# Factors Determining Callbacks to Job Applications by the Unemployed: An Audit Study*

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**Abstract**

We use an audit study approach to investigate how unemployment duration, age, and holding a low-level "interim" job affect the likelihood that experienced college-educated females applying for an administrative support job receive a callback from a potential employer. First, the results show no relationship between callback rates and the duration of unemployment. Second, workers age 50 and older are significantly less likely to receive a callback. Third, taking an interim job significantly reduces the likelihood of receiving a callback. Finally, employers who have higher callback rates respond less to observable differences across workers in determining whom to call back. We interpret these results in the context of a model of employer learning about applicant quality.

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The authors thank the Sloan Foundation for financial support. They also thank Joanna Lahey, Matthew Notowidigdo, and participants in workshops at CREST, Princeton University, Russell Sage Foundation, Sloan Foundation and UCLA for helpful commments and discussion.

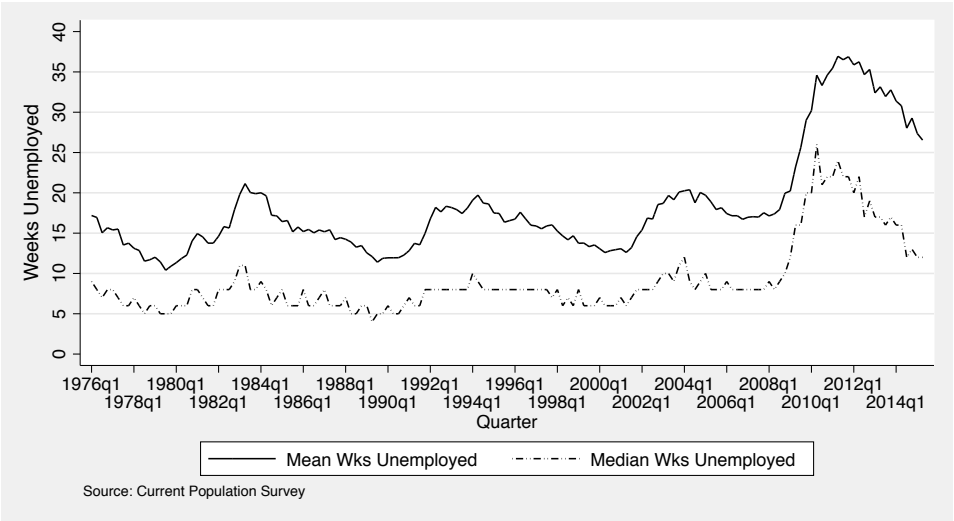


Figure 1: Mean and Median Duration of Unemployment Spells in Progress, by Quarter

# 1 Introduction

In this project, we use an audit study approach (e.g., Bertrand and Mullainathan, 2004), where we send carefully constructed fictitious job applications to posted job openings, in order to investigate how several characteristics of workers affect the likelihood they receive a callback when applying for a job. We focus on the recent employment history and age of applicants, paying special attention to the effects of unemployment duration and of taking a low-level, interim job. The study is motivated in part by the persistently long duration of unemployment spells experienced by workers in the Great Recession and its aftermath. This pattern is illustrated in Figure 1, which plots the mean and median duration of unemployment spells in progress by quarter from 1976 through 2014. Mean unemployment duration peaked in 2011 at almost 37 weeks and has exceeded 30 weeks in all quarters between 2010q1 and 2014q2. Both mean and median duration remain well above their levels at any point prior to 2008.

This shift toward longer unemployment spells underscores the importance of understanding whether workers who have been unemployed for a long period face more difficulty in finding a job. The labor force transition data suggests that this is the case. Figure 2 contains a plot of the monthly job finding rate (the probability of a U-E transition) by unemployment duration in months based on matched Current Population Survey (CPS) data from 2008-2014. This figure shows a sharp decline in the monthly job finding rate from about 25 percent early in unemployment spells to about 10 percent after one year. In order to study

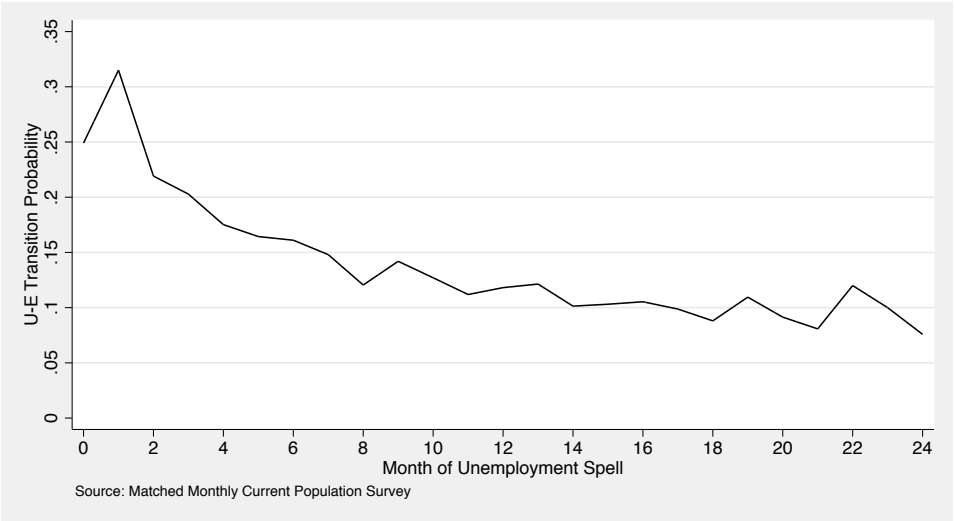


Figure 2: Monthly Job Finding Rate, by Duration of Unemployment, 2008-2014 DO BY AGE

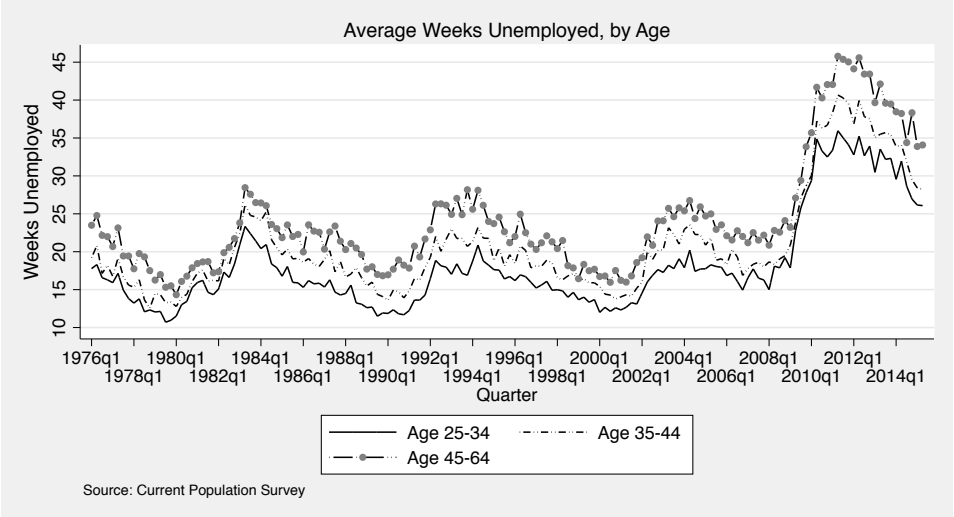


Figure 3: Mean Duration of Unemployment Spells in Progress, by Age Category

the effect of unemployment duration on the likelihood of callback, we randomly varied the duration of the current unemployment spell across applications in our audit study.

The study is also motivated by an interest in the obstacles that older unemployed workers face in job seeking. Figure 3 highlights the fact the average duration of unemployment spells in progress have historically been substantially longer for older workers. For example, from 2014q1-2015q2, the average duration of an in-progress unemployment spell was 28 weeks those aged 25-34, 31 weeks for those aged 35-44, and 36 weeks for those aged 45-64. The

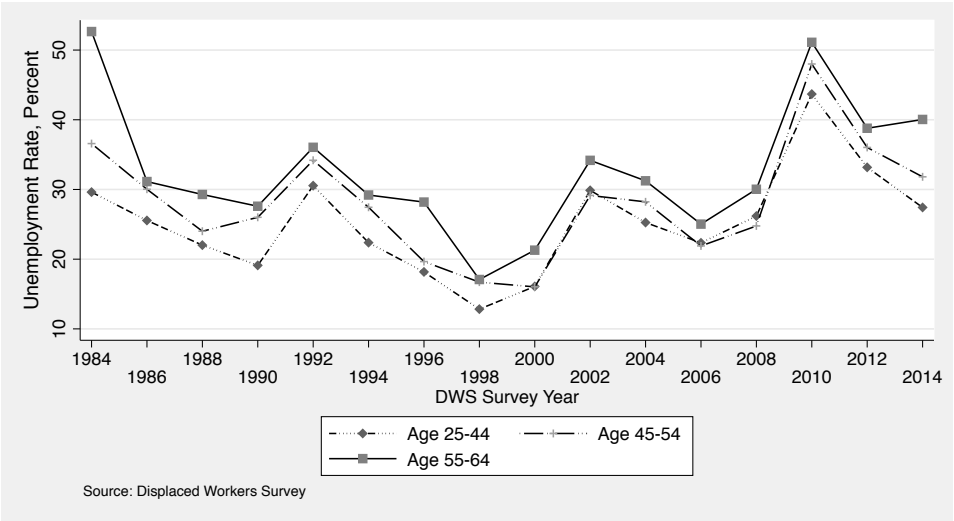


Figure 4: Unemployment Rate of Displaced Workers, by Age.

difficulty that older workers have finding jobs is further illustrated using data from the Displaced Workers Survey (DWS) from 1984-2014. Figure 4 illustrates that older job losers have historically had higher post-displacement unemployment rates (measured at the DWS survey date). Since the Great Recession period (job loss from 2007-2013), job losers 25-44 years old had a 26.3 percent unemployment rate while the unemployment rate was 29.9 percent for 45-54 year old job losers and 35.1 percent 55-64 year old job losers. The difficulties faced by older unemployed individuals lead some to spend long stretches out of work, and some never return to employment (Song and von Wachter 2014). Given these patterns, it is important to understand the role of age in hiring and its interaction with work history such as unemployment duration and interim jobs.

Our interest in age affected our study design in two ways. In contrast to several recent audit studies of the effect of employment history on call back rates, our sample consists of mature and older workers, for whom job loss and long-term unemployment may be particularly costly. In addition, to address the question of how age itself affects the likelihood of callback, we randomly varied applicant's age on a subset of applications, and we measured differences in callback rates.

Finally, we were interested in whether ending a recent spell of unemployment with a short-term, lower-level interim job (e.g., in retail sales) is an effective strategy for improving call back rates. It is well documented that in the aftermath of a job loss the degree of mismatch and non-standard work histories increases, in particular during recessions (e.g., Farber, 1999; Elsby, Hobijn, and Şahin, 2010). How interim jobs can affect call back rates

has direct practical relevance for unemployed workers seeking to obtain a good job while making ends meet. Additionally, it is important to understand the extent to which a rise in the incidence in interim employment affects call back, job finding, and, hence, unemployment duration. Yet relatively little is known about the consequences of taking a low-level interim job. Simple theories suggest it could have countervailing effects on callbacks. It might be that holding a low-level interim job signals that the applicant is ambitious and hard working, increasing the likelihood of callback. Alternatively, it might be that holding a low-level interim job suggests to the employer than the applicant is not suitable for the job for which the application was submitted. This could be a conscious choice of employers or a mechanical reading of the resume that rules out applicants whose most recent job was not related to the job for which the application was submitted. To investigate the role of a low-level interim job on the likelihood of a callback, we included such an interim job on a random subset of some applications, and we measured differences in callback rates.

In order to focus efficiently on the three variables of interest, we limit the range of variation in other dimensions as is common in studies of this type. Specifically, we limit our applications to administrative support jobs and we restrict the applicants to all be female and to have a four-year college education. While this does limit any claims we might make regarding the workforce as a whole, the facts that motivated our analysis regarding the incidence of long-term unemployment and the relationship of age with long-term employment do hold for this subgroup of the labor force. Figure 5 shows average duration of unemployment spells in progress from the CPS since 2003 for college-educated females in administrative support occupations. While the samples are considerably smaller than for those for the entire unemployed sample from the CPS (figure 4), there is a sharp increase in the average duration of unemployment for these women since the Great Recession, and the average duration of unemployment is significantly longer for older women.[1] Thus, the facts we presented in the introduction to motivate our analysis are important for the particular jobs we study.

Our findings are clear with regard to the three variables of interest. First, we find no relationship between unemployment duration and the callback rate. This is different from the results in Kroft, Lange, and Notowidigdo (2013) (KLN) and Ghayad (2014) in the U.S. Those papers find a negative relationship between callback rates and duration of unemployment that is concentrated in the first six or seven months of an unemployment

[1] Mean unemployment duration for college-educated females in administrative support occupations over the 2008-2014 period is 10.2 weeks longer for women aged 45-64 than for women aged 25-44 ($p$-value of difference less than $10^{-18}$).

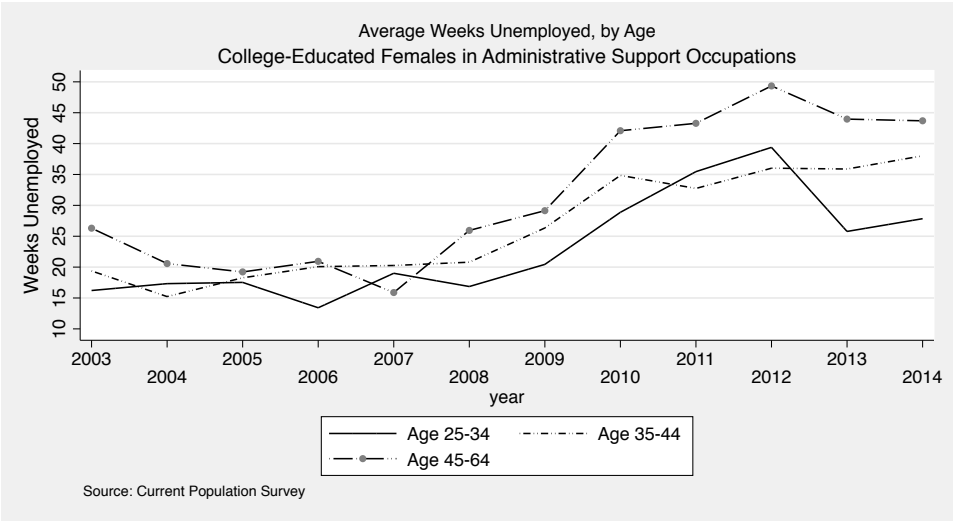


Figure 5: Mean Duration of Unemployment Spells in Progress, by Age. College-educated females in administrative support occupations.

spell. For longer spells, those papers estimate that the relationship between unemployment duration and the callback rate is flat. Our findings are closest to those in Nunley et al. (2014), who find no effect of unemployment duration, either past or present, on callbacks for relatively recent college graduates in the United States.[2] Eriksson and Rooth (2014), whose study of the Swedish market also found no effect of unemployment duration on callback rates for jobs that require a university degree, additionally found no effects before 6 months for lower-skilled jobs. As we discuss in detail below, there are many potential reasons for the differences across studies in results with regard to unemployment duration and callbacks. We can explore some of them with existing data, but more data collection is necessary to understand fully what drives the differences.

Second, we find that older workers (in their fifties) are significantly less likely to receive a callback than workers in their thirties and forties. This is consistent with the results in Lahey (2008), who large negative effects of age on callbacks for women seeking entry-level positions in the U.S.

Third, we find that taking a low-level interim job significantly reduces the likelihood of receiving a callback. This last result is similar to that in Nunley et al. (2014). That paper found that relatively recent college graduates in the U.S. had substantially lower callbacks if they were currently employed in jobs that did not require a college education and were not

[2] All of the fictitious applicants in our study had completed a four-year degree.

suited to the job for which they were applying.

Our results have some important implications. First, our findings help to underscore that the effect of unemployment duration on call back rates found for younger workers in KLN (2013) do not hold universally in the labor market. For the more seasoned female clerical workers we focus on, long-term unemployment has no causal effect on call back rates. Together with the other mixed findings in the literature, our finding calls into question whether the well-known decline in the probability of job finding with unemployment duration is primarily driven by a causal effect of unemployment duration due to employer behavior rather than arising from some other source, such as negative selection or changes in workers' search behavior. Future work should seek to understand better the heterogeneity in treatment effects between studies and demographic groups. Second, our results strengthens Lahey's (2008) finding and underscores that age discrimination may be a relevant phenomenon in the U.S. labor market. Since we focus on workers with longer labor force histories, our findings suggest that even substantial relevant labor market experience on the resumes we use do not diminish the negative effect of age on call backs. Third, at a practical level, the fact that interim jobs negatively affect the incidence of call back implies that unemployed workers may be better advised remaining unemployed rather than compromising on job quality (or at least they should not to advertise an interim job on their resume). Finally, our findings on interim jobs implies that employers do you use information on the resumes to make inferences even about mature and older workers. Standard employer learning theory would suggest that the availability of many signals for these workers reduces the effect of any given signal (e.g., Farber and Gibbons 1996). This could rationalize our zero result on the effect of unemployment duration, but not the significant effects of interim jobs we find. It is an open question whether these latter finding implies presence of employer learning in the sense of the theory even for older workers, or whether it is due to mechanical screening of CVs by human resource departments that may, for example, eliminate 'bad matches' based on the last entry on the CV.

An additional finding is that, among jobs that received four applications, the negative effect of age and interim job on the incidence of callback is substantially weaker (the effect of unemployment duration remains zero) for those employers with high callback rates (e.g., 3 callbacks out of 4 vs. 1 callback out of 4). This finding can be interpreted as an indication that employers with a high demand for workers become less selective in deciding whether or not to call back. This is consistent with the idea that particular signals on the resume may matter less for the incidence of callback in a tighter labor market.

The remainder of the paper proceeds as follows. Section 2 describes and motivates many details of the experimental design. Section 3 develops a model of employer learning to guide interpretation of results. Sections 4 presents the results of simple, univariate analyses of the experimental treatments on duration of unemployment, age, and interim job. Section 5 presents a multivariate analysis to gain additional precision of the estimates. Section 6 offers some analysis of the disparate findings in the literature, and Section 7 concludes.

# 2 Research Design

The design of our audit study reflects several considerations and constraints with implications for interpreting the results. Since as with any experiment in the social sciences, our design choices affect the internal and external validity of our results, we describe the design and setting of our study in detail.

An audit study consists in sending fake resumes to actual job postings and measuring the incidence of callback rates. The main estimates consists in differences in callback rates based on randomly assigned differences in resume characteristics, such as age, job characteristics, or employment dates. It is therefore paramount that the fake resumes and the variation in the informational content be constructed as realistic as possible.

To facilitate the tailoring of resumes and reduce idiosyncratic variation in callback rates by job type, we restricted both the type of jobs to which we sent our resumes and the demographic characteristics of the applicants. Applications were limited to white collar office jobs such as administrative or executive assistants, receptionists, secretaries, office associates, and the like. Because these jobs are disproportionately held by women, and gender differences are not our focus, all applicants had female names. Each applicant had a four-year bachelor's degree from a non-elite public university or college with a current admission rate higher than 65 percent. In contrast to previous studies, our fictitious applicants also had substantial work histories. The work histories consisted of three to six white collar office jobs, depending on age. Prior to the current spell, these work histories had no spells of unemployment longer than a month in the previous five years. Age or birth year were not listed in the resumes but could be inferred from year of college completion and work experience. There was no information included on the resumes regarding race, marital status or number of children.

The context of our audit study is nationwide in that we submitted job applications to openings in selected cities across the United States. To further be able to tailor our fictitious resumes to jobs and the local labor market, we selected eight cities. Because we also wanted

Table 1: Unemployment Rates, by City and Year

| Low Unemployment | 2012 | 2014 | High Unemployment | 2012 | 2014 |
|---|---|---|---|---|---|
| Dallas, TX | 6.6 | 5.0 | Charlotte, NC | 9.2 | 6.0 |
| Omaha, NE | 4.4 | 3.7 | Chicago, IL | 9.1 | 7.0 |
| Pittsburgh, PA | 7.2 | 5.6 | Sacramento, CA | 10.3 | 7.2 |
| Portland, ME | 6.1 | 4.6 | Tampa, FL | 8.3 | 6.1 |
| Average | 6.1 | 4.7 | Average | 9.2 | 6.6 |

to allow for differences in treatment effects by local unemployment rates, four of the cities we chose had relatively low unemployment rates at the start of our study (Dallas TX, Omaha NE, Pittsburgh PA, and Portland ME) and four of which had relatively high unemployment rates in 2012 (Charlotte NC, Chicago IL, Sacramento CA, and Tampa FL). Table 1 contains city-level unemployment rates for the eight cities in 2012 (early in our study period) and 2014 (late in our study period). The table illustrates the general improvement in the labor market during the extended recovery from the Great Recession. Unemployment rates fell in both the low- and the high-unemployment cities, and the relatively ordering of cities by unemployment rate was preserved across groups.

To further enhance the external validity of the experiment, the resumes were crafted to be plausible and tailored to prospective employers in each of the eight cities we study. Plausibility was created, as in Bertrand and Mullainanthan (2004), by crafting the fictitious resumes from actual resumes posted on a site we did not use for submissions. These actual (source) resumes were posted for job openings in the occupations we study, but in a city that was not in the experiment. Each element of each source resume was migrated to each of the eight target cities in which the experiment was conducted. This migration was performed by finding residential addresses, employers, and institutions of post-secondary education in the target city that are similar to those listed on the source resume.[3] Names were not migrated but instead selected to be common, according to the Social Security Administration, among people of the relevant age cohort, but not hispanic in origin. The names selected are neutral with regard to race and ethnicity (e.g., not obviously Asian, African-American, or Hispanic).

[3] Similarity for the address was defined by the (minimum) Mahalanobis distance between the source address and the target by census tract age, race, education, and income level. Similarity for employers was, for large businesses, achieved by replacing the source employer with its chief competitor in the target city. For small businesses, similarity was achieved by simple search for a target business in the same industry with approximately the same age and number of employees. For government work, the source employer was simply switched to that of the target jurisdiction. Similarity of the post-secondary schools was identified by simple search using national ranking, public/private status, size, and distance to the target city.

The appendix includes a sample of four resumes that vary with regard to the characteristics of interest (unemployment duration, age, and interim job).

The basic structure of the actual experiment follows now standard methods for "correspondence studies;" see, e.g., Bertrand and Mullainathan (2004), Lahey (2008), and KLN (2013). Specifically, we sent our crafted fictitious resumes in matched pairs or quadruples to openings posted on two online job boards. The experiment proceeded in four rounds, which are explained in detail below. Round 1 only randomly assigns unemployment duration to one of two resumes sent to the same job posting. Round 2 differs from round 1 in that both resumes sent to the same job posting receive a random unemployment duration. Round 3 differed from round 2 in that also the presence of an interim job is randomly assigned (independently of unemployment duration). Round 4 differs from round 3 in that also the implied age of the resume is randomly assigned. Details by round are:

1. (2,054 applications, 1,027 jobs.) Conducted between March and May 2012, the first round involved submitting two applications (treatment and control) to each of 1,027 job openings spread across the 8 cities. In this and all other rounds, the number of applications was roughly proportional to city size. The control applicant to each job had always just entered unemployment, while the treatment applicant had been unemployed for a number of weeks drawn at random from the set {4, 12, 24, 52}. The beginning of the unemployment spell was indicated on the resume by the end date of the applicant's most recent job. Thus the control applicant's resume indicated that her most recent job had ended in the month just prior to month the application was made. The applicant's age varied (35, 40, 55, or 56) across applications, but age did not vary within the applicant pair for specific job postings. Age was identified by year of graduation from college and re-enforced by the employment history. Formatting of resumes was randomly varied to avoid detection of the experiment.

2. (2,430 applications, 1,215 jobs.) In the second round, conducted between July and September 2012, the experimental design was identical to the first round with one exception. In this second round, each applicant had been unemployed for a number of weeks drawn at random, without replacement, from the set {0, 4, 12, 24, 52}. This change in design allowed us to account for the possibility that the two applicants in a pair were being directly compared by an employer and the control applicant, newly unemployed, was being mistaken for someone currently employed.

3. (1,668 applications, 834 jobs.) The third round of the experiment, conducted between

November 2013 and April 2014 used the same methods as in round two to submit applications in matched pairs.[4] In this round, however, we introduced the possibility that the applicant held an interim job. Applicants holding an interim job had just started work, the month prior to the month of the application, in a relatively low-skilled position at a chain restaurant, a big box retail store, or a grocery store. These interim jobs involved serving food, stocking shelves, or assisting customers at a register or on a retail floor, and were thus quite different from the career work on the rest of the resume. The randomization with respect to interim job was conducted at the application level, within matched pair. Thus, both the control and the treatment could be: employed in an interim job with some unemployment spell or unemployed with some other unemployment duration. We did not update the start dates of the resumes in this round, and the applicants therefore "aged." Applicant's age varied across job postings from the set {36, 37, 41, 42, 56, 57, 58}.

4. (6,072 applications, 1,518 jobs). In the fourth and final round, conducted between April and August 2014, we submitted 4 (rather than 2) applications to each of 1,581 openings spread across the eight cities. This increase in the number of applications per job was motivated by two interests. First, we wanted to speed data collection, which experience indicated could be done by without risking detection of the experiment by doubling the number of applications per job. Second, we wanted to produce experimental variation in age, within job. Thus, the four applications per job consisted of two each from two different groups. One pair consisted of younger applicants (37 or 42), and the other consisted of older applicants (57 or 58). Randomization with respect to holding an interim job and variation in unemployment duration was as in round three.

While gradually providing additional sources of variation, the fact that the experiment occurred in four stages does not affect our results. In the empirical work, we begin by analyzing the four rounds separately. We then show that the results that are comparable between the four rounds are sufficiently similar that we can analyze them together.

[4] The delay between rounds two and three was unintentional, and the result of two of the authors (Silverman and von Wachter) moving their primary appointments to different universities. Additionally, data were inadvertently collected in Portland OR rather than Portland ME in round 3. Since the relevant resumes were tailored to Portland ME, we do not include the Portland OR applications in the analysis. Thus, there are only 7 cities in Round 3.

# 3 A Model of Learning about Applicant Quality

When employers evaluate an applicant for a job, they have incomplete information about the quality of the worker. Employers use observable information available in the worker's application to form an expectation about the worker's quality. This information includes, among other things, worker demographics, education, work history, and unemployment experience. In this section, we develop a very simple model of employer learning about applicant quality in order to motivate the analysis and to provide clear predictions and a clear framework for interpreting the results of the audit study.

We assume a profit-maximizing, risk-neutral firm with a single worker. The output ($Y$) of the firm is equal to the quality of the worker ($\mu$). We assume all potential workers will be paid the same wage so that the firm is interested in hiring the most able worker among applicants for its job opening.[5] Our model captures the employer's process of integrating available information to form an expectation of applicant quality.[6]

Consider applicant $i$. The firm has incomplete information about $\mu_i$ and makes an inference based on a set of $k$ noisy signals. For the purposes of our study, these signals include, among other background information, the applicant's unemployment experience, age, and whether the applicant holds an interim job. Let $s_{ij}$ represent the $j^{th}$ noisy signal of $\mu_i$. We assume this $j^{th}$ signal satisfies

$$s_{ij} = \frac{1}{\alpha_j}\mu_i + \gamma_{ij}, \tag{1}$$

where $\gamma_{ij}$ is a normally distributed random variable with zero mean and variance $\sigma_j^2$. The parameters $\alpha_j$ are normalizations that account for the fact that some signals are positive and some are negative as well as for differential scaling of the signals. For example, unemployment duration would have $\alpha_j < 0$, but interim job might have $\alpha_j > 0$. The employer's inference problem is to combine the available information on $s_{ij}, j = 1, ..., k$ optimally in order to derive an expected value for applicant quality ($E(\mu_i|s_{i1}, ..., s_{ik})$).

Think of $s_{ij}$ as prior information on applicant quality so that the posterior beliefs about applicant quality can be derived using a standard Bayesian procedure. Given the distributional assumption regarding the $\gamma_{ij}$, each signal $s_{ij}$ about applicant quality is normally

[5] Note that the quality of applicants will likely depend on the offered wage.

[6] While we do not include sequential search in our model, such a model would clearly have the property that the employer will set a reservation worker quality level as part of the search process and call back those applicants whose expected quality exceeds this threshold. Thus, applicants with higher expected quality will be more likely to receive a callback.

distributed with mean $\mu_i/\alpha_j$ and variance $\sigma_j^2$. In describing how information about $s_{ij}$ is combined to form the employer's posterior distribution on applicant quality, it is convenient to use the precisions of the random variables rather than the variances. The precision ($h$) of a random variable is the inverse of the variance, so that $s_{ij}$ with variance $\sigma_j^2$ has precision $h_j \equiv 1/\sigma_j^2$. In this Normal Bayesian updating model, the posterior distribution of the employer's beliefs about $\mu_i$ is normal with a mean that is a precision-weighted average of the $k$ signals. The posterior expectation is

$$E(\mu_i|s_{i1}, ..., s_{ik}) = \frac{\sum_{j=1}^{k} h_j \alpha_j s_{ij}}{\sum_{j=1}^{k} h_j}. \tag{2}$$

Consider the implication of the model for the effect of signal $m$ on the likelihood of callback. The marginal effect of a change in $s_{im}$ is

$$\frac{\partial E(\mu_i)}{\partial s_{im}} = \alpha_m \left[ \frac{h_m}{\sum_{j=1}^{k} h_j} \right] \tag{3}$$

which takes the sign of $\alpha_m$. If signal $m$ is unemployment duration then, presumably, $\alpha_m \leq 0$, and the marginal effect of unemployment duration is negative. Thus, workers with longer unemployment duration have lower posterior mean worker quality. This makes their posterior expected quality less likely to exceed the necessary threshold and reduces the likelihood of callback. Analogously, if signal $m$ is age and age is a negative signal of worker quality, then $\alpha_m \leq 0$ and older workers have lower posterior mean worker quality. Again, this makes their posterior expected quality less likely to exceed the necessary threshold and reduces the likelihood of callback. Given the opposing predictions regarding the value of holding a low-level interim job, the sign of $\alpha_m$ in this case is unknown, and we have no clear prediction on how the likelihood of callback varies with the holding of a low-level interim job.

There are at least two second-order predictions of the model. First, related to unemployment duration, it is likely that there is more information about applicant quality in the duration of unemployment when the labor market is tighter (lower unemployment rate). In terms of the model, the precision associated with the unemployment duration signal is higher where the local unemployment rate is lower so that there is relatively more updating based on unemployment duration. Formally,

$$\frac{\partial^2 E(\mu_i)}{\partial s_{im} \partial h_m} = \alpha_m \left[ \frac{1}{\sum_{j=1}^{k} h_j} \right] \left[ 1 - \frac{h_m}{\sum_{j=1}^{k} h_j} \right] \tag{4}$$

which has the sign of $\alpha_m$. Because $\alpha_m \leq 0$ where $s_m$ represents unemployment duration, the negative marginal effect of unemployment duration on the likelihood of callback (equation 3)

is larger in absolute value in tighter labor markets (equation 4). In other words, the negative marginal effect of unemployment duration on the callback rate will be more substantial in stronger labor markets.[7]

The other second-order prediction of the model is that where there are more signals of worker quality, the marginal effect of any one signal will be smaller in absolute value. This is relevant when thinking about the role of applicant age. An older worker has more prior work experience. This comes in the form of more and perhaps longer prior jobs. In the context of the model, longer experience and more information increase the number of signals ($k$). The marginal effect of a particular signal is given in equation 3. On inspection of this relationship, an increase in $k$ simply increases the denominator in the term in brackets. The result is a reduction in the absolute value of the marginal effect any particular existing signal. This predicts, for example, that the marginal effect of unemployment duration will be smaller for older workers. Intuitively, older workers have a longer employment history that will dilute the effect of recent unemployment on the likelihood of callback.

A final prediction is not based strictly on the updating model. If an employer has a great need for workers as indicated by a higher callback rate for applicants to the particular job, then the employer may not be as selective. The result will be that the threshold posterior mean worker quality necessary for a callback will be lower where demand is high. A clear implication of this is that the marginal effect of particular worker attributes (unemployment duration, age, and the holding of a low-level interim job in case) on the likelihood of callback will be lower for less selective employers.

The foregoing model presents only one way in which employers may use resume information to draw inferences about applicant suitability for the job. Other approaches may include mechanical screening of resumes to filter out workers that are an obvious mismatch. Another approach would be screening based on tastes for particular worker attributes, such as age. We will not be able to test between alternative approaches, but keep those in mind when interpreting our findings.

# 4 Descriptive Analysis

We begin by separately analyzing the effect of our three main factors, duration of unemployment, worker age, and presence of interim job, separately. In the next section, we analyze

[7] This is a result found by Kroft, Lange, and Notowidigdo (2013).

the effect of these characteristics jointly. To set the stage, note that our mean callback rate across all rounds is 10.4 percent. One plausibility check that our resumes work as intended, is that the callback rate was significantly higher (12.2 percent) in our low-unemployment cities than in our high-unemployment cities (8.9 percent) with a $p$-value of the difference $< 0.0005$.

## 4.1 Duration of Unemployment

A primary focus of this study is to examine the effect of unemployment duration on the likelihood of an employer callback to a job application. All four rounds incorporated variation in weeks of unemployment including base values of 0 weeks, 4 weeks, 12 weeks, 24 weeks, and 52 weeks.[8] Table 2 contains mean callback rates overall and by round for each of the five baseline values for unemployment duration. There is no systematic relationship (positive or negative) between the probability of callback and the duration of unemployment. The hypothesis that the callback rates are equal across unemployment duration treatments cannot be rejected ($p$-value = 0.53 overall).[9]

The variation in unemployment duration treatment *within* job posting in each round offers the opportunity to examine within-posting variation in callback rates by unemployment treatment. The fixed-effect conditional logit analysis due to Chamberlain (1980) is a natural way to estimate this within-posting effect. Intuitively, the fixed-effect conditional logit conditions on the number of successes (callbacks) within each job posting and asks whether the applicants with longer unemployment durations were less likely to be among those who received the fixed number of callbacks. This approach ignores the job postings for which there was no variation in the outcome. In the 3076 job postings in rounds 1-3, for which there were 2 applications per job posting, 2591 postings had no callbacks and 229 postings had 2 callbacks. This leaves 256 postings with 1 callback. In the 1518 job postings in round 4, where there were 4 applications per job posting, 1215 postings had no callbacks and 30 postings had 4 callbacks. This leaves 150 postings with 1 callback, 85 postings with 2 callbacks, and 38 postings with 3 callbacks.

[8] These are the weeks of unemployment implicit in the applications at fixed dates. Since the applications were submitted over a period of time following that date, the actual durations seen by potential employers are somewhat longer. Actual unemployment duration exceed each base value by about 4 weeks on average (standard deviation of about 1.1 weeks for each base value).

[9] The hypothesis of equality of callback rates across unemployment duration treatments cannot be rejected within any of the four rounds, with $p$-values ranging from 0.23 in round 1 to 0.71 in round 3.

Table 2: Average Callback Rate, by Base Unemployment and Round

| Weeks U | Rnds 1-4 | Round 1 | Round 2 | Round 3 | Round 4 |
|---|---|---|---|---|---|
| 0 | 0.101 | 0.103 | 0.150 | 0.085 | 0.082 |
| | (0.006) | (0.010) | (0.016) | (0.016) | (0.009) |
| 4 | 0.099 | 0.121 | 0.124 | 0.081 | 0.089 |
| | (0.007) | (0.021) | (0.015) | (0.015) | (0.009) |
| 12 | 0.111 | 0.122 | 0.163 | 0.094 | 0.096 |
| | (0.007) | (0.021) | (0.017) | (0.016) | (0.010) |
| 24 | 0.108 | 0.085 | 0.144 | 0.105 | 0.010 |
| | (0.007) | (0.016) | (0.016) | (0.017) | (0.010) |
| 52 | 0.100 | 0.074 | 0.141 | 0.100 | 0.089 |
| | (0.007) | (0.016) | (0.016) | (0.017) | (0.009) |
| All | 0.104 | 0.101 | 0.144 | 0.093 | 0.091 |
| | (0.004) | (0.008) | (0.009) | (0.009) | (0.005) |
| N Postings | 4594 | 1027 | 1215 | 834 | 1518 |
| N Applications | 12224 | 2054 | 2430 | 1668 | 6072 |

Note: Numbers parentheses are standard errors clustered by job id.

We postpone estimation of the full Chamberlain fixed-effect logit model until Section 5 and, for now, present just estimates of the average callback rates by unemployment treatment conditional on the number of callbacks received for the job posting. Table 3 contains these callback rates conditional on the number of callbacks received. Column 1 of the table contains average callback rates by unemployment treatment for job postings in rounds 1-3 with a single callback. There is no obvious relationship between the callback rate and the unemployment treatment, and the hypothesis that callback rates are equal across treatments cannot be rejected ($p$-value = 0.85). Column 2 shows average callback rates in round 4 for job postings with 1-3 callbacks for each treatment. These appear to show, counter to expectations, that callback rates are higher where a longer unemployment spell is indicated on the application. However, once again the hypothesis that callback rates are equal across treatments cannot be rejected ($p$-value = 0.46). The last three columns of table 3 shows average callback rates in round 4 for job postings with 1, 2, and 3 callbacks respectively for each treatment. In no case can the hypothesis that callback rates are equal across treatments be rejected ($p$-values = 0.78, 0.32, and 0.91 respectively).

Overall, while we will revisit this question in more detail later, the simple comparison of means suggests that the length of unemployment spell indicated on a job application does not affect the probability of receiving a callback for the type of job we are considering (white-collar office support jobs).

Table 3: Average Callback Rate, by Unemployment and Number of Callbacks

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | Rounds 1-3 | Round 4 | Round 4 | Round 4 | Round 4 |
| Weeks U | 1 Callback | 1-3 Callbacks | 1 Callback | 2 Callbacks | 3 Callbacks |
| 0 | 0.493 | 0.354 | 0.250 | 0.397 | 0.690 |
| | (0.041) | (0.030) | (0.034) | (0.055) | (0.081) |
| 4 | 0.457 | 0.376 | 0.204 | 0.493 | 0.741 |
| | (0.052) | (0.033) | (0.037) | (0.050) | (0.081) |
| 14 | 0.548 | 0.432 | 0.267 | 0.524 | 0.795 |
| | (0.054) | (0.033) | (0.036) | (0.063) | (0.057) |
| 24 | 0.505 | 0.402 | 0.271 | 0.500 | 0.774 |
| | (0.052) | (0.031) | (0.034) | (0.056) | (0.071) |
| 52 | 0.505 | 0.421 | 0.250 | 0.577 | 0.731 |
| | (0.053) | (0.032) | (0.036) | (0.054) | (0.081) |
| N Postings | 256 | 273 | 150 | 85 | 38 |

Note: By construction, the average callback rate is 0.5 for postings with 1 callback in rounds 1-3. In round 4, the callback rate is 0.25 for postings with 1 callback, 0.5 for postings with 2 callbacks, and 0.75 for postings with 3 callbacks. Numbers parentheses are standard errors clustered by job id.

The theory outlined in Section 3 implied that the marginal effect of unemployment duration will be larger in tighter labor markets. This suggests that there might be a relationship between unemployment duration and the probability of callback in the low unemployment cities but not in the high unemployment cities. While we do not show the results here, we repeated our analysis separately in the low- and high unemployment cities. No perceptible relationship between unemployment duration and the callback rate was found in either group of cities.

## 4.2 Age

Figure 4 showed that older job losers are more likely to be unemployed at a fixed date subsequent to a job loss. It has been a long-standing question in labor economics whether the stark differences by age shown in the figure may partly reflect a reluctance by employers to hire older job applicants. More generally, age may be an important factor for employers when selecting new employees. This motivated the random variation of age of applicant in the resumes we submitted as part of our audit study, and, in this section, we present our estimates of callback rates as a function of applicant age.

Two applications were submitted to each of 3076 job postings in rounds 1-3, and each

Table 4: Average Callback Rate, by Age and Round

| | All | Round 1 | Round 2 | Round 3 | Round 4 |
|---|---|---|---|---|---|
| Age 35-37 | 0.110 | 0.092 | 0.147 | 0.092 | 0.103 |
| | (0.006) | (0.014) | (0.016) | (0.016) | (0.009) |
| Age 40-42 | 0.119 | 0.112 | 0.150 | 0.103 | 0.111 |
| | (0.007) | (0.015) | (0.016) | (0.016) | (0.010) |
| Age 55-58 | 0.089 | 0.099 | 0.136 | 0.084 | 0.076 |
| | (0.005) | (0.014) | (0.016) | (0.014) | (0.006) |
| All | 0.104 | 0.101 | 0.144 | 0.093 | 0.091 |
| | (0.004) | (0.008) | (0.009) | (0.009) | (0.005) |
| N Postings | 4594 | 1027 | 1215 | 834 | 1518 |
| N Applications | 12224 | 2054 | 2430 | 1668 | 6072 |

Note: Numbers parentheses are standard errors clustered by job id.

job posting was randomly assigned to an age category. Both applications to each job posting listed the same birth date as implied by the year of graduation from college.[10] Approximately one-third of the job postings were randomly assigned in each age category (32.5 percent aged 35-37. 33.5 percent aged 40-42, and 34.0 percent aged 55-58). Four applications were submitted to each of 1518 job postings in round 4. Two applications per posting were randomly assigned to be in the oldest age category (55-58) and the remaining two applications were assigned to be in a younger category. The result is that in round 4, roughly one-quarter of the applicants are 35-37 years of age, one-quarter of the applicants are 40-42 years of age, and half of the applicants are 55-58 years old.

The first column of table 4 contains the callback rates for all four rounds, both overall (last row) and by age group. The overall callback rate is 10.4 percent. There is not a significant difference between the callback rates for applicants aged 35-37 and applicants aged 40-42 ($p$-value of difference = 0.97). However, the callback rate for applicants aged 55-58 is substantially and significantly lower (by about 2 percentage points) than the callback rate for younger workers ($p$-values of differences $< 0.01$).

The remaining columns of table 4 contain the callback rates separately by round. While mean callback rates for workers age 55-58 are lower than the average callback rates for 35-42 year olds, these differences are not statistically significant from zero in the first three rounds. However, there is a substantial difference by age in round 4. In round 4, applicants aged

[10] In fact, the actual ages of the two applications for a posting could differ by one year given that age is determined by birth date and the applications were sometimes submitted on different dates.

Table 5: Average Callback Rate, Round 4, by Age and Number of Callbacks

| | 1-3 Callbacks | 1 Callback | 2 Callbacks | 3 Callbacks |
|---|---|---|---|---|
| Age 35-37 | 0.457 | 0.346 | 0.536 | 0.737 |
| | (0.029) | (0.026) | (0.067) | (0.058) |
| Age 40-42 | 0.511 | 0.326 | 0.709 | 0.763 |
| | (0.029) | (0.028) | (0.050) | (0.058) |
| Age 55-58 | 0.311 | 0.163 | 0.376 | 0.750 |
| | (0.022) | (0.019) | (0.043) | (0.041) |
| N Postings | 273 | 150 | 85 | 38 |

Note: By construction, the average callback rate is 0.25 for postings with 1 callback, 0.5 for postings with 2 callbacks, and 0.75 for postings with 3 callbacks. Numbers parentheses are standard errors clustered by job id.

55-58 have a 7.6 percent callback rate compared with callback rates in the 10 to 11 percent range for younger applicants ($p$-values of differences $< 0.005$).

The variation in age of applicant within job posting in round 4 offers the opportunity to examine within-posting variation in callback rates by age. As we did earlier with respect to the unemployment treatment, we focus on the job postings for which there was variation in the outcome. We ignore the job postings for which there was no variation in the outcome (The 1215 of 1518 postings with no callbacks and the 30 of 1518 postings with 4 callbacks). This leaves 150 postings with 1 callback, 85 postings with 2 callbacks, and 38 postings with 3 callbacks). While we do not estimate Chamberlain fixed-effect logit model directly at this point, we do present estimates of the average callback rates by age group conditional on the number of callbacks received for the job posting.

Table 5 contains mean callback rates in round 4 for postings that received 1 to 3 callbacks. The evidence is clear. Applicants in the oldest age groups received callbacks at a significantly lower rate than applicants in either of the two younger groups. For the 150 postings in which one of four applications received callbacks (for an aggregate callback rate of 25 percent), applicants in their 50s received callbacks at a rate 16 percentage points less than applicants their 30s or 40s (about a 50 percent lower callback rate). For the 85 postings postings in which two of four applications received callbacks (for an aggregate callback rate of 50 percent), applicants in their 50s received callbacks at a rate that is 16 percentage points less than applicants in their 30s (about a 30 percent lower callback rate) and 30.3 percentage points less than applicants in their 40s (about a 47 percent lower callback rate). There is no difference in callback rates by age for the 38 postings in which three of the four applications received callbacks. Applicants in each of the three age groups had callback rates very close

to the 75 percent overall rate.

Overall, Table 5 confirms the negative effect of age on callback even holding the job-specific callback rate constant. In addition, the finding of no difference in callback rates by age category for job postings with three callbacks is consistent with our hypothesis that worker characteristics are less important when employers are less selective, as indicated in this case by callbacks to 3 of 4 applicants. The high callback rate may reflect a need by the employers to fill a large number of jobs quickly. In this case the employer would accept most of the applicants and be less sensitive to individual characteristics. This implies that these employers should be less sensitive to other worker characteristics as well, and we examine this directly below. However, the overall pattern is clear. Employers are generally substantially less like to call back older job applicants.

## 4.3 Interim Jobs

An important decision facing an unemployed worker is whether to take an interim job at a lower level than, and not directly relevant to, the job the worker is seeking. The obvious positive aspect of taking such a job is that it provides income to the unemployed worker, particularly if the worker is not receiving unemployment compensation. Another possible advantage is that potential employers may infer from the fact that the worker has taken such a job that he/she is hardworking and strongly motivated to stay employed. However, it is possible that potential employers will infer that the worker is not of appropriate quality precisely because the he/she has been working in a lower level job. In some cases, this may be the result of the employer using some kind of automated or cursory screening of job applications that rejects applications if their most recent job is not relevant to the job for which the applicant is applying.

Which of these potential mechanisms is at work or which dominates is an empirical question that we address. Beginning in round 3, we introduced a treatment to interrupt a spell of unemployment with work at a low-level interim job. We defined an interim job as one with low wages and for which the candidate appeared ill-matched (in terms of education and previous experience). For example, the interim jobs included sales associate or cashier at a big box or grocery store, and restaurant server. The resumes with such jobs indicate that the job was currently held by the new applicants and started in the month just prior to the application. These jobs interrupted an unemployment spell of varying duration identical to those unemployment spells we investigate directly (0, 4, 12, 24, or 52 weeks). The randomization with respect to interim job was conducted at the application level, within job

Table 6: Average Callback Rate, by Interim Job and Round

| | All | Round 3 | Round 4 |
|---|---|---|---|
| All | 0.0916 | 0.0929 | 0.0912 |
| | (0.0047) | (0.0089) | (0.0055) |
| No Interim Job | 0.0982 | 0.0965 | 0.0986 |
| | (0.0058) | (0.0116) | (0.0067) |
| Interim Job | 0.0849 | 0.0894 | 0.0837 |
| | (0.0056) | (0.0109) | (0.0064) |
| Difference | -0.0132 | -0.0071 | -0.0149 |
| | (0.0063) | (0.0136) | (0.0072) |

Note: Numbers parentheses are standard errors clustered by job id.

posting. Interim jobs appeared on an application with probability 0.5. In round three, with two applications per job posting, there could be 0, 1, 2 applications with an interim job. In round four, with four applications per job posting, there could be 0, 1, 2, 3, or 4 applications with an interim job.

Of the 834 job postings analyzed in round 3, for 219 (26.3 percent) neither of the applications indicated an interim job, for 391 (46.9 percent) one of the two indicated an interim job, and for 224 (26.9 percent) both applications indicated an interim job. Of the 1518 job postings analyzed in round 4, for 77 (5.1 percent) none of the applications included an interim job, for 438 (28.9 percent) one of the applications included an interim job, for 516 (34.0 percent) two of the applications included an interim job, for 419 (27.6 percent) three of the applications included an interim job, and for 68 (4.5 percent) all four applications included an interim job.

The applications in rounds three and four varied randomly in unemployment duration and age, and this variation is independent of the variation in interim job. We account for these other dimensions of variation in the multivariate analysis below.

Table 6 contains mean callback rates for rounds 3 and 4 by whether or not an interim job was indicated on the application. The overall callback rate in rounds 3 and 4 was 9.2 percent. The call back rate was 9.8 percent where there was no interim job versus 8.5 percent where there was an interim job. This difference of 1.3 percentage points (15 percent) is statistically significant ($p$-value = 0.038). When analyzed separately by round, there is no difference in round 3 and a larger statistically significant difference in round 4 (9.9 percent with no interim job versus 8.4 percent with an interim job).

Given the within-job randomization of the existence of an interim job, we once again examine how callbacks vary with an interim job within job posting. Again, this analysis is

Table 7: Average Callback Rate, Rounds 3 and 4, by Interim Job and Number of Callbacks

| | 1 Callback Round 3 | 1-3 Callbacks Round 4 | 1 Callback Round 4 | 2 Callbacks Round 4 | 3 Callbacks Round 4 |
|---|---|---|---|---|---|
| No Interim Job | 0.556 | 0.432 | 0.314 | 0.515 | 0.718 |
| | (0.049) | (0.017) | (0.018) | (0.025) | (0.035) |
| Interim Job | 0.453 | 0.361 | 0.184 | 0.485 | 0.784 |
| | (0.042) | (0.020) | (0.018) | (0.025) | (0.037) |
| Difference | -0.102 | -0.071 | -0.130 | -0.029 | 0.066 |
| | (0.090) | (0.029) | (0.035) | (0.050) | (0.071) |
| N Postings | 59 | 273 | 150 | 85 | 38 |

Note: By construction, the average callback rate in round 3 is 0.5 for postings with 1 callback. Similarly, the average callback rate in round 4 is 0.25 for postings with 1 callback, 0.5 for postings with 2 callbacks, and 0.75 for postings with 3 callbacks. Numbers parentheses are standard errors clustered by job id.

restricted to applications to job postings for which there was variation in callback. Table 7 contains mean callback rates for postings in round 3 that received 1 callback and in round 4 for postings that received 1 to 3 callbacks. Although the point estimate of the difference in call-back rates for single-callback postings in round 3 is negative and substantial in magnitude, this difference is not statistically significant given the small number of postings (59) that meet the sample criteria. The difference in call-back rates for postings with one to three callbacks in round 4 is a statistically significant 7.1 percentage points ($p$-value=0.015). This difference is driven by a large negative difference in callbacks by interim job status (13.0 percentage points) for the 150 postings that received a one call-back ($p$-value $< 0.0005$). The differences in callback rates by interim job status for postings with 2 or 3 callbacks are not statistically significant.

The overall pattern of results suggests that holding a job that is lower skill and irrelevant to the job for which the individual is applying reduces the likelihood of a callback, at least for selective employers. It appears that an unemployed worker is better off remaining unemployed and searching for work rather than being employed in a low-level job while searching. Alternatively, if an applicant has taken a low-level interim job, they may be better off not listing this job on their resume.

In addition, again the finding of a significant difference in callback rates by interim job status in round 4 only for job with one callback and not for jobs with more callbacks is (as with age) is consistent with our hypothesis that worker characteristics are more important when employers are more selective, as indicated in this case by callbacks to a single applicant.

# 5 Multivariate Analysis

We now turn to a multivariate analysis that models the probability of call-back as a function of unemployment duration, age, and interim job. This analysis first uses both within- and between-posting variation in application characteristics. We choose the logit model for several reasons. In principle, it should provide a better approximation of the funcational form for binary choice probabilities with a relative low incidence.[11] Given the canonical sample design of recent audit studies that provide random variation *within*, a particular advantage of the logit model is that it provides a consistent approach that allows us to obtain estimates for that rely on within-posting variation via the Chamberlain fixed-effect logit model. Finally, the logit model allow us to contrast the fixed-effect estimater with a random effects logit, our preferred specification.

The random effects model accounts for the fact that job postings are randomly drawn from the underlying population and may differ in their mean callback rate. This model is appropriate (yields consistent estimates) where the baseline variation across job postings in their callback rates is uncorrelated with the observed applicant characteristics of interest. Given our approach in sending resumes to job listings with key characteristics varying randomly, we would not expect the job-specific callback rate to be correlated with resume characteristics so that estimates derived using the random effects model should be consistent. More generally, since the three treatments were assigned independently to resumes, there is no reason to expect that the multivariate analysis in general, and the conditional logit in particular, will affect our main results.

Table 8 presents the main results of our multivariate analysis. We report our findings in terms of odds ratios, which for small probabilities are approximately the ratio of probabilities of callback given a treatment vs. no treatment.[12] Age enters as a dummy variable for whether a worker is 55-58 years of age (rather than 35-42). The first three columns present results for the logit, random effects logit, and fixed-effects logit, respectively, pooling four rounds.

Recall that there is 1) within opening variation in unemployment duration in all rounds, 2) within opening variation in age only in round 4, and 3) within opening variation (or any

[11] We have reproduced these findings with linear probability and probit models, and the results are not affected by the choice of functional form.

[12] Let $p(1) \equiv Pr\{Callback = 1|X, D = 1\}$ and $p(0) \equiv Pr\{Callback = 1|X, D = 0\}$, where $D$ represents one of our right hand side dummy variables, and X represents the remaining variables in the model. Then the odds ratio $R$ is defined as $R \equiv \frac{p(1)/(1-p(1))}{p(0)/(1-p(0))} = exp\{\beta_D\}$, where $\beta_D$ is the coefficient on $D$. Where the probabilities involved are small, the odds ratio is approximately the ratio of probabilities $\left(\frac{p(1)}{p(0)}\right)$.

variation for that matter) in interim job holding only in rounds 3 and 4. The simple logit and random-effect logit models (columns 1 and 2) use all available variation for all factors, even if they were not randomly assigned within jobs. The between-job variation yields valid estimates, since the pairing of resumes with jobs was effectively random with respect to job and resume characteristics. To make sure our our results are not affected by the inclusion of variation between jobs, we then implement the fixed-effects logit model, which relies only on within opening variation. The within variation for unemployment duration is coming from all four rounds; it is coming from round 4 for age; it is coming from rounds 3 and 4 for interim job. To examine a specification where all three factors are treated symmetrically, we then restrict the analysis to round 4, where there are four applications per opening and within-opening variation in all three factors. The logit, random-effects logit, and fixed-effects logit for data from round 4 only is shown in in columns 4 to 6 of Table 8.

Given we have purposefully chosen to work with a homogeneous groups of workers, the only control variable (other than dummies for rounds in columns 1 and 2) is a dummy for whether the city was initially classified as one of our low unemployment cities (Dallas, Omaha, Pittsburgh, Portland ME) or as one of our high unemployment cities (Charlotte, Chicago, Sacramento, Tampa). This effect is identified only from between job-opening variation.

Overall and as expected, the results in Table 8 confirm our three main findings from the previous section. There is no detectable effect of unemployment duration on callback rates. The $\chi^2$ test statistic and corresponding $p$-value we present are for the null hypothesis that the four coefficients on the unemployment duration dummies are jointly equal to zero. In none of our models can we reject this null hypothesis. Again, we find there is a precisely estimated negative effect (an estimated odds ratio less than one) of age on the callback rate. Finally, there is a substantial negative effect of reporting holding an interim job on the callback rate.

The first column of table 8 shows basic logit estimates pooling all four rounds, clustering standard errors at the job level. The second column adds random effects. As expected, controlling for random variation in the callback rates across openings improves the fit of the model substantially (as indicated by the improvement in the log-likelihood value) and reduces standard errors slightly. The odds ratio on age drops from 0.8 to 0.57. We have no economic explanation for this, since the random effects are not correlated with the independent variable. However, their presence change the interpretation of the coefficient. Whereas the coefficients of the logit model can be interpreted as the average effect in the population,

Table 8: Logit, Random Effects Logit, and Conditional Logit Estimates: Odds Ratios

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Logit | RE Logit | FE Logit | Logit | RE Logit | FE Logit |
| Variable | All Rounds | All Rounds | All Rounds | Round 4 | Round 4 | Round 4 |
| 4 Weeks U | 0.973 | 0.948 | 0.951 | 1.092 | 1.103 | 1.053 |
| | (0.084) | (0.139) | (0.151) | (0.152) | (0.235) | (0.235) |
| 12 Weeks U | 1.140 | 1.260 | 1.278 | 1.206 | 1.388 | 1.413 |
| | (0.100) | (0.181) | (0.203) | (0.181) | (0.289) | (0.312) |
| 24 Weeks U | 1.084 | 1.158 | 1.170 | 1.243 | 1.388 | 1.350 |
| | (0.092) | (0.164) | (0.182) | (0.174) | (0.285) | (0.290) |
| 52 Weeks U | 0.990 | 1.111 | 1.178 | 1.092 | 1.310 | 1.353 |
| | (0.086) | (0.163) | (0.188) | (0.154) | (0.278) | (0.301) |
| Age 55-58 | 0.791 | 0.566 | 0.531 | 0.687 | 0.528 | 0.529 |
| | (0.055) | (0.059) | (0.063) | (0.056) | (0.063) | (0.063) |
| Interim Job | 0.850 | 0.725 | 0.715 | 0.839 | 0.735 | 0.728 |
| | (0.065) | (0.088) | (0.092) | (0.073) | (0.095) | (0.100) |
| Low Local U | 1.430 | 2.003 | — | 1.161 | 1.285 | — |
| | (0.117) | (0.292) | | (0.155) | (0.281) | |
| $\hat{\rho}$ | | 0.780 | | | 0.704 | |
| | | (0.011) | | | (0.024) | |
| Log L | -4018.4 | -3551.2 | -569.9 | -1840.8 | -1515.2 | -393.1 |
| $\chi^2$ | 4.14 | 4.52 | 4.42 | 2.86 | 4.02 | 4.20 |
| P-Value | 0.39 | 0.34 | 0.35 | 0.58 | 0.40 | 0.38 |
| Sample Size | 12224 | 12224 | 1604 | 6072 | 6072 | 1092 |

Note: The $\chi^2$ and P-value refer to the test statistic for the null hypothesis that the four coefficients on unemployment duration are jointly zero. Columns 1 and 2 include indicators for round of the experiment. Numbers in parentheses are standard errors. Standard errors in columns 1 and 4 are clustered at the job level.

coefficients of the random effects model are the effects holding constant the within-opening callback propensity. Third column contains estimates of the Chamberlain fixed-effect logit model, which uses only those job openings for which there was variation in callback rates (one callback in rounds 1-3 and one to three callbacks in round 4). As expected given the random assignment of characteristics to resumes, the fixed-effect estimates are virtually identical to the random-effect estimates in column 2. In order to formally compare the random and fixed effects models, we performed a Hausman test. The value of the $\chi^2$-test statistic (6 degrees of freedom) is 2.69 with $p$-value of 0.85, implying we cannot reject the hypothesis that the fixed effects are uncorrelated with the factors included in the model.

Columns 4-6 show the results of repeating the analysis using only data from round 4,

where there are four applications per opening and within-opening random variation in all three factors. The results are very similar compared to the model pooling all rounds. The only notable difference is that the coefficient on the dummy for a low local unemployment rate in columns 4 and 5 is not statistically significant (odds-ratio not significantly different from 1) anymore. Note, however, that round 4 was fielded substantially later than the earlier rounds, and, while differences in unemployment rates across labor markets persisted, they are smaller in 2014 (when round 4 was fielded) than earlier.

Column 6 then presents findings for the fixed-effect logit model for round 4. As we noted, the model is identified only from qudruplets of job applications in which callback varies (1-3 callbacks to 4 applications). Dropping the 1215 job postings for which we received no callbacks and the 30 job postings for which all four applications received callbacks leaves leaves 1092 observations for 273 job postings, a reduction of over 80% with respect to the full round 4 model in columns 4 and 5 (6072 observations for 1518 job postings). Nevertheless, the results in column 6 are very similar to those from the random effects logit in column 5, particularly with regard to the effect of age and interim job. Once again, we performed a Hausman test of the hypothesis that the fixed effects are uncorrelated with the factors included in the model. The value of the $\chi^2$-test statistic is 1.63 with $p$-value of 0.95, implying, as with the estimates for all four rounds, that we cannot reject the hypothesis that the fixed effects are uncorrelated with the factors included in the model.

Overall, the results in Table 8 confirm our main findings using the full power of the pooled sample. We tried various alternative specifications, none of which yielded additional statistically meaningful findings. In particular, we tried to assess whether the effects of unemployment duration, age, and interim jobs vary with the local unemployment rate. This is particularly interesting, because a key result of KLN's analysis was that the effect of unemployment duration on callback rates is lower in markets with higher unemployment rates. Not surprisingly, our finding, that unemployment duration on the resume does not affect the callback rate, does not vary with the local unemployment rate. We also do not find that the effect of age or interim jobs varies by the state of the local labor market.

Again mirroring our univariate analysis, in Table 9 we replicate the main logit model using observations only from round 4 separately for jobs with different numbers of callbacks. Column 1 from the table simply replicates column 4 from Table 8. Column 2 then shows the results when we drop jobs for which either all or none of the resumes we sent received a callback. Our results on age and interim jobs are unchanged, with older applicants and

Table 9: Logit Estimates for Round 4 by Number of Callbacks: Odds Ratios

| Variable | (1) Any Callback | (2) 1-3 Callbacks | (3) 1 Callback | (4) 2 Callbacks | (5) 3 Callbacks |
|---|---|---|---|---|---|
| 4 Week U | 1.092 | 1.119 | 0.761 | 1.470 | 1.400 |
| | (0.152) | (0.225) | (0.248) | (0.524) | (0.850) |
| 12 Weeks U | 1.206 | 1.450 | 1.113 | 1.702 | 1.692 |
| | (0.181) | (0.306) | (0.326) | (0.732) | (1.058) |
| 24 Weeks U | 1.243 | 1.287 | 1.227 | 1.525 | 1.564 |
| | (0.174) | (0.253) | (0.363) | (0.561) | (1.004) |
| 52 Weeks U | 1.092 | 1.314 | 0.925 | 2.081 | 1.179 |
| | (0.154) | (0.261) | (0.283) | (0.783) | (0.698) |
| Age 55-58 | 0.687 | 0.481 | 0.373 | 0.363 | 0.965 |
| | (0.056) | (0.076) | (0.086) | (0.132) | (0.447) |
| Interim Job | 0.839 | 0.758 | 0.476 | 1.016 | 1.423 |
| | (0.073) | (0.096) | (0.098) | (0.217) | (0.575) |
| Low Local U | 1.161 | 0.963 | 1.072 | 0.991 | 0.941 |
| | (0.155) | (0.091) | (0.048) | (0.037) | (0.087) |
| Constant | 0.107 | 0.889 | 0.686 | 1.085 | 1.955 |
| | (0.015) | (0.150) | (0.158) | (0.350) | (0.866) |
| Log L | -1840.8 | -712.1 | -326.9 | -223.0 | -84.5 |
| $\chi^2$ | 2.86 | 3.82 | 2.33 | 3.83 | 0.85 |
| P-Value | 0.58 | 0.43 | 0.67 | 0.43 | 0.93 |
| Sample Size | 6072 | 1092 | 600 | 340 | 152 |

Note: The $\chi^2$ and P-value refer to the test statistic for the null hypothesis that the four coefficients on unemployment duration are jointly zero. Numbers in parentheses are standard errors clustered by job id.

applicants who report holding an interim job substantially less likely to receive a callback.[13] Columns 3 to 5 in Table 9 then show the results for different number of callbacks per application. Consistent with the findings in our univariate analysis, the effect of age is present for only applications to jobs with one or two callbacks. There is no significant difference in callback rates by age for jobs with three callbacks. The effect of reporting the holding of an interim job is present only for applications to jobs with one callback. There is no significant difference in callback rates by interim jobs for jobs with two or three callbacks. Consistent with the earlier results, there is no relationship between the likelihood of callback and unemployment duration for any group we study.

[13] Note that column 2 in Table 9 uses the same sample as column 6 in Table 8, and the results are very similar.

The pattern of results in Table 9 confirms our finding from the descriptive analysis in Section 4 that employers who are eager to hire – and hence have a higher callback rate for their job posting – are less choosy, i.e., resume characteristics appear to matter less in determining callback. When employers are "hungry" for workers, they are less selective. This supports the view that a strong labor market can play an important role in reducing the disadvantage of particular types of applicants (e.g., older applicants) in searching for jobs.

# 6 Reconciliation with Earlier Work

Our finding of no relationship between the duration of unemployment and the likelihood of a callback for mature and older workers is consistent with some prior audit studies and at odds with others. The closest parallel studies that find important effects of unemployment duration is that of Kroft, Lange, and Notowidigdo (2013) and Ghayad (2014). Those studies finds that in the U.S. in 2011-2012 shorter unemployment spells reduced callback significantly for younger workers. In contrast, Nunley et al (forthcoming) finds that for relatively recent U.S. college graduates unemployment duration has no effect on callbacks. The results of a Swedish audit study of Eriksson and Rooth (2014) also pertain to younger workers, and imply no effect of shorter ongoing unemployment spells or past unemployment spells on the callback rate, but a negative effect of long current unemployment spells on callback.

While these studies follow a comparable basic blueprint, it is important to recognize that there are subtle and not-so-subtle differences in the implementation that could affect the results. In particular, our study is narrowly targeted at one type of worker in one type of job. By focusing on female administrative support workers with a 4-year college education, we have a relatively clean design without having to control for confounding variables. But this is at the cost of potentially limited external validity. Additionally, while we cover a fairly wide age range, we do not include the very young workers who are the focus of some of the earlier studies.

In this section, we explore differences among the studies that could account for the difference in results. We focus particularly on the Kroft, Lange and Notowidigdo analysis because 1) like ours, it is U.S. based in the post-Great-Recession period and encompasses most of our cities; 2) many of the jobs in their analysis are of the same type as ours, allowing for a direct comparison in callback rates; 3) the data are publicly available, allowing us to comparable models on their data and our data; 4) the paper has already been highly

influential. All of this provides strong motivation to carefully assess the extent to which their approach is comparable to ours.[14] For ease of exposition, we refer to this study as "KLN" and to our study as "FSvW".

In the following we focus on five key differences in the design and implementation of the KLN and FSvW studies that could account for the difference in results: 1) outcome measure, 2) type of job for which applications are submitted, 3) time period, 4) choice of cities, 5) education level, and 6) age range of the applicants. We consider each of these in turn.

## 6.1 The Outcome Measure

The KLN analysis focuses on callbacks that include a request for an interview while our study and those of Ghayad (2014) and Eriksson and Rooth (2013) focus on all callbacks, regardless of whether or not there was an interview request. This is reflected in a difference in reported callback rates. Our callback rate was 10.4 percent while the KLN callback-w/interview rate was 4.7 percent. Using data supplied by KLN, we calculate that the overall callback rate in KLN was 12.1 percent, comparable in magnitude to the callback rate we found.

The key question here is whether the KLN overall callback rate is negatively related to the length of unemployment spell. In order to address this question, we obtained a copy of the data KLN used. Using both these data and the data from our study, we estimate a simple model of the effect of unemployment duration on the probability of callback. The model we use is a simple logit model with only a constant and the duration of unemployment in months. Table 10 contains the results of this analysis. The first row of this table contains the estimate of the marginal effect of unemployment duration on the callback rate for the overall FSvW sample, and it confirms the finding of no significant relationship in our sample. The second and third rows of this table contain estimates of the marginal effect of unemployment duration on the callback rate for the overall KLN sample for the two definitions of callback. The estimate in row 2 uses KLN's preferred callback/interview measure and confirms their finding of a significant negative effect of unemployment duration. Our reanalysis of the KLN overall callback measure in row 3 shows an even stronger negative relationship between the duration of unemployment and the probability of callback. Thus the difference in outcome

[14] Ghayad (2014) collected data in the U.S. in 2012 for 3 broad occupations (administrative, sales, and professional) in four broad industries. Eriksson and Rooth (2014) collected data in Sweden in 2007 for 7 occupations (business sales assistant, cleaner, construction worker, machine operator, motor-vehicle driver, restaurant worker, and shop sales assistant). In contrast, our data were collected from 2012-2014 for a single broad occupation (white collar office jobs such as administrative or executive assistants, receptionists, secretaries, and office associates).

Table 10: Analysis of the KLN Applications in the FSvW Cities

| Sample | N Apps | Callback Rate | Marginal Effect U months |
|---|---|---|---|
| (1) FSvW Data | 12224 | 10.37 | 0.00001 |
| | | | (0.00061) |
| (2) KLN Callback/Interview | 9236 | 4.54 | -0.00086 |
| | | | (0.00024) |
| (3) KLN All Callback | 9236 | 12.05 | -0.00141 |
| | | | (0.00024) |
| (4) KLN Admin/Cler Jobs | 2690 | 3.61 | -0.00079 |
| | | | (0.00037) |
| (5) KLN 4-Year College | 3519 | 12.56 | -0.00202 |
| | | | (0.00053) |
| (6) KLN FSvW cities | 1130 | 12.12 | -0.00192 |
| | | | (0.00094) |
| (7) KLN Non-FSvW Cities | 8106 | 12.04 | -0.00133 |
| | | | (0.00037) |
| (8) KLN 19-22 Years Old | 674 | 10.68 | -0.00515 |
| | | | (0.00186) |
| (9) KLN 23-26 Years Old | 3840 | 11.59 | -0.00078 |
| | | | (0.00054) |
| (10) KLN 27-30 Years Old | 3622 | 12.78 | -0.00197 |
| | | | (0.00055) |
| (11) KLN 31-39 Years Old | 1100 | 12.09 | -0.00268 |
| | | | (0.00099) |

Note: Marginal effects on the probability of callback calculated from logit model of callback. Robust standard errors clustered by job id in parentheses.

measure is not a factor that can explain the difference in findings. The point estimate in row 3 of the table implies a reduction in the probability of callback of about 0.8 percentage points per month of unemployment. This is a reduction of about 7 percent at the mean of 12.05 percent, a substantial effect!

In order to maintain comparability with our analysis, our reanalysis of the KLN data continues using the measure of the overall callback rate rather than the callback/interview measure.

## 6.2 Variation in Job Type

All job applied for in the FSvW analysis were white-collar office support jobs and all applicants were female. The KLN analysis included applications for three types of jobs: 1) administrative support and clerical, 2) customer service, and 3) sales. The first KLN occupational group, administrative support and clerical, is comparable to the office support jobs in the FSvW analysis, and 96.4 percent of the 2690 applicants for these jobs in the KLN sample were female.

Row 4 of table 10 contains results of the analysis for the KLN administrative support and clerical jobs. The first thing to note is that the overall callback rate for these jobs in the KLN data is extremely low at 3.61 percent. There were only 97 callbacks to 2690 applications for this type of job. Still, there is a statistically significant negative relationship between unemployment duration and the probability of a callback. However, it is only about 56 percent as large as the estimated effect in the overall KLN sample. The point estimate in row 4 of the table implies a reduction in the probability of callback of about 0.5 percentage points. This is a reduction of about 13 percent at the mean callback rate of 3.61 percent, comparable to the implied effect for the full sample in row 3. We conclude that variation in the type of job does not account for the qualitative difference between our results and those of KLN.

## 6.3 Education Level

Related to job type is the skill level of the applicants. All applicants in the FSvW analysis were graduates of 4-year colleges. In contrast, the KLN analysis included applicants who had completed high school (20 percent), community college (42 percent), and 4-year college (38 percent). There is no difference in callback rates by education level in the KLN analysis, but it is worth investigating whether the relationship of the likelihood of callback with unemployment duration holds up for the KLN 4-year college graduates.[15]

Row 5 of table 10 contains results of the analysis for the KLN applicants who have a four-year college degree. The callback rate for these applicants is very close to the overall callback rate in the KLN data. The marginal effect of unemployment duration on the probability of callback is significantly negative for the KLN four-year college graduates and larger in magnitude than for the overall sample (compare rows 6 and 3 of table 10). We conclude that

[15] The $p$-value for test of independence of callback and education in a two-way table is 0.497.

variation in the education level of applicants does not account for the qualitative difference between our results and those of KLN.[16]

## 6.4 Time Period

The KLN analysis is based on job applications submitted between June 2011 and July 2012 while the FSvW analysis is based on applications submitted between March 2012 and August 2014. Clearly, the KLN analysis is much earlier in the period of recovery from the Great Recession. This may be part of the explanation for the fact that KLN find a much lower call-back rate to their applications for comparable jobs (3.61 percent for administrative/clerical jobs) than we find (10.4 percent).[17] However, the information-based theory highlighted by both KLN and FSvW suggests that, to the extent employers infer worker quality partly from unemployment duration, the negative effect of unemployment duration on the callback rate should *grow* as the recovery proceeds and the labor market strengthens. in fact, even for our data from round 1 in 2012 we find a zero effect, in contrast with the basic updating model.[18]

A potential source of reconciliation between the disparate findings of KLN and FSvW is suggested by our within-posting analysis. The results in (Table 9) suggest that observable characteristics are more important when callback rates are lower (e.g., 1 callback from 4 applications as opposed to 3 callbacks from 4 applications). The generally lower overall callback rates found by KLN are consistent with employers exercising more discretion in callbacks so that unemployment duration could play a more important role in the time period covered by their sample.

## 6.5 Geographic Variation

As explained in Section 2, FSvW analysis was designed to cover 8 metropolitan areas, 4 with relatively low unemployment rates (Dallas, Omaha, Pittsburgh, and Portland ME) and 4

[16] We also examined the smaller subset of the KLN sample that consisted of four-year college graduates applying for administrative/clerical jobs. The marginal effect of unemployment duration on the probability of callback is negative but not significantly different from zero in this smaller sample ($p$-value = 0.14). Given the small size of the sample (936 applicants), we do not draw any conclusion from this result.

[17] Eriksson and Rooth (2014) find a callback rate of 25 percent in their 2007 Swedish study. Ghayad (2014) finds a callback rate of 8.3 percent in his 2012 (post Great Recession) U.S. study. Note that these aggregate statistics refer to broader distributions of worker type.

[18] Indeed, KLN investigate cross-sectional variation in the marginal effect on call-back rates of unemployment duration by local unemployment rates (a second-order effect) and find that the marginal effect of unemployment duration on callback becomes more negative as the unemployment rate falls.

with relatively high unemployment rates (Charlotte, Chicago, Sacramento, and Tampa). In contrast, the KLN analysis covers 100 large American metropolitan areas.[19] Their analysis includes observations on 7 of the 8 cities used by FSvW, the exception being Portland ME. We investigate the extent to which differences in geographic coverage can account for the difference in findings across the two studies by using the 7-city subset of the KLN data to estimate our simple model of the effect of unemployment duration on the probability of callback.

Rows 6 and 7 of Table 10 contains the results of this analysis. Row 6 of the table contains estimates of the marginal effect of a month of unemployment on the probability of callback for the KLN subsample for the 7 FSvW cities. There are only 1130 applications in these cities so it is not surprising that the marginal effect of unemployment is estimated less precisely. However, the estimate is negative and significantly different from zero ($p$-value =0.042). The estimated marginal effect for the 8106 applications from the remaining 92 cities in the KLN sample, presented in row 7 of the table, is comparable in magnitude and significantly negative at conventional levels. These results imply that differences in the geographic composition of the KLN and FSvW samples are not likely to account for the differences in results.

## 6.6 Variation in Age

The differences in the implied age range of the resume is the most striking contrast between our and other audit studies of the effect of unemployment duration on callback. The distributions of age of applicants in the KLN and FSvW samples are largely non-overlapping. Applicants in the KLN sample range in age from 19-39, with 99 percent between 21 and 33, while applicants in the FSvW sample range in age from 35-58. As explained in our model in Section 3, this contrast has the potential to account for the different findings with regard to the relationship between unemployment duration and the probability of callback. KLN note themselves in their conclusion that it is important to assess whether their findings hold for older workers.

Rows 8-11 of table 10 contain analyses of the callback rate separately for four age groups in the KLN sample. Callback rates are similar across all four age groups, ranging from 10.7 percent to 12.8 percent.[20] The marginal effect of unemployment duration on the callback rate is estimated to be negative for all age groups. There are significant differences in the

[19] Ghayad (2014) covers the 25 largest metropolitan areas in the U.S.

[20] A $\chi^2$ test of independence of age and callback fails to reject independence ($p$-value =0.28).

marginal effect across age groups ($p$-value of test that all marginal effects equal = 0.047), but the absolute magnitude of the effect does not decline monotonically with age. The effect is largest by far in absolute magnitude for the youngest applicants (19-22 years old) then declines for applicants aged 23-26 before rising somewhat for applicants 27-30 and for applicants 31-39 (97.5 percent of whom are 31-34).

Given the substantial difference in the age ranges covered by KLN and our analyses, it is difficult to conclude anything from the age variation in the effect of unemployment duration within KLN's sample. However, age may be an important factor in accounting for the difference in findings. The older applicants used by FSvW have significant longer work histories that may outweigh any recent unemployment experience when resumes are evaluated by potential employers. The younger applicants used by KLN do not have nearly as extensive a history and so recent unemployment experience may get higher weight in the evaluation of applicants. We also note that the applicants in the Eriksson-Rooth (2014) Swedish study and the Ghayad (2014) U.S. study are all in their twenties with no more than about 5 or 6 years of experience, which may account for their findings of significant effects of unemployment duration on callback.

To summarize the comparison with KLN regarding the effect of unemployment duration on the callback rate, the differences in the outcome measure and the choice of cities do not appear to be important factors in understanding the difference in findings. The differences in job type and time period have the potential to explain some but not all of difference in findings. The differences between the studies in applicants' age is a strong candidate to explain the difference. However, the lack of overlap in the ages of applicants in the FSvW and KLN studies make it difficult to draw a definitive conclusion in this regard. Without a single study that includes a full range of ages, our conjecture that the importance of unemployment duration in determining callbacks declines with age remains suggestive rather than conclusive.

# 7 Final Comments

Based on our audit study of the determinants of the likelihood of callbacks to job applications, we find clear evidence that employers are less likely to call back older applicants (those in the fifties) than younger workers (those in their thirties and forties). This is consistent with work based on the Displaced Workers Survey and administrative data showing that older displaced workers are less likely to be employed subsequent to job loss (Farber, 2015) and to suffer

long-term nonemployment (Song and von Wachter 2014), and it has potentially important implications for the employment prospects of older job losers. We also find clear evidence that holding a relatively low-level interim job at the time of job application significantly reduces the likelihood of a callback. This suggests that employers may, either mechanically or by rule-of-thumb, over-weight the most recent employment spell in screening applications and suggests that those individuals who do take a lower-level interim job should not report such jobs on their applications.

Recent work reports contrasting findings between unemployment duration and the likelihood of callback for younger workers. While prominent papers find a negative relationship between short unemployment durations and callback for the U.S. (Kroft, Lange, and Notowidigdo, 2013; Ghayad, 2014), another study finds no such relationship (Nunley et al. 2014). Again focusing on younger workers, a related paper for Sweden finds no effect of short unemployment spells but negative effects of long unemployment spells on callback (Ericksson and Rooth, 2014). In our work we unambiguously find no relationship between unemployment and callback for mature and older workers. We attempt to reconcile our finding in this dimension with the work of KLN using their data and definitions comparable to ours, but cannot completely resolve the issue. Part of the difference may be time period since all of the earlier studies were fielded much earlier in recovery period from the Great Recession when the labor market was weaker. Another difference, and one we think worthy of further exploration, is that all of the earlier studies focus on younger job applications (mostly in their twenties) while our study focuses on job applicants from their mid-thirties to mid-fifties. While there are good theoretical reasons to suspect that unemployment duration could be less important for older job applicants, a single study that covers the full age spectrum is needed to draw a definitive conclusion on this issue.

Finally, our analysis of within-job-posting variation in callbacks, suggests that observable worker characteristics (age, interim job) are less important when employers are calling back a higher fraction of their applicants. Our interpretation of this finding is that when employers are hungry for workers, they are less selective in who they call back. This suggests the power of stimulating aggregate demand as a strategy to improve the employment prospects of applicants who otherwise would not "make the cut" of receiving any positive response to a job application.

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# Appendix – Sample Resumes

This appendix contains a set of four sample resumes.

1. Linda Carter, Sacramento, 0 weeks unemployment, older worker, no interim job.
2. Jennifer Smith, Pittsburgh, 24 weeks unemployment, medium age worker, no interim job.
3. Heather Adams, Dallas, 52 weeks unemployment, younger worker, interim job.
4. Linda Carter, Dallas, 12 weeks unemployment, older worker, interim job.

# Linda Carter

7041 Reichmuth Way
Sacramento, CA 95831

carterlinda880@gmail.com
(916) 919-9479

## WORK EXPERIENCE

**Reliable Crane & Rigging** Sacramento, CA
*Administrative Assistant/Receptionist* December 2008 – July 2014

- Responsible for all administrative and most accounting tasks
- Answered very busy telephones, handled customer walk-ins, took orders over the telephone
- Handled inventory, filing, invoicing, collections, updating the company website, and correspondence
- Accurately recorded vendor and customer invoices and payments and matched invoices to purchase orders
- Implemented improved billing and invoicing procedures with unprecedented results
- Personally reconciled over $60,000 in previously-uncollected debt within three months
- Developed excellent relationship with customers and vendors alike

**Wilke, Fleury, Hoffelt, Gould** Sacramento, CA
*Executive Legal Secretary* March 2002 – December 2008

- Acted as client contact both on the telephone and in person
- Operated under a very heavy work load, managing all administrative tasks
- Set up meetings and arranged travel
- Composed letters and court documents
- Tracked and accounted for all expenses
- Ensured that all work was completed in a timely and efficient manner

**Jacobson Markham, LLP** Sacramento, CA
*Executive Assistant* March 1998 – February 2002

- Responsible for setting up the practice of a formal federal judge
- Made extensive travel arrangements
- Performed extremely intensive calendaring and scheduling for meetings, appointments, etc.
- Drafted correspondence
- Provided all administrative support to members of the press, board members of prestigious organizations, outside counsel, etc.
- Worked without supervision for lengthy periods of time
- Acted as the point-of-contact for all matters relating to the practice
- Quickly became a favorite among the clients as well as others outside of the firm

**Stoel Rives, LLP** Sacramento, CA
*Receptionist/Administrative Assistant* June 1994 – November 1997

- Scheduled conference meetings and luncheons for various attorneys and legal secretaries
- Oversaw sending and receiving of faxes, packages, and other correspondence
- Typed final drafts of company documents
- Performed various filing tasks

- Answered multi-line telephone system and greeted clients

**California Department of Motor Vehicles** Sacramento, CA
*Secretary* November 1986 – May 1994

- Received business and personal telephone callers and provided information and guidance as needed
- Reviewed and distributed all incoming mail for the office
- Maintained office files and records for various property holdings
- Typed memos into final form from rough draft
- Maintained a system for tracking correspondence requiring a reply and alerting the staff of pending deadlines
- Prepared training and travel orders
- Maintained Time and Attendance cards and leave balances

**California Department of Motor Vehicles** Sacramento, CA
*Clerk Typist/Management Assistant* June 1982 – October 1986

- Reviewed and distributed all incoming mail for the office and recorded suspense dates
- Conducted research using various Department Directives and files in order to provide information necessary to develop administrative procedures for office programs
- Maintained the Directorate files and records for personnel programs
- Typed narrative reports, correspondence and complex reports for the office staff from rough draft
- Performed clerical duties in support of analysis and studies conducted on an individual basis

**Creekside Pet Resort** Sacramento, CA
*Doggie Day Camp Associate* April 1979 – January 1982

- Greeted the "pet parents" while checking in their dogs
- Set up a filing system for each dog to include shot records, assessments and the pet parents' information
- Assessed new dogs to verify they would be suitable for the day camp
- Made sure the dogs stayed safe while playing and interacting with other dogs

## EDUCATION

**California State University-Sacramento** Sacramento, CA
B.A. Sociology May 1978

## SKILLS

- Proficient in accounting software and all MS Office applications
- Able to multi-task, prioritize, and adapt as business needs evolve
- Very professional and highly dependable
- Can handle personnel issues, training, and travel coordination

# Jennifer Smith

514 Fisher Street ~ Pittsburgh, PA 15210

Sjennifer767@gmail.com 412-728-3344


Dec 2006 – Jan 2013 **Alliance Real Estate Associates, LLC,** Pittsburgh, PA

*Tenant Coordinator/Administrative Assistant*

- Assisted two property managers with onsite management of six property portfolios consisting of over 900,000 square feet
- Addressed and answered tenant questions resolving problems and concerns
- Monitored/received and followed up on all tenant requests and/or concerns using (Workspeed) online tenant request service system
- Conducted weekly tenant visits and documented issues
- Coordinated tenant functions
- Composed and typed memos and posted announcements to Workspeed
- Composed and typed correspondence to tenants regarding late rent notices and operating expenses
- Assisted property managers with annual budget preparation, obtained vendor proposals and executed contracts
- Assisted with monthly/weekly building evaluations and report preparations
- Assisted with A/R and AP reconciliations for vendors and tenants
- Prepared/received purchase orders

Jan 2005 – Dec 2006 **Bank of America,** Pittsburgh, PA

*Receptionist*

- Answered telephones, greeted visitors, maintained the lobby area, ordered office supplies and updated Excel employee database
- Handled the dissemination of all outgoing mail as well as distribution of incoming mail to appropriate staff
- Assisted HR with orientation as well as the interviewing process, making sure that all applications were filled out by interviewees and directing them to appropriate staff members
- Fingerprinted newly-hired employees, took pictures of new hires, and ordered lunch
- Put together credit files for Hub
- Pulled documents using the Imaging System, Research and problem –solving for customers
- Coordinated meetings, travel arrangements, office parties, and ball game events

Nov 2002 – Dec 2004 **Berger Real Estate,** Pittsburgh, PA

*Administrative Assistant*

- Provided backup secretarial support for nine senior Administrative Assistants, Directors, and other staff members
- Typed and designed excel spreadsheets, general correspondence, memos, charts, tables, and graphs
- Coordinated and set up all office and set up all-office and client meeting luncheons
- Managed all general office orders and online accounts for supplies
- Assisted Leasing/Property Management Department in preparing quarterly surveys, researched and updated owner/tenant information
- Assisted Finance Department with expense reports, typed correspondence, and provided administrative support as required
- Assisted Sales Department in coordinating, binding, and putting together offering memos for selling of buildings and provided administrative support as required
- Assisted with mass mailing of materials
- Scanned and fine-tuned pictures and other materials

Apr 1995 – Jul 2002 **Custom Cable Corp,** Pittsburgh, PA

*Administrative Assistant*

- Managed and coordinated daily office functions for major cable and construction companies
- Reported daily on company activities and work flow to the Regional and Project Managers
- Hired, trained, and supervised interns
- Encouraged and motivated staff to maintain contractual billing agreements
- Coded and processed weekly billing and invoices for payroll
- Maintained weekly quality control and work percentage on company field support team
- Researched and solved payroll problems
- Distributed held checks after discrepancies were taken care of to employees and contractors
- Maintained personnel information and files
- Oversaw that forms for employment were properly filled-out for new employees and contractors

Education

**Shippensburg University of Pennsylvania**

Bachelor of Arts, English, 1994

| | |
|---|---|
| Skills | • Word, Excel, MS Office Suite, PowerPoint, Outlook, Access, 60 wpm<br>• Accounts payable/receivable<br>• Team player<br>• Excellent communication and follow-up skills, organizational skills and business ethics |

# Heather Adams

1118 West Pleasant Run Road ~ DeSoto, TX 75115

heatheradams337@gmail.com 214-516-0279

Jul 2014– Present **Target,** Dallas, TX
*Cashier Team Member*

- Provides fast and friendly checkout service
- Resolves guest concerns in a calm, respectful manner

Mar 2010 – Jul 2013 **Harbour Group, Inc.,** Dallas, TX
*Administrative Assistant*

- Capably handled filing, faxing and copying tasks on a daily basis
- Wrote, proofread, and made letters signature-ready
- Professionally answered numerous phone calls using multi-line phones
- Copied and filed signed letters before returning to originator
- Handled scheduling and change of appointments for a very busy Executive Director
- Provided monthly printer counts**,** inventoried printer cartridges and toners, supplied buy list to IT personnel, and packaged and labeled empty printer cartridges/toners for shipping back to manufacturer for recycling

Jun 2006 – Mar 2010 **Drake Agency,** Dallas, TX
*Administrative Support*

- Printed CD labels and oversaw burning, scanning, and distribution of company CDs
- Created roster sign-in sheets in PDF format and updated roster sheets in Excel
- Updated files and books as needed for classes
- Formatted documents, adding page numbers, watermarks, and using a PDF Converter
- Edited PowerPoint presentations

Mar 2001 – Jun 2006 **Dallas Employment Service, Inc.,** Dallas, TX
*Administrative Assistant*

- Responsible for day-to-day secretarial needs: took dictation; typed letters, memos, reports; screened telephone calls; attended meetings; scheduled conference calls
- Managed daily administrative needs of Marketing and Operations Departments including maintenance of Microsoft Outlook calendars, coordination of travel arrangements, in-office meeting planning, and out-of-office meeting planning
- Answered multi-line telephone system and directed calls to appropriate staff

- Pre-interviewed visitors and guests as instructed
- Summarized research and prepared informational packets for staff dissemination
- Greeted internal and external clients and opened correspondence
- Maintained conference rooms and scheduled meetings and handled all travel arrangements
- Attended monthly board meetings, prepared minutes, illustrated monthly newsletters, handled in-unit billing and petty cash, and provided front desk coverage
- Disseminated all correspondence and memos
- Supported building manager and other staff with prompt professionalism

Education

**University of Texas-Tyler**
Bachelor of Arts, English, 1999

Skills

- Proven ability to work in fast-paced environment
- Detail oriented and capable of multi-tasking
- Excellent communication and language skills
- Adept at PowerPoint, Word, Excel and PDF editing

# Linda Carter

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Carrollton, TX 75006 214-516-0273

## WORK EXPERIENCE

**Target** Dallas, TX
*Service Desk Team Member* July 2014 – Present

- Resolves guest concerns promptly
- Neatly stocks shelves and maintains a clean store

**American Rigging, Inc.** Dallas, TX
*Administrative Assistant/Receptionist* December 2008 – April 2014

- Responsible for all administrative and most accounting tasks
- Answered very busy telephones, handled customer walk-ins, took orders over the telephone
- Handled inventory, filing, invoicing, collections, updating the company website, and correspondence
- Accurately recorded vendor and customer invoices and payments and matched invoices to purchase orders
- Implemented improved billing and invoicing procedures with unprecedented results
- Personally reconciled over $60,000 in previously-uncollected debt within three months
- Developed excellent relationship with customers and vendors alike

**Turley Law Firm** Dallas, TX
*Executive Legal Secretary* May 2002 – December 2008

- Acted as client contact both on the telephone and in person
- Operated under a very heavy work load, managing all administrative tasks
- Set up meetings and arranged travel
- Composed letters and court documents
- Tracked and accounted for all expenses
- Ensured that all work was completed in a timely and efficient manner

**Stephen Malouf Law Offices** Dallas, TX
*Executive Assistant* March 1998 – February 2002

- Responsible for setting up the practice of a formal federal judge
- Made extensive travel arrangements
- Performed extremely intensive calendaring and scheduling for meetings, appointments, etc.
- Drafted correspondence
- Provided all administrative support to members of the press, board members of prestigious organizations, outside counsel, etc.
- Worked without supervision for lengthy periods of time
- Acted as the point-of-contact for all matters relating to the practice
- Quickly became a favorite among the clients as well as others outside of the firm

**Anderson Jones Law Office** Dallas, TX

*Receptionist/Administrative Assistant* June 1994 – November 1997

- Scheduled conference meetings and luncheons for various attorneys and legal secretaries
- Oversaw sending and receiving of faxes, packages, and other correspondence
- Typed final drafts of company documents
- Performed various filing tasks
- Answered multi-line telephone system and greeted clients

**Texas Department of State Health Services** Austin, TX
*Secretary* November 1986 – May 1994

- Received business and personal telephone callers and provided information and guidance as needed
- Reviewed and distributed all incoming mail for the office
- Maintained office files and records for various property holdings
- Typed memos into final form from rough draft
- Maintained a system for tracking correspondence requiring a reply and alerting the staff of pending deadlines
- Prepared training and travel orders
- Maintained Time and Attendance cards and leave balances

**Texas Department of State Health Services** Austin, TX
*Clerk Typist/Management Assistant* June 1982 – October 1986

- Reviewed and distributed all incoming mail for the office and recorded suspense dates
- Conducted research using various Department Directives and files in order to provide information necessary to develop administrative procedures for office programs
- Maintained the Directorate files and records for personnel programs
- Typed narrative reports, correspondence and complex reports for the office staff from rough draft
- Performed clerical duties in support of analysis and studies conducted on an individual basis

**Camp Bow Wow** Dallas, TX
*Doggie Day Camp Associate* April 1979 – January 1982

- Greeted the "pet parents" while checking in their dogs
- Set up a filing system for each dog to include shot records, assessments and the pet parents' information
- Assessed new dogs to verify they would be suitable for the day camp
- Made sure the dogs stayed safe while playing and interacting with other dogs

## EDUCATION

**University of Texas-Tyler** Tyler, TX
B.A. Sociology May 1978

## SKILLS

- Proficient in accounting software and all MS Office applications
- Able to multi-task, prioritize, and adapt as business needs evolve
- Very professional and highly dependable
- Can handle personnel issues, training, and travel coordination