Sick and Tell: A Field Experiment Analyzing the Effects of an Illness-Related Employment Gap on the Callback Rate*

(Job Market Paper)

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Abstract

Using a résumé-based correspondence test, we compare the employment consequences of an illness-related employment gap to those of an unexplained employment gap. Previous research shows that employment gaps, in general, have adverse effects on the probability of getting hired. It is not clear, however, if employers view spells of joblessness due to health issues distinctly. To shed light on this, we present a model in which employers use information on employment gaps as a signal of unobserved productivity and healthcare costs. We investigate the empirical implications of the model by sending three types of fictitious résumés to real vacancies advertised online. One résumé indicates that the applicant is newly unemployed. The other résumés indicate employment gaps which are either unexplained or explained as being related to an illness. The results of the experiment show that while the callback rate of applicants with an illness-related employment gap is lower than that of the newly unemployed, applicants with illness-related employment gaps are more likely to receive a callback than identical applicants who provide no explanation for the gap. Our research provides evidence that employers use information on employment gaps as additional signals about workers' unobserved productivity.

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1 Introduction

Poor health may lead to a temporary gap in employment. Such joblessness can occur if health problems result in reduced ability to function in the workplace or if treatment interferes with work activities. For example, a worker may be diagnosed with cancer and exit the workforce for treatment. Even upon recovery and receiving a positive prognosis, labor market consequences of the illness may persist. Both the gap in the employment record and the health issue itself may be relevant to employers in deciding how to respond to a worker's application as she re-enters the labor market. In this paper we present the results of a résumé-based correspondence test designed to explore the effects of an illness-related employment gap on the probability that an applicant will receive a callback upon applying for a job.

Recent research confirms that employers are less likely to make callbacks to applicants with an employment gap on their résumés. However, prior work does not explore how this propensity changes when the gap results from an illness. On one hand, applicants with illness-related employment gaps may be particularly risky. Employers may be concerned that individuals with illness-related gaps will have lower current and future productivity given weaker physical strength, greater routine medical needs, and a higher likelihood of being sick in the future. There may be concerns as well that human capital depreciates more quickly in employment gaps for those dealing with health issues, as treatment takes precedence over job market considerations.[1] Moreover, employees with a history of poor health may impose higher health care costs on employers who offer health insurance. A strand of the literature provides evidence that employers are indeed sensitive to the health status of workers. In jobs where employers offer employer-sponsored health insurance, high health risk workers such as women, those who are obese and those who smoke, tend to receive lower wages to compensate for the higher health insurance premiums paid by employers.[2]

On the other hand, an unexplained gap may provide a different sort of negative signal to employers. Employer screening models suggest that employment gaps are negatively correlated with unobserved productivity.[3] As a result, employers may feel that the unemployed are less

[1]Human capital models suggest that skills of potential workers depreciate through periods of joblessness. See Acemoglu (1995), Ljungqvist & Sargent (1998).

[2]See Bhattacharya & Bundorf (2009), Cowan & Schwab(2011) and Cowan & Schwab (2016).

[3]See Vishwanath (1989) and Lockwood (1991).

productive on average. This may be reinforced by the suspicion that companies who have interviewed the applicant for other positions have found unfavorable indicators that prevented job offers.[4] Anecdotal evidence of such concerns is not difficult to find. Some employers even explicitly state in job ads that they do not consider unemployed job applicants.[5]

If the gap is explained as resulting from an illness, the applicant may be exempt from these conditional assessments. Illness strikes productive and unproductive workers alike. Moreover, a worker currently re-entering the labor market after an illness has not been subject to the scrutiny of other employers to the same extent as those who have been looking for work since the separation from previous employment. The expected productivity of a worker with an illness-related employment gap may be closer to that of the general worker population than to that of the long-term unemployed. For job applicants who experience a health shock, providing information on the reason for the employment gap may mitigate, if not eradicate, the unemployment bias.

We begin our study by developing a theoretical framework that helps to disentangle these competing effects. The model shows under what conditions researchers should expect that revealing the cause of a gap will increase or decrease the callback rate. The key to the results is that productivity is negatively correlated with experiencing an employment gap, but uncorrelated with becoming ill. Employment costs related to health issues, in contrast, are correlated with prior illness and uncorrelated with productivity. As a result, an unexplained gap gives negative information about expected productivity and an explained illness-related gap gives negative information about expected health costs. The clarity of these signals and the distributions of productivity and health costs determine the relative callback rates.

We then turn to an experiment that explores callback rates contingent on employment gaps that are either explained or unexplained. In our field experiment, carefully prepared résumés and corresponding cover letters were sent to employers who advertised vacancies in online job boards. For each vacancy, we sent three types of résumés. One résumé contained an explained illness-related employment gap while another contained an unexplained employment gap. These were in contrast to a third résumé where the applicant was newly unemployed (no gap). For illness-related and unexplained employment gaps, the résumés showed no employment over the

[4]See Oberholzer-Gee (2008).

[5]Legal experts say that the practice probably does not violate discrimination laws because unemployment is not a protected status, like age or race. However, New Jersey recently passed an anti-discrimination law against the unemployed and other states are considering similar legislation (Rampbell, 2011).

previous seven months or more.

To signal an illness-related employment gap, a phrase in the cover letter explained that the employment gap was due to a physical illness followed by a full recovery. An additional signal on medical history was sent via information in the résumé that indicates involvement in a cancer recovery support group. The corresponding cover letters of résumés with unexplained gaps did not provide any explanation for the gap. For the résumé of newly unemployed applicants, the length of the gap is limited to less than two months. Based on the literature, this is too short a gap to bring about adverse effects. The corresponding cover letter of newly unemployed applicants notes that the applicant left the last job because her family had to move from another state and that she is currently looking for a new job. We chose this control as our 'no gap' group because applicants who are currently working tend to have fewer callbacks. From March to September, 2016, we sent about 4,000 résumés to more than 1,200 sales, administrative, and accounting assistant jobs.

Outcomes are measured in terms of differences in the callback rate of each type of résumé. The results of the experiment show that newly unemployed applicants had the highest callback rate (27.4%). Consistent with previous studies, résumés with an employment gap received lower callback rates, indicating that such gaps negatively affect hiring outcomes. However, résumés with an explained illness-related gap received a higher callback rate than résumés with an unexplained gap (25.6 % versus 23.3%). Within the context of our theoretical model, these results suggest that the negative productivity signal of an unexplained gap outweighs undesirable factors associated with poor health history.

Our work contributes to the literature that examines how hiring probabilities depend on the duration of unemployment (i.e. duration dependence). Results from studies using non-experimental methods are mixed. In a review of the literature, Machin & Manning (1998), find little evidence supporting duration dependence. In contrast, a separate set of studies concludes that duration dependence plays a significant role in labor market outcomes.[6] As pointed out by Oberholzer-Gee (2008), non-experimental studies of duration dependence suffer endogeneity problems. The effects of employment gaps can be difficult to separate from the effects of other important worker characteristics that determine employment prospects.

Results from studies that use correspondence tests, where identification is derived from ex-

[6] See Lynch (1989), van den Berg & van Ours (1996), Imbens & Lynch (2006), and Shimer (2008) .

perimentally induced variation, provide more consistent results. Several such studies find that employment gaps beyond a threshold duration negatively affect the likelihood of being invited for an interview.[7] Some refinements of these findings have been considered. Eriksson & Rooth (2014) find that while contemporary employment gaps negatively affect the likelihood of getting a callback, past employment gaps do not. Kroft, Lange & Notowidigdo (2013) show that duration dependence is stronger when the labor market is tighter. Ghayad (2013) shows that positive traits such as work experience can compensate for employment gaps.

Our results provide an additional refinement by showing that explaining the gap as resulting from a medical issue can dampen duration dependence. This is important, in part, because health issues affect a large part of the potential labor force. For example, in 2014, the number of working age adults who were not in the labor force because of illness or disability reached 13 million, or 6.4 percent of the population.[8]

While not explicitly stated, the applications received by employers implied that each health-related gap was due to cancer. We chose cancer since its characteristics are consistent with our experimental design. Cancer treatment plausibly causes an employment gap for treatment. Patients who receive a good post-treatment prognosis can return to the labor market with undiminished productivity. Cancer is perceived to be onset-uncontrollable, which prevents employers from forming inferences about productivity from the diagnosis. Moreover, there is a chance that former patients may impose costs to employers through a future relapse or related healthcare issues. Thus, cancer per se, is not the focus of the paper but rather a reasonable proxy for health-related gaps more generally.

Nonetheless, by explaining the gap as related to cancer, we provide evidence on another poorly understood issue: the true impact of cancer survivorship on employment. Several studies confirm that cancer patients often are temporarily unable to work. Many also find high-rates of long-term unemployment (Bradley, Neumark, Lou & Schenk (2007), Jagsi, Hawley, Abrahamse, Li, Janz, Griggs, Bradley, Graff, Hamilton & Katz (2014)). While much of that literature has focused on supply-side issues (e.g. lingering effects of chemotherapy), our paper is the first to demonstrate the role of employers in the struggle of some cancer survivors to find work.

The remainder of the paper proceeds as follows. In Section 2, we give more detail on the

[7]Specifically, 9 months for Eriksson & Rooth (2014), 18 months for Oberholzer-Gee (2008), 6 months for Kroft, Lange & Notowidigdo (2013) and 6 months for Ghayad (2013).

[8]Based on the 2015 Annual Social and Economic Supplement to the Current Population Survey.

theoretical model. In Section 3, we describe the experimental design. Section 4 explains the empirical strategy while chapter 5 reports the results and interpretation. Section 5 concludes and provides suggestions for future studies.

2 Theoretical Framework

Before presenting the experimental design, we provide a theoretical framework that helps clarify the role of employment gaps in providing signals of productivity and health costs. We establish a simple framework to provide an example of how these signals can result in callback probabilities ordered: no gap, explained gap, unexplained gap. The key to this result is that productivity is correlated with the likelihood of getting a job offer but uncorrelated with the likelihood of becoming ill, while health costs[9] are correlated with illness and uncorrelated with job offers. As a result, an unexplained gap gives negative information about productivity and an explained gap gives negative information about health costs. The clarity of these signals and the distributions of productivity and health costs determine the relative callback rates.

Let θ be the expected benefit of a callback from the point of view of the employer. This expected benefit will depend on items such as the probability that the employer will want to hire the applicant after the callback, that the applicant will take the job, that she will do well in the job, stay in the job, etc. We refer to such items collectively as productivity. For simplicity we let θ be uniformly distributed such that

$$f_{\Theta}(\theta) = \begin{cases} 1 & \text{for } \theta \in [0,1] \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

The productivity measure θ is not observed by the employer. The employer does observe a signal $S \in \{n, i, u\}$ which may be informative about θ. A signal n means the applicant has no employment gap, i means an illness related gap, and u means an unexplained gap. By Bayes' law, the distribution of θ conditional on $S = s$ is

$$f_{\Theta}(\theta | S = s) = \frac{P(S = s | \Theta = \theta) f_{\Theta}(\theta)}{P(S = s)}. \tag{2}$$

[9]For simplicity, we refer to all potential negative consequences of hiring unhealthy workers as "health costs."

The signal depends on two shocks to the applicant in the previous period. A positive health shock means that the applicant was physically available to work. The probability of a positive health shock is independent of productivity and set to ω. A positive employment shock means that the worker, if healthy, had a job. This is correlated with productivity and for simplicity the probability of a positive shock is set to θ. Given this, $s = n$ if in the previous period the applicant received a positive health shock and a positive employment shock, $s = u$ if the applicant had a positive health shock but a negative employment shock, and $s = i$ if the applicant received a negative health shock. That is:

$$P(S = n|\Theta = \theta) = \omega\theta \tag{3}$$

$$P(S = u|\Theta = \theta) = \omega(1-\theta) \tag{4}$$

$$P(S = i|\Theta = \theta) = (1-\omega). \tag{5}$$

Given these conditional probabilities and equation (1) we can find the unconditional probability of each type of shock:

$$P(S = n) = \frac{\omega}{2} \tag{6}$$

$$P(S = i) = (1-\omega) \tag{7}$$

$$P(S = u) = \frac{\omega}{2}. \tag{8}$$

Equations (1) and (3)-(8) into (2) give the following conditional distributions

$$\begin{aligned} f_\Theta(\theta|S = n) &= 2\theta \\ f_\Theta(\theta|S = i) &= 1 \\ f_\Theta(\theta|S = u) &= 2(1-\theta) \end{aligned}$$

with support $\theta \in [0,1]$. From this and equation (1), the conditional expected productivities are

$$\begin{aligned} E(\theta|S=n) &= \frac{2}{3} \\ E(\theta|S=i) &= \frac{1}{2} \\ E(\theta|S=u) &= \frac{1}{3}. \end{aligned}$$

Note that $E(\theta|S=u) < E(\theta) = \frac{1}{2} = E(\theta|S=i)$. That is the expected θ conditional on $S=u$ is less than the unconditional expectation for θ while the expected θ conditional on $S=i$ is equal to the unconditional expectation. This reflects that employers learn something about productivity from applicants without illness related gaps but an illness related gap gives no information.

A firm may receive many applications for a position, However from the perspective of the researcher, each firm receives a triplet of applications. With a one-to-one correspondence between firms and triplets we use k to index both. Upon receiving this triplet, the problem for the firm is to maximize the expected net return to making callbacks, given by V_k. To maximize this, the firm chooses a callback strategy $C_k = \{c_{n,k}, c_{i,k}, c_{u,k}\}$, where $c_{n,k}, c_{i,k}, c_{u,k} \in \{0,1\}$ and $c_{s,k} = 1$ means make a callback to the applicant from triplet k with signal $S = s$. Finally, $c_{s,k} = 0$ means do not call that applicant back.

The value of V_k is equal to the sum of expected productivity and an idiosyncratic shock less an expected health care expenditure on the applicant if hired and a reservation level of returns. The shock $\varepsilon_{s,k}$ is known to the employer before making callbacks. It represents idiosyncratic items unobservable to the researcher that increase or decrease the value of a callback from the employer's perspective. Let $E(H|S=s)$ be the expected health related cost from hiring an agent given signal s. This could be insurance costs, costs due to lost work days in the future, lost productivity, a higher probability of future separation, etc. Let R_k be a reservation level of expected returns which must be exceeded in order to warrant a callback. This can reflect the cost of a callback, recruitment, training, etc. We can write the firm's problem in dealing with this triplet as

$$\max V_k = \max_{C_k} \sum_{s\in\{n,i,u\}} \left[E(\theta|S=s) + \varepsilon_{s,k} - E(H|S=s) - R_k\right] \tag{9}$$

Stated differently, the firm decides independently whether to respond to each applicant in the triplet.

We normalize health costs such that $E(H|S=n) = E(H|S=u) = 0$ and set $E(H|S=i) = hE(\theta|S=i) = \frac{h}{2}$. Given this, $E(\theta|S=i) - E(H|S) = \frac{1-h}{2}$. We economize on notation by setting $T_{s,k} \equiv \varepsilon_{s,k} - R_k$. Then equation (9) simplifies to

$$V_k = \max_{C_k} \left[\frac{2}{3} - T_{n,k}\right] + \left[\frac{1-h}{2} - T_{i,k}\right] + \left[\frac{1}{3} - T_{u,k}\right].$$

The optimal strategy for the firm is

$$C_k = \begin{cases} \{1,1,1\} & \text{if} \quad T_{n,k} \leq \frac{2}{3}, T_{i,k} \leq \frac{1-h}{2}, T_{u,k} \leq \frac{1}{3} \\ \{1,1,0\} & \text{if} \quad T_{n,k} \leq \frac{2}{3}, T_{i,k} \leq \frac{1-h}{2}, T_{u,k} > \frac{1}{3} \\ \{1,0,1\} & \text{if} \quad T_{n,k} \leq \frac{2}{3}, T_{i,k} > \frac{1-h}{2}, T_{u,k} \leq \frac{1}{3} \\ \{1,0,0\} & \text{if} \quad T_{n,k} \leq \frac{2}{3}, T_{i,k} > \frac{1-h}{2}, T_{u,k} > \frac{1}{3} \\ \{0,1,1\} & \text{if} \quad T_{n,k} > \frac{2}{3}, T_{i;k} \leq \frac{1-h}{2}, T_{u,k} \leq \frac{1}{3} \\ \{0,1,0\} & \text{if} \quad T_{n,k} > \frac{2}{3}, T_{i,k} \leq \frac{1-h}{2}, T_{u,k} > \frac{1}{3} \\ \{0,0,1\} & \text{if} \quad T_{n,k} > \frac{2}{3}, T_{i,j} > \frac{1-h}{2}, T_{u,k} \leq \frac{1}{3} \\ \{0,0,0\} & \text{if} \quad T_{n,k} > \frac{2}{3}, T_{i,k} > \frac{1-h}{2}, T_{u,k} > \frac{1}{3}. \end{cases}$$

To simplify even more, we let $T_{n,k}, T_{i,k}, T_{u,k}$ be *i.i.d.* $u[0,1]$. This allows us to easily find the probability that a firm chooses any strategy C_k; i.e. $P(C_k = \{c_{n,k}, c_{i,k}, c_{u,k}\})$. This will in turn be equal to the share of firms having this strategy in the population of firms $P(C = \{c_n, c_i, c_u\})$. In particular we find

$$\begin{aligned} P\{1,1,1\} &= \tfrac{1-h}{9} \\ P\{1,1,0\} &= \tfrac{2(1-h)}{9} \\ P\{1,0,1\} &= \tfrac{1+h}{9} \\ P\{1,0,0\} &= \tfrac{2(1+h)}{9} \\ P\{0,1,1\} &= \tfrac{1-h}{18} \\ P\{0,1,0\} &= \tfrac{1-h}{9} \\ P\{0,0,1\} &= \tfrac{1+h}{18} \\ P\{0,0,0\} &= \tfrac{1+h}{9}. \end{aligned}$$

We now turn attention to the percentage of instances in which each signal is favored. An application in a triplet with signal $S = s$ is favored if the application receives a callback while at least one other application in the triplet does not. Let $P(F|S = s)$ be the probability that an application with signal s is favored. For example, $P(F|S = n) = P\{1, 1, 0\} + P\{1, 0, 1\} + P\{1, 0, 0\}$. Given this

$$P(F|S = s) = \begin{cases} \frac{5+h}{9} & \text{if} \quad s = n \\ \frac{7(1-h)}{18} & \text{if} \quad s = i \\ \frac{2+h}{9} & \text{if} \quad s = u \end{cases}$$

so

$$P(F|S = n) > \max\{P(F|S = i), P(F|S = u)\}$$

and

$$P(F|S = i) > P(F|S = u) \text{ iff } h < \frac{1}{3}.$$

This shows that so long as h is not too large, applicants with no gap are most likely to be preferred, followed by an illness gap and an unexplained gap. However, all will be preferred in some share of the cases.

To find the probability of a callback, we add $P\{1, 1, 1\}$ to $P(F|S = s)$. This gives

$$P(C|S = s) = \begin{cases} \frac{2}{3} & \text{if} \quad s = n \\ \frac{1-h}{2} & \text{if} \quad s = i \\ \frac{1}{3} & \text{if} \quad s = u \end{cases}$$

so that

$$P(C|S = n) > \max\{P(C|S = i), P(C|S = u)\}$$

and

$$P(C|S = i) > P(F|S = u) \text{ iff } h < \frac{1}{3}.$$

This shows that so long as h is not too large, applicants with no gap are most likely to get a callback followed by an illness gap and an unexplained gap.

3 Experimental Design

The correspondence test methodology has been used to provide insights on hiring discrimination based on race, ethnicity, immigration, gender, sexual orientation and age.[10] The method involves sending similar job applications to employers posting jobs with the only difference being a characteristic that signals membership to a group. We employ this methodology to study how employers respond to a job applicant's illness-related employment gap compared to unexplained gap or no gap.

The experiment was carried out between March, 2015, and September, 2016. Over this period, we surveyed eligible employment ads from multiple online job boards. For each job ad, we customized fictitious résumés and sent them to employers. We then measured employers' responses to our fictitious job seekers' application.[11]

We chose the following occupations: sales and customer service, clerical/administrative assistant and accounting assistant jobs.[12] We targeted these jobs for several reasons. First, these types of jobs do not require complex skills and are fairly similar across firms which allows us to easily create suitable generic résumés. Second, there are enough numbers of available jobs in online job boards in these fields to conduct a sufficiently powered study. We limited our sample to job ads that required 6 or fewer years of work experience. We restricted our experiment to 15 of the most populous cities of the United States.[13] We chose jobs that allowed direct uploads of résumés and cover letters to apply. We eliminated any ad where applicants were asked to call or appear in person or that required résumés to be submitted to external websites.

We recorded available information about the job, including the date the job ad was posted, position, company name, company address, telephone number and job requirements (education level and skills required). We also recorded whether the ad explicitly stated that the employer

[10] See Bertrand Mullainathan (2004), Arai, Bursell, Nekby (2011), Arceo-Gomez Campos-Vazquez (2014), Baert, Cockx, Gheyle, Vandamme (2013), Carlsson Rooth (2007), Drydakis Vlassis (2010), Neumark, Burn Button (2015), Oreopoulos (2011), Pedulla (2014), Petit (2007), Drydakis (2009), Riach Rich (2006), Weichselbaumer (2003).It has been extended to identify hiring penalties associated with motherhood, physical unfitness, obesity and criminal record. For examples, see Correll, Benard, Paik (2007), Rooth (2011), Rooth (2009) Pager (2003).

[11] The experimental protocol was reviewed and approved by the Institutional Review Board at Kansas State University.

[12] As in Bertrand and Mullainathan (2004) and Kroft, Lange & Notowidigdo (2013).

[13] New York, NY; Los Angeles, CA; Chicago, IL; Houston, TX; Philadelphia, PA; Phoenix, AZ; San Antonio, TX; San Diego, CA; Dallas, TX; San Jose, CA; Jacksonville, FL; Indianapolis, IN; San Francisco, CA; Austin, TX; Columbus, OH.

required physical capacity to lift objects and whether it required a stable job history. Moreover, we also collected information on whether the ad stated that the employer provided employer-sponsored health insurance and other benefits. This information was used to create the résumés and where relevant, was used in the statistical analysis. We collected jobs and sent résumés by batch. More specifically, the size of a batch depends on the available jobs at the particular time of data collection and ranges from about 30 to 150 jobs. We prepared and sent the résumés for one batch of job ads before collecting a new batch of job ads.

Three equally qualified artificial résumés and corresponding cover letters were customized for each job ad. These three résumés sent to a single job ad constitute one triplet.[14] Using the résumé randomizer developed by Lahey and Beasley (2007), we then randomly assigned treatments and other résumé details to each type of résumé.[15]

All of the résumés that we sent indicated a contemporary employment gap. The résumés differed in terms of the duration of the employment gaps and assignment of the explanation for the gap.[16] Thus if applicable, the type of employment gap was explicitly explained in the cover letter and an additional signal was sent using the interest section of the résumé. By differing the employment gaps and gap explanation (or the lack of it) in each of the résumés in a triplet, we can identify the effects of the types of employment gaps on the employment prospects of job seekers. Each résumé in the triplet belonged to one of the following three treatment groups.

A résumé in treatment group 1 signaled an applicant who was newly unemployed. We used newly unemployed, rather than currently employed, as Kroft, Lange & Notowidigdo (2013) and Eriksson & Rooth (2014) find that a currently employed worker is less likely to be called back for an interview than a newly unemployed individual. Kroft, Lange & Notowidigdo (2013) suggest that employers may perceive individuals who engaged in on-the-job search as less loyal and prone to job hopping. In addition, some jobs require workers to start immediately which may be typical of the sample of jobs in our experiment. To minimize these effects, the corresponding cover letter indicated that the applicant resigned from her last employment due to a family decision to relocate from Seattle.[17] Applicants with this type of gap are said to have no relevant

[14] Accordingly, we have 1,257 triplets since we applied to 1,257 jobs.

[15] We exported these characteristics assignment to a spreadsheet, which was used as input to résumé creation in Microsoft Word using the Mail Merge function.

[16] Non-employment duration appeared on the résumé in the form of an end date for the applicant's most recent job. For example, if the résumé is assigned a 8-month employment then the end date of the applicant's last job is 8 months from the date the résumé was sent.

employment gap.

A résumé in treatment group 2 contained a signal that the applicant had an illness-related gap for a notable period of time. For most of the sample this was 7 to 12 months. For 5% of the sample this was 20 to 22 months. In this treatment, a phrase in the cover letter explained that the gap is due to a medical illness followed by a complete recovery. An additional signal on the medical history was sent via information in the résumé which indicated involvement in a support group for cancer survivors. This implied that the illness associated with the employment gap was cancer, though this was not stated explicitly.

We chose cancer because cancer treatment is more likely to cause an employee to stop working, causing an employment gap. Cancer patients who receive a good post-treatment prognosis can return to the labor market with the comparable level of productivity as workers with no poor health history. Cancer is also perceived to be onset-uncontrollable, which prevents employers from forming inferences about productivity from the diagnosis. The possibility of relapse is also a concern for job applicants with cancer history. Further, health insurance costs for employers are likely to increase, since previous episodes of cancer are treated as a pre-existing condition that raise premiums.

A résumé in treatment group 3 contained an employment gap that is comparably long with treatment group 2. However, no explanation is provided for the employment gap in the résumé and cover letter. The employer, then, was free to assume the underlying reason behind the applicant's spell of joblessness.

In order to provide a signal of one's health issues in the résumés' of treatment group 2, we indicated that the applicant is a Member/Organizer of a cancer survivor group. To balance the three groups, we also assigned an alternative activity in the interest section of the résumés of treatment group 1 and treatment group 3. The applicant is either a volunteer for the "Watch the Wild" program or is interested in drawing, painting and running.

We chose common first names in 1990 and last names that were most likely to signal that the applicant was Caucasian to prevent any name-based employment discrimination from influencing the results. For females, we used Jessica Smith, Ashley Johnson and Rachel Miller. For males, we chose Joshua Smith, Andrew Johnson and Ryan Miller. Each name was assigned a corresponding telephone number and email address. To easily track the callback, we assigned

[17] The explanation is necessary to prevent employers from assuming that the applicant is not readily available for work or prone to job-hopping.

the name, a corresponding telephone number and e-mail address based on the treatment type. Those who were assigned treatment 1, for example, were assigned the name Rachel Miller and the corresponding email address and telephone number. The email addresses were all gmail accounts. We used Vumber to get three online telephone numbers by city, one for each treatment group. These did not appear any different than regular phone numbers to the employer, but had the benefit that the calls and voicemails were recorded in an online account and no physical phones were required. Residential addresses on the résumés were selected carefully to ensure that they were realistic. We used Zillow.com to get real addresses but we changed the housing/apartment number/letters to generate fictitious addresses.

Since we targeted jobs that required 6 years or less of experience, we designed the work histories such that the total years of experience was about 6 years. Each résumé was designed such that the applicant had two jobs, no unemployment since high school graduation, but were currently not employed. We created job histories by first randomly assigning the length of contemporary unemployment. As mentioned above, the length of the employment gap is conditional on the treatment assignment. We derived the end-dates of the last job by subtracting the length of contemporary unemployment from the date the résumé was planned to be sent. We then randomly assigned the tenure in the last job (12, 24 or 36 months) which then determined the start date of the last job and the end date of the first job. We assigned the tenure in the second job such that the number of years of work experience in the first and second job added up to about 6 years. The tenure in the first job determined the start date of the first job and the date of high school graduation.

We collected a sample of acceptable job histories from real résumés downloaded in job search sites. Based on these histories, we selected three options for the following fields for each type of job: first job and job responsibilities, and second job and job responsibilities. We randomly assigned the first and second job to the résumés in each triplet. As in Neumark, Burn & Button (2015), we followed a defined profile of responsibility, showing a progression of jobs from lower to higher-level jobs.[18] We added employer names and addresses to each job on our final job histories. We used employers that were active at the time and in the region listed.

[18] For example, in retail sales, the first job starts with the lower responsibility job like a cashier position and then the applicant works his/her way through becoming sales associate (hoping to step up to management positions). For administrative assistants, workers start as a receptionist before working their way to an administrative officer position.

We designated half the résumés to be high skilled (or high quality), and half to be low skilled. This would enable us to see if the employment consequences of illness-related gaps vary by quality. We combined the measures used by Kroft, Lange Notowidigdo (2013) and Neumark (2015) to define a measure of quality for each résumé. All low-quality résumés had typographical errors and had no additional signals of productivity/skills. We had three types of high quality résumés and each type of high quality résumé had different additional signals of productivity. High quality type 1 résumé had an extra level of education, additional proficiency such as proficiency in *Quickbooks* software and indicated fluency in Spanish as a second language. An extra level of education means that if the job required high school completion, we listed an associate degree or if the job required an associate degree, we listed a bachelor degree. High quality type 2 résumés had acquired a certificate, an *"Employee of the Month"* award and did not have typographical error. The third high quality résumé had academic honors, notable achievement in previous work and had an an additional skill different from the additional skill of type 1 high quality résumés. All the résumés in a triplet were of same quality.

We created three résumé templates. Templates were randomly assigned to each résumé created. There are no same templates used in a triplet to prevent the employers from detecting the experiment. For each job ad, the résumé randomizer assigned whether the triplet would be all male or all female.

For each city, we selected universities and corresponding degrees, community colleges and corresponding degrees, and high schools by city listed on each résumé. We selected universities that do not fall on the tier 1 to tier 3 categories defined by Hersch (2014). We randomly assigned these based on the education levels. To be consistent with our story that the treatment 1 applicant just moved from Seattle, we always assigned a school from Seattle for treatment group 1.

Once the résumés were generated, we converted the files to PDF formats. We named the files based on the name or initials of the applicant. We made sure that the filename style differs within triplet (e.g. "Rachel Miller", "R.Miller", or "Miller, Rachel") to minimize chances of detecting the experiment. Appendix A provides a sample résumé and cover letter for each of the treatment groups. The first two pages in Appendix A show a sample cover letter and résumé of a newly unemployed applicant. The next two pages show a sample cover letter and résumé of an applicant with an illness-related employment gap. These are followed by a sample cover letter and résumé of an applicant with an unexplained gap. In sending the résumés, we randomly assigned the order by which the résumés were sent. For each triplet, the second résumé is sent at least a day after the first résumé was sent. We recorded the day the résumé was sent in the database.

We measured whether a given résumé elicits a callback, textback or e-mailback for an interview. For each phone, text or e-mail response, we used the content of the message left by the employer (name of the applicant, company name, telephone number for contact) to match the response to the corresponding résumé/job ad pair.[19] We defined a callback as a personalized phone or e-mail contact by a potential employer. Usually the callback was a request for an interview, but employers also contacted applicants asking for more information or stated that they have a few questions. After hearing from employers, we sent a message to them that the applicant is no longer available for the job.

4 Empirical Strategy

Our empirical strategy consists of comparing the average callback rates across treatment groups and conducting various regression analyses to analyze the data we gathered from the experiment. Our regression analyses start with checking whether our results are consistent with previous studies showing that contemporaneous employment gaps adversely affect employment prospects. To do this, we estimate the following equation:

$$C_{jk} = \alpha + \delta G_{jk} + \mathbf{R}'_{jk}\Gamma + \mathbf{E}'_{k}\Lambda + \epsilon_{jk} \tag{10}$$

where C_{jk} is a callback indicator that equals 1 if applicant j who applied for job k received an invitation to a job interview, G_{jk} is a dummy variable that equals 1 if applicant j who applied for job k has an employment gap (i.e. illness-related employment gap or an unexplained employment gap), $\mathbf{R}$ is vector of résumé attributes and $\mathbf{E}$ is a vector of employer/job advertisement attributes.[20] Given that the résumé characteristics are randomized across treatment groups, δ

[19] Any attempt by employers to contact applicants via postal mail cannot be measured in our experiment since the addresses are fictitious.

[20] $\mathbf{R}$ includes dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the applicant etc. $\mathbf{E}$ includes dummy variables for occupation, required education level and experience, full-time jobs, commission-based jobs, employer-sponsored health insurance, physical requirements and location of the job.

gives the unbiased estimate of the impact of having any employment gap on the callback rate relative to the newly unemployed since the omitted variable is the dummy variable for the newly unemployed. The vectors Γ and Λ provide the effects of résumé and job advertisement attributes on the callback probability, respectively.

Our main goal in this paper is to analyze the effect of explaining an illness-related employment gap on workers' likelihood of being invited to a job interview. Thus the next thing we do is to estimate the following equation where instead of pooling all employment gaps into one variable, we separately estimate the effect of each type of employment gap:

$$C_{jk} = \alpha + \beta_1 I_{jk} + \beta_2 U_{jk} + \mathbf{R}'_{jk}\Gamma + \mathbf{E}'_k\Lambda + \epsilon_{jk} \tag{11}$$

I_{jk} is a dummy variable that equals 1 if applicant j who applied for job k has an illness-related employment gap, U_{jk} is a dummy variable that equals 1 if applicant who applied for job k has an unexplained employment gap and the rest of the variables are same as in Equation 10. Given that the résumé characteristics are randomized across treatment groups, β_1 gives the unbiased estimate of the mean impact of explaining an illness-related employment gap relative to the hiring rate of the newly unemployed and β_2 gives the unbiased estimate of the mean impact of not explaining an illness-related employment gap relative to the hiring outcome of the newly unemployed. Again, the omitted variable is the dummy variable for newly unemployed.

As a robustness check, we estimate Equation 11 using OLS estimation as well as probit estimation (and provide marginal effects). Moreover, we estimate the following fixed effects model to control for fixed effects at the job ad level:

$$C_{jk} = \alpha + \beta_1 I_{jk} + \beta_2 U_{jk} + \mathbf{R}'_{jk}\Gamma + \mu_k + \epsilon_{jk} \tag{12}$$

where μ_k represents the fixed effect of k^{th} job.

Since a small sample of the résumés that were assigned an illness-related gap and unexplained gap have an employment gap of more than 20 months, it also informative to modify and estimate Equations 10 to 12 to include an additional dummy variable for the employment gap that lasted for more than 20 months. The coefficient of this additional variable can be interpreted as the mean impact of having more than 20 months in gap, given that the applicant has either an illness-related gap or unexplained gap. This coefficient tells us if having a longer employment gap matters once we control for more information on the gap.

5 Results

In this section, we present the overall descriptive statistics and then turn to the results. Column 1 of Table 1 presents the overall callback rate for the sample. Included in brackets under each rate is the number of résumés sent in that cell. We sent a total of 3,717 résumés to 1,257 job ads. The overall callback rate is 25.5 percent. Unlike the Deming, Yuchtman, Abulafi, Goldin & Katz (2016), we find that the callback rates did not differ between low and high quality résumés. The callback rate is higher for female-sounding names compared to male-sounding names. Applications sent to sales jobs received higher callbacks compared to administrative and accounting assistant jobs.

In the following subsections, we compare the callback rates among treatment groups and subgroups and discuss the regression results and interpretation.

5.1 Comparing the Mean Callback Rates

Column 2 to 4 of Table 1 show the average callback rate of applicants who are newly unemployed, with illness-related gaps and with unexplained employment gaps. Overall, there is evidence of negative duration dependence. Row 1 shows that 27.4 percent of the newly unemployed applicants received a callback compared to the average callback rate of 24.5 percent for applicants with employment gap (illness-related or unexplained). This holds true by type of quality, gender and occupation.

When employers are given more information about the type of employment gap, they appear to consider this additional information in their callback decisions. Comparing columns 3 and 4, we see that the average callback is lower for applicants with an unexplained employment gap (23.3 percent) vis-á-vis applicants with and explained illness-related employment gap (25.6 percent). This represents a difference in callback rates of 2.3 percentage points, or 10 percent. Except for low quality type résumés and accounting jobs, the observation of lower callback rates for unexplained gap can be seen in most sub-groups in Table 1.

Table 1: Mean Callback Rates by Type of Employment Gap

	(1) All	(2) Newly Unemployed	(3) Illness-related gap	(4) Unexplained gap
Overall	25.5 [3771]	27.4 [1257]	25.6 [1257]	23.3 [1257]
Low Quality	25.5 [1956]	26.5 [652]	23.8 [652]	26.2 [652]
High Quality	25.4 [1815]	28.4 [605]	25.0 [605]	22.8 [605]
Male	23.3 [2025]	24.6 [675]	23.6 [675]	21.8 [675]
Female	27.9 [1746]	30.8 [582]	28.0 [582]	25.1 [582]
Retail	36.0 [1566]	37.9 [522]	37.0 [522]	33.0 [522]
Administrative Assistant Jobs	18.2 [1200]	19.5 [400]	18.0 [400]	17.0 [400]
Accounting Assistant Jobs	17.8 [1005]	20.6 [335]	15.8 [335]	17.0 [335]

The number of résumés sent in each particular group is provided in the brackets.

As in Bertrand & Mullainathan (2004), we tabulate the distribution of callbacks at the firm or triplet level. In each of the cells in columns 2 and 3 of Table 2, the first row indicates the firm's callback strategy, $C_k = \{c_{n,k}, c_{i,k}, c_{u,k}\}$ where $c_{n,k}, c_{i,k}, c_{u,k} \in \{0,1\}$ and $c_{s,k} = 1$ means the k^{th} firm made a callback to the applicant with signal s and $c_{s,k} = 0$ means the k^{th} firm did not call that applicant with signal s back.[21] The second and third rows under each cells in columns 2 and 3 respectively contain the percentage and the number of firms with row 1 callback strategy. Equal treatment occurs when either no applicant gets called back or all the types of applicants in a triplet receive a callback. The newly unemployed applicant is favored when either only the

[21]For example, callback strategy, $C_k = \{c_{n,k}, c_{i,k}, c_{u,k}\} = \{1,1,0\}$ means that for triplet k, the employer called the applicants with signals n (no gap) and i (illness-related employment gap) and did not call the applicant with signal u (unexplained employment gap).

newly unemployed gets called back, or the newly unemployed is one of the two applicants in the triplet who received a callback. Similarly, the applicant with an illness-related employment (unexplained employment) gap is favored when either only the applicant with an illness-related employment (unexplained employment) gets called back, or the applicant with an illness-related employment (unexplained employment) is one of the two applicants in the triplet who received a callback.

In column 1 of Table 2, we report the percentage and number of firms that showed equal treatment and the same statistics of firms who favored each treatment group. Equal treatment occurs for about 77.2 percent of the ads but most of that is due to the high fraction of ads for which no callbacks are recorded (62.9 percent of the ads). Approximately, 14 percent of job ads call all the applicants in the triplet. Newly unemployed applicants are favored by 13.2 percent of the employers. Applicants with an explained illness-related gap, on the other hand, are favored by only 11.4 percent of employers while applicants with unexplained employment gap were the least favored with only 9.1 percent of employers favoring this group.

Using the test of proportion, we test the null hypotheses that there is symmetry in : 1) favoring of newly unemployed over applicants with an illness-related gap ($Ho : nF = iF$); 2) favoring of newly unemployed over applicants with an unexplained gap ($Ho : nF = uF$); and 3) favoring of applicants with an illness-related gap over applicants with an unexplained gap ($Ho : iF = uF$). Given a $p-value$ of 0.169, we do not reject $Ho : nF = iF$ which suggests that the difference between the fraction of employers favoring newly unemployed and the fraction of employers favoring applicants with illness-related gap is not statistically different from each other. However, we reject the $Ho : nF = uF$ and $Ho : iF = uF$ because the test gives $p-values$ of 0.001 and 0.057, respectively. Rejecting $Ho : nF = uF$ suggests that there is statistical difference between the rate by which employers favor the newly unemployed relative to the rate by which employers favor applicants with unexplained employment gap. Rejecting $Ho : iF = uF$ suggests that there is statistical difference is also observed if we compare the rate by which employers favor applicants with illness-related gaps and the rate by which employers favor applicants with unexplained employment gaps.

Table 2: Distribution of Firms' Callback Strategy, $C_k = \{c_{n,k}, c_{i,k}, c_{u,k}\}$

Equal Treatment 77.2 [970]	{0, 0, 0} 62.9 [791]	{1, 1, 1} 14.2 [179]	
Newly Unemployed Favored (nF) 13.2 [166]	{1, 0, 0) 5.3 [67]	{1, 1, 0} 4.8 [60]	{1, 0, 1} 3.1 [39]
Illness-related Employment Gap Favored (iF) 11.4 [143]	{0, 1, 0} 3.7 [46]	{1, 1, 0} 4.8 [60]	{0, 1, 1} 2.9 [37]
Unexplained Employment Gap Favored (uF) 9.1 [114]	{0, 0, 1} 3.0 [38]	{1, 0, 1} 3.1 [39]	{0, 1, 1} 2.9 [37]

The first line in each of the cells in columns 2 to 4 represents the callback strategy of the form, $\{c_{n,k}, c_{i,k}, c_{u,k}\}$ while the first line in column 1 sums up the relevant callback strategies to determine the share of firms that showed equal treatment and unequal treatment. Across all cells in the table, the second line is the percentage of firms while the third row contains the number of firms.

5.2 Regression Results

In this subsection, we present the regression results of the empirical models represented by equations 10 to 12. Our main results show that applicants with explained illness-related employment gaps receive higher callbacks than otherwise identical applicants that offer no explanation for the gap.

Our experiment finds negative duration dependence that is consistent with studies closely related to our paper. Table 3 presents a regression analyses of the effect of having a contemporaneous employment gap (relative to newly unemployed applicants) on the probability of getting hired. These estimates pool Treatment 2 and Treatment 3 together. Columns 1 to 3 are estimated using OLS estimation, probit estimation[22] and linear estimation with fixed effects, respectively. Relative to applicants who are newly unemployed, the effect of having an employment gap that is at least 7 months is negative and significant at the 1 percent level. The callback rate is reduced by 12 percent (0.03/0.255) for applicants with any type of employment gap. The results are robust across linear specifications (with and without job advertisement fixed effects)

[22]Coefficients reflect marginal effects.

and non-linear specification.

A small proportion of workers were assigned employment gaps gaps of more than 20 months. We include an additional dummy equal to 1 when the gap is greater than 20 months in columns 4 to 6. The changes in the coefficient of the employment gap are small and not significant and the coefficient of the additional dummy is also not significant. As a result, we see no evidence that employment gaps longer than 12 months further reduce employment prospects. This is consistent with the results of Kroft, Lange & Notowidigdo (2013) and Eriksson & Rooth (2014) which suggest that callbacks decline sharply for mid-long spells (up to around 9 months) but is flat for unemployment durations thereafter. After a length threshold is reached, additional length of employment gaps does not explain the adverse effect of employment gaps.

Table 3: The Effect of Having an Employment Gap on the Callback Rate

Dependent Variable: Callback Dummy	(1)	(2)	(3)	(4)	(5)	(6)
Employment Gap	-0.030***	-0.031***	-0.030***	-0.034***	-0.035***	-0.029***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)
Gap Duration>20				0.066	0.059	-0.023
				(0.040)	(0.037)	(0.034)
OLS	X			X		
Probit		X			X	
Fixed Effects: (Job Ads)			X			X
Callback Rate Ave. (%)	25.5	25.5	25.5	25.5	25.5	25.5
Observations	3,771	3,771	3,771	3,771	3,771	3,771
R-squared	0.090		0.012	0.091		0.012
Number of Job Ads			1,257			1,257

The dependent variable is the callback dummy. Control variables include dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the applicant, for occupation type, required education level and experience, full-time jobs, commission-based jobs, employer-sponsored health insurance, physical requirements and location of the job. Columns 1 to 3 were estimated without controlling for gaps greater than 20 months. Columns 4 to 6 include a dummy controlling for gaps greater than 20 months. Columns 2 and 5 give the results of a probit regression using dprobit command in Stata 12. The coefficients reported in these columns (2 and 5) are estimated marginal changes in the probability for estimated discrete changes for the dummy variables. Robust standard errors are in parentheses and are clustered at the job vacancy level: *** p<0.01, ** p<0.05,* p<0.1.

Table 4: The Effect of Having an Explained Illness-related Gap and an Unexplained Gap on the Callback Rate

Dependent Variable: Callback Dummy	(1)	(2)	(3)	(4)	(5)	(6)
Illness-related Gap	-0.019*	-0.019*	-0.018*	-0.022*	-0.022*	-0.019*
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)
Unexplained Gap	-0.042***	-0.042***	-0.041***	-0.046***	-0.046***	-0.038***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
Gap Duration>20				0.074	0.069	-0.062
				(0.058)	(0.055)	(0.047)
Unexplained Gap x Gap Duration >20				-0.017	-0.019	0.075
				(0.085)	(0.068)	(0.068)
F (Illness-related = Unexplained)	*0. 0.038*	*0.036*	*0.035*	*0.046*	*0.044*	*0.090*
Ave. Callback Rate	25.5	25.5	25.5	25.5	25.5	25.5
OLS	X			X		
Probit		X			X	
Fixed Effects: Job Ad			X			X
Observations	3,771	3,771	3,771	3,771	3,771	3,771
R-squared	0.091		0.013	0.092		0.014
Number of Job Ads			1,257			1,257

The dependent variable is the callback dummy. Control variables includes dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the applicant, for occupation type, required education level and experience, full-time jobs, commission-based jobs, employer-sponsored health insurance, physical requirements and location of the job. Columns 1 to 3 were estimated without controlling for a gap duration greater than 20 months. Columns 4 to 6 include a dummy controlling for gaps greater than 20 months. Columns 2 and 5 give the results of a probit regression using dprobit command in Stata 12. The coefficients reported in these columns (2 and 5) are estimated marginal changes in the probability for an estimated discrete change. The F (Illness-related Gap = Unexplained Gap) provides the F-statistic needed to test the null hypothesis that the coefficient of an illness-related gap is equal to the coefficient of the unexplained gap. Robust standard errors are in parentheses and are clustered at the job vacancy level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

To fully control for résumé and job characteristics, we estimate equations Equations 11 and 12. Columns 1 and 2 of Table 4 show estimates of Equations 11 using OLS and probit while column 3 shows the linear estimation result controlling for the fixed effects at the job ad level

(Equation 12). The coefficients of the illness-related gap and the unexplained gaps are negative and significant at the 1 and 10 percent levels, respectively, indicating that applicants with any type of employment gap have worse employment prospects relative to newly unemployed applicants.

In order to answer our main research question, we compare the magnitude of the coefficients for an illness-related gap and an unexplained gap to show if the effect of explaining a gap mitigates its negative effect on employment. Indeed, relative to the newly unemployed, applicants with an unexplained gap receive fewer callbacks (4.2 percentage points less) than the those with an illness-related employment gap (1.9 percentage points less). Relative to the mean callback rate (25.5 percent), an illness-related employment gap reduces callback rates by approximately 7 percent. An unexplained employment gap, however, reduces the callback rate is reduced by 16 percent. Results from the F-test reject the null hypothesis that the marginal effect of the two types of employment gaps are the same. These results are robust across several specifications, including controlling for the job ad fixed effects. Our main results show that applicants with explained illness-related employment gaps fare better in attracting callbacks than otherwise identical applicants that offer no explanation for the gap.

The theoretical framework presented in Section 2 suggests that preferring potential workers known to have a poor health history over those with an identical, but unexplained, employment spell is not necessarily irrational. In a model with heterogeneous workers and uncertainty, employers do not directly observe productivity of job applicants. Given a positive correlation of general employment gaps and low productivity, firms take observed employment gaps as signals of productivity. When there are health shocks, we show that it is in the best interest of the employers to hire job applicants with an illness-related employment gap over applicants with unexplained gaps. It seems then that this form of ambiguity aversion may arise from the profit-maximizing behavior of firms.

5.3 The Role of the Physical Requirements of the Job, Employer-Sponsored Insurance and Disability Discrimination Law

To further explore our results, we analyze how job-related physical requirements, employer-sponsored insurance (ESI), and the strictness of the state disability discrimination law (DDL) affect the relative callback probability of each treatment group. We do this in order to determine if any evidence exists for possible alternative mechanisms underlying our results.

First, employers might take an illness-related gap as a signal for weaker physical ability that may interfere with current or future productivity. To test the influence of perceived physical limitations, we use data from the job advertisement on the physical requirements of the job to create a dummy variable, "Physical Requirements", which is equal to 1 if the job advertisement explicitly mentions that the job entails physical strength such as standing and lifting objects. We interact this variable with the treatment group dummies. Table 5 shows that the coefficient of the interaction of an illness-related gap and physical requirements of the job is negative but not significant. However, the size of the coefficient (-0.013 for column 1)is large relative to the impact of an illness employment gap in jobs without a physical requirement (-0.021 for column 1). By contrast, there is no additional callback reduction in jobs with physical requirements for those with unexplained gaps.

Second, employers that offer employer-sponsored insurance may want to avoid applicants with an illness-related gap because of their higher expected medical costs. We use data from the job advertisement on the offer of employer-sponsored insurance to create a dummy variable, "Health Insurance", which is equal to 1 if the job advertisement explicitly mentions that the employer provides employer-sponsored insurance. Table 5 shows that the coefficient of the interaction of the dummy variable for illness-related gaps and "Health Insurance" is positive and not significant. The coefficient of the interaction of the dummy variable for unexplained gaps and "Health Insurance" is negative and significant at 10 percent level. Neither estimate suggests that the offer of health insurance negatively affects job prospects of applicants with poor health histories. However, our ability to make a stronger conclusion about the role of employer sponsored insurance in explaining our results is tempered by two important weaknesses. Firstly, we rely on explicit reports of insurance availability in a job advertisement, and thus might misclassify some jobs that offer insurance but do not advertise as such. Secondly, the offer of health insurance is strongly correlated with firm size, which may confound the estimates if firm size affects perception of gaps for reasons unrelated to health costs.

In explaining the stronger negative effects of an unexplained gap over an explained illness gap, we consider whether the federal DDL (i.e. the American Disabilities Act (ADA)) and state DDLs impact how employers behave when faced with information on the health history of workers. Do these laws induce employers to react more carefully in their treatment against

Table 5: Job Characteristics and the Effect of Employment Gaps on the Callback Rate

Dependent Variable: Callback Dummy	(1)	(2)	(3)	(4)	(5)	(6)
Illness-related Gap	-0.021*	-0.021*	-0.018	-0.025*	-0.026**	-0.022*
	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
Unexplained Gap	-0.045***	-0.046***	-0.039***	-0.033**	-0.034**	-0.025*
	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.013)
Health Insurance	-0.012	-0.014		-0.000	-0.003	
	(0.024)	(0.025)		(0.029)	(0.029)	
Physical Requirements	-0.013	-0.017		-0.017	-0.021	
	(0.046)	(0.040)		(0.037)	(0.033)	
Illness-related Gap x Physical	-0.013	-0.013	-0.012			
	(0.043)	(0.038)	(0.043)			
Unexplained Gap x Physical	-0.000	0.001	0.013			
	(0.039)	(0.037)	(0.039)			
Illness-related Gap x Health Insurance				0.011	0.014	0.009
				(0.026)	(0.027)	(0.026)
Unexplained Gap x Health Insurance				-0.047*	-0.045*	-0.050*
				(0.027)	(0.025)	(0.027)
OLS	X			X		
Probit		X			X	
Fixed Effects: Job Ad			X			X
Observations	3,771	3,771	3,771	3,771	3,771	3,771
R-squared	0.092		0.014	0.092		0.017
Number of Job Ads			1,257			1,257

The dependent variable is the callback dummy. Control variables includes dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the applicant, for occupation type, required education level and experience, full-time jobs, commission-based jobs, employer-sponsored health insurance, physical requirements and location of the job. Columns 3 and 6 gives the results of a probit regression using dprobit command in Stata 12. The coefficients reported in columns 3 and 6 are estimated marginal changes in the probability for estimated discrete changes for the dummy variables. Robust standard errors are in parentheses and are clustered at the job vacancy level: *** p<0.01, ** p<0.05, * p<0.1 .

those claiming a severe past health issue? To test this, we exploit state variation in the minimum size threshold for employer coverage (See Table 6). We create a dummy variable, "Discrimination Disability Law," which is equal to 1 when the state is more strict in their state disability law and 0 if less strict. Because the ADA automatically applies to employers with 15 or more employees, we consider states with a state DDL that applies to firms with fewer than 15 employees as "more strict". Whether firms with fewer than 15 employees are covered by any state disability law varies across state. We estimate the effect of the interaction of the strictness of disability law with the treatment group dummies. Table 7 shows the coefficients of the interaction of the "Discrimination Disability Law" dummy variable and treatment group dummies. The coefficient of the interaction of illness-related gap dummy and "Discrimination Disability Law" dummy is positive, albeit not significant. This is suggestive that employers may favor the applicants with illness-related gaps because of stricter discrimination laws in their state. However, to the extent that states whose state DDL cover smaller companies are not necessarily stricter in enforcing the law, our dummy variable, "Discrimination Disability Law" may not be a good proxy for strictness.

Table 6: Variation in State Disability Discrimination Law (DDL)

	Accommodations not required	Accommodations required
DDL covers only public employers	AL, MS	
DDL covers private employers with:		
1+ employees	SD	AK, CO, DC, HI, IL*, ME, MI, MN, MT, ND, NJ, VA, VT, WI
2 or more employees		WY
3 or more employees		CT
4 or more employees		IA, KS, NM, NY*, OH*, PA*, RI
5 or more employees		CA*, ID
6 or more employees		MA, MO, NH, OR
8 or more employees	TN	WA
9 or more employees	AR	
12 or more employees		
15 or more employees	GA, NV	GA, NV, AZ*, DE, FL*, IN* KY, MD, NC, NE, OK, SC, TX*, UT
20 or more employees		LA

Those marked with * are the states included in our sample.

Source: Ameri, Schur,Adya, Bentley, McKay,Kruse & Sullivan. (2014).

Table 7: Discrimination Laws and the Effect of Employment Gaps on the Callback Rate

Dependent Variable: Callback Dummy	(1)	(2)	(3)
Illness-related Gap	-0.041**	-0.039**	-0.039**
	(0.016)	(0.016)	(0.016)
Unexplained Gap	-0.052***	-0.052***	-0.045***
	(0.018)	(0.017)	(0.017)
Disability Discrimination Law	-0.601***	-0.998***	
	(0.055)	(0.001)	
Illness-related Gap x Disability Discrimination Law	0.032	0.032	0.033
	(0.022)	(0.023)	(0.022)
Unexplained Gap x Disability Discrimination Law	0.012	0.011	0.012
	(0.023)	(0.024)	(0.023)
OLS	X		
Probit		X	
Fixed Effects: Job Ad			X
Observations	3,771	3,771	3,771
R-squared	0.092		0.015
Number of Job Ads			1,257

The dependent variable is the callback dummy. Control variables includes dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the applicant, for occupation type, required education level and experience, full-time jobs, commission-based jobs, employer-sponsored health insurance, physical requirements and location of the job. Column 3 gives the results of a probit regression using dprobit command in Stata 12. The coefficients reported in column 3 are estimated marginal changes in the probability for estimated discrete changes for the dummy variables. Robust standard errors are in parentheses and are clustered at the job vacancy level: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In summary, our results on the effects of physical requirements of the job, employer-sponsored insurance, and disability discrimination law suggest that these factors do not play a significant role in determining the differential impact of an unexplained gap and an illness-related gap. However, we exercise caution in ruling out such factors altogether, as our study was not specifically powered to test these hypotheses.

6 Concluding Remarks

As of 2015, nearly one-third of the the US population suffered from some chronic health condition. Unsurprisingly, a large portion of potential workers (nearly 13 million adults in 2014) exited the labor force as a result of illness or disability. The loss of productivity from these workers who exited the labor market adds to the overall cost of health problems to society. One way to minimize the cost is to ensure that workers with poor a health history, but the ability to return to work, are able to do so. However, their employment gaps may adversely affect their employment prospects. Further, the recent recession has refocused on how increased spells of joblessness affect the prospect of reentry into the workforce.

Our paper aims to shed light on the relative prospects of job applicants with different types of gaps in their employment records. We compare the effects of illness-related employment gaps, no employment gaps and unexplained employment gaps. We have two main findings. First, job applicants with illness-related employment gaps have slightly worse callback rates than newly unemployed applicants, which indicates some degree of unemployment stigma, even for those who report being forced out of work for illness-related reasons. Second, applicants with explained illness-related employment gaps fare substantially better in attracting callbacks than otherwise identical applicants that offer no explanation for the gap.

We provide a theoretical model showing that such behavior is not necessarily irrational. In this model, heterogeneous workers and employers do not directly observe productivity of job applicants. Firms, however, can observe employment gaps and take these as signals of productivity and healthcare costs. When health shocks are seen as unrelated to productivity, we show that it is often in the best interest of employers to hire job applicants with an illness-related employment gap over applicants with unexplained gaps, as the illness related explanation provides a positive signal about their unobserved productivity.

Our paper is limited to the effects on callback rates and cannot provide evidence on the impact on final job-finding rates. Despite these limitations, we believe that our study provides insights on employer behavior that underlie the documented employment gap. In particular, our model and results suggest that the productivity signalling value of long spells of joblessness likely play a larger role than other explanations, such as human capital depreciation, in the increased difficulty faced by these workers in finding a new job.

Future work can determine whether the effects of health-related employment gaps found here differ across types of illness. Future work might also explore the behavioral transmission mechanisms underlying the effects of illness-related employment gaps on employment prospects. For example, are illness-related gaps that are perceived to be caused by controllable factors treated differently from those perceived to be caused by uncontrollable factors? We are also unable to determine the extent to which the relatively favorable job market conditions at the time of our study influenced the large relative penalty faced by applicants with unexplained gaps. A simple extension of the model may suggest a more strongly negative signal from an unexplained gap in high employment settings than in times of widespread unemployment.

7 References

Acemoglu, D. (1995). Public Policy In A Model Of Long-Term Unemployment. Economica, 161-178.

Ameri, M., Schur, L., Adya, M., Bentley, S., McKay, P., Kruse, D., & Sullivan, K. (2014). The Disability Employment Puzzle: A Field Experiment on Employer Hiring Behavior.

Arai, M., Bursell, M. B. M., & Nekby, L. (2011). The Reverse Gender Gap in Ethnic Discrimination: Employer Priors Against Men and Women with Arabic Names. ULB – Universite Libre de Bruxelles, DULBEA Working Papers: 11-09.

Arceo-Gomez, E. O., & Campos-Vazquez, R. M. (2014). Race And Marriage in the Labor Market: A Discrimination Correspondence Study In A Developing Country. American Economic Review, 104(5), 376-380.

Baert, S., Cockx, B., Gheyle, N., & Vandamme, C. (2013). Do Employers Discriminate Less if Vacancies are Difficult to Fill? Evidence From a Field Experiment. Universite Catholique de Louvain, Institut de Recherches Economiques et Sociales (IRES), Discussion Papers (IRES - Institut de Recherches Economiques et Sociales): 2013001.

Baillon, A., & Bleichrodt, H. (2015). Testing Ambiguity Models Through The Measurement Of Probabilities For Gains And Losses. American Economic Journal: Microeconomics, 7(2), 77-100.

Bhattacharya, J., Bundorf, M. K. (2009). The Incidence of the Healthcare Costs of Obesity. Journal of Health Economics, 28(3), 649-658.

Bertrand, M., & Mullainathan, S. (2004). Are Emily and Greg More Employable Than Lakisha and Jamal? A Field Experiment on Labor Market Discrimination. American Economic Review, 94(4), 991-1013.

Bradley, C. J., Neumark, D., Luo, Z., & Schenk, M. (2007). Employment and Cancer: Findings from a Longitudinal Study of Breast and Prostate Cancer Survivors. Cancer Investigation, 25(1), 47-54.

Carlsson, M., & Rooth, D. (2007). Evidence of Ethnic Discrimination in the Swedish Labor Market Using Experimental Data. Labour Economics, 14(4), 716-729.

Correll, S. J., Benard, S., & Paik, I. (2007). Getting a Job: Is There a Motherhood Penalty?. American Journal of Sociology, 112(5), 1297-1339.

Cowan, B., Schwab, B. (2011). The Incidence of the Healthcare Costs of Smoking. Journal of Health Economics, 30(5), 1094-1102.

Cowan, B., Schwab, B. (2016). Employer-Sponsored Health Insurance and the Gender Wage Gap. Journal of Health Economics, 45, 103-114. Chicago

Deming, D. J., Yuchtman, N., Abulafi, A., Goldin, C., Katz, L. F. (2016). The Value of Post-secondary Credentials in the Labor Market: An Experimental Study. The American Economic Review, 106(3), 778-806.

Drydakis, N. (2009). Sexual Orientation Discrimination in the Labour Market. Labour Economics, 16(4), 364-372.

Drydakis, N., & Vlassis, M. (2010). Ethnic Discrimination in the Greek Labour Market: Occupational Access, Insurance Coverage and Wage Offers. Manchester School, 78(3), 201-218.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. The Quarterly Journal of Economics, 643-669.

Eriksson, S., & Rooth, D. (2014). Do Employers Use Unemployment as a Sorting Criterion When Hiring? Evidence From a Field Experiment. American Economic Review, 104(3), 1014-1039.

Funk, C. E. (2013). Thereby Hangs a Tale-Stories of Curious Word Origins. Read Books Ltd.

Ghayad, R. (2013). The Jobless Trap. Northeastern University.

Goffman, E. (2009). Stigma: Notes On The Management Of Spoiled Identity. Simon and Schuster.

Kellner, C., & Riener, G. (2014). The Effect Of Ambiguity Aversion On Reward Scheme Choice. Economics Letters, 125(1), 134-137.

Hersch, J., & Shinall, J. B. (2016). Something to Talk About: Information Exchange Under Employment Law. University of Pennsylvania Law Review, Forthcoming.

Hersch, J. (2014). Catching Up is Hard To Do: Undergraduate Prestige, Elite Graduate Programs, and the Earnings Premium. Vanderbilt Law and Economics Research Paper 14-23.

Ho, G. C., Shih, M., Walters, D. J., & Pittinsky, T. L. (2011). The Stigma of Unemployment: When Joblessness Leads To Being Jobless.

Imbens, G. W., & Lynch, L. M. (2006). Re-Employment Probabilities Over The Business Cycle. Portuguese Economic Journal, 5(2), 111-134.

Jagsi, R., Hawley, S. T., Abrahamse, P., Li, Y., Janz, N. K., Griggs, J. J., Bradley, C., Graff, J., Hamilton, A. & Katz, S. J. (2014). Impact of Adjuvant Chemotherapy on Long Term Employment of Survivors of Early Stage Breast Cancer. Cancer, 120(12), 1854-1862.

Keenan, P. S., Buntin, M. J. B., McGuire, T. G., & Newhouse, J. P. (2001). The Prevalence of Formal Risk Adjustment in Health Plan Purchasing. INQUIRY: The Journal of Health Care Organization, Provision, and Financing, 38(3), 245-259.

Kroft K, Lange F & Notowidigdo M. (2013). Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment. Quarterly Journal of Economics [serial online]. 128(3):1123-1167.

Lahey, J. N., & Beasley, R. A. (2009). Computerizing Audit Studies. Journal of Economic Behavior & Organization, 70(3), 508-514.

Ljungqvist, L., & Sargent, T. J. (1998). The European Unemployment Dilemma. Journal of Political Economy, 106(3), 514-550.

Lockwood, B. (1991). Information Externalities In The Labour Market And The Duration Of Unemployment. The Review of Economic Studies, 58(4), 733-753.

Lynch, L. M. (1989). The Youth Labor Market In The Eighties: Determinants Of Re-Employment Probabilities For Young Men And Women. The Review of Economics and Statistics, 37-45.

Machin, S. & Manning, A. (1998). The Causes and Consequences Of Long-Term Unemployment in Europe, CEPDP, 400. Centre for Economic Performance, London School of Economics and Political Science, London, UK.

Neumann, J. V., & Morgenstern, O. (1944). Theory Of Games And Economic Behavior (Vol. 60). Princeton: Princeton University Press.

Neumark, D., Burn, I., & Button, P. (2015). Is It Harder for Older Workers to Find Jobs? New and Improved Evidence from a Field Experiment (No. W21669). National Bureau of Economic Research.

Oberholzer-Gee, F. (2008). Nonemployment Stigma As Rational Herding: A Field Experiment. Journal of Economic Behavior & Organization, 65(1), 30-40.

Oreopoulos, P. (2011). 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.

Pager, D. (2003). The Mark of a Criminal Record. American Journal of Sociology, 108(5), 937-975.

Pedulla, D. S. (2014). Penalized or Protected? The Consequences of Non-Standard Employment Histories for Male and Female Workers.

Petit, P. (2007). The Effects of Age and Family Constraints on Gender Hiring Discrimination: A Field Experiment in the French Financial Sector. Labour Economics, 14(3), 371-391.

Rampbell, C. (2011). The Help-Wanted Sign Comes With a Frustrating Asterisk. The New York Times [New York], 25 July 2011.

Riach, P. A., & Rich, J. (2006). An Experimental Investigation of Sexual Discrimination in Hiring in the English Labor Market. B.E.Journal of Economic Analysis and Policy: Advances in Economic Analysis and Policy, 6(2), 1-20.

Rooth, D. (2009). Obesity, Attractiveness and Differential Treatment in Hiring: A Field Experiment. Journal of Human Resources, 44(3), 710-735.

Rooth, D. (2011). Work Out or Out Of Work–The Labor Market Return To Physical Fitness and Leisure Sports Activities. Labour Economics, 18(3), 399-409.

Shimer, R. (2008). The Probability Of Finding A Job. The American Economic Review, 98(2), 268-273.

Shimer, R. & Werning, I. (2008). Liquidity and Insurance for the Unemployed, American Economic Review, 98(5): 1922-42.

Snow, A., & Warren, R. S. (2005). Ambiguity About Audit Probability, Tax Compliance, and Taxpayer Welfare. Economic Inquiry, 43(4), 865-871.

Van den Berg, G. J., & Van Ours, J. C. (1996). Unemployment Dynamics and Duration Dependence. Journal of Labor Economics, 100-125.

Vishwanath, T. (1989). Job Search, Stigma Effect, And Escape Rate From Unemployment. Journal of Labor Economics, 487-502.

Weichselbaumer, D. (2003). Sexual Orientation Discrimination in Hiring. Labour Economics, 10(6), 629-642.

Weiner, B., Perry, R. P., & Magnusson, J. (1988). An Attributional Analysis of Reactions to Stigmas. Journal of Personality and Social Psychology, 55(5), 738.

Wu, S. & Green, A., Projection of Chronic Illness Prevalence and Cost Inflation, unpublished RAND research, 2000.

Appendix A: Sample Résumés & Corresponding Cover Letters

Treatment Group 1: Newly Unemployed

September 22, 2016

Company W
Brooklyn, NY

Dear Sir/Madam:

I am writing in regards to the open Sales Associate position that your company recently advertised online.

I am an experienced job applicant who is adept in dealing with customers and selling products. I am a strong team player who is able to work in any diverse & fast-paced commercially driven environment.

I resigned from my last job because our family had to move here from Seattle.

I would love to have an opportunity to be associated with your company.
Please find attached my current resume for your careful consideration.

I look forward to hearing from you at your earliest convenience.

Yours sincerely,

Ryan Miller
2348 Midland Ave
Staten Island, NY 10306
Email: millerryan238@gmail.com
Telephone: 646.766.9116

Treatment Group 1: Newly Unemployed

Ryan Miller

Address line 1 Telephone: 646.766.9116
Staten Island, NY 10306 Email: millerryan238@gmail.com

OBJECTIVE

Seeking a position where my sales skills and experience can be use to contribute to a company that provides opportunities for professional advancement

SKILLS

I have great customer service skills, computer skills (including cash register operation), and soft skills such as teamwork and communication skills. I am also a quick learner.

EDUCATION

High School 3, Seattle, WA, 2010

EXPERIENCE:

Company R, Seattle, WA

September 2012 - September 2016

Retail Sales Associate

- Assessed customer needs and concerns and offered product solutions
- Provided accurate processing for all customer transaction
- Maintained selling floor presentations, and restocked them as needed
- Handled all returns courteously and professionally

Company P, Seattle, WA

September 2010 - September 2012

Service Clerk

- Greeted and assisted guests in finding appropriate departments, aisles, services and products
- Organized merchandise products and count store inventory
- Installed and maintained store displays and signage to match company standards and accurately reflect weekly sales

COMMUNITY WORK

I have volunteered for the Watch the Wild program.

Treatment Group 2: Illness-related Gap

September 21, 2016

To whom it may concern:

I am writing in response to your advertisement for the position of Sales Associate, and would like to submit my resume for the position. I believe I will be able to contribute to the success of your company. I have 6 years of work experience. I was most recently associated with Company X in Brooklyn, NY, where I gained important lessons and skills in achieving sales target and providing high-quality customer service.

I stopped working because I had a medical issue. It is now taken care of and I am ready to get back to work.

I have attached my resume so that you can see my professional skills and qualifications in greater detail. I hope you will grant me an opportunity to meet you in person to discuss my application further. I am looking forward to hearing from you.

Sincerely,

Joshua Smith

Treatment Group 2: Illness-related Gap

Joshua Smith

Address Line 1
Queens, NY 11428
Email: smith.joshua.work@gmail.com
Cell: 347-851-8963

OBJECTIVE
To work as a sales asociate in an environment that allow for professional growth opportunities

WORK EXPERIENCE

Sales Specialist

Company X	**Brooklyn, NY**	**December 2012 - December 2015**

- Engaged with customers to quickly identify and meet their needs
- Marketed new sales and promotions
- Assisted with store inventory, merchandising, and display organization
- Opened and closed cash registers, tallied daily totals, and processed money deposits

Customer Service/Sales Associate

Company Y	**Brooklyn, NY**	**December 2009 - December 2012**

- Used POS cash registers to complete transactions and process returns
- Helped customers find merchandise within the store
- Helped customers with the in-store kiosk and in placing orders from the Staples website
- Ensured that the assigned section were neat and tidy for the following day

CORE COMPETENCIES
Excellent customer services skills; Proficient in Data Entry; Proficient in Microsoft Word, Excel and PowerPoint; POS system

EDUCATION
High School 1, New York, NY, 2009

INTEREST

Organizer/Member, Cancer survivors' group

Treatment Group 3: Unexplained Gap

September 20, 2016

Human Resource Staff
Company W
Brooklyn, NY

Dear Sir/Madam:

I would like to apply for the position of Sales Associate at Company W.

As a Sales Associate with Company S, I gained extensive experience in sales/customer service. I also enjoy helping and interacting with customers which has helped me succeed in my job. My personality and qualifications make me a suitable candidate for the position.

Please contact me at your earliest convenience to discuss how I may fit in at your company. I look forward to hearing from you and thank you for your time.

Warmly,

Andrew Johnson

Treatment Group 3: Unexplained Gap

Name	Andrew Johnson
Address	Address line 1 Brooklyn, NY 11224
Telephone number	(585) 209-5129
E-mail	andrewethanjohnson@gmail.com

Objective	To obtain a sales associate position within an established company that can offer an opportunity for career advancment
Education	High School 2, New York, NY, 2009
Experiences	**Sales Associate** Company S, Brooklyn, NY, January 2013 - January 2015 Responsibilities: Understood shoppers' needs and provided options and advice on meeting those needs; Maintained knowledge of current sales, promotions, policies regarding payment and exchanges as well as security practices; Conducted sales transaction using the POS system; Cleaned and organized the store, including the checkout desk and displays **Server** Company T, Brooklyn, NY, January 2009 - January 2013 Responsibilities: Ensured that every guest felt important and welcome; Presented the menu, answered questions, and made suggestions regarding food and beverage and took orders; Followed all cash handling policies and procedures; Pre-bused tables, maintained table cleanliness, and bused tables
Professional Skills	Strong customer service skills. Cash handling. Proficient in Internet Explorer and Microsoft Office Word/Excel. Team player. Strong interpersonal skills. Easily manage multiple priorities/tasks
Other Activities	Drawing, Running and Photography