Sick and Tell: A Field Experiment Analyzing the Effects of an Illness-Related Employment Gap on the Callback Rate[1]

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Abstract

Using a randomized audit study design, we find that the job callback rate for applicants with a long, illness-related employment gap caused by cancer is lower than that of the newly unemployed but significantly higher than those whose employment gap is unexplained. Our results suggest that a credible explanation of an employment gap can substantially reduce its scarring effect and that workers with a previous illness do not face a uniquely large rehiring penalty. While previous research shows that jobless spells reduce employment prospects, our results and model provide new insight into the signalling process underlying those findings.

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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.[1] 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 he/she re-enters the labor market.

Recent research confirms that employers are less likely to make callbacks to applicants with an employment gap on their résumés. However, little work has been done to explore how this propensity changes when the gap results from an illness. Competing effects make it unclear whether explaining a recent employment gap as resulting from an illness will increase or decrease the chances of a callback. On one hand, this explanation may signal a variety of potential costs related to the illness. For example, employers may be concerned that such individuals will have lower current and future productivity if they associate past illness with weaker physical strength, recurring medical needs, or a higher likelihood of being sick in the future. Moreover, employees with a history of poor health may impose higher health care costs on employers who offer health insurance.[2] Throughout the paper, we refer to all such concerns collectively as impacting the 'health cost' of hiring a worker.

On the other hand, leaving the gap unexplained might provide an avoidable adverse signal of ability. Employer screening models suggest that employment gaps are negatively correlated with

[1]Leaving one's job may not be voluntary. Laws that protect workers with medical conditions have limitations. The Americans with Disabilities Act (ADA) requires employers with 15 or more employees to provide "reasonable accommodations" to workers with disabilities as long as employees can still carry out the essential functions of the job. If the condition results in undue hardship to the company or prevents workers from performing essential functions, employees may be let go. The Family and Medical Leave Act (FMLA) requires employers to grant eligible employees up to 12 weeks of unpaid medical leave during 12-month period. However, employees who did not work 1250 hours for the company and employees who work for a company with fewer than 50 employees within a 75-mile radius of the work site are ineligible for FMLA benefits.

[2]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 (Cowan and Schwab, 2016), those who are obese (Bhattacharya and Bundorf, 2009) and those who smoke (Cowan and Schwab, 2011), tend to receive lower wages to compensate for the higher health insurance premiums paid by employers.

unobserved productivity.[3] A sustained period of unemployment can cause employers to revise an applicant's expected ability downward.[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] However, if illness is perceived to strike the more and less able alike, workers with an illness-explained employment gap may be exempt from this downward revision.

This paper considers theoretically and empirically whether explaining an unemployment spell as resulting from illness, particularly cancer, can improve callback rates. We begin by developing a framework that helps to disentangle the competing effects of explaining the gap. In our model, all applicants are currently unemployed. Some, however, were employed in the previous period and thus have no gap in their employment record. Employers learn two important things from the worker having no employment gap. First, the worker must have been sufficiently healthy to hold a job. Second, the worker was able to find a job in an economy that leaves some willing workers unemployed. We assume that applicants with a recent illness will have higher future health costs and that workers with greater ability have a higher probability of being employed. This allows employers to use the observation of recent employment to update beliefs regarding the health costs and ability of the applicant.

While workers with no employment gap have an advantage in the labor market, the effect of a gap depends on its cause. An illness-explained gap signals higher health costs. However, since the worker was not in the labor market, no ability signal from employment is generated. As such, employers do not update expectations of ability relative to the general pool of applicants. In contrast, expected ability is revised downward for workers with an unexplained gap, while expected health costs are the same as those with no gap.

All told, then, having no employment gap signals high ability and low health costs, an illness-explained gap signals average ability and high health costs, and an unexplained gap signals low

[3]See Vishwanath (1989) and Lockwood (1991). Bonoli (2014), Bonoli and Hinrichs (2012) and Van Belle et al. (2018) provide empirical evidence that long term unemployment is a negative signal.

[4]We use employment gap and unemployment interchangeably in this paper. We loosely define unemployment as a situation of being unable to find work or being out of the labor force.

[5]A review of job vacancy postings on popular sites like Monster.com, CareerBuilder and Craigslist revealed hundreds that said employers would consider (or at least "strongly prefer") only people currently employed or just recently laid off (Rampell, 2011).

health costs and low ability. We describe a setting where these expectations translate to callback rates for the three types of workers. Workers with no employment gap receive the highest callback rate while relative callback rates for the others depends on the size of health costs and the differences in expected ability. In Appendix A, we show that these findings are robust to considering productivity depreciation from an employment gap, or productivity enhancement from employment.

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 illness-explained 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).

To signal an illness-explained employment gap, a phrase in the cover letter explained that the employment gap was due to a physical illness followed by a full recovery.[6] An additional signal of 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.

We chose cancer because cancer treatment is likely to cause an employee to stop working, creating an employment gap (Mehnert, 2011). Cancer patients who receive a good post-treatment prognosis can return to the labor market with productivity comparable to unaffected workers.[7] Cancer is also perceived to be onset-uncontrollable, which prevents employers from forming inferences about productivity from the diagnosis.[8] 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 raises premiums.[9]

[6]Numerous articles provide advice to applicants with illness-related employment gaps to simply state in their cover letter that "they had to stop working to undergo treatments but are now ready to re-join the workforce." For example, see Giltner (2018) and Williams (2017).

[7]Bradley and Bednarek (2002) confirm that cancer survivors are productive and perform well in the workplace.

[8]Weiner et al. (1988) find that cancer is perceived to be onset-uncontrollable.

[9]Although the Affordable Care Act (ACA) now prohibits insurers from charging different premiums to individuals based on

Outcomes are measured in terms of differences in the callback rate of each type of résumé. The results 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 illness-explained gap received a higher callback rate than résumés with an unexplained gap (25.6% versus 23.3%). In our regression analysis we find that both types of gaps garner fewer callbacks relative to no gap, and that this effect is significantly more pronounced for unexplained gaps.

The findings of the experiment provide evidence that a credible explanation for unemployment can be helpful in diminishing the associated scarring of an employment gap. Specifically, explaining the gap as resulting from a non-mental medical issue dampens the adverse impacts of previous unemployment. This result is important for several reasons. First, it suggests that other credible explanations might be similarly effective. Second, health-explained gaps alone are quantitatively important. Health issues affect a large part of the potential labor force in the U.S. and illness-explained employment gaps are likely quite common. In 2014, the number of working age adults who were not in the labor force because of illness or disability reached 16.3 million, or 6.5 percent of the U.S. population.[10] The potential challenge of reintegrating these individuals appears to be growing. Between 2011 and 2017, the share of the disabled among individuals who are not in the labor force but want a job increased by 19%. Among the unemployed, the disabled share rose by nearly a third to 10 percent over the same time period.[11]

Our theoretical framework provides a useful link with previous research on unemployment scarring. Within the context of our model, the results suggest a substantial role for a signalling or screening mechanism in determining callback rates, which is consistent with Kroft et al. (2013). Further, health costs associated with prior illness do not seem to be a large concern to employers.

their health status, premium levels reflect the health status of the risk pool as a whole (American Academy of Actuaries, 2016).

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

[11]Based on the Bureau of Labor Statistics annual "Persons with a Disability: Labor Force Characteristics" reports for ages 16-64, which uses data from the Current Population Survey. The figures may underestimate the disabled share because the definition of disability in the CPS is restricted to people who are deaf, blind, or have serious difficulty walking, climbing, dressing, bathing, doing errands alone, concentrating, remembering, or making decisions because of physical or mental, or emotional conditions. Unlike the ADA definition, it excludes individuals who have been diagnosed with a serious health condition such as cancer but are now fully recovered.

In particular, they are not large enough to undo the advantage of explaining away the cause of unemployment. Our theory also provides a useful framework for understanding why unemployment scarring may be limited when the reasons for joblessness appear orthogonal to worker productivity, such as in Deryugina et al. (2018)'s study of employment among Hurricane Katrina victims.

Our paper contributes to a growing set of research that considers health and disability discrimination in employment and other settings. For example, Ravaud et al. (1992), Ameri et al. (2018) and Baert (2016) use correspondence study methods to demonstrate that applicants with disabilities unrelated to job-specific demands receive fewer callbacks than non-disabled applicants. To our knowledge, Baert et al. (2016) is the only other correspondence study that directly compares callback rates from applicants with health related employment gaps and non-health gaps. However, the paper focuses on the effects of mental illness (i.e. depression) in Belgium and does not include physical illness. In contrast to our findings, results from this smaller-scale correspondence study show no significant difference between an employment gap caused by mental illness and an unexplained employment gap.

Though we chose to use cancer as the signalled illness in our experiment largely for theoretical reasons, we also provide novel evidence on the impact of cancer survivorship on employment. Several studies confirm that cancer patients are less likely to work (Bradley et al., 2002a,b) and tend to have long-term unemployment (Bradley et al., 2007).[12] Osmani and Okunade (2019) estimate total foregone earnings from lost working days of cancer survivors of at least $2 billion. While much of the 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. Though we find that recovering cancer patients fare better than the general pool of non-employed workers, they still suffer a callback penalty.

A focus on cancer is clearly narrow in relation to the broad set of illness and injury that could result in an explained gap. We discuss how this and other experimental design choices impact the interpretation of our results in Section 5.4. Though our findings may not generalize to other

[12] Using Canadian data, Stewart (2001) also demonstrates that, relative to the general labor pool, unemployment spells are longer for those who report any severe health limitations or departing from a previous job for health reasons.

health-explained gaps, the results still have broad application since the estimated 6 million cancer survivors of prime working age (between 20 and 64) represent a substantial portion of the U.S. population (Miller et al., 2019). According to the U.S. Cancer Statistics Working Group, there were 725,546 new cancer patients of working age (20-64 years old) in 2017. If this group had the same labor force participation rate of as the working age population (78.2 percent), then nearly 600,000 workers were newly diagnosed with cancer that year. The general five year cancer survival rate of 69 percent (American Cancer Society, 2019) suggests 391,490 of those workers became new survivors. Applying to all cancers the Blinder et al. (2017) finding that 19 percent of workers with breast cancer did not retain their jobs after treatment yields 74,383 new survivors in 2017 alone at risk of experiencing a cancer-related employment gap. For a sense of scale, that estimate of the annual flow of new unemployed cancer survivors is equivalent to 15 percent of all disabled workers who were unemployed in 2017. Though these calculations are rough, the conclusion that cancer survivors are abundant in the workforce is inescapable.

Finally, our results support the growing evidence of a scarring effect of unemployment. This is a meaningful contribution in light of earlier mixed results using non-experimental findings.[13] As pointed out by Oberholzer-Gee (2008), non-experimental studies of duration dependence suffer endogeneity problems, and results from studies that use correspondence tests, where identification is derived from experimentally induced variation, provide more consistent evidence of scarring.[14] Several such studies find that employment gaps beyond a threshold duration negatively affect the likelihood of being invited for an interview.[15] Some refinements of these findings have been considered. Eriksson and Rooth (2014) find that while contemporary employment gaps negatively affect the likelihood of getting a callback, past employment gaps do not. Kroft et al. (2013) show

[13]In a review of the literature, Machin and Manning (1999) find little evidence that long periods of unemployment adversely impact future job prospects ('negative duration dependence'). In contrast, Lynch (1989), Van den Berg and Ours (1996), Imbens and Lynch (2006) and Shimer (2008) conclude that duration dependence plays a significant role in labor market outcomes.

[14]While Nunley et al. (2017) and Farber et al. (2016) do not find statistical evidence linking unemployment spells of different duration to employment opportunities, a number of studies find evidence that unemployment spells have negative effects on employment prospects. This includes Eriksson and Rooth (2014), Ghayad (2013), Kroft et al. (2013), Oberholzer-Gee (2008), Baert et al. (2016), Baert and Verhaest (2019) and Birkelund et al. (2017).

[15]Specifically, 9 months for Eriksson and Rooth (2014), 18 months for Oberholzer-Gee (2008), 6 months for Kroft et al. (2013) and Ghayad (2013).

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 findings provide additional evidence consistent with an empirically important scarring effect, and support the idea that employment gaps can be partially compensated.

The remainder of the paper proceeds as follows. In Section 2, we detail the theoretical model. In Section 3, we describe the experimental design. Section 4 explains the empirical strategy while Section 5 reports the results, interpretation, potential threats to internal and external validity, and other limitations. Section 6 concludes and provides suggestions for future studies.

2 Theoretical Framework

In this section, we model how signals from previous employment and health history as reflected in job applicants' résumés affect their likelihood of getting a callback from employers. Our model demonstrates that callback rates depend on the perceived costs associated with illness and the extent to which employment history signals lead to revisions of expected ability. It then clarifies conditions where explaining an employment gap as resulting from illness will increase the chances of a callback. An extension in Appendix A further shows how depreciation of human capital from an employment gap or productivity enhancement from employment can affect relative callback rates.

2.1 Factors determining callbacks

An employer's decision to call back an individual applicant for further consideration is complicated. Any aspect of a job application, from content to format, might influence a potential employer. For our purposes, though, we limit these factors to three categories: the expected ability of the worker, the expected health-related costs of hiring the worker, and all other factors. We discuss each category below.

2.1.1 Expected ability

Job applications permit applicants to claim an ability to do the job well and provide supporting evidence. Education, work history, and previous accomplishments, for example, are presented to show preparedness for the job. However, our model and experiment focus on the information content of employment gaps so we randomize over other factors.

As a modeling convenience, we assume that each employment arrangement lasts a single period. This can be generalized. The essential feature is that the ability distribution of job-seekers is known and constant. We further assume that the ability of any worker can be summarized by the parameter θ, which is a realization of the random variable Θ. A higher value of θ means a higher level of ability and Θ is distributed uniformly over the unit interval.

The information content of recent employment is rooted in an understanding that the more able are more likely to be employed. Formally, we assume each worker in each period receives a positive or negative employment shock. A positive employment shock means the worker has a job so long as her health allows her to work. The probability of a positive employment shock for an agent with ability θ is θ^ρ where $\rho > 0$.

To be employed, a worker must have both a positive employment shock and good health. We formalize the notion that illness can strike anyone with equal probability by setting the exogenous probability of good health to ω, regardless of ability. Of course, poor health itself may make a worker less productive than he/she would have been with good health. With no loss of generality, we consider such cases under expected health costs below.

In this environment, each application contains a signal S where $S \in \{n, i, u\}$. Workers with no gap in employment provide signal $S = n$ by listing employment in the previous period. Workers unavailable for work in the previous period due to illness provide signal i. By virtue of having an employment gap that is not explained, those who were unemployed due to poor luck in the job market provide signal u.

As shown in Appendix A, employers use these signals to update beliefs regarding ability such that

$$E\left(\theta|S=s\right)=\begin{cases}\frac{\rho+1}{\rho+2} & \text{if} \quad s=n\\ \frac{1}{2} & \text{if} \quad s=i\\ \frac{\rho+1}{2(\rho+2)} & \text{if} \quad s=u.\end{cases} \tag{1}$$

Consider the second line of Equation (1). Since illness is unrelated to ability, nothing is learned about θ when employers observe signal i. Therefore, workers with an illness-explained gap are drawn from the same distribution as workers in the general population. Thus, the conditional expected productivity of θ is equal to the unconditional expected productivity. Given our uniform distribution, this is $E\left(\theta|S=i\right)=\frac{1}{2}$.

Next consider the first line of Equation (1), which refers to applicants with signal $S=n$. The probability distribution function for these applicants is increasing in θ (see Equation (9) in Appendix A). While the employer does not learn θ from the signal, it learns that ability is drawn from a distribution where higher ability is more likely and updates its expected level of ability for these applicants. Since $\frac{\rho+1}{\rho+2}>\frac{1}{2}$, this is an upward revision. Similarly, for applicants with unexplained gaps, the employer learns that ability is drawn from a distribution where lower ability is more likely. Since $\frac{\rho+1}{2(\rho+2)}<\frac{1}{2}$, this is a downward revision of expected ability.

2.1.2 Expected health costs

As a signal of ability, an illness-explained gap is superior to an unexplained gap. However, an illness-explained gap also has a downside. Firms might feel that a worker who has been ill will be less productive because of the illness per se, even if illness is not related to innate ability. There may also be direct costs to hiring an ill worker, such as accommodations or increased group health insurance premiums. Regardless of the source, a perception that illness makes a worker less promising weighs against the decision to provide them a callback.

It is not relevant in our modeling whether poor health is a signal of productivity loss or higher employment costs. For convenience, we refer to both possibilities as health costs. The only feature of health costs relevant to employers is the association of these costs with the signals. Let H be the health cost associated with a particular applicant. We assume $E(H|S=i) = hE(\theta|S=i)$ where $0 \leq h < 1$ and $E(H|S=n) = E(H|S=u) = 0$. That is we set the expected health cost of a worker with a negative health shock to be proportional to expected ability and normalize the expected health cost for those with a positive health shock to zero.

2.1.3 Other factors

For the purposes of our investigation, we assume all factors other than expected ability and health costs can be considered as random. Specifically, these other influences on a firm's hiring decision can be summarized as separate draws from a common continuous probability distribution. For a large number of firms indexed by k and applicants indexed by j, each application observed by the firm draws the random variable $\varepsilon_{s,k,j}$ from distribution $g_{s,k,j}(\varepsilon_{s,k,j}) \equiv g(\varepsilon_{s,k,j})$. This distribution is common across firms, applicant signals, and applicants. The value of $\varepsilon_{s,k,j}$ is the stochastic element of the callback decision.

2.2 Callback rates

Upon reviewing job applications, the firm decides on a callback strategy. The review reveals the expected ability and health cost of the applicants as well as random variables $\varepsilon_{s,k,j}$. To economize on notation, we assume the expected benefit to the firm of a callback moves one-for-one directly with an increase in expected ability and inversely with an increase in expected health cost or $\varepsilon_{s,k,j}$. We further assume that $\varepsilon_{s,k,j}$ follows a uniform distribution over the interval $[0,1]$. While not required, this proves convenient in interpreting our results and leads to little loss of generality.

In our experiment, each firm receives a triplet of applications. Each application in the triplet contains a signal $s \in \{n,i,u\}$ and each signal is represented in the triplet. Upon receiving the triplet, the problem for firm k is to maximize the expected net return to making callbacks. Considering the applications in the triplet, the firm chooses a callback strategy $C_k = \{c_{n,k}, c_{i,k}, c_{u,k}\}$, where $c_{s,k} \in \{0,1\}$. Setting $c_{s,k} = 1$ means the firm makes a callback to the applicant with signal $S = s$. Setting $c_{s,k} = 0$ means the firm does not call that applicant back. For each item in the triplet, the firm views a different signal and a different value of $\varepsilon_{s,k,j}$. In each case, the firm makes the callback if and only if the expected benefit of the callback is positive. That is, the firm makes a callback if and only if $E(\theta|S=s) - E(H|S=s) - \varepsilon_{s,k,j} > 0$.

From our experiment, we observe the share of applications who receive a callback, conditional on the employment signal. As shown in Appendix A, the corresponding conditional expected callback rates in our model are $P(C|S=s) = E(\theta|S=s) - E(h|S=s)$ where $P(C)$ is the probability of a callback.

From Equation (1) and expected health costs, we define $\Delta_{i,u}$ as the difference in callback rates between workers with an illness-explained and an unexplained gap:

$$\Delta_{i,u} = \left(\frac{1}{2} - \frac{\rho+1}{2(\rho+2)}\right) - \frac{h}{2}. \tag{2}$$

The term in parenthesis in Equation (2) represents the advantage in expected ability for illness-explained workers. The opposing downside of signal i relative to u is the associated health cost, $\frac{h}{2}$. We expect to see illness-explained gaps yield more callbacks only if the difference in expected ability is sufficiently large or health costs are sufficiently small.

Note that the advantage of signal i over u increases as ρ decreases. As formalized in Appendix A, with ρ smaller, fewer workers with higher ability end up with a negative employment shock. With fewer high skilled workers in the mix, applicants with signal u are more distinct from those with signal i causing a larger revision of expected ability. Put differently, when ρ is small, unexplained joblessness is a more highly informative negative signal, which ill applicants avoid sending. Thus, $\Delta_{i,u} > 0$ occurs when an unexplained gap leads to a large downward revision in expected ability (ρ small) and when health costs are low.

Similarly, we define $\Delta_{n,i}$ as the difference in callback rates between workers with no gap and an illness explained gap:

$$\Delta_{n,i} = \left(\frac{\rho+1}{\rho+2} - \frac{1}{2}\right) + \frac{h}{2}. \tag{3}$$

Since $\Delta_{n,i}$ is always positive, workers with no gap are expected to receive more callbacks than those with an illness-explained gap. There are two reasons for this. First, those with an illness-explained gap receive a negative signal regarding health costs. Second, those with no gap receive a positive signal regarding expected ability. The market advantage of this is given by the item in parenthesis in Equation (3). Employers assign an expected ability of $\frac{\rho+1}{\rho+2}$ to a worker with no gap rather than the population expected ability of $\frac{1}{2}$. The upward revision decreases as ρ decreases. With ρ smaller, more workers with low ability have a positive employment shock so employers cannot infer much about ability differences from applicants with n and signal i.

Overall, not working deprives ill workers of the positive ability signal conveyed by those with no employment gap. However, when only very low ability workers are likely to be jobless (i.e. ρ is small), that positive signal is uninformative and less valuable. Under those same conditions, then, an unexplained gap is very informative, and much more damaging, and so the illness explanation conveys considerable positive information. Thus, an explanation for joblessness orthogonal to ability (e.g. illness) is most useful when ρ and h are small.[16] We return to this point in discussing our empirical results.

3 Experimental Design

We conducted a résumé-based correspondence study to measure the impact of each type of signal on callback rates. The method involves sending similar job applications to employers posting jobs, and randomly varying a characteristic of interest, such as a signal of group membership. Researchers have previously used the correspondence test methodology to study hiring discrimination based on race, ethnicity, immigration, gender, sexual orientation and age.[17] More recently, a number of papers have used this method to examine the effects of human capital characteristics on employment prospects.[18] A subgroup of this research includes the research on the effects of employment gaps.[19] We used the same methodology to further explore how employers respond to

[16] Formally, as ρ decreases, $\Delta_{i,u}$ increases and $\Delta_{n,i}$ decreases. A smaller value of h has the same directional effects. As such, large values of $\Delta_{i,u}$ and relatively small values for $\Delta_{n,i}$ are consistent with relatively low values for ρ and h.

[17] Gaddis (2018), Baert (2018), Oh and Yinger (2015), Riach and Rich (2002) and Zschirnt and Ruedin (2016) provide a more comprehensive review of this body of literature.

[18] For example, Deming et al. (2016), Darolia et al. (2015) and Deterding and Pedulla (2016) evaluate how employers value post-secondary education from for-profit institutions.

[19] As noted above, this includes Eriksson and Rooth (2014), Ghayad (2013), Kroft et al. (2013), Oberholzer-Gee (2008), Baert et al. (2016), Baert and Verhaest (2019), Birkelund et al. (2017), Nunley et al. (2017) and Farber et al. (2016).

different types of employment gaps.

Our experiment was carried out between March, 2016, 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.[20]

We limit our experiment to sales, customer service, clerical, and accounting assistant jobs. These occupations generally do not require complex skills and are fairly standard across firms, which facilitates standardizing suitable generic résumés. They are also available in sufficient quantity to conduct a well powered study.[21] We considered only job ads that required 6 or fewer years of work experience in 15 of the most populous cities of the United States.[22] We chose jobs that allowed direct uploads of résumés and cover letters and ignored ads where applicants were asked to call or appear in person or that required résumés to be submitted to external sites. We collected jobs and sent résumés by batch.[23]

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. Accordingly, we have 3,771 applications corresponding to 1,257 triplets since we applied to 1,257 jobs. Using the résumé randomizer developed by Lahey and Beasley (2009), we then randomly assigned treatments and other résumé details to each type of résumé. All of the résumés 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.[24] 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.

Each résumé in the triplet belonged to one of three treatment groups. A résumé in Treatment

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

[21]Bertrand and Mullainathan (2004) and Kroft et al. (2013) also consider these three occupations.

[22]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.

[23]The size of a batch ranged from about 30 to 150 jobs, depending on the availability of jobs at the specific time of data collection.

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

Group 1 signaled an applicant who was newly unemployed. For the résumé of newly unemployed applicants, the length of the gap is zero to two months. Based on the literature, this is too short a gap to bring about adverse effects. We used newly unemployed, rather than currently employed, as Kroft et al. (2013) and Eriksson and Rooth (2014) find that a currently employed worker is less likely to be called back for an interview than a newly unemployed individual. Kroft et al. (2013) suggest that employers may perceive individuals who engage in on-the-job searches as less loyal and prone to job hopping. In addition, some jobs require workers to start immediately. 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.[25]

A résumé in Treatment Group 2 contained a signal that the applicant had an illness-explained gap for a notable period of time. For most of the sample this was 7 to 12 months. However, due to a coding mistake, an unemployment duration of between 20 and 22 months was assigned for 5% of the sample in Groups 2 and 3. In Treatment Group 2, a phrase in the cover letter explained that the gap was due to a medical illness followed by a complete recovery. Our choice of cancer as the illness is discussed in the introduction. An additional signal on the medical history was sent via information in the résumé which indicated involvement in a support group for cancer survivors. The inclusion of the support group involvement implies that the illness associated with the employment gap was cancer, though this was not stated explicitly.

A résumé in Treatment Group 3 contained an employment gap of comparable length to Treatment Group 2. However, no explanation was provided for the employment gap in the résumé and cover letter.

In order to provide a signal of health problems in the résumé of Treatment Group 2, we indicated that the applicant was 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 was either a volunteer for the "Watch the Wild" program or was interested in drawing, painting and running.

[25] Relocation provides a credible signal of job availability uncorrelated with productivity.

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. Since name-based discrimination happens when names act as signals of other information, primarily race or ethnicity, our choice of names prevents the name-effect from affecting the callback rate.

Each name was assigned a corresponding telephone number and email address. To easily track the callback, we assigned 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 modified the house/apartment numbers of real addresses to provide fictitious but credible variants.

Since we targeted jobs that required 6 years or less of experience, we designed the work histories such that total years of experience summed to 6 years. In each résumé, the applicant had two jobs, no unemployment since high school graduation, but were currently not employed. We then randomly assigned the length of contemporary unemployment based 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), so that the number of years of work experience in the first and second job summed to approximately 6 years.

We collected a sample of acceptable job histories from real résumés downloaded in job search sites and randomly assigned the first and second job to the résumés in each triplet. As in Neumark et al. (2019), we followed a defined profile of responsibility, showing a progression of jobs from lower to higher-level jobs.[26] Employer names and addresses for each job were taken from active employers at the time in the relevant region.

We designated half the résumés to be high-skilled (or of high quality), and half to be low-skilled. This enables us to see if the employment consequences of illness-explained gaps vary by quality. As in Kroft et al. (2013) and Neumark et al. (2019), low-quality résumés had typographical errors and no additional signals of productivity/skills while high-quality résumés included two types of such signals. 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.[27] High-quality type 2 résumés had acquired a certificate, an *"Employee of the Month"* award and no typographical errors. The third high-quality résumé had academic honors, notable achievement in previous work and an additional skill. All the résumés in a triplet were of the same quality.

We created three résumé templates. Templates were randomly assigned to each résumé created and were not repeated in a triplet to prevent 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 (2019). We randomly assigned these based on the education levels. To be consistent with our story that the Treatment 1 applicant just moved from Seattle, these résumés were assigned a school from Seattle.

To minimize chances of detection, the generated résumés were given filenames of different styles based on the applicant name ((e.g. "Rachel Miller", "R.Miller", or "Miller, Rachel"). Appendix B provides a sample of the résumé and cover letter for each of the treatment groups (newly unemployed, unexplained, and illness), respectively. We randomly assigned the sending order of the résumés. For each triplet, the second (third) résumé was sent at least a day after the first

[26]For example, in retail sales, the first job starts with a lower responsibility job (e.g. cashier) and then the applicant progresses to sales associate. For administrative assistants, workers started as a receptionist before becoming administrative officers.

[27]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.

(second) résumé was sent.

We measured whether a given résumé elicits a call, text or e-mail back from a potential employer.[28] We defined a callback as a personalized phone, e-mail or text 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

We use the data from the experiment to compare callback rates across treatment groups. We first examine the uncontrolled mean callback by type and classify triplets by the relative performance of the treatment arms. We then estimate the relative callback rates using regression analysis. Our first specification pools the arms with gaps (i.e. Treatment Groups 2 and 3) in order to check the consistency of our results with previous studies showing that applicants who have not worked in over six months face diminished employment prospects.

Our main goal in this paper is to analyze the effect of explaining an illness-explained employment gap on workers' likelihood of receiving a callback. Thus, we estimate the following equation in which, instead of pooling the groups with employment gaps, we separately estimate the effect of each type of gap:

$$C_{jk} = \alpha + \beta_1 I_{jk} + \beta_2 U_{jk} + \mathbf{R}'_{jk}\Gamma + \mathbf{E}'_k\Lambda + \epsilon_{jk} \tag{4}$$

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, I_{jk} is a dummy variable that equals 1 if applicant j who applied for job k has an illness-explained employment gap, U_{jk} is a dummy variable that equals 1 if applicant j who applied for job k has an unexplained employment gap, **R** is vector of résumé attributes and **E** is a vector of employer/job advertisement attributes.[29]

[28] Any attempt by employers to contact applicants via postal mail could not be measured since the addresses are fictitious.

[29] **R** includes dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the

Random assignment ensures that β_1 gives the unbiased estimate of the mean impact of explaining an illness-explained 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-explained employment gap relative to the hiring outcome of the newly unemployed. We also conduct a test of equality between the illness and unexplained arms, and report the p-values. In all specifications, standard errors are clustered at the job vacancy level.

As a robustness check, we estimate Equation (4) using probit estimation (and provide marginal effects). Moreover, we estimate a job ad fixed effects model:

$$C_{jk} = \alpha + \beta_1 I_{jk} + \beta_2 U_{jk} + \mathbf{R}'_{jk}\Gamma + \mu_k + \epsilon_{jk} \tag{5}$$

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

5 Results

Overall callback rates for the sample are given in column 1 of Table 1. Included in brackets under each rate is the number of résumés sent in that cell. We sent a total of 3,771 résumés to 1,257 job ads. The overall callback rate is 25.5 percent. Unlike Deming et al. (2016), we find that overall callback rates did not differ between low-quality and high-quality résumés. Female-sounding names were more likely to receive callbacks compared to male-sounding names, and sales jobs had higher callback rates compared to administrative and accounting assistant jobs.

5.1 Comparing the Mean Callback Rates

The average callback rate by treatment arm is shown in columns 2 to 4 of Table 1. Overall, we find evidence consistent with the scarring effects of unemployment. Newly unemployed applicants received the highest callback rate (27.4 percent), more than the rate for applicants with either type of employment gap (25.6 percent for illness-explained and 23.3 percent for unexplained). The penalty associated with an employment gap holds across quality, gender and occupation.

applicant etc. **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.

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 2.3 percentage points lower for applicants with an unexplained employment gap than for those with an illness-explained employment gap. This represents a reduction of 9 percent relative to the average callback rate of 25.5 percent. Except for accounting jobs, the unexplained gap group has the lowest callback rate across résumé and job sub-groups. We explore heterogeneity in more detail in the next section.

As in Bertrand and Mullainathan (2004), we tabulate the distribution of callbacks at the firm or triplet level. In each of the cells in columns 2 to 4 of Table 2, the first line indicates the firm's callback strategy, $C_k = \{c_{n,k}, c_{i,k}, c_{u,k}\}$ where $c_{n,k}, c_{i,k}, c_{u,k} \in \{0, 1\}$. For each signal $s \in \{n, i, u\}$, $c_{s,k} = 1$ 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 applicant with signal s back. The second and third lines in each cell in columns 2 to 4 contain the percentage and the number of firms with the line 1 callback strategy.

Equal treatment occurs when either no applicant gets called back or all applicants in a triplet receive a callback. The newly unemployed applicant is favored when either only the 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-explained (unexplained) employment gap is favored when either only the applicant with an illness-explained (unexplained) gap gets called back, or the applicant with an illness-explained (unexplained) gap is one of the two applicants in the triplet who received a callback.

In the first cell of column 1 of Table 2, we report the percentage and number of firms that showed equal treatment. In cells 2-4 of column 1, we report these statistics for firms which favored each treatment group. The second and third lines in each cell in column 1 contain the percentage and the number of firms that gave equal treatment or favored any of the applicants.

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

TABLE 1.

Mean Callback Rates by Type of Employment Gap

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

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

by 13.2 percent of the employers. Applicants with an illness-explained 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. The major driver of the difference between the two groups with a gap is the callback disparity for triplets with precisely two callbacks (11 percent of the total sample). For these jobs, the illness group receives a callback in 71 percent of cases, and the unexplained group a callback 55 percent of the time. The disparity is even larger when one of the callbacks goes to the recently unemployed group (61 to 39 percent).

TABLE 2

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

	(1)	(2)	(3)	(4)
(1)	Equal Treatment 77.2 [970]	{0, 0, 0} 62.9 [791]	{1, 1, 1} 14.2 [179]	
(2)	Newly Unemployed Favored 13.2 [166]	{1, 0, 0} 5.3 [67]	{1, 1, 0} 4.8 [60]	{1, 0, 1} 3.1 [39]
(3)	Illness-explained Gap Favored 11.4 [143]	{0, 1, 0} 3.7 [46]	{1, 1, 0} 4.8 [60]	{0, 1, 1} 2.9 [37]
(4)	Unexplained Gap Favored 9.1 [114]	{0, 0, 1} 3.0 [38]	{1, 0, 1} 3.1 [39]	{0, 1, 1} 2.9 [37]

Note: The total number of triplets is 1257. The first line in each of the cells in columns 2 to 4 represents the callback strategy of the firm, $\{c_{n,k}, c_{i,k}, c_{u,k}\}$ 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 line contains the number of firms.

5.2 Regression Results

In this subsection, we present the regression estimates of the models in Equations (4) to (5). Our main results show that (a) the newly unemployed are robustly preferred to those with any type of gap, and (b) applicants with illness-explained employment gaps receive higher callbacks than otherwise identical applicants who offer no explanation for the gap.

Our experiment finds unemployment scarring that is consistent with Kroft et al. (2013) and Eriksson and Rooth (2014). Table 3 presents various 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 Group 2 and Treatment Group 3 together. Columns 1 to 3 are estimated using OLS estimation, probit estimation and linear estimation with job 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. Based on the 27.4 percent callback rate of the newly unemployed, an employment gap of any kind reduces callback rates by 11 percent. The results are robust across all specifications. As in all correspondence experiments, there is some chance that the signals are not interpreted, or even noticed, as intended. As such we take these to be conservative estimates of the potential impact.

Approximately five percent of applications were inadvertently assigned employment gaps of more than 19 months, instead of the typical range of 7 to 12 months.[30] We exploit this variation to determine if longer gap lengths are associated with higher employment penalties. The results (column 4) suggest that longer spells increase the unemployment penalty by nearly 2 percentage points, a fairly large reduction in callbacks. However, given the small number of long duration applications, the estimate is imprecise.[31]

To answer our primary research question, we separately estimate the impact of each type of gap, as in Equations (4) and (5). Columns 1 and 2 of Table 4 show Equation (4) estimated via OLS and probit, respectively, while column 3 shows the linear estimation result controlling for fixed effects at the job ad level (Equation (5)). The coefficients of the illness-explained gap and the unexplained gap are negative and significant at the 1 and 10 percent levels, respectively, indicating that applicants with any type of employment gap have worse callback rates relative to newly unemployed applicants.[32]

To determine whether explaining a gap mitigates its negative effect on employment, we compare the magnitude of the coefficients for an illness-explained gap and an unexplained gap. 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-explained employment gap (1.9 percentage points less). Relative to the mean callback rate of the newly unemployed (27.4 percent), an illness-explained employment gap reduces the callback rate by approximately 7 percent. An unexplained

[30]These errors occurred at random and their distribution is balanced between illness-related gaps and unexplained gaps.

[31]The findings in Kroft et al. (2013) and Eriksson and Rooth (2014) suggest that callback rates decline sharply for mid-long jobless spells (up to around 9 months), but remain flat for unemployment durations thereafter. Though our study was not powered to specifically test this hypothesis, the limited evidence here stands in contrast to that result.

[32]If we exclude the triplets with employment gap duration of 20-22 months, the results are quite similar to the results in each of the column of Table 4.

TABLE 3

The Effect of Having an Employment Gap on the Callback Rate

Dependent Variable: Callback Dummy	(1)	(2)	(3)	(4)
Employment Gap	-0.030***	-0.031***	-0.030***	-0.029***
	(0.010)	(0.010)	(0.010)	(0.010)
Gap Duration $\geqslant 20$				-0.023
				(0.034)
OLS	X			
Probit		X		
Fixed Effects: (Job Ads)			X	X
Observations	3,771	3,771	3,771	3,771
R-squared	0.090		0.012	0.012
Number of Job Ads			1,257	1,257

Note: The dependent variable is the callback dummy. The average callback of the omitted group (newly unemployed) is 27.4 percent. Control variables include dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the applicant, occupation type, required education level, required experience, full-time job, commission-based job, employer-sponsored health insurance, physical requirements and location of the job. Columns 1 to 3 were estimated without controlling for gaps greater than or equal 20 months. Column 4 includes a dummy controlling for gaps greater than 19 months. Column 2 gives the results of a probit regression. The coefficients reported in this column are estimated marginal changes in the probability for a discrete change in the dummy variables. Robust standard errors are in parentheses and are clustered at the job vacancy level. *** $p<0.01$, ** $p<0.05$,* $p<0.1$.

employment gap, however, reduces the callback rate by 15 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 job ad fixed effects.

Our main results show that applicants with illness-explained employment gaps fare better than otherwise identical applicants who offer no explanation for the gap, but worse than those without any gap. The ordering of employer preferences is consistent with our theoretical model, and allows us to make further refinements. In particular, the results suggest that employers are not as concerned about the cost of having poor health, h, as they are about the potential lower productiv-

TABLE 4

The Effect of the Type of Employment Gap on the Callback Rate

Dependent Variable: Callback Dummy	(1)	(2)	(3)
Illness-explained Gap	-0.019*	-0.019*	-0.018*
	-0.011	-0.011	-0.011
Unexplained Gap	-0.042***	-0.042***	-0.041***
	-0.011	-0.011	-0.011
p-value: Illness=Unexplained	0.038	0.036	0.035
OLS	X		
Probit		X	
Fixed Effects:			X
Job Ad			
Observations	3771	3771	3771
R-squared	0.091		0.013
Number of Job Ads			1257

Note: The dependent variable is the callback dummy. The average callback of the omitted group (newly unemployed) is 27.4 percent. Control variables includes dummy variables for tenure, résumé quality, résumé template, order of sending within the triplet, gender of the applicant, occupation type, required education level, required experience, full-time job, commission-based job, employer-sponsored health insurance, physical requirements and location of the job. Column 2 gives the estimated marginal effects resulting from a probit regression. The *p*-value from the F-test tests the null hypothesis that the coefficient of an illness-explained gap is equal to the coefficient of the unexplained gap. Robust standard errors are in parentheses and are clustered at the job vacancy level. ***$p<0.01$, ** $p<0.05$, * $p<0.1$.

ity signalled by an unexplained gap. Moreover, given that the difference in callback rates between the newly unemployed and illness gap groups ($\Delta_{n,i}$) is slightly smaller than difference between the illness and unexplained group ($\Delta_{i,u}$), h and ρ cannot be jointly large, and $\rho < 1$. That corresponds to an environment for previously ill workers where avoiding the negative ability signal of an unexplained gap is more valuable than gaining the positive signal of previous employment.

5.3 Heterogeneity in Treatment Effects

We explore the heterogeneity in the treatment effects in Table 5. In each column of Panel A, we split the sample based on a résumé characteristic (i.e. quality, job type and gender) assigned at the

TABLE 5

The Effect of Having an Employment Gap on the Callback Rate, By Groups

Panel A: Regression Results

	Résumé Quality		Occupation			Gender	
	Low	High	Sales	Admin	Acctg	Men	Women
Illness Gap	-0.002	-0.042***	-0.010	-0.016	-0.035*	-0.010	-0.028*
	(0.016)	(0.015)	(0.021)	(0.017)	(0.018)	(0.015)	(0.017)
Unexplained Gap	-0.028*	-0.059***	-0.054***	-0.026	-0.045**	-0.031**	-0.054***
	(0.016)	(0.016)	(0.020)	(0.016)	(0.021)	(0.015)	(0.018)
Observations	1,956	1,815	1,566	1,200	1,005	2,025	1,746

Panel B: *p*-values from Within Sample F-tests

	Low	High	Sales	Admin	Acctg	Men	Women
Illness Gap =Unexplained Gap	0.111	0.229	0.034	0.439	0.635	0.148	0.173

Panel C: *p*-values from Between Sample F-tests

	Low=High	Sales=Admin	Sales=Acctg	Admin=Acctg	Men=Women
Illness Gap	0.10	0.73	0.23	0.41	0.56
Unexplained Gap	0.19	0.62	0.62	0.40	0.32

Note: In Panel A, the dependent variable is the callback dummy. The omitted variable is a dummy variable for the newly unemployed gap. Control variables include dummy variables for tenure, résumé template, order of sending within the triplet, required education level, required experience, full-time job, commission-based job, employer-sponsored health insurance, physical requirements and location of the job. The coefficients are marginal effects calculated from a probit regression. Robust standard errors are in parentheses and are clustered at the job vacancy level. Estimates from OLS and fixed-effects regression yield very similar results (not reported). *** $p<0.01$, ** $p<0.05$,* $p<0.1$. In Panel B, the p-value is from the F-test of the null hypothesis that the coefficient of the illness-explained gap is equal to the coefficient of the unexplained gap within each sample. In Panel C, the p-value is from the F-test of the null hypothesis that the coefficient on one variable in one sample is the same as the coefficient on the same variable in another sample.

job level, and estimate Equations (4) and (5).[33] The ordering of the callback rate estimates remains the same in all sample splits.[34] That is, the coefficient of the unexplained gap is more negative than the coefficient of the illness gap, and the callback rate for both is less than the newly unemployed group. Thus, the implied preference ordering of employers holds across résumé characteristics and

[33]For the sake of brevity, we omit results on the effects of the presence of physical requirements of the job and employer-sponsored insurance. Estimates suggest that neither of these factors play a significant role in determining the differential impact of an unexplained gap and an illness-explained gap.

[34]Estimated coefficients from regression models without the covariates are very similar.

job types. Though point estimates exhibit some degree of heterogeneity, Panels B and C show that within and between sample differences are not significant at the 5 percent level of significance in most cases. Panel B shows the *p*-value from the F-test of the null hypothesis that the coefficient of the illness-explained gap is equal to the coefficient of the unexplained gap within each sample. We are able to reject equality at the 5 percent level only in the case of sales jobs. Panel C shows the *p*-value from the F-test of the null hypothesis that the coefficient in one sample is the same as the coefficient of the same variable in another sample. At the five percent level, we fail to reject the null hypothesis of differences in coefficients for all between-subsample comparisons. Differences by résumé quality for the illness-explained gap coefficient are the most precisely estimated. The estimated 0.04 difference in magnitude between the low and high quality groups carries a *p*-value of 0.10.

Given the reduced power of these subsample comparisons, it is nonetheless interesting to discuss the different magnitudes of point estimates across treatment arms and the potential sources of these differences. For example, for jobs that were sent high quality résumés, the point estimate of the callback penalty for having an unexplained gap is large (-.059), and the illness gap penalty is only slightly smaller (-.042). The unexplained gap penalty in the low quality résumé group is only half as large as that found in the high quality group, and the penalty is almost entirely mitigated by the illness explanation. Comparing the results by job type yields a somewhat different pattern. The penalty for an unexplained gap is large, significant, and of comparable magnitude for both jobs requiring the most qualifications (accounting) and for those requiring the least (sales). However, the illness explanation mitigates less than a quarter of the unemployment penalty in accounting jobs, while applicants with an illness-explained gap in sales jobs suffer almost no penalty.

The variation in the pattern of result across contexts may arise from potentially different evaluations of the signals sent by the gaps. In our model, a large unexplained gap penalty that cannot be mitigated with an illness explanation is consistent with larger generic hiring probabilities, meaning a larger value of ρ.[35] With ρ larger, the positive signal of no gap leads to a larger upward revision

[35]The penalty for an unexplained gap, $\Delta_{n,u} = \frac{(\rho+1)}{2(\rho+2)}$ is increasing in ρ and the the mitigation effect, $\Delta_{i,u}$, is decreasing in ρ from Equation (2).

of expected productivity from the population value. At the same time, the negative signal of an unexplained gap leads to a smaller downward revision in expected productivity. For this reason, when ρ is larger, the value of the positive signal is more important than avoiding the negative signal. Equivalently, when ρ is larger, workers are hurt more from lacking the positive signal (large overall penalty) and hurt less by not avoiding the negative penalty (small mitigation from a health explanation). Thus, for employers faced with higher quality résumés, the presence of a gap is very informative (in a negative sense), and the health signal has little mitigation power. In contrast, in the low quality résumé gap group, the presence of a gap is less informative, leading to a smaller unexplained gap penalty, and greater mitigating power of the health signal.

To understand why we see large penalties for unexplained gaps in both sales and accounting jobs, but only high illness-explained gaps in the latter, note that the value of the illness explanation lies in avoiding sending a negative signal of ability. However, those with an illness-explained gap cannot fully recover the same high ability signal sent by a non-gap applicant. Thus, it is reasonable that avoiding the negative signal may be quite valuable in jobs with low requirements (i.e. sales), but not very valuable in jobs with more onerous requirements that likely set a higher ability threshold (i.e. accounting).[36]

Though the foregoing explanation emphasizes the ability signaling mechanism, an alternative interpretation is available from the generalization of the model in Appendix A. There, the generalized counterparts to $\Delta_{n,i} + \Delta_{i,u}$ and $\Delta_{i,u}$ show that the total penalty increases, and mitigation decreases, with higher rates of unemployment related human capital depreciation and employment related productivity gains.[37] When productivity differences stem from employment differences, unemployment gaps are more heavily penalized whether explained or not. However, when unemployment itself is a cause of productivity gaps, illness explanations should be less mitigating, as explaining a gap's reason is less informative. Thus, a large gap for both groups should arise in the

[36]For simplicity, we do not explicitly model heterogeneity in returns to ability across industries. However, a straightforward implication from the conditional densities in Equation (9) of Appendix A is that the ability of the illness explanation to mitigate an employment gap penalty is weak when employers disproportionately value only high realizations of θ.

[37]While we cannot rule out different perceptions of health costs across subgroups, it is unlikely that h would differ strongly across white collar job types or based on résumé quality.

case of a job type where skill depreciation may be rapid (e.g. accounting), but the illness explanation would have more mitigating power in jobs where skill depreciation is less of a concern (e.g. sales).[38]

The pattern of heterogeneity does not allow us to distinguish between the relative importance of ability signaling and skill depreciation in explaining unemployment gaps. Both may be at play, which allows for a variety of results. Further, features present in real job markets may lead to explanations for differences in subgroups that lie outside the model. For example, in comparing callback rates by gender, we find that women face a higher unexplained and illness-explained penalty. While the illness explanation mitigates similar amounts of the penalty for each gender, women are able to mitigate a smaller proportion than men. However, the value of ρ and patterns of human capital accumulation do not likely differ by gender. In that case, higher average health costs, h, for women may play a role in the weaker relative mitigation, but the gender differences suggest additional causes of high penalties for women.

5.4 Potential Threats to Internal and External Validity

While the experiment was designed to hold constant factors other than employment history as much as possible, practical considerations affected the résumé construction in potentially important ways. This subsection discusses factors that potentially bias estimated treatment effects (internal validity), as well as reasons the experiment's results may not apply to other settings (external validity).

5.4.1 Internal Validity

Age. One concern is that applicants with employment gaps (either illness-explained or unexplained) are older by 6 to 10 months.[39] Age may negatively affect the likelihood that an applicant with a gap receives a callback, as older workers may be perceived as less able to learn new tasks or occupational skills, less adaptable to changes in the workplace, less ambitious and willing to work hard, have less physical strength, and be more likely to have health problems (Carlsson and

[38] We thank an anonymous referee for suggesting this alternative explanation.

[39] The difference in age arises because the résumés are generated to keep total job experience the same for all applicants in the triplet. Depending on the exact length of the assigned gap, as well as the fact that the newly unemployed group have 0-2 months of joblessness, applicants with gaps are older by anywhere from 6 to 10 months.

Eriksson, 2017).

However, age effects are unlikely to explain the lower callback rates of applicants with gaps in this study. In addition to the relatively small age gap, (less than a year), the applicants here range from 24 to 30 years old. In contrast, age-related employment penalties found in the literature are generally for substantially older workers and larger age gaps. Farber et al. (2016), for example, find a negative age effect on callbacks when comparing fictitious workers in their upper 50s to a group two decades younger. Even Carlsson and Eriksson (2017), who find relatively early age effects, do not find a consistent age related gradient before age 40.

While the age difference is small, because it systematically varies by treatment status, we cannot rule out the its potential influence.[40] However, the impact of age should have no influence on the validity of estimated differences between illness-explained and unexplained gaps.

Relocation signal. To explain the contemporaneous unemployment in Treatment 1, the cover letter notes that the family has just relocated. Because the treatment arms with unemployment gaps do not contain a relocation signal, one concern is that the estimates of unemployment scarring could be at least partially explained by employer perceptions of relocated employees.[41] For example, this explanation could negatively impact the callback rate, and underestimate scarring, if past work experience does not give these applicants the same location-specific skills gained by applicants in Treatment Groups 2 and 3. While this possibility cannot be ruled out, it would likely lead to bigger differences in the scarring penalty by occupation than are estimated here. Second, it may also potentially signal marital status, which has a more negative effect for women. Again, however, we find that the overall scarring effect for women is, in fact, higher than it is for men. Nevertheless, it is possible that the scarring effect is underestimated as a result of the relocation signal in the cover letter of Treatment Group 1.

Volunteering experience. As discussed in the experimental design, an extracurricular activity

[40] Indeed, the effect of the employment gaps on the call back rate may even be underestimated if the older workers are seen as more attractive at a relatively young age. For example, the employer survey from Carlsson and Eriksson (2017) find that workers who are 30 years old are perceived to have more ability to learn new tasks, be adaptable and ambitions compared to a worker workers who are less that 30.

[41] Similar to the case of age effects, the potential role of relocation signal should not affect the validity of estimated callback differences between illness-explained and unexplained gaps.

was randomly assigned to résumés of Treatment Groups 1 and 3. Including volunteer work served to balance one of the illness signals in résumés for Treatment Group 2, which indicates that the applicant is a Member/Organizer of a cancer survivor group. At random, half the résumés in Treatment Groups 1 and 3 were assigned a volunteering activity, while the other half were assigned a recreational interest (e.g. painting). However, volunteering itself may have an independent effect on callback rates (Baert and Vujić, 2018). This volunteering premium may come from employer's preference for collaboration with pro-social employees and/or belief that their other employees' or customers have a taste in this respect. Alternatively, employers may also believe that applicants with volunteering experience derive desirable human capital from such experience.

We test this volunteering premium in our data by comparing résumés assigned to volunteer or extracurricular treatments. We find no evidence that the type of activity in the interest section had an economically or statistically significant impact on callback rates.[42]

5.4.2 External Validity

While our study provides evidence that a credible explanation for unemployment can be helpful in diminishing the associated scarring of an employment gap, our results may not generalize across the following:

Age Groups. Illness-related gaps for older applicants may have a more pronounced negative effect on callbacks than the effect for younger applicants as in our experiment. Older applicants with illness-related gaps could be perceived to be more likely to suffer recurrence, need more time to recover, or experience greater productivity loss compared to younger applicants with this type of gap. Any of these could increase perceived health costs signaled by an illness, discouraging employers from hiring older applicants with illness-related gap.

Other Illnesses. The effect of illness-related gaps may vary across illnesses. The behavioral transmission mechanisms underlying the effects of illness-explained employment gaps may be different across illnesses. For example, cancer, which is the implied illness explaining the gap in our study, is not generally considered to be avoidable. As such, it is not indicative of the

[42]Results available upon request.

health-relevant behaviors of the victim. Would results be different if the the explaining illness was perceived to be caused by controllable factors? Employment gaps caused by diseases that are likely to be more recurrent could also signal higher health cost in terms of greater work absenteeism. In such cases, a health explained gap might give a different sort of signal relevant to job prospects. Further, though our model assumes ability is independent of both illness and recovery, it is possible that employers may interpret recovery itself as a positive ability signal.

More generally, because the applicants in our experiment signal full recovery, our study does not address the full suite of reasons that a health shock may lead to negative long-term labor market consequences. These may include long term productivity implications of the health problem itself. However, conditional on recovery, we do not find evidence that the signal of illness additionally burdens reemployment beyond the absence itself. Future extensions of this research could better examine both the variety of potential health shocks and the long-term implications of illness-related gaps by varying the description and history associated with the illness signal.

Other Occupations. The experiment considers only a small set of occupations: sales and customer service, clerical/administrative assistant, and accounting assistant jobs. In line with the previous literature, we targeted these jobs for both their availability and standardization. However, they are generally not physically demanding positions, and employers hiring for occupations that require physical strength may be more likely to disfavor applicants with illness-related gaps. Further, ADA provision allow employers to discriminate against disabled individuals who cannot do essential functions. As a result, health-related cost may be higher in these occupations, leading to larger illness-explained penalties, as employers think that applicants with poor health history may not be able to perform core duties.

Other Explanations Our study finds that explaining the employment gap as illness-related mitigates the unemployment penalty for applicants. That suggests job applications are better-off explaining health related gaps rather than leaving the absence unexplained. However, the explanation provided in the experiment was intentionally designed to minimize employer perceptions of recurring health problems (i.e. full recovery, onset-uncontrollable illness). It is not clear that an illness signal without such features would yield similarly positive results. Nor do we know if these results hold for other types of explanations responsible for employment gaps and potentially uncorrelated with ability, such as caring for ill-family members. These uncertainties represent fruitful areas for future research. One avenue could expand on the general theoretical model provided here and derive more specific conditions under which credibly revealing the cause of unemployment would be beneficial. Another could explore empirically how other types of explanations for employment gaps impact callback rates.

5.4.3 Other Limitations

We are 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. Future work can also determine whether the effects of health-related employment gaps found here differ across types of physical illness.

Lastly, our study is unable to disentangle the effects of the reason for the job loss and the duration of the gap. Much of the literature on scarring is concerned with duration dependence. That is, the literature is concerned with the extent to which the length of unemployment itself contributes to scarring. Since duration dependence is not our focus, we do not separately vary the reason for previous job separation and employment gap duration for the two groups with gaps. As such we can not conclusively distinguish between the relative importance of the initial job loss and continued unemployment signal.[43] However, in our experiment we focus on illness, which credibly explains both separation and duration, and thus departs slightly from the typical empirical setting. Future work may be able to disentangle how duration and separation individually contribute to the signalling mechanism underlying unemployment scarring.

[43] For example, the relative preference of employers for the illness group may stem from favoring unemployed workers who lose their jobs because of health reasons. Holding the reason for job separation constant between the two groups and sending a distinct signal of the reason for jobless duration would be difficult to achieve in practice for this particular research question. Any mention of health issues in the unexplained group would blur the distinction between the treatment arms, and an alternative explanation of separation for the illness group may discredit the health duration signal. More importantly, however, the experimental condition here mirrors the more common occurrence: health shocks are simultaneously a source of job separation and prolonged joblessness.

6 Conclusion

Our paper sheds light on the relative prospects of job applicants with an unexplained gap versus those with an illness-explained gap in their employment record. A substantial literature has demonstrated that employment gaps negatively affect job seekers. However, little is known about workers whose gaps stem from a common source: illness.

We provide a theoretical model showing how firms may rank potential workers with different types of gaps. Firms value high productivity and low health-related costs among employees. Employment gaps give imperfect signals of these qualities in applicants. An unexplained gap provides a negative signal of productivity but is uninformative about the expected health-related costs of hiring a particular worker. An illness-explained gap signals higher health costs but is uninformative about expected productivity. The absence of a gap signals high productivity and low health costs.

In sorting job applications, the firm observes these signals, updates expectations, combines expectations with idiosyncratic concerns, and decides which applicants to call, if any. Firms call applicants with no gap more frequently than all others. The relative callback rate of workers with an unexplained gap versus an illness-explained gap is less clear. If, in relative terms, expected productivity is revised sharply downward upon observing an unexplained gap, the productivity effect dominates; we expect fewer calls when a gap is unexplained. If instead expected health costs, on a relative basis, are revised sharply upward for a health-explained gap, the cost effect dominates; we expect fewer calls to workers who left the labor force for health reasons.

Relative callback rates, then, are an empirical question. Our résumé-based correspondence test confirms the unambiguous part of our theory and helps answer the open empirical question. As in previous literature we find that workers with no gap are most likely to receive a callback. Among those with gaps, callback rates are higher when an illness explains the gap. More specifically, illness-explained gaps lead to a small decrease in callback rates relative to those with no gap. However, contingent on having a gap, explaining that the gap is related to an illness leads to a substantial increase in the callback rate. Once explained as a health issue, a gap loses its productivity-signalling value. It does, however, signal higher health costs. Our results suggest that the first of these effects dominates the second.

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Appendix A. Details of the Theoretical Model.

In this appendix we provide additional details regarding the model presented in Section 2. We first show how to derive Equation (1). To find expected θ conditional on s, we need the conditional distributions of θ. By Bayes' law, the distribution of θ conditional on $S = s$ is

$$f_{\Theta}(\theta|S=s) = \frac{P(S=s|\Theta=\theta)\, f_{\Theta}(\theta)}{P(S=s)}. \tag{6}$$

Here $f_{\Theta}(\theta) = 1$ for $\theta \in [0,1]$ and 0 otherwise and $P(S=s|\Theta=\theta)$ is given by

$$P(S=s|\Theta=\theta) = \begin{cases} \omega\theta^{\rho} & \text{if} \quad s=n \\ 1-\omega & \text{if} \quad s=i \\ \omega(1-\theta^{\rho}) & \text{if} \quad s=u. \end{cases} \tag{7}$$

The first line reiterates that a worker will have no gap only if he/she had a positive health outcome (probability ω) and a positive labor market outcome (probability θ^{ρ}). The second indicates that poor health occurs with probability $1-\omega$ regardless of ability. The third line is the probability of good health but poor luck in the job market.

Integrating over θ in Equation (7) we find

$$P(S=s) = \begin{cases} \frac{\omega}{\rho+1} & \text{if} \quad s=n \\ 1-\omega & \text{if} \quad s=i \\ \frac{\omega\rho}{\rho+1} & \text{if} \quad s=u. \end{cases} \tag{8}$$

From Equations (7) and (8) into (6) we have

$$f_{\Theta}(\theta|S=s) = \begin{cases} (\rho+1)\,\theta^{\rho} & \text{if} \quad s=n \\ 1 & \text{if} \quad s=i \\ \frac{(\rho+1)(1-\theta^{\rho})}{\rho} & \text{if} \quad s=u. \end{cases} \tag{9}$$

Given Equation (9), it is straightforward to find the expected productivities in Equation (1).

Next we show that the conditional expected callback rates in our model are $P(C|S=s) = E(\theta|S=s) - E(H|S=s)$. Consider an example callback strategy. If $C_k = \{1,1,0\}$, the firm makes a callback to the those with no gap and an illness-explained gap, but not to an applicant with an unexplained gap. Putting Equation (1) and expected health costs into the condition for callbacks, we have

$$C_k = \{1,1,0\} \text{ iff } \begin{cases} \varepsilon_{n,k,j} < \frac{\rho+1}{\rho+2} \\ \varepsilon_{i,k,j} < \frac{1}{2} - \frac{h}{2} \\ \varepsilon_{u,k,j} > \frac{\rho+1}{2(\rho+2)}. \end{cases} \tag{10}$$

Thus $C_k = \{1,1,0\}$ means that $\varepsilon_{n,k,j}$ and $\varepsilon_{i,k,j}$ are sufficiently small and $\varepsilon_{u,k,j}$ is sufficiently large where the relevant cutoff points are determined by ρ and h. Other callback strategies will be similar, but with one or more inequality reversed. With a uniform distribution for $\varepsilon_{s,k,j}$, the probability that $E(\theta|S=s) - E(H|S=s) - \varepsilon_{s,k,j} > 0$ holds is given by the right-hand side of the inequalities in (10).[44] Thus the conditional expected callback rates are

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

This is equivalent to $P(C|S=s) = E(\theta|S=s) - E(h|S=s)$.

We now formalize that with ρ smaller, more workers with low ability have a positive employment shock and fewer workers with higher ability have a negative employment shock. In this environment, negative signals (i.e. joblessness) are more informative for employers than positive signals (i.e. no gap). The first panel of Figure 1 shows the conditional p.d.f. of θ from Equation (9) for a worker with no employment gap when ρ=.5 and again when ρ=2. When ρ is smaller, the p.d.f. shifts upward for smaller values of θ and downward for higher values of θ. With more of

[44] With many firms and applicants, this will also be the share of applications with each signal receiving a callback.

the mass of the distribution associated with the lower skill levels, more workers with low ability receive positive shocks. Given this, observing a positive shock leads to a small upward revision in expected productivity.

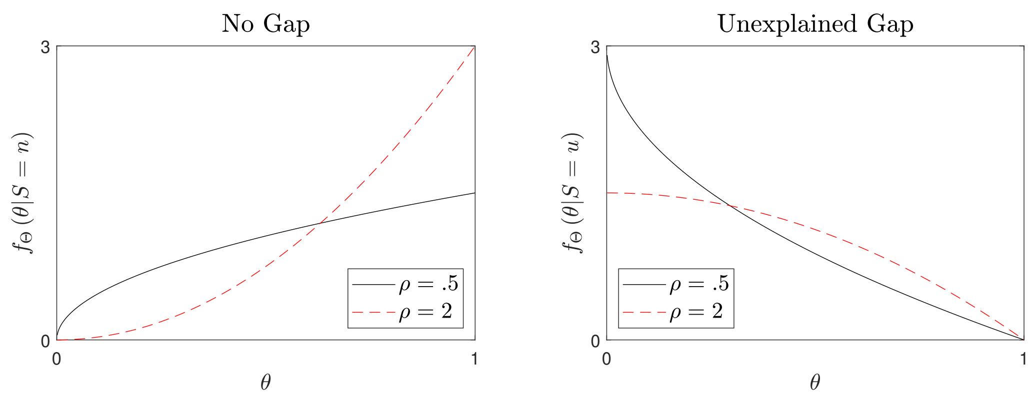

Figure 1: The first panel shows the p.d.f. from the first line of Equation (9) for ρ=.5 and ρ=2. The second panel shows the p.d.f. from the third line of Equation (9) for these same values.

The second panel of Figure 1 shows the conditional p.d.f. of θ for a worker with an unexplained employment gap. As in the no gap case, when ρ is smaller, the p.d.f. shifts upward for smaller values of θ and downward for larger values of θ. With less of the mass of the distribution associated with the higher skill levels, fewer workers with higher ability have a negative employment shock. As such, a negative employment shock (unexplained gap) motivates a larger downward revision in expected productivity.

Finally, it is straightforward to extend our model to the case where workers gain (lose) productivity from previous-period employment (joblessness). Suppose employers believe that recently employed workers increase productivity through training or learning-by-doing. Let $\gamma \geq 0$ represent this productivity gain so that the currently employed benefit the firm in proportion to $(1+\gamma)\,\theta$ rather than θ. Conversely, suppose that jobless workers benefit the firm in proportion to $(1-\delta)\,\theta$ rather than θ where $0 < \delta < 1$ represents the rate of depreciation of productivity due to unemployment. Under these circumstances Equations (2) and (3) become:

$$\begin{aligned}\Delta_{i,u} &= (1-\delta)\left(\frac{1}{2}-\frac{\rho+1}{2(\rho+2)}-\frac{h}{2}\right)\\ \Delta_{n,i} &= \left(\frac{(1+\gamma)(\rho+1)}{\rho+2}-\frac{(1-\delta)}{2}\right)+\frac{h(1-\delta)}{2}.\end{aligned}$$

In this more general case, we see that $\Delta_{i,u}$ is decreasing in δ as well as in ρ and h. Also $\Delta_{n,i}$ is increasing in γ and δ as well as in ρ and h. Furthermore, from these we find

$$\Delta_{n,i}+\Delta_{i,u}=\frac{1}{2}\frac{\rho+1}{\rho+2}(2\gamma+\delta+1).$$

Thus the total unemployment penalty is again increasing in ρ and is also increasing in both γ and δ.

Appendix B: Sample Résumés & 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