	-0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.009)
Underemployed	-0.041***	-0.040***	-0.040***	-0.040***	-0.041***	-0.040***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
p-value from F-test for Joint Significance of Unemployment Duration Variables	0.635	0.632	0.647	0.640	0.463	0.568
Controls:						
Résumé	No	Yes	Yes	Yes	Yes	Yes
Month	No	No	Yes	Yes	Yes	Yes
City	No	No	No	Yes	Yes	Yes
Industry	No	No	No	No	Yes	Yes
Job Advertisement	No	No	No	No	No	Yes
Observations	9396	9396	9396	9396	9396	9396

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. *** indicates statistical significance at the one-percent level. The estimates presented in Panel A combine all unemployment durations into one unemployment variable, while the estimates in Panel B allow for different length unemployment spells to affect the callback rate differently. Six colums of estimates are presented, which vary depending on which control variables are held constant. In column 1, we begin with a simple regression model in which no controls (other than the unemployment and underemployment variables) held constant. In columns 2-6, we successively add control variables to the regression models. The résumé controls are discussed in Section 3.1 and Appendix Section A1.1, and the month, city, industry and job-advertisement controls are described in Section 3.4.

Table 6: Past Employment Versus Contemporaneous Employment

	Duration of Unemployment Spell			
	3, 6, or 12 Months	3 Months	6 Months	12 Months
	(1)	(2)	(3)	(4)
Unemployed who were Underemployed versus Underemployed	0.017*	0.025**	0.017	0.008
	(0.009)	(0.013)	(0.014)	(0.014)
Unemployed who were Adequately Employed versus Adequately Employed	−0.006	−0.001	−0.005	−0.010
	(0.010)	(0.014)	(0.015)	(0.014)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. * and ** indicate statistical significance at the 10- and five-percent levels, respectively. There are two rows of estimates. The first row compares applicants who are unemployed but were underemployed in the past to applicants who are underemployed at the time of application, while the second row compares applicants who are unemployed but were adequately employed in the past to applicants who are adequately employed at the time of application.

Table 7: Internship Experience as a Mitigating Factor

	(1)	(2)	(3)	(4)
Underemployed versus	−0.049***	−0.027**	−0.067***	−0.044***
Adequately Employed	(0.009)	(0.012)	(0.014)	(0.017)
Worked as Interns?				
Underemployed	No	Yes	No	Yes
Adequately Employed	No	No	Yes	Yes

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. *, ** and *** indicate statistical significance at the 10-, five-, and one-percent levels, respectively. The estimates in each column differ based on whether the underemployed and/or adequately-employed applicants worked as interns while completing their Bachelors degrees. Whether the applicants did or did not work as interns while comnpleting their degrees is indicated with a 'Yes' or 'No' below the estimates.

Table 8: Unemployment Rates by Metropolitan Areas

Metropolitan Area	Mean (1)	Minimum (2)	Maximum (3)
Atlanta	8.3%	7.6%	8.8%
Baltimore	7.3%	6.7%	7.9%
Boston	6.2%	5.7%	6.8%
Dallas	6.4%	6.0%	6.7%
Los Angeles	9.2%	8.3%	10.0%
Minneapolis	5.2%	4.7%	6.0%
Portland	7.8%	7.1%	8.7%

Notes: Data on metropolitan unemployment rates are from the Bureau of Labor Statistics (BLS). In particular, the data are assessible via the following webpage: http://www.bls.gov/schedule/archives/metro_nr.htm. We use the data from the BLS to obtain the unemployment rates during the period in which our experiment took place, which is from January 2013 through July 2013. Column 1 presents the average unemployment rate in each metropolitan area over the seven-month period; column 2 present the minimum unemployment rate for each metropolitan area over the seven-month period; and column 3 presents the maximum unemployment for each metropolitan area over the seven-month period.

Table 9: Unemployment, Underemployment, and Labor-Market Conditions

	Unemployed 3, 6, or 12 Months versus Employed	Unemployed 3 Months versus Employed	Unemployed 6 Months versus Employed	Unemployed 12 Months versus Employed	Underemployed versus Adequately Employed
	(1)	(2)	(3)	(4)	(5)
Tight Labor Markets	0.003	0.012	0.001	−0.004	−0.038***
	(0.011)	(0.015)	(0.016)	(0.015)	(0.011)
Loose Labor Markets	0.004	0.026*	−0.003	−0.007	−0.067***
	(0.009)	(0.015)	(0.014)	(0.016)	(0.015)
Loose Labor Markets versus Tight Labor Markets	0.001	0.015	−0.005	−0.003	−0.029
	(0.014)	(0.021)	(0.021)	(0.022)	(0.018)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. * and *** indicate statistical significance at the 10- and one-percent levels, respectively. The number of observations in the relatively tight labor markets is 4140 and the number of observations in the relatively loose labor markets is 2734. The estimates presented in column 1, columns 2-4 and column 5 are based on different regression models designed to generate the estimated callback differential listed above the column numbers (See Appendix Section A4.4 for details). The estimates in column 1 compare job seekers with unemployment spells of three, six or 12 months to those who are employed; column 2 compare job seekers with unemployment spells of three months to those who are employed; column 3 compare job seekers with unemployment spells of six months to those who are employed; column 4 compare job seekers with unemployment spells of 12 months to those who are employed; and column 5 compare job seekers who are underemployed to those who are adequately employed. The first row of estimates is based on comparisons within the relatively tight labor markets; the second row of estimates is based on comparisons within relatively loose labor markets; and the third row of estimates computes the relative difference (as indicated by the column heading) in relatively loose labor markets versus that in relatively tight labor markets. Put differently, the estimates in row 3 are computed as the difference in the estimates between row 2 and row 1 for each column.

Appendix

A1 Data

A1.1 Résumé Characteristics

Applicant Names

Following the work of other correspondence studies, we randomly assign names to applicants that are distinct to a particular racial group. For our purposes, we chose eight names: Claire Kruger, Amy Rasumussen, Ebony Booker, Aaliyah Jackson, Cody Baker, Jake Kelly, DeShawn Jefferson, and DeAndre Washington. Claire Kruger and Amy Rasmussen are distinctively white female names; Ebony Booker and Aaliyah Jackson are distinctively black female names; Cody Baker and Jake Kelly are distinctively white male names; and DeShawn Jefferson and DeAndre Washington are distinctively black male names. The first names and surnames were taken from various websites that list the most female/male and the blackest/whitest names. The Census breaks down the most common surnames by race, and we chose our surnames based on these rankings.[1] The whitest and blackest first names, which are also broken down by gender come from the following website: `http://abcnews.go.com/2020/story?id=2470131&page=1`. The whitest and blackest first names for males and females are corroborated by numerous other websites and the baby name data from the Social Security Administration.

The names listed above are randomly assigned with equal probability. Once a name has been randomly assigned within a four-applicant group (i.e. the number of résumés we submit per job advertisement), that name can no longer be assigned to the other applicants in the four-applicant pool. That is, there can be no duplicate names within a four-applicant pool.

We created an email address and a phone number for each name, which were all created

[1] Here is the link to the most common surnames in the U.S.: `http://www.census.gov/genealogy/www/data/2000surnames/index.html`.

through http://gmail.com. Each applicant name had an email address and phone number that is specific to each city where we applied for jobs. As an example, DeAndre Washington had seven different phone numbers and seven different email addresses. For each city, we had the emails and phone calls to applicants within a particular city routed to an aggregated Google account, which was used to code the interview requests.

Street Address

Four street addresses were created for each city. The addresses are created by examining house prices in and around the city in which the applications are submitted. Two of these addresses are in high-socioeconomic-status areas, while the other two are in low-socioeconomic-status areas. High-socioeconomic-status addresses are in areas where house prices on the street are in excess of $750,000, while those in low-socioeconomic-status addresses are in areas where house prices on the street are less than $120,000. We obtained house price information from http://trulia.com. Each applicant is assigned one of the four possible street addresses within each city. Applicants are assigned high- and low-socioeconomic-status addresses with equal probability, i.e. 50 percent. The table below shows the high- and low-socioeconomic street addresses used for each city.

Addresses				
	High Socio-Economic 1	High Socio-Economic 2	Low Socio-Economic 1	Low Socio-Economic 2
Atlanta	4164 Paran Pines Dr Nw Atlanta, GA 30327	908 Kings Ct Ne Atlanta, GA 30306	698 Moreland Ave Se Atlanta, GA 30316	4300 Rosewell Rd Atlanta, GA 30342
Baltimore	207 Club Rd Baltimore, MD 21210	2303 Essex St Baltimore, MD 21224	2998 Sollers Point Rd Baltimore, MD 21222	2803 Roselawn Ave Baltimore, MD 21214
Boston	590 E 8Th St Boston, MA 02127	71 School St Boston, MA 02129	38 Messinger St Boston, MA 02126	1409 River St Apt 37 Boston, Ma 02136
Dallas	3443 Normandy Ave Dallas, TX 75205	7360 Paldao Dr Dallas, TX 75240	3906 Antigua Dr Dallas, TX 75244	18211 Muir Cir Dallas, TX 75287
Los Angeles	6970 La Presa Dr Los Angeles, CA 90068	181 S Gardner St Los Angeles, CA 90036	10738 Gorman Ave Los Angeles, CA 90059	5608 Fortuna St Los Angeles, CA 90011
Minneapolis	1832 Kenwood Pkwy Minneapolis, MN 55405	4628 W Lake Harriet Pkwy Minneapolis, MN 55410	2526 Ulysses Ne St Minneapolis, MN 55418	4301 14th S Ave Minneapolis, MN 55407
Portland	5472 Sw Champion Pl Portland, OR 97225	3239 Sw 55Th Dr Portland, OR 97221	5715 Se 83Rd Ave Portland, OR 97266	309 N Bridgeton Rd Portland, OR 97217

Universities

The fictitious applicants were randomly assigned one of four possible universities. The universities are likely recognizable by prospective employers, but they are unlikely to be regarded as prestigious; thus, we can reasonably conclude that "name recognition" of the school plays little role as a determinant of receiving an interview from a prospective employer. In addition, each of the applicants is randomly assigned each of these four universities at some point during the collection of the data. While the university one attends likely matters, our data suggest that the universities that we randomly assigned to applicants do not give an advantage to our fictitious applicants. That is, there is no difference in the interview rates between the four possible universities.

Academic Major

The following majors were randomly assigned to our fictitious job applicants with equal probability: accounting, biology, economics, english, finance, history, management, marketing, and psychology. We chose these majors because they are commonly selected majors by college students. In fact, the Princeton Review[2] rates business-related majors as the most selected by college students; psychology is ranked second; biology is ranked fourth; english is ranked sixth; and economics is ranked seventh.

Grade Point Average and Honor's Distinction

Twenty-five percent of our fictitious applicants are randomly assigned an résumé attribute that lists their GPA. When an applicant is randomly assigned this résumé attribute, a GPA of 3.9 is listed. Twenty-five percent of the fictitious applicants were randomly assigned an Honor's distinction for their academic major. Note that applicants were not randomly assigned both of these attributes; that is, applicants receive one of the two or neither. Below is an example of how the "Honor's" (left) and "GPA" (right) traits were signaled on the résumés.[3]

[2]Visit the following webpage: `http://www.princetonreview.com/college/top-ten-majors.aspx`.

[3]The university name was replaced with XYZ to conform to the terms of the agreement with our institutional review boards.

Education

Bachelor of Science, May 2010
University of XYZ
English (Honors)

Education

University of XYZ
Bachelor of Science, May 2010
English
GPA 3.9

(Un)Employment Status

Applicants were randomly assigned one of the following (un)employment statuses: employed at the date of application with no gap in work history, unemployed for three months at the date of application, unemployed for six months at the date of application, unemployed for 12 months at the date of application, unemployed for three months immediately following their graduation date but currently employed, unemployed for six months immediately following their graduation date but currently employed, and unemployed for 12 months immediately following their graduation date but currently employed. Applicants receive no gap in their work history at a 25 percent rate, while the different unemployment spells are randomly assigned with equal probability (12.5 percent). The (un)employment statuses are not mutually exclusive. It is possible for two workers in a four-applicant pool to be randomly assigned, for example, a three-month current unemployment spell. The unemployment spells were signaled on the résumés via gaps in work history, either in the past or currently.

In-Field, Out-of-Field, Internship and College Work Experience

For each job category (i.e. banking, finance, management, marketing, insurance and sales), applicants were randomly assigned "in-field" or "out-of-field" work experience. "In-field" work experience is specific to the job category that the applicant is applying. "Out-of-field" experience is either currently working or having previously worked as a sales person in retail sales. Ultimately, out-of-field experience represents a form of "underemployment," as a college degree is not a requirement for these types of jobs. Fifty percent of applicants are randomly assigned "in-field" experience, and the remaining 50 percent of applicants are randomly assigned "out-of-field" experience. Twenty-five percent of the applicants were randomly assigned internship experience during the summer 2009, which is the summer before they complete their Bachelor's degree. The internship experience is specific to the job category. All of the applicants were assigned work experience while completing their college degree, which consisted of working as a barista, tutor, customer service representative and sales associate. The following series of tables provide detailed information on each type of work experience by job category:

Banking		
	Job Title	Resume Description
Infield 1	Bank Branch Assistant Manager	•Evaluate present market conditions to decide resource allocation to different products and services •Design employee schedules, appointed temporary workforce for a busy seasons, and interview and hire all new employees •Kept in depth records of all industry activities to attain the regulatory needs •Focus on process flow improvement by examining sales relationships and visit several company locations frequently to ensure smooth processes •Produce thorough budgets for the number of operations, tracked the actual expenditures and reviews exceptions •Train and handle a number of employees and build operational principles •Manage branch employees with a focus on branch compliance
Infield 2	Bank Branch Assistant Manager	•Trained 30 new employees and attained significant improvements in their productivity over time •Visited several company locations frequently to ensure smooth processes •Maintain records of cash limits, checks, deposits, fund transfer, money orders, debit cards issued and other banking activities •Suggested new methods for business, developing services for business clients and reducing wait for the personal account clients •Overhauled accounting systems, bookkeeping operations, and interview processes •Provide support in all clerical responsibilities and other daily tasks within the bank
Internship 1	Equity Capital Markets Intern	•Created analytical models and spreadsheets •Assessed market capacity for equity products •Analyzing cost of capital of various financing options
Internship 2	Capital Markets Intern	•Created statistical models to capture and present quantitative data •Generated reports and prepared presentations to assist senior managers •Used Excel and Access to perform analysis and conduct research

Finance		
	Job Title	Resume Description
Infield 1	Accounts Payable	•Prepare and analyze fund statements, balance sheets and salary schedules for firm and her subsidiaries •Responsible for supporting program managers in the development and analysis of financial reports, and spending plans •Review all invoices for appropriate documentation and approval prior to payment •Responds to questions and makes calls regarding billing problems; acts as a liaison between department and vendors
Infield 2	Financial Advisor	•Conduct in-depth reviews of clients' financial circumstances and prepared plans best suited to their requirements •Design detailed financial strategies and explained reports to cliental •Contact clients with news of new financial products or changes to legislation that may affect their savings and investments •Meet all regulatory aspects of the role, e.g. requirements for disclosure, and costs of services provided •Responsible for preparing and maintaining financial statements and invoices in an accurate manner
Internship 1	Financial Analyst Intern	•Conducted financial and business analysis to generate insights that influenced cross-functional decision-making •Led process innovation to drive efficiency and deliver insightful perspective on key business drivers •Leveraged data and information systems to forecast performance and articulate key drivers of change
Internship 2	Financial Analyst Intern	•Conducted financial and business analysis to generate insights that influenced cross-functional decision-making •Led process innovation to drive efficiency and deliver insightful perspective on key business drivers •Leveraged data and information systems to forecast performance and articulate key drivers of change

Insurance		
	Job Title	Resume Description
Infield 1	Insurance Sales Agent	•Customize insurance programs to suit individual customers, often covering a variety of risks •Develop marketing strategies to compete with other individuals or companies who sell insurance •Seek out new clients and develop clientele by networking to find new customers and generate lists of prospective clients •Prepared activity reports with the interpretation, implementation and enforce company policies, strategies and procedures •Monitor insurance claims to ensure they are settled equitably for both the client and the insurer •Inspect property, examining its general condition, type of construction, age, and other characteristics, to decide if it is a good insurance risk •Resolved clients' claim issues in assistance of manager
Infield 2	Insurance Sales Agent	•Sell various types of insurance policies to businesses and individuals on behalf of insurance companies, including automobile, fire, life, property, medical and dental insurance or specialized policies such as marine, farm/crop, and medical malpractice •Strive to achieve optimum customer satisfaction and access coverage, liability and damage •Responsible for appointing a legal representative for the court cases and communicating with the agents to resolve the issues •Ensure that policy requirements are fulfilled, including any necessary medical examinations and the completion of appropriate forms •Calculate premiums and establish payment method
Internship 1	Intern	•Asked probing and challenging questions to uncover a prospective clients needs •Identified and understood a prospect's needs to help create solutions •Handled objections and effectively built relationships
Internship 2	Intern	•Asked probing and challenging questions to uncover a prospective clients needs •Identified and understood a prospect's needs to help create solutions •Handled objections and effectively built relationships

Marketing		
	Job Title	Resume Description
Infield 1	Marketing Specialist	•Conducted qualitative and quantitative research to help guide new creative efforts •Evaluated all potential sponsorship/partnership opportunities •Researched multi-channel marketing efforts of five key advertisers to prepare comprehensive report on how to target consumers for agency-wide project •Directed and manage 4 internal staff and network of 3 external local-market agencies/consultants •Developed, sold, moderated, and interpreted results for more than 100 qualitative focus groups and one-on-one sessions for firm •Evaluated target markets and proposed marketing strategies •Turned 17% sales decline into 20% increase in two years by overhauling entire marketing effort and launching company's first-ever national advertising campaign
Infield 2	Marketing Specialist	•Analyzed regular corporate retail sales reports and tailor each local marketing profit-plan with retail leadership •Programs increased average store traffic 21% and sales averaging 12%, contributing to unprecedented growth •Explored multi-cultural trends and developed volumetric sales analysis to convince firm to address diverse '"non-traditional" audiences across all brands •Created 5 integrated and multi-tiered new store opening programs in domestic & international locations •Designed, developed and implemented marketing and sales campaigns, fundraisers, employee incentive programs and contests •Introduced planning discipline and mass advertising techniques to entertainment retailer with more than ten million in sales •Managed all phases of direct mail projects; monitored production teams; recruited and guided vendors; oversaw print operations and coordinated mailing process
Internship 1	Marketing Business Analyst Intern	•Analyzed the divisional business to identify problems, opportunities, and trends •Executed elements of the marketing plan, including price promotions •Managed multiple projects
Internship 2	Marketing Business Analyst Intern	•Analyzed the divisional business to identify problems, opportunities, and trends •Executed elements of the marketing plan, including price promotions •Managed multiple projects

Sales		
	Job Title	Resume Description
Infield 1	Sales Representative	•Sold and marketed packaging products to manufacturers in a two-state territory •Managed account base of 70 which is an increase of 14 accounts over from previous year •Assigned responsibility to mentor/develop three inside salespeople for promotion to outside sales positions •Recaptured 4 lost accounts during first year of employment •Developed strong referral system which provides continuous leads for new business development •Exceptional leadership, organizational, oral/written communication, interpersonal, analytical, and problem resolution skills •Named "Salesman of the Month" four times during work tenure
Infield 2	Sales Consultant	•Proactive leader with refined business acumen and exemplary people skills. Facilitate a team approach to achieve organizational objectives, increase productivity and enhance employee morale •Helped develop an expansive plan to increase sales by over 30% over the next five years •Conduct new product training for the sales force and dealer network including providing test units to region managers and key dealers for use in demonstrations. •Quick study, with an ability to easily grasp and put into application new ideas, concepts, methods and technologies •Dedicated, innovative and self-motivated team player/builder •Thrive in both independent and collaborative work environments •Review product pricing and gross margin goals for existing products annually
Internship 1	Sales Intern	•Assisted sales representatives, who sold Auto, Home, Life, and other insurance products •Spent time out of the office observing and assisting with sales events •Worked with Sales Reps to identify prospective customers using established lead methods
Internship 2	Sales Future Leader Intern	•Utilized analytical and fact-based selling skills to grow volume, revenue, and profitability goals for the assigned territory •Activated local and national marketplace initiatives and promotions through merchandising products and building creative displays •Performed at a fast pace in a self-motivated position

Out-of-Field & College		
	Job Title	Resume Description
Outfield 1	Sales Associate[1]	•Team leader in sales for two consecutive months •Greet patrons at door and assisted them in locating their desired purchases •Manage sales desk while assisting customers with purchase •Promote company brands whenever possible •Communicate to manager any possible areas of improving the customer service experience •Restock items on sales floor as needed •Handle customer complaints and problems in the most efficient way possible
Outfield 2	Retail Associate	•Open and close cash registers, performing tasks such as counting money, separating charge slips, coupons, and vouchers, balancing cash drawers, and making deposits •Recommend, select, and help locate or obtain merchandise based on customer needs and desires •Describe merchandise and explain use, operation, and care of merchandise to customers •Place special orders or call other stores to find desired items
College 1	Barista	•Ensured counters, customer areas are neat, clean and presentable •Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment •Served food, beverages, or desserts to customers in a fast paced environment •Followed cash handling procedures and cash register policies
College 2	Tutor[2]	•Worked with students to help them better understand ___________[3] concepts •Identified the preferred communication style of the students and adjusted tutorial sessions accordingly •Taught tailored large-group review sessions before exams
College 3	Customer Service Representative	•Served as a resource by providing accurate and current information regarding recreation and university-related programs and facilities •Maintained current certifications in first aid, CPR, and AED. •Counseled peers on personal, academic, and career concerns •Assist with data entry of fitness and intramural participants into Access database and IMTrack
College 4	Sales Associate	•Asked lifestyle questions to thoroughly understand customer needs, offers relevant services, solutions, and accessories so customer can make informed decision to complete their purchase •Leveraged on-line resources, tools, and peer knowledge to self-train •Utilized all relevant sales tools to drive profitable growth

Notes:
1. For jobs within the 'Sales' field, this job title was changed to Retail Associate.
2. The candidate was a tutor for their specific major. For example, if candidate A was a finance major, he/she would be a finance tutor)
3. The first bullet point within the resume description had a tailored line for each major but followed the same outline (e.g., Economics tutor - •Worked with students to help them better understand **economic** concepts)

A1.2 Sample Résumés

In this section, we present a few résumés that capture the essence of our résumé-audit study. The names of schools and companies where the applicants attended and worked have been removed per our agreement with our respective institutional review boards.

Ebony Booker

ebonybooker231@gmail.com
(678) 753-5139
908 Kings Ct Ne
Atlanta, GA 30306

Education

ABC University
Bachelor of Science, May 2010
Management

Work Experience

May 2010 - July 2012
Administrative Assistant
XYZ Company

•Communicated with managers and coordinated the financial reporting of five locations to consolidate financial data
•Decentralized accounts payable to facilitate transition from cost centers to profit centers, and trained employees in the new system
•Recognized for efforts to identify new processes to improve quality, reduce costs, and increase margin
•Coordinated the administration of product orders, understood customer needs and guaranteed delivery of company's commitment
•Accustomed to working in fast-paced environments with the ability to think quickly and successfully handle difficult clients
•Excellent interpersonal skills, ability to work well with others, in both supervisory and support staff roles
•Developed strong relationships with established accounts while acquiring new accounts

September 2006 - May 2010
Sales Associate
DEF Company

•Asked lifestyle questions to thoroughly understand customer needs, offers relevant services, solutions, and accessories so customer can make informed decision to complete their purchase
•Leveraged on-line resources, tools, and peer knowledge to self-train
•Utilized all relevant sales tools to drive profitable growth

Cody Baker

codybaker589@gmail.com
(404) 913-4459
4300 Rosewell Rd
Atlanta, GA 30342

Education

University of ABC
Bachelor of Science, May 2010
Psychology
GPA 3.9

Work Experience

Sales Associate
May 2010 - Present
XYZ Company

•Team leader in sales for two consecutive months
•Greet patrons at door and assisted them in locating their desired purchases
•Manage sales desk while assisting customers with purchase
•Promote company brands whenever possible
•Communicate to manager any possible areas of improving the customer service experience
•Restock items on sales floor as needed
•Handle customer complaints and problems in the most efficient way possible

Customer Service Representative
September 2006 - May 2010
University of ABC Recreation Center

•Served as a resource by providing accurate and current information regarding recreation and university-related programs and facilities
•Maintained current certifications in first aid, CPR, and AED.
•Counseled peers on personal, academic, and career concerns
•Assist with data entry of fitness and intramural participants into Access database and IMTrack

DeShawn Jefferson

d2jefferson@gmail.com
(678) 653-0550
698 Moreland Ave Se
Atlanta, GA 30316

Education

Bachelor of Science, May 2010
University of ABC
Management

Work Experience

XYZ Company
May 2010 - Present
Distribution Assistant Manager

•Responsible and accountable for the coordinated management of multiple related projects directed toward strategic business and other organizational objectives
•Build credibility, establish rapport, and maintain communication with stakeholders at multiple levels, including those external to the organization
•Maintain continuous alignment of program scope with strategic business objectives, and make recommendations to modify the program to enhance effectiveness toward the business result or strategic intent
•Fostered customer loyalty by ensuring that our customers fully utilize the value of our solutions and services
•Direct the coordination of all implementation tasks involving third party vendors as well as provide consultation to clients on system implementation
•Coach, mentor and lead personnel within a fast paced environment

DEF Company
May 2009 – September 2009
Project Management Intern

•Implemented a program to reduce operation costs
•Designed a new program to increase employee moral
•Handled multiple projects simultaneously and effectively built relationships

GHI Company
September 2006 - May 2010
Barista

•Ensured counters, customer areas are neat, clean and presentable
•Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment
•Served food, beverages, or desserts to customers in a fast paced environment
•Followed cash handling procedures and cash register policies

DeAndre Washington
deandre.washington129@gmail.com
(971) 225-0374

309 N Bridgeton Rd Slipb
Portland, OR 97217

Education

Bachelor of Science, May 2010
University of Colorado at ABC
Accounting

Work Experience

May 2010 - Present
Sales Representative
XYZ Company

•Sold and marketed packaging products to manufacturers in a two-state territory
•Managed account base of 70 which is an increase of 14 accounts over from previous year
•Assigned responsibility to mentor/develop three inside salespeople for promotion to outside sales positions
•Recaptured 4 lost accounts during first year of employment
•Developed strong referral system which provides continuous leads for new business development
•Exceptional leadership, organizational, oral/written communication, interpersonal, analytical, and problem resolution skills
•Named "Salesman of the Month" four times during work tenure

Sales Future Leader Intern, May 2009 – September 2009
DEF Company

•Utilized analytical and fact-based selling skills to grow volume, revenue, and profitability goals for the assigned territory
•Activated local and national marketplace initiatives and promotions through merchandising products and building creative displays
•Performed at a fast pace in a self-motivated position

GHI Company, September 2006 - May 2010
Barista

•Ensured counters, customer areas are neat, clean and presentable
•Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment
•Served food, beverages, or desserts to customers in a fast paced environment
•Followed cash handling procedures and cash register policies

Aaliyah Jackson
Aaliyah.Jackson321@gmail.com
(971) 225-0726
309 N Bridgeton Rd Slipb
Portland, OR 97217

Education

Bachelor of Science, May 2010
University of ABC
Finance (Honors)

Work Experience

XYZ Company (May 2010 - December 2012)
Retail Associate

•Open and close cash registers, performing tasks such as counting money, separating charge slips, coupons, and vouchers, balancing cash drawers, and making deposits
•Recommend, select, and help locate or obtain merchandise based on customer needs and desires
•Describe merchandise and explain use, operation, and care of merchandise to customers
•Place special orders or call other stores to find desired items.

DEF Company (September 2006 - May 2010)
Barista

•Ensured counters, customer areas are neat, clean and presentable
•Maintained sanitized and polished counters, steam tables, and other cooking equipment, and clean glasses, dishes, and fountain equipment
•Served food, beverages, or desserts to customers in a fast paced environment
•Followed cash handling procedures and cash register policies

A1.3 The Application Process

We applied to online postings for job openings in six categories: banking, finance, insurance, management, marketing and sales. To obtain a list of openings, we chose specific search criteria through the online job posting websites to find the appropriate jobs within each of the aforementioned job categories. We further constrained the search by applying only to jobs that had been posted in the last seven days within 30 miles of the city center.

Job openings would be applied to if they had a “simple” application process. An application process was deemed “simple” if it only required a résumé to be submitted or if the information to populate the mandatory fields could be obtained from the résumé (e.g., a candidate’s name or phone number). Jobs that required a detailed application were discarded for two reasons. First and foremost, we wanted to avoid introducing variation in the application process that could affect the reliability of our results. A detailed application specific to a particular firm might include variation that is difficult to hold constant across applicants and firms. Second, detailed applications take significant time, and our goal was to submit a large number of résumés to increase the power of our statistical tests. Job openings were discarded from our sample if any of the following were specified as minimum qualifications: five or more years of experience, an education level greater than a bachelor’s degree, unpaid or internship positions, or specific certifications (e.g., CPA or CFA).

We used the résumé-randomizer from Lahey and Beasely (2009) to generate four résumés to submit to each job advertisement. Templates were created for each job category (i.e. banking, finance, insurance, management, marketing and sales) to incorporate in-field experience. After the résumés were generated, we then formatted the résumés to look presentable to prospective employers (e.g., convert Courier to Times New Roman font; make the applicant’s name appear in boldface font, etc.). We then uploaded the résumés and filled out required personal information, which included the applicant’s name, the applicant’s location, the applicant’s desire to obtain an entry-level position, the applicant’s educational attainment (i.e. Bachelor’s), and whether the applicant is authorized to work in the U.S. All job advertisement identifiers and candidate information was recorded. Upon receiving a interview request, we promptly notified the firm that the applicant was no longer seeking employment to minimize the cost incurred by firms.

A2 Occupation Codes from the American Community Survey

To match, as closely as possible, the occupations randomly assigned to the fictive applicants in our experiment, we use the `occ1990` variable from the American Community Survey (ACS). The occupation codes from the ACS chosen to match the occupations used in our experiment are presented in Appendix Table A2. The data from the ACS on occupations match the occupations used in our experiment reasonably well. We use the occupation data from the ACS to produce the statistics presented in Table 2.

A3 Past Unemployment Spells

The estimates presented in Table 5 do not differentiate between "front-end" and "back-end" unemployment spells. As a part of our experimental design, 75 percent of our fictitious applicants were assigned a gap in work history. With equal probability, applicants were assigned an unemployment spell that either occurred immediately after they graduated from college or at the time that they were submitting applications to prospective employers. The former are referred to as front-end gaps, while the latter are referred to as back-end gaps. In the next specification, we examine impact of front-end and back-end unemployment spells on employment opportunites as well as the relative difference between front- and back-end unemployment spells. We estimate that following regression model:

$$callback_{imcfj} = \beta_0 + \beta_1 front_i + \beta_2 back_i + \mathbf{X}_i'\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \quad (1)$$

All subscripts and variables in equation 1 are defined in the main text, except $front$ and $back$. The variable $front$ is a dummy variable that equals one when an applicant is assigned a three-, six- or 12-month unemployment spell immediately following graduation and zero otherwise, and the variable $back$ is a dummy variable that equals one when an applicant is assigned a three-, six- or 12-month current unemployment spell and zero otherwise. The base category in the equation above is job seekers with no gaps in their work histories. Thus, β_1 gives the average difference in the callback rate between applicants with front-end unemployment spells and applicants without a front-end or a back-end unemployment spell, and β_2 gives the average difference in the callback rate between applicants with current unemployment spells and applicants without a front-end or a back-end unemployment spell. The linear combination of parameters $\beta_2 - \beta_1$ gives the average difference in the callback rate between applicants with current unemployment spells and applicants with unemployment spells that occurred immediately after graduating from college. The estimates from the equation above are presented in Table A5, which indicate that the callback rates between applicants with front-end and back-end unemployment spells and applicants who had no gaps in their work histories are not economically or statistically different from one another. In addition, the callback differential between applicants with back-end gaps and applicants with front-end gaps is not economically or statistically significant.

In the next specification, we consider the impact of different length front-end and back-end unemployment spells. In particular, we estimate the following regression model:

$$\begin{aligned} callback_{imcfj} = \beta_0 &+ \beta_1 front_i^{3mo} + \beta_2 front_i^{6mo} + \beta_3 front_i^{12mo} \\ &+ \beta_4 back_i^{3mo} + \beta_5 back_i^{6mo} + \beta_6 back_i^{12mo} \\ &+ \mathbf{X}_i^{'}\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{2}$$

All subscripts and variables in equation 2 are defined in the main text, except $front^{3mo}$, $front^{6mo}$, $front^{12mo}$, $back^{3mo}$, $back^{6mo}$ and $back^{12mo}$. The variable $front^{3mo}$ is a dummy variable that equals one when an applicant is assigned a three-month unemployment spell immediately after graduating from college and zero otherwise; $front^{6mo}$ is a dummy variable that equals one when an applicant is assigned a six-month unemployment spell immediately after graduating from college and zero otherwise; $front^{12mo}$ is a dummy variable that equals one when an applicant is assigned a 12-month unemployment spell immediately after graduating from college and zero otherwise; $back^{3mo}$ is a dummy variable that equals one when an applicant is assigned a three-month current unemployment spell and zero otherwise; $back^{6mo}$ is a dummy variable that equals one when an applicant is assigned a six-month current unemployment spell and zero otherwise; and $back^{12mo}$ is a dummy variable that equals one when an applicant is assigned a 12-month current unemployment spell and zero otherwise. The base category is job seekers with no gaps in their work histories. Thus, the β_k give the average difference in the callback rate between applicants with a particular unemployment spell relative to that for applicants without a front-end or back-end unemployment spell. Linear combinations of the β_k can be used to test for differences in the callback rate between, for example, applicants with a 12-month back-end unemployment spell and applicants with a 12-month front-end unemployment spell (i.e., $\beta_6 - \beta_3$). The estimates for the β_k and an exhaustive set of comparisons between applicants with different length front-end and different length back-end unemployment spells are presented in Table A6. Rather than comment on each of the estimates presented in Table A6, it is sufficient to note that none of the estimated callback differentials are statistically significant, and it is difficult to argue that any of the estimated differentials are important in an economic sense.

A4 Details on the Estimates Presented in Tables 6, 7 and 9

A4.1 Table 6 (Section 4.2)

In the manuscript, Table 6 make two comparisons. First, we compare the callback rates of the unemployed who were underemployed in the past to the underemployed. Second, we compare the unemployed who were adequately employed to the adequately employed. The estimates presented in Table 6 are based on two different regression models. In what follows, we explain these regression models and indicate the parameters and linear combinations of parameters used to produce the estimates in Table 6. For the estimates in column 1 of Table 6, we use the following regression model:

$$\begin{aligned} callback_{imcfj} = \beta_0 + \beta_1 unemp_i + \beta_2 under_i + \beta_3 unemp_i \times under_i \\ + \mathbf{X}_i^{'}\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{3}$$

All subscripts and variables in equation 3 are defined in the main text. Equation 3 above is identical to equation 2 depicted in Section 3.4 of the manuscript. The estimates in rows 1 and 2 of column 1 are based on equation 3. In particular, the estimate in row 1 is that for $\beta_1 + \beta_3$ and the estimate in row 2 is that for β_1.

To produce the estimates in rows 1 and 2 of columns 2, 3 and 4, we replace the *unemp* variable with the unemployment-duration-indicator variables, which are defined in Appendix Section A3 (i.e. $back^{3mo}$, $back^{6mo}$ and $back^{12mo}$). The regression model that we estimate is specified as follows:

$$\begin{aligned} callback_{imcfj} = \beta_0 + \beta_1 back_i^{3mo} + \beta_2 back_i^{6mo} + \beta_3 back_i^{12mo} \\ + \beta_4 under_i + \beta_5 back_i^{3mo} \times under_i + \beta_6 back_i^{6mo} \times under_i \\ + \beta_7 back_i^{12mo} \times under_i + \mathbf{X}_i^{'}\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{4}$$

For the estimates in row 1, the following linear combinations of parameters are estimated to produce the coefficients and standard errors in columns 2, 3 and 4, respectively: $\beta_1 + \beta_5$, $\beta_2 + \beta_6$ and $\beta_3 + \beta_7$. For the estimates in row 2, the following parameters are estimated to produce the coefficients and standard errors in columns 2, 3 and 4, respectively: β_1, β_2 and β_3.

In Appendix Table A7, we present the main effects with interaction terms. That is, we present the estimates for the β_k from equations 3 and 4. The coefficients on the interaction terms are of interest, as positive (negative) numbers indicate that the unemployed who were underemployed far better (worse) than their contemporaneously-underemployed counterparts. The estimates for the interaction terms are each positive, an indication that the currently underemployed fair worse in terms of job opportunities than their unemployed-who-were-underemployed counterparts. This pattern in the data is also captured by the estimates presented in Table 6 in the main text.

A4.3 Table 7 (Section 4.3)

In Table 7 of the manuscript, we investigate whether internship experience, a resume attribute that has a large positive impact on callback rates, mitigates the harm caused by underemployment. To investigate this, we estimate a variant of equation 2 from Section 3.4 that add an interaction effect between underemployment, unemployment and internship experience. In particular, we estimate

$$\begin{aligned} callback_{imcfj} = \beta_0 &+ \beta_1 unemp_i + \beta_2 under_i + \beta_3 intern_i \\ &+ \beta_4 unemp_i \times under_i + \beta_5 unemp_i \times intern_i \\ &+ \beta_6 under_i \times intern_i + \beta_7 unemp_i \times under_i \times intern_i \\ &+ \mathbf{X}_i' \gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{5}$$

All variables and subscripts from equation 5 are defined in the main text, except *intern*. The variable *intern* is a zero-one indicator variable that equals one when an applicant worked as an intern while completing their Bachelors degree and zero otherwise. In Table 7, we are interested in comparing applicants who are underemployed and adequately employed at time of application. We compute callback differential between the following groups: underemployed and adequately-employed applicants without internship experience (column 1), underemployed applicants who worked as interns and adequately-employed applicants who did not work as interns (column 2); underemployed applicants who did not work as interns and adequately-employed applicants who worked as interns (column 3); and underemployed and adequately-employed applicants who worked as interns (column 4). The estimate in column 1 is that for β_2; the estimate in column 2 is that for $\beta_2 + \beta_3 + \beta_6$; the estimate in column 3 is that for β_3; and the estimate in column 4 is that for $\beta_2 + \beta_6$.

A4.4 Table 9 (Section 4.4)

To produce the estimates in Table 9, which tests whether the effects of unemployment in general, different length unemployment spells and underemployment have different effects across relatively "tight" and "loose" labor markets, we estimate three different regression models. The first specification considers the effects of unemployment spells of any length within relatively tight and relatively loose conditions and between labor markets with relatively loose and relatively tight conditions. This specification does not allow the effects of unemployment to vary across the length of the spell. The second specification is an augmented version of the first specification that allows the effect of unemployment to vary based on the length of the spell. The third specification focuses on estimating the impact of underemployment at the time of application in relatively "tight" and relatively "loose" labor markets as well as a comparison of the effects of current underemployment in relatively loose versus relatively tight labor markets. The first specification is

$$\begin{aligned} callback_{imcfj} = \beta_0 + \beta_1 unemp_i + \beta_2 tight_c + \beta_3 slack_c \\ + \beta_4 unemp_i \times tight_c + \beta_5 unemp_i \times slack_c \\ + \mathbf{X}_i^{'}\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{6}$$

All variables and subscripts are defined in the main text, except *tight* and *slack*. The variable *tight* equals one for cities with relatively "tight" labor-market conditions and zero otherwise, while the variable *slack* equals one for cities with relatively "loose" labor-market conditions and zero otherwise. The linear combinations of parameters that are of interest are $\beta_1 + \beta_4$, $\beta_1 + \beta_5$ and $\beta_5 - \beta_4$, which give the estimated percentage point differences in callback rates between (a) job seekers who are unemployed versus those who are employed in tight labor markets, (b) job seekers who are unemployed versus those who are employed in loose labor markets and (c) callback gap between the unemployed and employed in loose relative to tight markets, respecitvely. From Table 9, the estimate for $\beta_1 + \beta_4$ is presented in row 1 of column; $\beta_1 + \beta_5$ is presented in row 2 of column 1; and $\beta_5 - \beta_4$ is presented in row 3 of column 1.

The second specification is

$$
\begin{aligned}
callback_{imcfj} = \beta_0 &+ \beta_1 back_i^{3mo} + \beta_2 back_i^{6mo} + \beta_3 back_i^{12mo} \\
&+ \beta_4 tight_c + \beta_5 slack_c + \beta_6 back_i^{3mo} \times tight_c \\
&+ \beta_7 back_i^{6mo} \times tight_c + \beta_8 back_i^{12mo} \times tight_c \\
&+ \beta_9 back_i^{3mo} \times slack_c + \beta_{10} back_i^{6mo} \times slack_c \\
&+ \beta_{11} back_i^{12mo} \times slack_c + \mathbf{X}_i^{'}\gamma + \phi_m + \phi_c + \phi_f + \phi_j \\
&+ u_{imcfj}.
\end{aligned}
$$

All variables and subscripts are defined in the main text or the Appendix. The linear combinations of parameter that are of interest are $\beta_1 + \beta_6$, $\beta_2 + \beta_7$, $\beta_3 + \beta_8$, $\beta_1 + \beta_9$, $\beta_2 + \beta_{10}$, $\beta_3 + \beta_{11}$, which give the percentage point differences in callback rates between (a) job seekers who are unemployed for three months versus those who are employed in tight labor markets, (b) job seekers who are unemployed for six months versus those who are employed in tight labor markets, (c) job seekers who are unemployed for 12 months versus those who are employed in tight labor markets, (d) job seekers who are unemployed for three months versus those who are employed in loose labor markets, (e) job seekers who are unemployed for six months versus those who are employed in loose labor markets, and (f) job seekers who are unemployed for 12 months versus those who are employed in loose labor markets. The estimates for $\beta_1 + \beta_6$, $\beta_2 + \beta_7$, and $\beta_3 + \beta_8$ are presented in row 1 of columns 2, 3 and 4, respectively. The estimates for $\beta_1 + \beta_9$, $\beta_2 + \beta_{10}$ and $\beta_3 + \beta_{11}$ are presented in row 2 of columns 2, 3 and 4, respectively. We are also interested in the following linear combinations of parameters: $\beta_9 - \beta_6$, $\beta_{10} - \beta_7$ and $\beta_{11} - \beta_8$. These linear combinations provide tests of whether the effects of a given duration of unemployment (i.e. 3, 6 or 12 months) has different effects in relatively tight and loose labor markets. The estimates for $\beta_9 - \beta_6$, $\beta_{10} - \beta_7$ and $\beta_{11} - \beta_8$ are presented in row 3 of columns 2, 3 and 4, respectively.

The third specification is

$$
\begin{aligned}
callback_{imcfj} = \beta_0 &+ \beta_1 under_i^{emp} + \beta_2 under_i^{unemp} + \beta_3 infield_i^{unemp} \\
&+ \beta_4 tight_c + \beta_5 slack_c + \delta_1 under_i^{emp} \times tight_c \\
&+ \delta_2 under_i^{unemp} \times tight_c + \delta_3 infield_i^{unemp} \times tight_c \\
&+ \delta_4 under_i^{emp} \times slack_c + \delta_5 under_i^{unemp} \times slack_c \\
&+ \delta_6 infield_i^{unemp} \times slack_c + \mathbf{X}_i^{'}\gamma + \phi_m + \phi_c + \phi_f + \phi_j \\
&+ u_{imcfj}.
\end{aligned}
$$

All variables and subscripts are defined in the main text, except $under^{emp}$, $under^{unemp}$ and $infield^{unemp}$. The variable $under^{emp}$ is a zero-one indicator for an applicant who is underemployed at the time of application; $under^{unemp}$ is a zero-one indicator for an applicant who is unemployed at the time of application but was underemployed previously; and $infield^{unemp}$ is a zero-one indicator for an applicant who is unemployed at the time of application but was adequately employed previously. The linear combinations of parameters that are of interest are $\beta_1 + \delta_1$ and $\beta_1 + \delta_4$, which give the percentage point differences in the callback rates between (a) job seekers who are underemployed versus those who are adequately employed in tight labor markets and (b) job seekers who are underemployed versus those who are adequately employed in loose labor markets. We also compute the estimated coefficient and standard error for $\delta_4 - \delta_1$, which tests whether the harm stemming from underemployment is worse (or better) in relatively tight or loose labor markets.

A5 Underemployment and Socioeconomic Status

In Appendix Table A8, we investigate whether a proxy for socioecomic status – an applicant's street address – affects the callback gap between applicants who became underemployed relative to those who became adequately employed. Appendix Table A8 is divided into three panels. In Panel A, we lump together all applicants, i.e those who are employed and unemployed. But in the Panels B and C, we focus exclusively on employed and unemployed applicants, respectively. We use two different regression models to produce the estimates in Appendix Table A8. The estimates presented in Panel A are based on the following regression model:

$$\begin{aligned} callback_{imcfj} &= \beta_0 + \beta_1 under_i + \beta_2 highses_i + \beta_3 under_i \times highses_i \\ &+ \mathbf{X}_i^{\prime}\gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{7}$$

in which *callback* and *under* are defined in the main text. The variable *highses* is a zero-one indicator that equals one when an applicant is randomly assigned a street address in an area with house prices exceeding \$750,000, which is a proxy for high socioeconomic status. If an applicant is not assigned a high socioeconomic status address, they are assigned an address in an area with house prices below \$100,000. From equation 7, β_1 gives the difference in the callback rate between the ever-underemployed and the ever-adequately-employed with low-socioeconomic-status addresses (Panel A, Column 1); $\beta_1 + \beta_3$ gives the difference in the callback rate between the ever-underemployed and the ever-adequately-employed with high-socioeconomic-status addresses (Panel A, Column 2); and β_3 tests whether the callback differentials in Columns 1 and 2 of Panel A are different from one another (Panel A, Column 3).

For the estimates in Panels B and C, we rely on the following specification:

$$\begin{aligned} callback_{imcfj} = \beta_0 &+ \beta_1 under_i + \beta_2 unemp_i + \beta_3 highses_i \\ &+ \beta_4 under_i \times unemp_i + \beta_5 under_i \times highses_i \\ &+ \beta_6 unemp_i \times highses_i + \beta_7 under_i \times unemp_i \times highses_i \\ &+ \mathbf{X}_i' \gamma + \phi_m + \phi_c + \phi_f + \phi_j + u_{imcfj}. \end{aligned} \tag{8}$$

All variables are either defined in the main text or in the Appendix. Based on equation 8, β_1 gives the difference in the callback rate between the underemployed and the adequately-employed with low-socioeconomic-status addresses (Panel B, Column 1); $\beta_1 + \beta_5$ gives the difference in the callback rate between the underemployed and the adequately-employed with high-socioeconomic-status addresses (Panel B, Column 2); β_5 tests whether the callback differentials in Columns 1 and 2 of Panel B are different from one another (Panel B, Column 3); $\beta_1 + \beta_4$ gives the difference in the callback rate between the unemployed who were underemployed and the unemployed who were adequately-employed with low-socioeconomic-status addresses (Panel C, Column 1); $\beta_1+\beta_4+\beta_5+\beta_7$ gives the difference in the callback rate between the unemployed who were underemployed and the unemployed who were adequately-employed with high-socioeconomic-status addresses (Panel C, Column 2); and $\beta_5 + \beta_7$ tests whether the callback differentials in Columns 1 and 2 of Panel C are different from one another (Panel C, Column 3).

For the most part, the estimates presented in Appendix Table A8 reveal no systematic difference in callback rates between underemployed and adequately employed with and without high-socioeconomic-status street addresses. The only exception is for the unemployed: the previously underemployed with low-socioeconomic-status street addresses fare worse than the previously underemployed with high-socioeconomic-status street addresses. However, the difference between these two differences (i.e. the estimate in Column 3 of Panel C) is not statistically different from zero.

Table A1: Sensitivity Check – Imposing Various Sample Restrictions

	Excluding Sales	Including Only Sales	Excluding Insurance	Including Only Insurance	Excluding Sales and Insurance	Including Only Sales and Insurance
	(1)	(2)	(3)	(4)	(5)	(6)
*Panel A: Effects of Unemployment and Underemployment*Unemployed						
Unemployed	0.006	0.003	0.006	0.002	0.007	0.002
	(0.007)	(0.017)	(0.007)	(0.021)	(0.007)	(0.013)
Underemployed	−0.030***	−0.070***	−0.031***	−0.108***	−0.016**	−0.080***
	(0.006)	(0.014)	(0.006)	(0.021)	(0.006)	(0.012)
Panel B: Effects of Unemployment Duration and Underemployment						
Unemployed	0.009	0.024	0.014	−0.000	0.010	0.016
3 Months	(0.010)	(0.023)	(0.010)	(0.032)	(0.010)	(0.019)
Unemployed	0.010	−0.009	−0.001	0.054	0.002	0.014
6 Months	(0.011)	(0.023)	(0.010)	(0.037)	(0.010)	(0.020)
Unemployed	−0.000	−0.007	0.006	−0.049	0.010	−0.023
12 Months	(0.010)	(0.023)	(0.010)	(0.032)	(0.010)	(0.019)
Underemployed	−0.030***	−0.070***	−0.031***	−0.109***	−0.016**	−0.081***
	(0.006)	(0.014)	(0.006)	(0.021)	(0.006)	(0.016)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. ** and *** indicate statistical significance at the five- and one-percent levels, respectively.

Table A2: Occupation Codes from the ACS that are Similar to the Occupations Used in Experiment

	Banking	Finance	Insurance	Management	Marketing	Sales	Under-Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
`occ1990` codes from the ACS	007	023	253	021	013	256	275
	025	026		022		376	276
		255				247	
		337					
		338					
		343					

Table A3: Salary Data from `indeed.com`

Occupations Used in Experiment	Employment Type	Earnings
Retail Associate	Underemployment	$22,000.00
Sales Associate	Underemployment	$21,000.00
Bank Branch Assistant Manager	Adequate Employment	$51,000.00
Accounts Payable	Adequate Employment	$30,000.00
Financial Advisor	Adequate Employment	$79,000.00
Insurance Sales Agent	Adequate Employment	$65,000.00
Distribution Assistant Manager	Adequate Employment	$66,000.00
Administrative Associate	Adequate Employment	$45,000.00
Marketing Specialist	Adequate Employment	$59,000.00
Sales Represenative	Adequate Employment	$41,000.00
Sales Consultant	Adequate Employment	$48,000.00

Table A4: Sensitivity Check – Alternative Coding of Underemployment Variable

	Coefficient		Standard Error	Coefficient		Standard Error
	(1)		(2)	(3)		(4)
Unemployed	0.006		(0.007)	–		–
Underemployed	−0.037	***	(0.006)	−0.037	***	(0.006)
Unemployed 3 Months	–		–	0.012		(0.010
Unemployed 6 Months	–		–	0.006		(0.010)
Unemployed 12 Months	–		–	− 0.001		(0.009)

Table A5: The Impact of Front- and Back-End Gaps on Job Opportunities

	Base Category	
	No Gap in Work History	Front-End Gap
	(1)	(2)
Front-End Gap	−0.0021	–
	(0.0082)	–
Back-End Gap	0.0043	0.0064
	(0.0081)	(0.0074)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. See Appendix Section A3 for details on how these estimates are obtained.

Table A6: The Impact of Different Length Front- and Back-End Gaps on Job Opportunities

	Base Category					
	No Gap in Work History	Three-Month Front-End Gap	Six-Month Front-End Gap	Twelve-Month Front-End Gap	Three-Month Back-End Gap	Six-Month Back-End Gap
	(1)	(2)	(3)	(4)	(5)	(6)
Three-Month	0.0061	–	–	–	–	–
Front-End Gap	(0.0115)	–	–	–	–	–
Six-Month	−0.0038	−0.0099	–	–	–	–
Front-End Gap	(0.0108)	(0.0130)	–	–	–	–
Twelve-Month	−0.0082	−0.0143	−0.0044	–	–	–
Front-End Gap	(0.0107)	(0.0126)	(0.0122)	–	–	–
Three-Month	0.0114	0.0053	0.0152	0.0195	–	–
Back-End Gap	(0.0107)	(0.0129)	(0.0126)	(0.0119)	–	–
Six-Month	0.0047	−0.0015	0.0084	0.0128	−0.0067	–
Back-End Gap	(0.0112)	(0.0133)	(0.0129)	(0.0125)	(0.0126)	–
Twelve-Month	-0.0027	-0.0088	0.0011	0.0054	-0.0141	-0.0074
Back-End Gap	(0.0104)	(0.0129)	(0.0127)	(0.0121)	(0.0125)	(0.0121)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. See Appendix Section A3 for details on how these estimates are obtained.

Table A7: Interaction Effects Between Unemployment and Underemployment

	Coefficient	Standard Error	Coefficient	Standard Error
	(1)	(2)	(3)	(4)
Unemployed	-0.006	(0.010)	–	–
Underemployed	-0.048***	(0.008)	-0.048***	(0.008)
Unemployed × Underemployed	0.023*	(0.013)	–	–
Unemployed 3 Months	–	–	-0.001	(0.014)
Unemployed 6 Months	–	–	-0.005	(0.015)
Unemployed 12 Months	–	–	-0.011	(0.014)
Unemployed 3 Months × Underemployed	–	–	0.026	(0.019)
Unemployed 6 Months × Underemployed	–	–	0.023	(0.020)
Unemployed 12 Months × Underemployed	–	–	0.020	(0.020)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. * and *** indicate statistical significance at the 10- and one-percent levels, respectively.

Table A8: Interactions Effects between Underemployment and Socioeconomic Status

	Low Socioeconomic Status (1)	High Socioecnomic Status (2)	High Socioecnomic Status versus Low Socioeconomic Status (3)
Panel A: All Applicants			
Underemployed versus	−0.040***	−0.039***	0.001
Adequately Employed	(0.008)	(0.008)	(0.012)
Panel B: Employed Applicants			
Underemployed versus	−0.043***	−0.054***	−0.011
Adequately Employed	(0.011)	(0.011)	(0.016)
Panel C: Unemployed Applicants			
Underemployed versus	−0.036***	−0.015	0.021
Adequately Employed	(0.014)	(0.015)	(0.020)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. *** indicate statistical significance at the 1 percent levels, respectively. The estimates are presented in three different panels: Panel A combines unemployed and employed applicants; Panel B focuses on employed applicants; and Panel C focuses on unemployed applicants. Appendix Section A5 describes how the estimates in this table are obtained.

Table A9: Senstivity Check – Alternative Classifications of Labor-Market Conditions

	Treatment Group				
	Unemployed 3, 6, or 12 Months	Unemployed 3 Months	Unemployed 6 Months	Unemployed 12 Months	Underemployed
	(1)	(2)	(3)	(4)	(5)
Tight Labor Markets	0.003	0.012	0.001	−0.004	−0.038***
	(0.011)	(0.015)	(0.016)	(0.015)	(0.011)
Loose Labor Markets	0.007	0.013	0.010	0.000	−0.056***
	(0.008)	(0.012)	(0.013)	(0.012)	(0.011)
Loose Labor Markets versus Tight Labor Markets	0.004	0.001	0.008	0.005	−0.019
	(0.013)	(0.019)	(0.021)	(0.019)	(0.015)

Notes: Estimates are marginal effects from linear probability models. Standard errors clustered at the job-advertisement level are in parentheses. *** indicate statistical significance at the 1 percent levels, respectively. The full sample of 9396 observations are used to produce the estimates in columns (1)-(5). There are a total of 4140 observations in the relatively tight labor markets, and there are 5256 observation in the labor markets with relatively loose conditions. Column (1) compares job seekers with unemployment spells of three, six or 12 months to those who are employed; column (2) compares job seekers with unemployment spells of three months to those who are employed; column (3) compares job seekers with unemployment spells of six months to those who are employed; column (4) compares job seekers with unemployment spells of 12 months to those who are employed; and column (5) compares job seekers who are underemployed to those who are adequately employed. The estimates presented in this table are comparable to those in Table 9. The difference in the estimates is the definition of labor markets with relatively 'loose' conditions. The definition for the relatively 'tight' labor markets is identical to that used in Table 9. As a result, the estimates in row 1 are identical to those in Table 9. However, the estimates for rows 2 and 3 are slightly different, but the same patterns in the data are present.