Duration Dependence and Labor Market Conditions: 
Theory and Evidence from a Field Experiment

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Abstract

This paper studies “negative duration dependence” – the adverse effect of a longer unemployment spell – by sending fictitious resumes to real job postings in 100 U.S. cities. Preliminary results from the ongoing field experiment suggest that the callback rate is decreasing in the length of the worker’s unemployment spell, with a majority of the decline occurring during the first six months. We also explore how this effect varies with local labor market conditions, and we find evidence that duration dependence is stronger when the labor market is tighter. We develop a theoretical framework that shows how the sign of this interaction effect can be used to discern among leading models of duration dependence based on employer screening, employer ranking, and human capital depreciation. Our results suggest that employer screening plays an important role in generating duration dependence. (JEL J64)

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1 Introduction

Does the length of time out of work diminish a worker’s job market opportunities? This question attracts substantial attention from policymakers and researchers alike, reflecting the widespread belief that the adverse effect of a longer unemployment spell – what economists call “negative duration dependence” – undermines the dynamism of the labor market and entails large social costs. Despite this widespread interest, it has proven very difficult to credibly establish that a longer unemployment duration has a strong causal effect on an individual’s job finding probability. The state of the empirical literature is succinctly summarized by Ljungqvist and Sargent (1998), who write: “It is fair to say that the general evidence for duration dependence is mixed and controversial.”

In this paper, we provide some of the first experimental evidence of duration dependence using a large-scale resume audit study. We submit fictitious resumes to real, online job postings across the 100 largest metropolitan areas in the U.S. In designing each resume, we explicitly randomize both the employment status and the length of the current unemployment spell, if the worker is not currently employed. Therefore, the spell length is (by construction) orthogonal to other characteristics of the resume that are observable by potential employers. To allay the concern that the unemployment spell length is not salient to employers, we administered a web-based survey to MBA students. Our survey results indicate that the length of the current spell is salient to the survey participants; in particular, subjects were able to recall a worker’s employment status and unemployment spell length with roughly the same degree of accuracy and precision as other resume characteristics, such as education and job experience. We conclude that the way we represent unemployment durations on the resumes is salient to those making hiring decisions. Therefore, the experimental variation in unemployment durations in our experiment allows us to identify the causal effect of unemployment durations on callback rates.

Turning to our empirical evidence, both simple plots of the raw data and nonparametric regression results show clear visual evidence of negative duration dependence, with the effect most pronounced during the first six months of unemployment. Preliminary regression results confirm these patterns: the estimated effect of unemployment duration on the probability of a callback is both statistically and economically significant. At average levels of market tightness, we find that the callback rate declines rapidly during the first 6 months of unemployment and stabilizes afterwards. At 6 months of unemployment, callbacks are about 40 percent lower than at 1 month of unemployment. To benchmark the magnitude of this result, Bertrand

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2 Throughout the paper we use the term “duration dependence” in place of “negative duration dependence”.
3 As we discuss further in section 2 below, the central challenge is the standard econometric problem of distinguishing state dependence from unobserved heterogeneity in observational data.
4 Oberholzer-Gee (2008) and Eriksson and Rooth (2011) also investigate how employers respond to unemployment spells using a resume audit study. Oberholzer-Gee (2008) analyzes Swiss employer responses to 628 resume submissions. Eriksson and Rooth (2011) submit 8,466 job applications to 3,786 employers in Sweden and compare the effects of contemporary and past unemployment spells. Both of these studies find evidence that long-term unemployment reduces the probability of being called for an interview. Neither of these papers consider how duration dependence varies across local labor markets.
and Mullainathan (2004) found that White sounding names received about 50 percent more callbacks than African-American sounding names.

Our empirical evidence suggests that employers discriminate against the long-term unemployed. The second contribution of this paper is to try to uncover the mechanism that leads to this form of employer discrimination. Several models are consistent with discrimination against the unemployed: employer screening (Vishwanath 1989; Lockwood 1991), employer ranking (Blanchard and Diamond 1994), and skill depreciation (Acemoglu 1995). We develop a simple “mechanical model” that shows how duration dependence varies with market tightness – the ratio of vacancies to unemployed workers – is useful in discerning among these models. As we show and discuss below, employer screening predicts a positive interaction between duration dependence and labor market tightness, employer ranking predicts a negative interaction, and skill (or human capital) depreciation predicts no interaction. This theoretical prediction motivates our decision to implement the experiment across 100 local labor markets and forms the basis of our second empirical test which estimates how duration dependence varies with several proxies for market tightness.5

To implement this test, we consider three complementary approaches. First, we specify a linear probability model for the callback rate, where the intercept and slope coefficient on unemployment duration are both allowed to vary across cities (i.e., we allow for heterogeneity in the treatment effect and in the city-specific average callback rate). This specification is directly motivated by our theoretical results which indicate that there is a one-to-one correspondence between the intercept - the callback rate for a newly unemployed individual - and the level of market tightness. This theoretical result allows us to interpret the correlation between the intercept and slope coefficients across cities as the correlation between market tightness and duration dependence.

We estimate this model using both fixed effects and random effects approaches. Our fixed effect results indicate that the slope parameter is negatively correlated with the intercept; in other words, duration dependence is stronger in cities that have tighter labor markets.6 Unlike the fixed effects approach, which imposes no structure on the covariance between the intercept and slope parameters across cities, the random effects approach assumes that the intercept and slope parameters are jointly drawn from a normal distribution. Consistent with our fixed effects estimates, we find that the random effects on the intercept and slope coefficient are negatively correlated, with the estimated correlation in the two approaches being quite similar.

A more traditional approach to estimating the relationship between duration dependence and market tightness is to rely on proxies for market tightness that are outside of the sample, such as the unemployment

5Our field experiment therefore belongs to the Competing Models class, using the taxonomy developed by Card, DellaVigna, Malmendier (2011).
6It is well known that OLS estimates of the intercept and slope coefficients are correlated. In our setting, this creates a spurious negative correlation between the estimated intercept and slope coefficients across cities. We provide a novel correction for this "mechanical bias" and show that it performs quite well in monte carlo simulations.
rate. We implement this more conventional test by estimating a linear probability model where we allow the marginal effect of unemployment duration on the callback rate to vary with measures of market tightness based on city unemployment rates. We find suggestive evidence that duration dependence is stronger when the monthly unemployment rate in the city is relatively low, and we also find similar evidence using the within-city change in the unemployment rate between 2008 and 2011. Taken together, our empirical tests indicate that the magnitude of duration dependence is significantly larger when the local labor market is relatively tight. As such, they provide suggestive evidence in support of the employer screening model.

We emphasize that all of our reported results are preliminary (especially the results exploiting variation across cities), as our current sample size is roughly 60% of the size of the full experimental sample. The full experimental sample will permit more detailed robustness tests to verify that the correlation between duration dependence and labor market tightness is not being conflated with other characteristics of the local labor market. Additionally, the full experimental sample will also allow for sub-group analysis (comparing men and women, high-skill and low-skill workers, etc.). Currently, we do not find any statistically significant differences in our estimates of duration dependence that vary by gender, education, or job category.

The remainder of the paper proceeds as follows: Section 2 compares our experiment to the previous literature on estimating duration dependence. Section 3 develops the mechanical model, which nests the screening model. Section 4 describes the main results from the screening model, the ranking model, and the human capital depreciation model. Section 5 presents survey evidence consistent with our assumption that the unemployment spell displayed on CVs is salient. Section 6 describes the experimental design. Section 7 discusses our preliminary results from the experiment. Section 8 concludes.

2 Previous Research

It is difficult to identify duration dependence with observational data. The central challenge is that the composition of the population at risk of leaving unemployment varies with the spell length, making it difficult to know whether the population job finding rate declines with spell length because individual job finding rates decline with spell length (“true” duration dependence), or because the pool at risk has shifted towards individuals with low job finding rates (“unobserved heterogeneity”). Only in the former case does the prior unemployment spell length have a genuine causal effect on future job finding rates.

Previous work has shown that without functional form assumptions on job finding rates, it is not possible to distinguish between duration dependence and unobserved heterogeneity using observational data with a single unemployment spell for each individual (Heckman and Singer 1984). Multiple-spell data can resolve this identification problem, but at the cost of strong assumptions on how job finding rates vary across

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7See Imbens and Lynch (2006), for example.
8For a summary of the duration dependence literature, see Machin and Manning (1998).
unemployment spells within an individual.

Given these limitations of non-experimental data, we take an alternative approach to provide new evidence on duration dependence. Following Bertrand and Mullainathan (2004), Lahey (2008), and Oreopolous (2011) – who study racial discrimination, age discrimination, and discrimination against immigrants, respectively – we send a large number of fictitious resumes to real job postings, and we record whether a given resume receives a “callback” for an interview. Unlike these previous papers, we design the experiment to explicitly focus on comparing results across local labor markets by carrying out the experiment in a large number of cities.

Our research design most directly uncovers duration dependence that arises due to employer behavior. The experiment does not provide any insight into whether the unemployed become discouraged with increase durations (Krueger and Mueller 2011) or whether their reservation wages over time (Kasper 1967). Another important limitation of our study is that we do not observe actual job offers. Rather, we observe whether interviews are granted, which is only one component of the hiring process. We discuss in detail below how this limitation affects the design of our theoretical model as well as the interpretation of our experimental results.

3 A Mechanical Model of Duration Dependence in Unemployment

This section describes a mechanical model of job finding rates. The model generates two predictions: first, job finding rates decline with the duration of unemployment; second, duration dependence strengthens in tighter labor markets. We label the model “mechanical” since it is not explicitly based on microfoundations; in particular, it does not specify an information structure, firm objectives and behavior, or a wage setting process. This approach is intentional, as it demonstrates that the predictions of the model are general: any behavioral model that maps into the reduced form of this mechanical model generates the same comparative statics. We show below that the model nests a wide class of screening models, including a generalized version of the model in Lockwood (1991).

We begin by assuming that all workers who match with a firm are interviewed. The model predictions in this section therefore apply to job finding rates, rather than callback rates. In section 3.4, we relax this assumption and introduce an interview stage into the hiring process. Interviewing is costly and firms interview only promising applicants. In that section, we explicitly incorporate heterogeneity between agents at the interview stage and show that predictions of the model for job finding rates extend to callback rates. The audit experiment which identifies the effect of durations on callback rates thus allows us to test the model on hiring proposed here.

\footnote{Previous research has noted that even with individual-level data on job offer arrival rates, it is difficult to separately identify whether duration dependence comes from employer or worker behavior (Blau and Robins 1990).}
3.1 Model Setup

We consider economies in steady state, allowing us to drop cohort and time identifiers from the notation. The life-cycle of workers in our economy is very stylized. Each period, a mass 1 of individuals is born into unemployment. Individuals retire according to a Poisson process with arrival rate $\delta$, which does not depend on labor market status. Once they find a job, workers remain employed until they retire. At birth, agents are assigned to one of two types. The types differ in their productivity which is given by $y \in \{l, h\}$. We index the two types using the same $\{l, h\}$. A fraction $\pi_0$ of agents are born as high type.

3.2 Mechanical Relations

Let $\pi(d)$ be the proportion of unemployed individuals of high productivity with an incomplete spell of length $d$. Assume that the proportion of high productivity individuals at duration $d = 0$ (denoted $\pi_0$) is strictly in the interior of the unit interval; there are both high and low productivity individuals among the newly unemployed. The job finding rate, conditional on worker type $y \in \{h, l\}$ and $\pi$, is denoted by $h_y(\pi(d))$. We make two key assumptions on the type-specific job finding rates.

Assumption 1 $h_h(\pi) > h_l(\pi)$ – high productivity workers exit unemployment at higher rates than low productivity workers.

Assumption 2 $\frac{\partial h_y(\pi)}{\partial \pi} \geq 0, y \in \{h, l\}$ – the type-specific job finding rates increase in the share of productive individuals in the economy.

We next consider an expression for the average productivity of the unemployed at a given duration. Clearly, the share of productive types at $d$ depends on the type-specific hazard up to $d$:

$$\pi(d) = \frac{\pi_0 \exp \left(-\int_0^d (h_h(\pi(\tau)) + \delta) d\tau\right)}{\pi_0 \exp \left(-\int_0^d (h_h(\pi(\tau)) + \delta) d\tau\right) + (1 - \pi_0) \exp \left(-\int_0^d (h_l(\pi(\tau)) + \delta) d\tau\right)}$$ (1)

For convenience, we define $\theta(d) = \frac{\pi(d)}{1 - \pi(d)}$ and $\theta_0 = \frac{\pi_0}{1 - \pi_0}$. $\theta(d)$ represents the relative share of high and low productive workers in the economy at duration $d$.\footnote{Many of the properties of $\theta(d)$ will be inherited by $\pi(d)$ since $\pi$ is a positive, monotone function of $\theta$.} $\theta(d)$ is linked to the hazard rates as follows:

$$\theta(d) = \frac{\pi(d)}{1 - \pi(d)} = \theta_0 \exp \left(\int_0^d (h_l(\pi(\tau)) - h_h(\pi(\tau))) d\tau\right)$$ (2)
The population job finding rate is defined as:

\[ h(\pi (d)) = (1 - \pi (d)) h_l (\pi (d)) + \pi (d) h_h (\pi (d)) \] (3)

Expression (3) shows that the population job finding rate varies with the spell length through two channels: (1) it depends directly on \( \pi (d) \) and (2) it depends indirectly on \( \pi (d) \) through \( h_y (\pi) \). The next two definitions capture these two sources of variation in the job finding rate.

**Definition 1** [True Duration Dependence] We say that there is “true” negative duration dependence if individual job finding rates vary with the length of the unemployment spell, \( \frac{\partial h_y (\pi)}{\partial d} < 0 \).

**Definition 2** [Unobserved Heterogeneity] We say that there is “unobserved heterogeneity” if the population at risk of leaving unemployment shifts to less productive types at longer durations, \( \frac{\partial \pi (d)}{\partial d} < 0 \).

In practice, the population job finding rate might decline with duration due to the presence of both true duration dependence and unobserved heterogeneity. Additionally, in this model the two sources interact as true duration dependence arises in response to changes in the distribution of types among the unemployed. Ultimately, both depend on how \( \pi (d) \) varies with \( d \). The next proposition states that the proportion of high types among the unemployed declines with duration.

**Proposition 3** As long as \( \pi (d) \) is in the interior of \([0,1]\), the proportion of the high skill type and the population job finding rate both decline strictly with duration: \( \frac{\partial \pi (d)}{\partial d} < 0 \), \( \frac{\partial h_y (\pi (d))}{\partial d} < 0 \). The job finding rate conditional on type, declines weakly with duration \( d \): \( \frac{\partial h_y (\pi (d))}{\partial d} \leq 0 \) for \( y \in \{ l, h \} \).

**Proof.** The fact that the proportion of high skill types declines among the unemployed follows directly Assumption 1. By Assumption 2, we have \( \frac{\partial h_y (\pi (d))}{\partial d} = \frac{\partial h_y (\pi (d))}{\partial \pi (d)} \frac{\partial \pi (d)}{\partial d} \leq 0 \). Finally, differentiating the population job finding rate in (3) gives \( \frac{\partial h(\pi (d))}{\partial d} = (1 - \pi (d)) \frac{\partial h_l (\pi (d))}{\partial d} + \pi (d) \frac{\partial h_h (\pi (d))}{\partial d} + \frac{\partial \pi (d)}{\partial d} (h_h (\pi (d)) - h_l (\pi (d))) < 0 \).

\[ \] 3.3 Duration Dependence and Market Conditions

To study how duration dependence interacts with market tightness, we now impose more structure on the hazard rate. In particular, we assume that a single worker and a single firm randomly meet according to the constant returns to scale (CRS) matching function \( m(U, V) \), where \( U \) and \( V \) are the number of unemployed workers and vacancies, respectively.\(^{11}\) Let \( x = \frac{V}{U} \) denote labor market tightness. Under the CRS assumption, the rate at which unemployed individuals are matched with vacancies is \( m_U (x) = m(U, V) = \)

\(^{11}\)Blanchard and Diamond (1994) consider a setting with multilateral matching where a firm can meet with multiple workers. This matching structure has important implications which we discuss below.
We assume time is continuous and \( \lim_{x \to \infty} (m_u(x)) = \infty \) and \( \lim_{x \to 0} (m_u(x)) = 0 \). The arrival rate \( m_u(x) \) captures the idea that applicants meet open vacancies at a random rate that depends only on market tightness.

Next, when a firm and a worker meet, the probability a worker is hired is given by the function \( l_y(\pi; d; x) \). We assume that \( l_h(\pi) > l_l(\pi) \) and \( \frac{\partial l_y(\pi)}{\partial \pi} \geq 0 \). Under these assumptions, the type-specific job finding rate takes the following form:

\[
h_y(\pi; d; x) = m(x) \times l_y(\pi; d; x) \quad \text{for} \quad y \in \{l, h\}
\]

The hazard function \( h_y(\pi) = m_u(x) \times l_y(\pi; d; x) \) satisfies Assumptions 1 and 2 above. Market tightness enters directly through the matching function and implicitly because the fraction \( \pi(d; x) \) of productive workers at \( d \) depends on \( x \). To make this dependence explicit, we write \( \pi(d; x) \). It is important to note that conditional on \( \pi, x \) and \( y \) are weakly separable in the job finding rate: the relative hazard rates across types are independent of \( x \), conditional on \( \pi \).

Given this structure on the hazard rate, we now describe how duration dependence varies with market tightness. As a measure of the strength of duration dependence, we define the function \( r(d; x) = \frac{h(d; x)}{h(0; x)} \), the ratio of the job finding rate evaluated at \( d \) to the job finding rate for the newly unemployed. From Proposition 3, \( r(d; x) \) is declining in \( d \), since \( h(d; x) \) is declining in \( d \). An intuitive measure of duration dependence would be the cross-derivative of this function: \( \frac{\partial^2 r(d; x)}{\partial d \partial x} \). However, the cross-derivative is local, and it can be positive for some values of \( d \) and negative for others. As it turns out, our measure has no general implications for such local measures of duration dependence. Instead, we will use a global measure that holds for all positive values of \( d \). We will say that duration dependence is stronger in tighter labor markets; i.e., \( x > x' \to r(d; x) < r(d; x') \) for any \( d \).

We now show that the model has a clear testable implication for how the function \( r(d; x) \) varies with market tightness. In the steady state, \( r(d; x) \) for tight labor markets (large \( x \)) lies everywhere below the function \( r(d; x) \) observed in loose labor markets (small \( x \)). This implication can be used to test models that map into the mechanical structure described above. We can write

\[
r(\pi(d; x); x) = \frac{m(x) \left( \pi(d; x) l_h(\pi; d; x) + (1 - \pi(d; x)) l_y(\pi; d; x) \right)}{m(x) \left( \pi_0 l_h(\pi_0) + (1 - \pi_0) l_y(\pi_0) \right)}
\]

\[
= \frac{\pi(d; x) l_h(\pi; d; x) + (1 - \pi(d; x)) l_y(\pi; d; x)}{\pi_0 l_h(\pi_0) + (1 - \pi_0) l_y(\pi_0)}
\]

\[
= r(\pi(d; x))
\]

Thus, variation in \( r(d; x) \) with respect to \( x \) arises because \( \pi(d; x) \) implicitly depends on market tightness.

\(^{12}\)Analogously, the rate at which vacancies meet applicants is \( m_v(x) = \frac{m(U, V)}{V} = m(U, 1) \). The relation between the two arrival rates is given by \( m_u(x) = x m_v(x) \).
Proposition 4 \textit{Duration dependence is more negative if markets are tighter}: \( r(d; x) > r(d; x') \) for all \( d > 0 \) if \( x < x' \).

\textbf{Proof.} See Appendix B. ■

The intuition of this result is that in tighter labor markets, high productivity workers are less likely to experience long unemployment durations because they are more likely to match early on with firms and be hired relative to low productivity workers. Therefore, high unemployment duration workers are more likely to be low productivity in tight labor markets, which strengthens duration dependence.

In summary, we have shown that any model which maps into our mechanical model delivers two predictions: (i) negative duration dependence (Proposition 3), and (ii) a positive interaction between duration dependence and market tightness (Proposition 4). We will test these predictions directly using our experimental data. However, in our audit experiment, we do not observe hiring decisions, but rather whether applicants are called in for interviews ("callbacks"). Therefore, we adapt the model to incorporate resume-level heterogeneity and to specifically account for callbacks.

### 3.4 Callback Rates and Heterogeneity

In this section, we adapt the mechanical model to examine callbacks. This extension aligns our model more closely with the empirical work in the audit study, which measures callbacks for interviews rather than hiring decisions. In doing so, we also allow for individual-level heterogeneity. We do this since resumes differ on dimensions other than unemployment duration. We discuss how this heterogeneity may give rise to unobserved heterogeneity or composition bias in observational studies, and we use this to motivate our approach of randomizing durations to identify true duration dependence.

Callback rates in principle depend on individual characteristics as well as the duration of unemployment. Some characteristics on a resume (such as gender, education and experience) can be easily controlled. However, resumes are complex and it is difficult to fully control for all characteristics. We represent these characteristics by \( \phi \) and denote their distribution conditional on type \( y \) and duration \( d \) by \( \Phi_y(.|d) \). The distribution unconditional on type is given by \( \Phi(.|d) \). Let us denote the callback rate by \( c(\pi(d; \phi), d, \phi; x) \).

If firms only care about the expected productivity of workers, then the callback rate can be written as \( c(\pi(d; \phi); x) \). Below, we also consider the case where firms do not use unemployment duration to predict productivity or condition callback decisions; in this case, we write the callback rate as \( c(\phi; x) \).\footnote{This may arise for example, if the "unemployment gap" on the resume is not salient to firms or if workers do not report their current spell length.}

\footnotetext[13]{\( \Phi(.|d) \) is equal to \( \pi(d)\Phi_y(.|d) + (1 - \pi(d))\Phi_t(.|d) \).}
in no case do callbacks depend directly on the type of worker, since the worker type is unobserved and firms can only use observable characteristics \((d, \phi; x)\) to determine which applicants to call back for an interview.

When callback rates depend only on the productivity prior \(\pi(d; \phi)\) (as is the case in the specific employer screening model developed below), then the population job finding rate, conditional on \(\phi\), is obtained by replacing \(h_y(\pi(d))\) with \(h_y(\pi(d; \phi))\) and \(\pi(d)\) with \(\pi(d; \phi)\) in equation (3). We assume that callback rates are weakly increasing functions of the prior: \(\frac{\partial \gamma(\pi(d; \phi))}{\partial \pi(d; \phi)} \geq 0\), which immediately implies the following corollary to Propositions 3 and 4:

**Corollary 5** If callback rates are weakly increasing in \(\pi\), we have that callback rates exhibit duration dependence: \(\frac{\partial \gamma(\pi(d; \phi))}{\partial d} \leq 0\). Conditional on \(\phi\), the relative ratio of callback rates \(r_c(d; x, \phi) = \frac{c(\pi(d; x; \phi))}{c(\pi_0(x))}\) has \(r_c(d; x, \phi) \geq r_c(d; x', \phi)\) if \(x < x'\).

**Proof.** Immediate.

This implies that in principle, we can use callback rates to test the implications on hazard rates that we derived above. In particular, the sign of \(\frac{\partial \gamma(\pi(d; \phi))}{\partial d}\) reflects true duration dependence in callback rates. This is because the worker type itself does not affect callback rates once all the characteristics of the resume \((\phi)\) are accounted for. Consequently, bad luck that leads to a longer duration at the individual level will lead to callback rates that decline at the individual level. This true duration dependence reflects the belief that firms hold about the fraction of productive workers conditional on the duration \(d\).

For practical reasons, it may be difficult to empirically test for true duration dependence in callback rates using observational data. If an econometrician cannot fully account for the impact of \(\phi\) on callbacks, the estimate of \(\frac{\partial \gamma(\pi(d; \phi))}{\partial d}\) may be confounded by composition bias. To fix ideas, consider the extreme case where callbacks depend only on \(\phi\), so that we may write the callback rate as \(c(\phi)\). Furthermore, assume that \(c'(\phi) > 0\). This represents a situation where firms do not condition their callback decisions on \(d\); there is no true duration dependence under this formulation. Assume that \(\phi\) is unobserved by the econometrician. The population callback rate \(c(d)\) is defined as follows:

\[
c(d) \equiv \int c(\phi) \frac{d\phi}{d\phi} d\phi
\]  

(8)

In Appendix B, we establish that \(c'(d) < 0\). Intuitively, the unemployment distribution shifts to those with low \(\phi\) as spell lengths increase; resumes with long current spells of unemployment are more likely to be low \(\phi\) and thus likely to have lower callback rates, even in the absence of true duration dependence. Thus, in the absence of any true duration dependence, callback rates will decline unless we are able to control for all relevant components of the CV.

This problem matters because there are countless characteristics of resumes that might be relevant for
callback rates. Even though the econometrician might have access to the entire resume, he will not know 
the complete mapping between callbacks and all of the variables on the resume and potential interactions 
between them. Several other problems arise in observational studies. First, one would also need to control 
for the type of jobs that applications are being submitted to. Second, using observational data, one might 
not have a large enough sample size to identify how unemployment varies with duration for long durations. 
The distribution of current spells tends to be concentrated among durations less than 1 year. For these 
reasons, it will be very difficult in practice to credibly estimate duration dependence using non-experimental 
approaches.

In our resume audit study, randomization of unemployment durations ensures that the distribution of 
unobserved characteristics $\phi$ is independent of the duration of unemployment, and so the composition bias 
described above will be absent.\footnote{Additionally, since we can control the distribution of durations for our resumes, we can ensure that we can estimate precise callback rates at all durations.} Since we randomize unemployment duration, we recover how the average 
callback rate evolves with duration, where the average refers to the distribution. To see what our experiment 
recovers, we define the distribution $\Phi(.)$ as the distribution of characteristics on our experimental set of CVs. 
This distribution will, unfortunately, not be the population distribution. Thus, we recover the following 
object:

$$
\bar{c}(d) = E_{\Phi} [c(\pi(d;\phi))] |d| = \int_{\phi} c(\pi(d;\phi)) \, d\Phi(\phi)
$$

The function $\bar{c}(d)$ is an average over the callback rates for which the above corollary holds and the 
predictions of this corollary therefore also apply to $\bar{c}(d)$. This implies that we can use the callback rates 
elicited in our experiment to test the implications of the model.

It is worth noting that even conditional on $\phi$, the population job finding rate, $h(\pi(d;\phi))$, will nevertheless 
decline in $d$ due in part to unobserved heterogeneity. This occurs since $h_h(\pi(d;\phi)) > h_l(\pi(d;\phi))$. To see 
the intuition for this, consider a firm who interviews a high type and a low type worker, both of whom have 
the same value of $\phi$. As we show in the screening model below, it is more likely that a firm draws a relatively 
higher signal ($z$) for the high type worker. Thus, workers with long durations will be those with low values 
of $\phi$ and low values of $z$. An econometrician who observes $\phi$ – but not the signal $z$ at the hiring stage – may 
be led to conclude that there is true duration dependence in hazard rates when in fact the estimates are 
picking up a selection effect. Thus, in a sense, it is easier to identify true duration dependence in callback 
rates, since an econometrician only needs to condition on the information that a potential employer sees at 
the interview stage, not the hiring stage.
Employer Screening, Skill Depreciation, and Employer Ranking

The mechanical model described in section 3 is not based on behavioral microfoundations but rather on reduced form assumptions on hiring rates. This is intentional to show that its predictions are fairly general — any structural model that has the same implications for hiring and matching rates generates the same predictions. However, the model is not so general so as to be vacuous: there are behavioral models which do not map into this structure and which do not generate the same predictions. In this section, we informally discuss the three leading behavioral models of employer-driven duration dependence. These models are developed more formally in Appendices C, D, and E.

In Appendix C, we develop a simple screening model of employer-driven duration dependence.\textsuperscript{16} Matching frictions and firm screening of workers interact to generate duration dependence in job finding rates. Search frictions result in equilibrium unemployment: unemployed workers and vacancies meet at a rate determined by aggregate unemployment and vacancies in the economy. Upon a meeting between a vacancy and a job seeker, the potential employer obtains a signal (the CV) on worker productivity. Interviewing an applicant is costly, and firms call applicants for interviews only if they receive sufficiently high signals. If a worker is called in for an interview, the firm observes an additional signal, providing new information on worker productivity. A worker with a sufficiently high signal is hired and earns his outside option. In this model, firms lower their priors about individuals with long durations, since they believe that these have been found wanting by other potential employers. This induces negative duration dependence.

The screening model satisfies the three conditions of the simple mechanical model. First, the matching structure implies weak separability between market tightness and \( \pi \). Second, high productivity workers signal their type during the interview and are hired at greater frequency than low productivity workers. Third, the hiring rate increases with \( \pi \) because employers’ prior is \( \pi \).

In the screening model, duration dependence gets stronger in tight labor markets. In tight markets, employers believe that the unemployed were evaluated more frequently and rejected by potential employers and firms therefore adjust their priors more. In contrast, in loose markets, it is less likely that applicants met with firms in the past. Thus, screening predicts that as labor markets tighten, duration dependence gets stronger. Therefore, the screening model can be tested by examining duration dependence in callback rates and how duration dependence interacts with market tightness.

As a contrast to the screening model, we consider two alternative models of duration dependence that do

\textsuperscript{16}Our model is related to Lockwood (1991). However, we depart from Lockwood in two ways. First, we allow for an interview stage that is distinct from the hiring stage. Second, in the hiring stage, we allow for a more general signal distribution. In particular, Lockwood (1991) imposes that applicants signals are either high or low and that productive types always send the high signal, whereas unproductive types send the high signal with a probability less than one. Lockwood’s model results in extreme duration dependence in the sense that upon hitting a certain duration, the probability of finding a job for a low productive type declines to zero. This extreme assumption makes it difficult to map empirical results into the framework of Lockwood (1991). By allowing for a more general, continuously distributed signal, we allow for a continuous form of duration dependence; in our model job finding rates decline smoothly with durations.
not map into the structure above. The first model, which is developed in Appendix D, is a model of human capital depreciation. The rate at which applicants meet firms is again governed by a matching function that depends on market tightness. Individuals' human capital affects their productivity in all firms in the same way. This human capital – common to all employers – depreciates while workers are unemployed and the rate of this depreciation does not depend on market tightness. In addition to this common human capital component, there is a worker-firm specific match component. In order to isolate the implications of human capital depreciation from screening considerations, we assume that firms are fully informed about the human capital parameter. However, firms need to interview workers in order to learn their match-specific component. As in the simple screening model, wages are given by a fixed outside option.\footnote{The screening model can allow for less restrictive assumptions on wage setting. What is required is that applicants and firms, upon receipt of the signal, are more likely to enter into an employment relationship if the expected productivity of a worker is higher. We conjecture that most bargaining models satisfy this requirement.} The expected firm surplus from a given match therefore declines if an applicant has been unemployed for longer and the model generates negative duration dependence. However, the frequency with which the unemployed are matched to firms does not affect the speed with which their human capital depreciates. Therefore, this model does not generate any interaction between duration dependence and market tightness.

In Appendix E, we consider the well-known ranking model proposed by Blanchard and Diamond (1994). This model emphasizes the consequences of crowding in the labor market; vacancies potentially receive multiple applications. It is assumed that if a firm meets multiple workers, it hires the worker with the minimum duration. The ranking model predicts that job finding rates decline with unemployment durations. Intuitively, a worker with a long duration is more likely to face competition for a job and more likely to be rejected. Therefore, the ranking model also generates negative duration dependence. However, in tight markets, applicants for a given position are less likely to face competition from applicants with shorter durations. Therefore, under ranking duration dependence is less negative if labor markets are tight.

The key insight from our theoretical framework is that these three mechanisms for duration dependence (screening, ranking, and human capital depreciation) differ in their prediction about how duration dependence varies with local labor market conditions: screening generates a positive interaction effect, ranking generates a negative interaction effect, and human capital depreciation does not generate an interaction effect. Therefore, by estimating how duration dependence varies with labor market tightness, we will be able to shed light on the relative importance of these mechanisms. This theoretical prediction motivates a key aspect of the design of our resume audit study, which focuses on estimating duration dependence in a large number of local labor markets.
5 Measuring Salience of Resume Characteristics

Our field experiment assumes that the information on a job applicant’s CV is salient to employers. To test this assumption, we designed and conducted a web-based survey. A link to the survey was e-mailed to 365 MBA students at the University of Chicago Booth School of Business. A total of 91 students completed the survey. This section summarizes the design and results of the survey; more details on the survey can be found in the Appendix.

The survey takes place in three stages. First, respondents are asked to read a hypothetical job posting and to consider two resumes for the job opening (see Appendix Figure A1). The respondent was asked to select one of the two resumes to contact for an in-person job interview. Second, once the respondent made a selection, she was then asked to recall specific information on the resume such as total work experience, tenure at last job, level of education, current employment status, and the length of unemployment spell (Appendix Figure A2). We use these responses to evaluate the extent to which the various characteristics on the resume are salient to subjects. Third, we asked respondents several demographic questions; in particular, whether they had prior experience evaluating resumes (Appendix Figure A3).

To empirically measure salience, we rely on two proxies: (1) the fraction of time the respondents correctly recall the information, and (2) the correlation between the reported and true answers. As shown in Appendix Table A1, across both of our measures of salience, respondents are able to recall information about applicant’s employment status and length of unemployment spell about as well as they are able to recall information about other resume characteristics (such as education, total work experience, and tenure at last job). When we restrict the sample to respondents who report having “high experience” reviewing resumes in column (2), we find that the respondents are even more likely to correctly identify employment status and the length of unemployment spell. These results are consistent with our assumption that the employment status and the length of unemployment spell are salient features of the fictitious resumes.

6 Experimental Design

The design of the field experiment closely follows the experimental design and protocols of Bertrand and Mullainathan (2004), Lahey (2008), and Oreopolous (2011) in generating fictitious resumes, finding job postings, and measuring callback rates. All of the experimental protocols (and the survey instrument from previous section) were reviewed and approved by the Institutional Review Board (IRB) at the University

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18 Importantly, the survey was designed so that the respondent was unable to view the resumes again after making her selection.

19 One important caveat to our interpretation is that the survey respondents are not a representative sample of the individuals evaluating resumes in our field experiment. Nonetheless, we find it reassuring that our results persist in the subsample of MBA students with high levels of experience actually reviewing resumes.
of Chicago. The IRB placed several constraints on the field experiment.\(^{20}\) First, none of the researchers involved in the study could contact the firms at any time, either during or after the experiment. Second, in order to ensure that the individual representatives of the prospective employers could never be identified, we were required to delete any e-mails or voice messages that we received from employers after ascertaining the information from the message needed for the experiment. Finally, we were not able to preserve any identifying information about the prospective employers other than the industry. By contrast, we were approved to preserve richer information on the characteristics of the job posting, such as the posted wage, required experience, etc.

The setting for our experiment is a major online job board in the U.S. Through this online job board, we will email four resumes to each of 3,000 job openings for an eventual total of 12,000 resumes. We submit resumes to job openings in 100 metropolitan areas (MSAs) across the U.S. We use 400 unique local phone numbers (four for each MSA), and we have created 4,000 unique email addresses, and we use both the phone numbers and email addresses to track callbacks on an ongoing basis.

We began by generating a list of 3,000 combinations of MSAs and job categories to which we submit resumes. In this list, the distribution of resumes largely mirrors the population distribution across MSAs. However, we have chosen to overweight the ten MSAs with the highest unemployment rates in order to help identify the interaction between market tightness and unemployment duration in callbacks. In each city, 25% of resumes are for Administrative/Clerical, 35% are for Customer Service, and 40% are for Sales. We generated a list of job types and MSAs according to this sampling strategy, and the order in which we apply to job categories and MSAs is determined by random draws without replacement from this list.

Upon being assigned an MSA and job category, a research assistant visits the online job board and searches for jobs within the pre-determined city for the pre-determined job type. When picking jobs, we use several rules of thumb. First, we do not pick jobs that are posted by recruiting agencies. Second, we avoid independent outside sales positions (e.g., door-to-door salespersons selling knives). Third, we do not pick jobs that require advanced skill sets, licenses, or advanced degrees (beyond a standard 4-year college degree). Typically, a job opening within a given category and MSA that satisfies these criteria is immediately available, or (in rare cases) becomes available within one or two weeks.

The fictitious resumes are then created or adapted to fit this job opening. The design of the resumes is based on roughly 1,200 real resumes that we have collected from various online job boards. The resumes were selected based on the job categories we focus on: i.e., individuals applying to Administrative Support/Clerical, Customer Service, and Sales positions. We created ten resume templates that are based on the most frequent resume formats observed in this database. From this set of templates, four templates are selected according the following rule. If a research assistant applied to a given MSA and job category

\(^{20}\) The web-based survey instrument was approved with no additional constraints.
combination before, she will reuse the templates from that application. Otherwise, she will randomly draw four templates from the ten possible templates, drawing without replacement to ensure that no two resumes being sent to a given job will share the same resume template.

There are five more steps in designing a fictitious resume:

1. We decide whether each resume will be male or female. For two of the job categories (Customer Service and Sales), we send two female and two male resumes. For Administrative/Clerical jobs, we send four female resumes. This decision is consistent with the protocol of Bertrand and Mullainathan (2004). Besides having four resumes of potentially mixed gender, we also alter the “quality” of each resume. This means we will either have a set of one high-quality male, one high-quality female, one low-quality male, and one low-quality female resumes or we will have a set of two high-quality and two low-quality female resumes (depending on the gender ratio that the job category calls for). The “quality” differs by certain basic skills, additional work history, and additional years of education.

2. We randomly generate a name for the resume. The bank of names has been chosen based on common frequency census data and are chosen to be minimally informative about the race of the applicant.

3. We choose the home address, phone number, and email address. We have four phone numbers and addresses per city and assign one of each to a resume.

4. We update the fictitious resume’s job history, educational history, skill set, and the objective summary to match the job we apply to. This means that if the job is for an Administrative Assistant position, we will identify a resume with experience as an Administrative/Executive Assistant. The work history is dependent upon the job requirements. Additionally, we never share work histories between resumes that are sent to the same city. Education is also determined by the job’s requirements. Low-quality resumes are always given the baseline requirement, and high-quality resumes are usually “bumped up” an education level (that is, if the job requires a 2-year degree, low-quality resumes will read as such while high-quality ones are given 4-year degrees. This effect isn’t applied to jobs already requiring a 4-year degree). Location of education is found by looking for large, local degree-granting institutions. Again, these are used to keep the applicant anonymous. Finally, we verify that there is not a real individual with a similar background on any the major social network and job network websites (e.g., Facebook and LinkedIn).

5. The final and most important step is to randomize employment status and the length of the current unemployment spell.

We track callbacks from employers by matching voice or email messages to resumes. We record the date of the callback, and we follow Bertrand and Mullainathan (2004) by defining a callback as a message from an
employer explicitly asking to set up an interview. The callbacks were coded independently by two Research Assistants (RAs) who were not otherwise involved in the project, and the two RAs have agreed virtually all of the time. In Appendix Table A4, we report results which use an alternative definition of a callback based on whether the employer left any voice message at all, even if the message simply asked for more information. We plan to also use the date and time of the callback to see if employers reveal preferences over the four resumes sent to each job.

In terms of the experimental design, we have created two treatment groups:

- **Treatment Group 1**: Individuals are randomly assigned to employment status “Employed” with probability 0.25. Let \( E_{i,c} \) denote an indicator variable that equals 1 if individual \( i \) in city \( c \) is employed and 0 otherwise.

- **Treatment Group 2**: Individuals that are unemployed are randomly assigned an (integer) unemployment duration or “gap” (in months) according to a discrete uniform distribution on the interval [1, 36]. Let \( d_{i,c} \) denote the (randomly assigned) unemployment spell for individual \( i \) in city \( c \). Employed individuals are assigned \( d_{i,c} = 0 \). Let \( y_{i,c} \) be a callback indicator that equals 1 if individual \( i \) in city \( c \) receives a callback for an interview.

In our analysis of the experimental data below, we run the following linear probability model that includes, for efficiency gains, individual, job, and city characteristics \( X_{i,c} \):

\[
y_{i,c} = \beta_0 + \beta_1 E_{i,c} + \beta_2 \log(1 + d_{i,c}) + X_{i,c} \Gamma + \varepsilon_{i,c}
\]

(9)

Given our randomized design, the coefficients \( \beta_1 \) and \( \beta_2 \) provide unbiased estimates of the mean impact of being employed versus unemployed and the mean impact of changes in unemployment duration (conditional on being unemployed). Since the effect may differ in magnitude across different unemployment durations, we also report nonparametric estimation results. In particular, we examine the data nonparametrically by using local linear regression techniques to plot callback rates as a function of unemployment durations. We will also examine the robustness of our results to using alternative specifications, such as a probit model.\(^{21}\)

To examine how duration dependence varies with local labor market conditions, we pursue two complementary approaches. First, we use the sample of unemployed individuals to estimate fixed effects and (correlated) random effects models of the following form:

\[
y_{i,c} = \delta^c + \gamma^c \log(1 + d_{i,c}) + X_{i,c} \Gamma + \varepsilon_{i,c}
\]

(10)

\(^{21}\)When we consider interactions in non-linear models such as the probit model, we estimate the interaction effects using Ai and Norton (2003).
In the fixed effects model, $\delta^c$ is a city fixed effect and $\gamma^c$ is a city-specific estimate of the effect of unemployment duration. In the random effects model, $\delta^c$ is a city random effect and $\gamma^c$ is a city-specific random coefficient on unemployment duration. This specification is directly motivated by our mechanical model which indicates that there is a one-to-one relationship between the intercept $\delta^c$ (i.e., the callback rate for a newly unemployed individual) and the level of market tightness. Therefore, the covariance between $\delta^c$ and $\gamma^c$ (i.e. $E[(\delta^c - \hat{\delta}^c)(\gamma^c - \hat{\gamma}^c)]$) indicates the extent to which duration dependence varies with market tightness. For the fixed effects model, we prove in the Appendix that an unbiased estimate of this covariance is given by the following expression:

$$E[(\delta^c - \hat{\delta}^c)(\gamma^c - \hat{\gamma}^c)] = \frac{1}{C} \sum_{c=1}^{C} \delta^c \hat{\gamma}^c + \frac{1}{C} \sum_{c=1}^{C} \sigma^2_{c} N^c E[c \log(1 + d)] Var(\log(1 + d))$$  

(11)

where $C$ is the total number of cities in the sample, $\hat{\delta}^c$ and $\hat{\gamma}^c$ are the estimated city fixed effects and city-specific estimates of the effect of unemployment duration, $\sigma^2_{c}$ is the estimated city-specific residual variance and $N^c$ is the number of observations in the city. The second term in equation (11) represents a bias correction to account for the negative correlation between the city-specific estimates $\hat{\delta}^c$ and $\hat{\gamma}^c$. Intuitively, the slope and intercept estimates in an OLS regression are correlated, so in order to obtain an unbiased estimator of the covariance of the estimated intercept and slope parameters across cities, we need to adjust for this “mechanical” bias using equation (11) above. We then convert the covariance estimate to a correlation by dividing by the standard deviation of the estimates city-specific interaction terms and the estimates of the city fixed effects.\footnote{We adjust the estimates of standard deviation of the interaction terms and city fixed effects by a “shrinkage factor” based on an estimate of the residual variance.}

For the random effects model, the covariance is estimated by specifying that $\delta^c$ and $\gamma^c$ are jointly normally distributed and estimating the variance-covariance parameters of the joint normal distribution.

Our second approach to estimating how duration dependence varies with market tightness is to estimate the following linear probability model:

$$y_{i,c} = \beta_0 + \beta_1 \log(1 + d_{i,c}) + \beta_2 \log(1 + d_{i,c}) \times u_c + \beta_3 u_c + X_{i,c} \Gamma' + \xi_{i,c}$$  

(12)

This specification includes an interaction between log duration and proxies for market tightness formed using city monthly unemployment rates ($u_c$). We explore several alternative specifications for the functional form of $u_c$, as described below; in particular, we consider both cross-sectional variation in city unemployment rates as well as changes in city unemployment rates in the years leading up to the experiment.

Before turning to our empirical results, we note several methodological points. First, we can be reasonably confident that the target information, in our case, the current “gap” since the last employment stated on
the resume, is salient to the employer, given our survey evidence in Section 5. Second, since our experiment takes place in a real-world labor market, we can be much more confident that our results are generalizable. Moreover, the fictitious resumes and the way that the current unemployment spell is conveyed on the CV match the exact format of actual resumes in the labor market. Thus, there is no reason to suspect that a fictitious CV sent to a job opening would be viewed any differently by an employer than an actual CV.

7 Preliminary Results

To date, we have submitted 6866 resumes, covering 96 of the 100 metropolitan areas selected for the full experiment. Of these 6866 resumes, 5325 of the resumes had (ongoing) unemployment spells of at least one month, with the remaining 1541 resumes conveying that the worker was currently employed. This sample is significantly smaller than the sample size suggested by our power calculations. Nevertheless, the current experimental sample already yields several interesting results. In particular, we present clear evidence of negative duration dependence in callback rates. We also present suggestive evidence, using unemployment rates to proxy for labor market tightness, that duration dependence becomes stronger when labor markets are tight.

Table 1 reports descriptive statistics for the sample. About 12 percent of our resumes elicit some response by employers. However, not all of these are callbacks for interviews. About one-third of total callbacks were classified as callbacks for interviews, for a total callback rate of about 4 percent. In terms of demographics, roughly two-thirds of our resumes are female, and most of our resumes show relatively little experience. Mean experience is 5 years with a max of 15 years of experience. Compared to the types of jobs that individuals are applying to, the resume sample is fairly educated: one-third of the respondents have college degrees. This is primarily due to our strategy of sending out both resumes that just match the minimum requirements and resumes that are of higher quality. Due the randomized design of the field experiment, there is balance across all covariates (across employed/unemployed and across the distribution of unemployment durations), as shown in Table 2.

7.1 Estimating Duration Dependence

Before turning to regression results, we begin with a simple plot of the average callback rate. Using the sample of unemployed individuals \( N = 5325 \), Figure 1 reports the relationship between unemployment duration and the callback rate. The figure shows a clear negative relationship, with the steepest decline coming in the early months. Figure 2 shows a similar pattern using the ratio of the callback rate in each bin divided by the callback rate in the first bin (i.e., the lowest unemployment durations). This figure corresponds more closely to the function \( r(d; x) \) defined above. We also report nonparametric (local linear)
regression results for the relationship between callback rates and unemployment duration in Figure 3. The nonparametric regression results are constrained to be (weakly) monotonic following the rearrangement procedure of Chernozhukov, Fernandez-Val, and Galichon (2003). The bootstrapped standard errors in Figure 3 are uniform confidence intervals. We can therefore reject the null hypothesis that there is no relationship between unemployment durations and callback probabilities based on the inability to draw any horizontal line through the plotted confidence intervals.

The evidence from regressions confirms this visual analysis. Table 3 reports OLS regression results estimating equation (9). Column (1) reports results using only the sample of unemployed workers. The results show that longer unemployment durations are associated with lower callback rates. A 1 log point change in unemployment duration is associated with a 1.0 percentage point decline in the callback probability ($p = 0.017$), from a mean of 4.0 percentage points. Column (2) reports similar results using the entire sample, and, interestingly, there is a statistically significant difference in callback rates between employed and unemployed individuals: employed applicants are actually less likely to receive callbacks. In discussions with human resource professionals, we learned that some employers would prefer to hire a short-term unemployed worker over a worker who is currently employed, which is consistent with these preliminary results. Column (3) reports analogous results when we use indicator variables for ranges of potential unemployment durations, with the omitted category representing 1-6 months of unemployment. These results are qualitatively similar, with both columns showing statistically significant evidence that longer unemployment durations are associated with lower callback rates. This column also confirms that the majority of the decline occurs in the first six months, as the coefficients on the indicators for duration windows larger than six months are not statistically significantly different. This motivates column (4), which simply reports the difference in callback rates across unemployment durations above and below six months. As expected given the randomized nature of the data, the results in this table are insensitive to the exclusion of controls (Appendix Table A3).

7.2 Duration Dependence and Labor Market Conditions

The results presented so far address the question of whether callback rates vary with unemployment duration. However, they do not address the question of how this relationship varies with market tightness. To explore this question, we first provide visual evidence. Figures 4 and 5 show plots analogous to Figures 1 and 2, but they split the experimental sample depending on whether the local unemployment rate is above or below 8.0%. As before, we first show (Figure 4) the raw callback rates and then we show (Figure 5) the relative callback rate (callback rate divided by average callback rate in first two months of unemployment) that...
correspond to the function $r(d; x)$ introduced in Section 3. As discussed in Section 4, the screening model implies that $\frac{\partial r(d; x)}{\partial x} < 0$ for all $d$ (except $d = 0$), whereas the ranking model implies that $\frac{\partial r(d; x)}{\partial x} > 0$, and the human capital depreciation model implies that $\frac{\partial r(d; x)}{\partial x} = 0$. Figure 4 therefore allows us to adjudicate among these models and it finds evidence in favor of the screening model: the relative callback rates are always lower in markets with lower unemployment. These patterns are robust to other proxies for labor market tightness; for example, figures 6 and 7 show similar results when the sample is split based on whether the unemployment rate increased by more than 4 percentage points between 2008 and 2011.

The regression evidence confirms the visual evidence from these figures. We begin with a simple test of whether there is heterogeneity in duration dependence across labor markets. Table 4 reports results which test whether the effect of unemployment duration on callbacks is the same across all metropolitan areas based on our fixed effects estimates from equation (10). We interact a full set of metropolitan area fixed effects with unemployment duration and conduct an F-test of equality across all of the estimated coefficients for these interaction terms. The results in column (1) show that the effect of unemployment duration is not the same across all metropolitan areas, as the p-value of this test is strongly statistically significant ($p < 0.001$). To test exactly how the effect of unemployment duration varies with market tightness, we construct an estimate of the correlation between the estimates of the city-specific interaction terms and the city fixed effects estimated in equation (10). Consistent with the results in Figures 4 through 7, we estimate a statistically significant negative correlation between $\delta^c$ and $\gamma^c$; i.e., $\text{corr}(\delta^c, \gamma^c) = -0.730$; s.e. $= 0.331$. Under the assumption that the city fixed effects are valid proxies for market tightness, these results imply that duration dependence is stronger (i.e., more negative) in tight labor markets, consistent with the predictions of the employer screening model.

The remaining columns in Table 4 repeat this same exercise, reporting the covariance in equation (11), but replacing $\log(d)$ with other covariates in $X_{i,c}$. Columns (2) and (3) show that the callback rate of customer service jobs and sales jobs (relative to admin/clerical jobs) varies strongly across cities. However, we do not find significant evidence that these city-specific effects are correlated with the average callback rate within the experiment. In other words, cities with higher average callback rates are not relatively more likely to call back applicants to customer service jobs or sales jobs, even though these jobs have higher average callback rates. We interpret this as evidence against a “mechanical” interpretation of our results in column (1): specifically, these results are inconsistent with low average callback rates in a city simply being associated with attenuating the effect of all covariates. In this case, one would expect that cities with higher average callback rates to also have higher callback rates for customer service jobs and sales jobs relative to admin/clerical jobs, and we do not find evidence that this is the case. Columns (5) through (7)

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$24$ See the Appendix for details on constructing standard errors for inference.

$25$ When we replace $\log(1 + d)$ with one of the covariates in $X_{i,c}$, we place $\log(1 + d)$ in $X_{i,c}$ vector.
test for similar heterogeneous effects across labor markets for the effect of gender, education, and years of experience, and we find no evidence that the effect of any of these covariates varies across cities.

Table 5 reports similar results based on estimating a correlated random coefficients model, where the regression model in equation (10) above is given an alternative interpretation: specifically, $\delta^c$ is assumed to be a city-specific random effect and $\gamma^c$ is a city-specific random coefficient on unemployment duration. The random coefficients are allowed to be flexibly correlated and assumed to be jointly normally distributed across cities. As in Table 4, we report whether we find evidence that the random coefficients on unemployment duration are statistically significantly different, and we also report estimates of the correlation between the random coefficient and the city-specific random effect. The results are qualitatively similar: only for unemployment duration are the random coefficient estimates significantly correlated with the city-specific random effects, and the negative estimated correlation ($\text{corr}(\delta^c, \gamma^c) = -0.911$; s.e. = 0.155) implies that cities with higher average callback rates within the experiment have stronger duration dependence.

Our final test of how duration dependence varies with labor market conditions uses metropolitan area unemployment rates to construct various (observable) proxies for market tightness. These results are reported in Table 6, which reports OLS regression results estimating equation (12). Using several alternative functional forms for unemployment duration and the unemployment rate, we consistently estimate that the effect of unemployment duration is lower when the unemployment is relatively high, though the precision varies somewhat across specifications. This is consistent with the results in Table 4 and Table 5; across all of these tables, we interpret the results as most consistent with the screening model discussed above, as the results suggest the magnitude of negative duration dependence increases with market tightness.

Finally, the Appendix reports several additional results to verify the robustness of our results and explore variation across different subsamples. First, we show that our results are extremely similar across various combinations of covariates (Appendix Table A3). Next, we show that our results are qualitatively similar using an alternative callback definition (Appendix Table A4). Finally, we report results based on analysis of demographic sub-samples (Appendix Table A5). Although the results in this table are based on an incomplete experimental sample and therefore fairly imprecise, the point estimates suggest somewhat larger duration dependence estimates for women (as compared to men) and for high-skill workers (as compared to low-skill workers). However, none of these differences across sub-samples are statistically significant at conventional levels.

We anxiously await the results from the remaining 5134 resumes - we expect these to tighten the standard errors by about 25%, but can’t predict the effect on the point estimates reported here. We expect these results to be available in mid-2012.
8 Conclusion

This paper discusses preliminary results from an ongoing field experiment studying duration dependence. Our preliminary results suggest that the likelihood of receiving a callback declines with the length of unemployment. This effect is especially pronounced in the first few months after becoming unemployed. Our estimates suggest that this effect is quantitatively important, and, additionally, our preliminary results suggest that duration dependence is lower when jobs are relatively abundant. However, we emphasize that the results presented here are from a partial experimental sample, and we expect to complete the submission of all 12,000 resumes (completing our experimental sample) within the next several months.

Our conceptual framework shows that these results are most consistent with a model where employers statistically discriminate against workers with longer unemployment durations, and we emphasize that our preliminary results are not easily generated by a model of human capital depreciation when the rate of human capital depreciation is the same across labor markets. The results are also not consistent with a model of duration dependence based on a simple model of employer ranking (Blanchard and Diamond 1994). Therefore, we conclude that our results are consistent with employer screening playing a role in generating duration dependence, although we emphasize that we do not rule out the existence of these other mechanisms. In future work we are planning to separately identify employer screening from human capital depreciation by combining the data from our experiment with a rich structural model.

Our study suggests several additional areas for future research. First, we think it is important to expand our analysis to a broader segment of the economy. We suspect this will be difficult to do with a resume audit study, but there may be creative ways to approximate our field experiment in settings where online job search is less prevalent. Second, duration dependence has implications for the nature of long-term unemployment and the design of unemployment insurance (Shimer and Werning 2006; Pavoni 2009). Finally, employer-driven duration dependence of the kind we estimate may imply that firms create inefficiently many vacancies and apply an inefficiently strict screening threshold for both interviewing and hiring. In ongoing work, we are investigating these normative issues that arise under this screening.
References


Appendix A: Properties of Incomplete and Complete Spells

We distinguish between two duration concepts—"incomplete" and "completed spells". That is, we define the random variable $D$ as the length of an unemployed worker’s incomplete spell. This random variable is to be distinguished from $S$, the length of a completed spell of unemployment. Clearly, realizations $s$ and $d$ of these random variables satisfy $s \geq d$. Denote the conditional distribution and density functions of completed spells at time $t$ as $G^S_y(t)$ and $g^S_y(t)$. For incomplete spells, we will use the notation $G^D_y(t)$ and $g^D_y(t)$.

There is a connection between the distribution of completed and ongoing spells in the steady state. Salant (1977) demonstrates that in the steady-state, the density of on-going spells is connected to the distribution of completed spells as follows:

$$g^D_y(t) = \frac{1}{1 - G^S_y(t)} \text{ for } t \geq 0$$

(13)

We can also define the escape rate conditional on spell length as the rate at which individuals leave the population of unemployed at $t$. This can be expressed as a function of the density and distribution of completed spells:

$$h_y(t) = \frac{g^S_y(t)}{1 - G^S_y(t)} = - \frac{d}{dt} \ln \left( \int_x^\infty g^S_y(x) dx \right)$$

Rewriting this, we get

$$\frac{d}{dt} \ln [1 - G^S_y(t)] + h_y(t) = 0$$

$$\frac{d}{dt} [1 - G^S_y(t)] + (1 - G^S_y(t))h_y(t) = 0$$

This is a first-order differential equation with a variable coefficient. The general solution of this equation, the distribution function for completed spells, satisfies:

$$\Pr(S > t) = 1 - G^S_y(t) = \exp \left( - \int_0^t h_y(\tau) d\tau \right)$$

(14)

This is simply the probability that the individual has not been hired up to $S$. And, this implies the following density:

$$g^S_y(t) = h_y(t) \exp \left( - \int_0^t h_y(\tau) d\tau \right)$$

(15)

Appendix B: Proof of Proposition 3 and Composition Bias

Proof of Proposition 3

From expression (6), it is clear that $r(\pi(d; x) ; x)$ increases in $\pi(d; x)$. Therefore, to establish the proposition, we need to establish the relationship between $\pi(d; x)$ and $x$. It is sufficient to sign the relationship between $\theta(d, x)$ and $x$.

First, note that $\theta(0, x) = \theta(0, x')$ for $x \neq x'$. This follows from the assumption that $\pi(0; x) = \pi_0$. Next, from (2), it is simple to show that

$$\frac{\partial \theta(d; x)}{\partial d} = -m(x) \times \theta(d; x) \times (l_h(\pi(d; x)) - l_l(\pi(d; x)))$$

Since $m'(x) > 0$ and $l_h(\pi_0) > l_l(\pi_0)$, $\left| \frac{\partial \theta(d; x)}{\partial d} \right| > \left| \frac{\partial \theta(d; x)}{\partial d} \right|$. This establishes that for small $\varepsilon > 0$, $x' > x \Rightarrow \theta(\varepsilon; x) > \theta(\varepsilon; x')$. In other words, the share of high types is initially lower in tighter markets. This is intuitive as high types get selected out of unemployment relatively faster.
To complete the proof, we need to show that $\forall \ d > 0$, $x' > x \Rightarrow \theta(d; x) > \theta(d; x')$. We will proceed by contradiction. Suppose that this were not true. Then since $\theta(d; x')$ initially lies below $\theta(d; x)$, $\exists d^* > 0$ such that $\theta(d^*; x) = \theta(d^*; x')$ and $\theta(d^* + \varepsilon; x') < \theta(d^* + \varepsilon; x')$. By the definition of $d^*$, $\left| \frac{\partial \theta(d^*; x')}{\partial d} \right| > \left| \frac{\partial \theta(d^*; x)}{\partial d} \right|$. However, this would imply that $\theta(d^* + \varepsilon; x) > \theta(d^* + \varepsilon; x')$, a contradiction. Thus, it follows that a single crossing property has to hold for $\theta(d; x)$ and $\theta(d; x')$. And, since $\theta(0; x) = \theta(0; x')$, we have that $\theta(d; x) > \theta(d; x')$ and consequently $r(d; x) > r(d; x')$ for all $d > 0$.

**Composition Bias**

Recall equation (8)

$$c(d) = \int c(\phi) \frac{d\Phi(\phi|d)}{d\phi} d\phi$$

Differentiating with respect to $d$ yields:

$$c'(d) = \int c(\phi) \frac{d^2\Phi(\phi|d)}{d\phi dd} d\phi$$

(16)

Note that

$$\Phi(\phi|d) = \pi(d) \Phi_h(\phi|d) + (1 - \pi(d)) \Phi_l(\phi|d)$$

where $\pi(d) = \int \pi(d, \phi) d\Phi(\phi|d)$. Hence,

$$\frac{d\Phi(\phi|d)}{d\phi} = \pi(d) \frac{d\Phi_h(\phi)}{d\phi} + (1 - \pi(d)) \frac{d\Phi_l(\phi)}{d\phi}$$

Thus,

$$\frac{d^2\Phi(\phi|d)}{d\phi dd} = \frac{d\pi(d)}{dd} \left( \frac{d\Phi_h(\phi)}{d\phi} - \frac{d\Phi_l(\phi)}{d\phi} \right)$$

Plugging this back into (16), we get

$$c'(d) = \frac{d\pi(d)}{dd} \left[ \int c(\phi) d\Phi_h(\phi) - \int c(\phi) d\Phi_l(\phi) \right]$$

$$c'(d) = \frac{d\pi(d)}{dd} \left[ E_h[c(\phi)] - E_l[c(\phi)] \right]$$

By the proposition above, $\frac{d\pi(d)}{dd} < 0$. By first-order stochastic dominance and the fact that $c'(\phi) > 0$, the expression inside the brackets is positive. This establishes that $c'(d) < 0$.

**Appendix C: Model of Employer-Screening**

In this section, we show that a model of search frictions with employer screening will satisfy the requirements of the mechanical model of Section 2. We assume that (i) firms open vacancies subject to a zero-profit condition; (ii) workers and firms meet according to a reduced-form meeting function; (iii) upon meeting a worker, firms receive a signal $\phi$ on the worker’s productivity and decide whether or not to interview the worker at a cost; (iv) some applicants are called back for an interview (a costly screen) where the firm obtains additional information in the form of signal $z$. If the expected profit of firms exceeds the required wage then individuals are offered jobs. The expected profit depends on the wage and we need to make an assumption on wage setting. In the simplest version of the model, we assume that wages offered by all firms will equal the outside opportunity of workers which is denoted by $b$. As we show below, this model maps into the mechanical structure discussed in Section 2 since (i) a matching function of the required type is assumed to govern the rate at which firms and workers meet; (ii) hiring rates conditional on matching decline with
\( \pi (d; \phi) \) and (iii) high type applicants are more likely to be hired conditional on matching than low type applicants.

While we discuss the model for the simplest possible form of wage setting with \( w = b \), it is also possible to allow for more general forms of wage setting. For instance, we could assume that wages are set to be equal to \( b \) plus a fixed share in the expected surplus from a given job. For instance, we might expect that \( w = b + \lambda (E[y|\pi (d; \phi), z] - b) \) where \( \lambda \in [0, 1] \). In this case, firms would invite fewer individuals for interviews, since the expected surplus \((1 - \lambda) (E[y|\pi (d; \phi), z] - b)\) going to the firm would be smaller and thus the interview costs would be covered in fewer cases. Therefore a model with surplus sharing will have inefficiently low interview rates. Notwithstanding the fact that the welfare implications would differ under this form of wage setting, it is possible to show that the requirements (ii) and (iii) on hiring rates conditional on matching will still be satisfied and that therefore the predictions of the mechanical model still apply.

**Model Setup**

**Population Dynamics and Workers**

We maintain the assumptions on matching and on the life-cycle of individuals that we have described in Section 2.1. In addition, we assume that workers receive benefits \( b \) when unemployed and we assume that \( l < b < h \). These benefits are constant with respect to productivity and they determine the outside option of unemployed workers.\(^{26,27}\)

**Firms / Vacancies**

There is no fixed cost to opening a vacancy, but each period that a vacancy is open a flow cost \( c \) needs to be paid. There is free-entry.\(^{28}\) Filling or keeping open the current vacancy does not affect the ability to open future vacancies, nor does it have any impact on the costs and benefits associated with any future vacancies. Thus, firms fill vacancies as soon as they find a match such that the expected profit of the vacancy is positive. Firms care only about the productive type of a worker.

We assume that firms offer a wage of \( b \). Offering \( b \) represents a Nash equilibrium because we assume that applicants accept job offers with a pay-off equal to the expected pay-off from remaining unemployed. If all firms offer \( b \), then the pay-off from remaining unemployed is also \( b \) and workers accept these job offers. Further, no firm has an incentive to make a higher offer.

Once a vacancy is filled, it generates an output stream \( y \) until the individual retires. Since the wage \( b \) exceeds the productivity of the less able type, firms have an interest in hiring high productivity workers.\(^{29}\) We assume that firms hold rational expectations. Thus, firms beliefs about the probability that a worker of duration \( d \) and signals \( \phi \) and \( z \) is of high type will equal the distribution that arises in equilibrium.

**The Signals**

We assume the same matching process as described above. Upon meeting, firms observe how long an individual has been unemployed (a draw \( d \) from the random variable \( D \)). The firm also observes an additional signal \( \phi \) on the productivity of the worker - which we interpret to reflect the unobserved characteristics of the CV as described above. Given this additional signal, the firm can decide whether or not to interview the worker at a fixed cost \( \xi \). If the firm chooses to interview the worker, it then receives another signal \( z \) on the worker type \( y \). Without loss of generality, we assume that this signal represents new information about

\(^{26}\)Type fully predicts productivity in this model. Another formulation would allow type to determine productivity probabilistically. See Gonzalez and Shi (2009) for learning model.

\(^{27}\)Kraeger and Mueller (2011) find empirical support for the observation that the reservation wage does not vary with unemployment durations. See also Kasper (1967) as well as Feldstein and Poterba (1984).

\(^{28}\)The matching technology generates a rate of matching for a given vacancy that is independent of the number of vacancies a firm opens. Further, the flow cost of maintaining a vacancy is likewise independent of the number of vacancies a firm opens. These constant returns to scale assumptions imply that the size of firms is indeterminate. We will therefore treat each vacancy as a firm in its own right.

\(^{29}\)We are assuming here that firms hold onto non-profitable workers (\( b > l \)) forever. In other words, ex ante profits are driven to 0 in eqm but ex post there will be workers on which firms make losses. The assumption that relationships are maintained regardless of their productivity is clearly ad-hoc. We have in mind that firms incur losses on workers that are not productive and that they will therefore strive to avoid hiring low-productivity workers.
the worker type that is orthogonal to the prior $\pi(d, \phi)$ that firms hold about worker productivity when they make call-back decisions. For simplicity, we assume that distribution of the scalar signal only depends on the type $y$ and write the distribution function for $z$ conditional on productivity $y$ as $F^z_y(\cdot)$. Assume further that $F^z_1(\cdot)$ and $F^z_h(\cdot)$ satisfy a monotone likelihood ratio property. This captures the idea that $z$ is informative about the underlying type.

**Assumption 3** [Monotone Likelihood Ratio] $F^z_1(\cdot)$ and $F^z_h(\cdot)$ satisfy the MLR property so that $\frac{f^z_h(k)}{f^z_1(k)}$ (strictly)$^{30}$ increases in $k$. $^{31}$

Implied in this assumption is first-order stochastic dominance ($F^z_1(k) - F^z_h(k) > 0$ for all $k$). Continuous distributions satisfying MLR include the exponential family and the normal distribution. This assumption implies that firms pursue a "reservation signal policy" for both call-backs and hiring decisions. When a firm has observed $(Z = z, \phi, D = d)$, the firm decides whether or not to hire the worker.

**Equilibrium**

We begin by defining an equilibrium and the pay-off functions for firms in this economy. Denote by $J_u$ the value of an open vacancy, by $J_m$ the value of matching to an applicant before deciding on whether to interview this applicant and by $J_I$ the value of having interviewed an applicant with duration $d$ and signal $z$. Equation (17) says that the return on an unfulled vacancy depends on the flow cost of each vacancy, market tightness $x$, and the joint distribution of duration and signals $G^D(d, \phi)$ in the population. At rate $m_v(x)$, a vacancy meets with a worker, who is drawn from the joint distribution of incomplete spells (see Appendix A) and signals $\phi$: $G^D(d, \phi)$:

$$r J_u = -c + m_v(x) \int_d \int_{\phi} J_m(d, \phi) dG^D(d, \phi)$$

(17)

The value of a match depends on the signal $\phi$ drawn for this match and the duration $d$ of the applicant. This value equals the maximum of the value of keeping the vacancy open and the expected value of interviewing the worker net of interview cost $\xi$$^{32}$:

$$J_m(d, \phi) = \max \left\{ J_u, \int_z J_I(d, z, \phi) dF(z|d, \phi) - \xi \right\}$$

(18)

The distribution $F(z|d, \phi)$ depends only on the prior $\pi(d, \phi)$:

$$F(z|d, \phi) = \pi(d, \phi) F_h(z) + (1 - \pi(d, \phi)) F_l(z)$$

$$= F(z|\pi(d, \phi))$$

Upon interviewing the candidate, the firm updates its beliefs and obtains the value $J_I(d, z, \phi)$. $J_I(d, z, \phi)$ is the maximum of the expected present discounted value of profits from hiring this interviewee and the value of rejecting her and keeping the vacancy open. The expected flow return to a filled vacancy is the expected productivity conditional on the observed signals net of the wage ($b$). Expected productivity depends on the prior $\pi(d)$ as well as the signals $\phi$ and the signal $z$. $^{33}$ With rate $\delta$, individuals retire and the match is consequently dissolved. Thus, the flow return from a filled vacancy is discounted using both the interest rate

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$^{30}$By assuming that the likelihood ratio strictly increases, we ensure that as $z$ increases, the posterior probability of being the high type will approach 1.

$^{31}$WLOG, because we can always reassign the support of $z$.

$^{32}$Here we assume that to hire an applicant, an interview is always necessary. This assumption can be justified by the fact that workers in our experiment are always required to submit a CV to a vacancy and rarely are they offered a job at this stage.

$^{33}$To form this expectation, firms use the joint distribution of incomplete durations, signals, and productivity at time t: $G^D(D, Z, y, t)$.
The rational expectations equilibrium consists of $x = V/U$, an interview rule, a hiring rule, and a joint distribution $G^D(d, \phi, z, y)$ that satisfy:

1. Firms interview workers if and only if 
   \[ J_I(z, \pi(d, \phi)) \geq \xi. \]
2. Firms hire workers if and only if 
   \[ E[y|\phi, d, z] \geq b. \]
3. Given $x$ and implied $M_u(x)$, vacancies do not earn profits in expectation: $J_u = 0$.
4. Beliefs about the distribution of productivity $\pi(\phi, d)$ equal the equilibrium realized distribution $\pi(\phi, d)$.

### Characterizing Firm’s Behavior

It is easy to show the hiring rates in this model satisfy the two requirements of the mechanical model. We will show this for a given $\phi$. These properties of the hiring rates are maintained when we aggregate across $\phi$.

1. **Conditional on $\pi$, hiring rate for high types exceeds that for low types.**
   For a given $\pi(d, \phi)$, the interview rate is the same for high or low types. However, the expected productivity $E[y|\phi, d, z] = E[y|\phi(d), z]$ increases in $z$. Since $F_h(z)$ FOSD $F_l(z)$, high types are more likely to receive high signals than low types. The equilibrium condition 2 on hiring is therefore satisfied more often for high rather than low types.

2. **Conditional on type, hiring rates increase in $\pi$**
   By FOSD, we have that $F(z|\pi)$ increases in $\pi$ and that $J_I(z, \pi)$ increases in $z$ and $\pi$. Therefore, 
   \[ \int_z J_I(z, \pi(d, \phi)) dF(z|\pi(d, \phi)) \] increases in $\pi$. Thus, call-back rates for any type of worker (high or low) increase in $\pi$, satisfying the conditions of corollary 3. Furthermore, we have again that $E[y|\pi, z]$ increases in $\pi$. Since the type-specific distribution $F_y(z)$ does not depend on $\pi$, hiring rates for a given type increase in $\pi$.

Thus, both conditions on hiring rates and the matching structure of the mechanical model are satisfied by this screening model. Furthermore, the condition of corollary 3 is satisfied. It follows that the model exhibits negative duration dependence and that the model implies that duration dependence worsens if markets are tighter.

### Appendix D: Model of Human Capital Depreciation

An alternative interpretation of duration dependence in unemployment hazards is that workers skills depreciate during unemployment. We will present here a simple model that captures this idea. Our main point is that this model does not imply that that duration dependence interacts with market tightness. We can thus test this model based on human capital depreciation against the screening model using the interaction between market tightness and unemployment durations.

In contrast to the screening model, the idea of skill depreciation does not emphasize information problems on the part of employers about the productivity of applicants. Instead, human capital explanations are models in which all information about the general skills of workers are known to employers. Assume therefore that, conditional on $\phi$, all individuals have the same market skills. Instead of introducing an additional variable, we will simply assume that $\phi$ equals the human capital / productivity of a worker. Let $\phi$ at $d = 0$.
be given by $\phi_0$ and use $\Phi$ to denote the distribution of $\phi_0 : \phi_0 \sim \Phi$. We assume that individual human capital depreciates exponentially at rate $\rho$ while unemployed. At $d > 0$, individual human capital is given by $\phi(d) = \phi_0 \exp(-\rho d)$.

In addition to general human capital, we assume that the match between workers and firms has a match specific component. That is, we assume that the output of any match is given by $\phi + \varepsilon_{ij}$ where $\varepsilon_{ij}$ is independent of $\phi$ and drawn from distribution $F_\varepsilon$. The independence assumption on $\varepsilon$ captures the intuition that this component does not depend on worker or firm characteristics but is instead specific to each match.

As above, the unemployed and vacancies are matched at rate $m(x)$. Upon meeting, a firm observes $\phi$ and $d$, but needs to interview a worker in order to discover the match specific component $\varepsilon$. As before, we assume that interviews are costly and for simplicity we assume that firms can not hire a worker without interviewing her first.

The value function for an open vacancy is very similar to that of the screening model given in eq. (17):

$$ rJ_u = -c + m_v(x) \int_d d \phi_0 J_m(d, \phi_0) dG(d, \phi_0) \tag{21} $$

Upon meeting, the firm again has to choose whether to interview the worker with characteristics $\phi$ and $d$, and pay the interview cost of $\xi$. The problem is similar to the one above, except that the expectation is taken over the match specific component $\varepsilon$

$$ J_m(d, \phi_0) = \max \left\{ J_u, \int_{\varepsilon} J_1(\phi_0, d, \varepsilon) dF(\varepsilon) - \xi \right\} \tag{22} $$

We maintain the wage setting assumption that workers are paid their outside option $b$. The value of a filled vacancy is therefore

$$ J_1(d, \phi_0, \varepsilon) = \max \left\{ J_u, \frac{1}{r + \delta} (\phi_0 \exp(-\rho d) + \varepsilon - b) \right\} $$

Imposing the free entry condition, we have that a job is filled if

$$ \varepsilon \geq b - \exp(-\rho d) \phi_0 \tag{23} $$

Thus, conditional on matching and interviewing, the rate at which interviewees with $(\phi_0, d)$ are hired is $l(\phi_0, d) = 1 - F_\varepsilon(b - \exp(-\rho d) \phi_0)$. This rate declines in $d$. Now, since $J_1(d, \phi_0, \varepsilon)$ increases in $\phi_0$ and decreases in $d$, we have that the call-back rate $c(\phi_0, d)$ increases in $\phi_0$ and decreases in $d$. We thus have that the hiring rate has $h(\phi_0, d) = m(x)c(\phi_0, d)l(\phi_0, d)$ satisfies $\frac{\partial h(\phi_0, d)}{\partial d} < 0$.

Thus, the model generates true duration dependence in hiring rates and our experiment will find true duration dependence in call-back rates $c(\phi_0, d)$. However, consider the functions $r(d, x) = \frac{h(d, x, \phi_0)}{m(x, \phi_0)}$ and $r^c(d, x) = \frac{c(d, x, \phi_0)}{c(0, \phi_0)}$ that we have used to generate a testable implication for models following the structure of the mechanical model described in Section 2. For the model based on human capital depreciation, these two functions are:

$$ r(d, x, \phi_0) = \frac{c(\phi_0, d)l(\phi_0, d)}{c(\phi_0, 0)l(\phi_0, 0)} $$

$$ r^c(d, x, \phi_0) = \frac{c(\phi_0, d)}{c(\phi_0, 0)} $$

Neither of them depend on market tightness $x$. Therefore, it is possible to distinguish the depreciation model from the screening models described above exploiting the functions $r^c(d, x, \phi_0)$. Crucial however is

\footnote{We assume that the firm knows the relationship $\phi(d) = \phi_0 \exp(-\rho d)$ so, given $\phi$ and $d$, it can recover $\phi_0$. Thus, observing $\phi$ and $d$ is equivalent to observing $\phi_0$ and $d$. We adopt this convention when defining the value functions below.}
again that the distribution of characteristics \( \phi \) is adequately controlled for – and as we argue above, this requires experimental data of the type we exploit below.

**Appendix E: Ranking as an Alternative Model of Employer Generated Duration Dependence**

As an alternative to screening, Blanchard and Diamond (1994) (BD) developed a model of employer driven duration dependence building on the idea of ranking. According to the ranking model, vacancies accept multiple applications over a discrete, positive duration of time and then rank all applications against each other according to their duration. The ranking hypothesis is that firms hire the applicant with the shortest duration. Naturally, this model as discussed by BD generates duration dependence.

In each period, workers are assumed to send out an application with probability \( a \). BD further assume that markets are large in the sense that \( U(d) \) and \( V \to \infty \), where \( U(d) \) is the number of unemployed with duration less than \( d \).\(^{35}\) Given this assumption, the probability that any vacancy receives an application of an individual with duration \( d \) or less is equal to \( 1 - \exp \left( -\frac{aU(d)}{V} \right) \).

Since applications are independently assigned to vacancies, this probability is also the probability that an applicant of duration \( d \) will find himself applying to a vacancy for which another individual with a shorter duration also applies. The probability that an unemployed individual of duration \( d \) finds a job is therefore equal to the product of the probability that he sends an application times the probability that nobody of shorter duration applies to the same vacancies. Denoting by \( h_R(d) \) the hazard function from leaving unemployment in BD’s model, we obtain\(^{36}\):

\[
h_R(d) = a \exp \left( -\frac{aU(d)}{V} \right)
\] (24)

In this model, the probability a worker matches with a firm, \( m_u(x) = a \), does not depend on market tightness.\(^{37}\) Conditional on a worker matching with a firm, the probability he gets hired is \( l(d) = \exp \left( -\frac{aU(d)}{V} \right) \).

Thus, the job finding rate \( h_R(d) \) has a similar structure to the mechanical model above; namely the match probability times the hiring probability.

Since \( U(d) \) is by construction an increasing function, we have that \( \frac{\partial h_R(d)}{\partial d} < 0 \). Thus, the ranking and the screening models both generate true duration dependence and it is not possible to distinguish between them on the basis of this finding. However, as we will argue below, the models differ fundamentally in how labor market conditions affect duration dependence – screening predicts that tighter markets lead to more duration dependence, whereas ranking predicts that tighter markets lead to less duration dependence.

**Interaction Between Duration Dependence and Market Conditions**

Consider the function \( r_R(d) = \frac{h_R(d)}{h_R(0)} \) obtained from the ranking model:

\[
r_R(d) = \exp \left( -a \frac{U(d) - U(0)}{V} \right) = \exp \left( -a \frac{U(d)}{V} \right)
\] (25)

where we use the fact that in continuous time there is no mass of individuals with durations less than or equal to \( d = 0 \). Thus, we see directly how duration dependence as measured by \( r_R(d) \) depends on a particular measure of market conditions: the ratio of the currently unemployed with durations shorter than \( d \) to the total number of vacancies. If market conditions tighten in the sense that this ratio declines, then

\(^{35}\)We do not fully develop the BD model here, but refer the reader to the original work.

\(^{36}\)This is equation (15) in BD.

\(^{37}\)Blanchard and Diamond note that in a more realistic model, \( a \) would depend on the state of labour market. They do not consider this possibility.
\( r_R(d) \) increases.\(^{38}\) Thus, in this sense tighter labor markets are associated with less duration dependence.

Therefore, we can distinguish the screening, human capital depreciation and the ranking model by either (i) examining whether durations vary with current or with past market conditions or (ii) by examining whether duration dependence is more or less negative in permanently tighter labor markets. It is this second implication that we use to motivate the design and implementation of our resume audit study.

**Appendix F: Measuring Salience of Resume Characteristics Using Web-Based Survey of MBA Students**

Our experiment assumes that employers are aware of (and can therefore respond to) information about a job applicant’s unemployment spell. To test this assumption, we designed and conducted a web-based survey. We recruited 365 first-year MBA students at the University of Chicago Booth School of Business by e-mail on April 9, 2012, and the web-based survey was successfully completed by 90 MBA students.\(^{39}\) The students did not receive any compensation for participation, and they took roughly 5-10 minutes on average to complete the survey.\(^{40}\)

The survey took place in three stages. In the first stage (Appendix Figure A1), respondents were asked to read a hypothetical job posting and consider two resumes for the job opening. The job posting was chosen at random from one of three candidate job postings. These job postings were designed based on real job postings from our field experiment, each one corresponding to one of the three job categories used in the field experiment (i.e., administrative/ clerical, sales, customer service). We created six candidate resumes for each of the three possible job postings, and the two resumes presented to the respondent are chosen randomly from the appropriate set of six (and ordered randomly on the web page). These resumes were designed based on the fictitious resumes actually used in our field experiment. After being presented with the job posting and the two resumes, the respondent was then asked to select one of the two resumes to contact for an in-person job interview.

In the second stage (Appendix Figure A2), the respondent was required to perform two tasks. First, she was asked to recall specific information on each of the two resumes, such as total work experience, tenure at last job, level of education, current employment status, and the length of unemployment spell.\(^{41}\) Importantly, the respondent was precluded from viewing the resumes after making her selection. If the respondent attempted to click the “Back” button on her browser, she was warned that this would invalidate her survey response. Second, the respondent was asked to indicate which two resume attributes were most important in evaluating the job applicant’s resume, and to rank these two attributes by importance.\(^{42}\) In the third stage of the survey (Appendix Figure A3), the respondent is asked several demographic questions.

We use the responses to the “recall” questions in the second stage to measure the salience of the various resume characteristics. The results are reported in Appendix Table A1. The full sample used to measure salience comprises all of the resumes evaluated by all of the respondents, which is \(N = 180\), since each of the 90 respondents had to recall information for two resumes.

In Panel A of Appendix Table A1, we report results which compute how often the respondent correctly recalled the information, and we repeat this for each resume characteristic. The first row shows that respondents were able to correctly recall the level of education on the resume 65% of the time. This is similar to 66% of the time that the respondents were able to correctly recall whether or not the job applicant was currently employed. The respondents were particularly likely to recall the number of jobs that the applicant held; this information is correctly recalled 85% of the time. The last three rows of Panel

\(^{38}\)We refer the reader to Blanchard and Diamond who show more directly that \( h(d) = a \exp \left( -a \frac{U(d)}{V} \right) \) is decreasing in labor market tightness, \( \frac{d}{d} \).

\(^{39}\)There were 91 students who completed the survey, but one of the responses contained missing responses for most of the requested information and so was dropped from the analysis.

\(^{40}\)We measure time-to-completion by treating the IP address of the respondent as a unique identifier.

\(^{41}\)The ordering of these questions was chosen at random for each respondent.

\(^{42}\)The ordering of these attributes was chosen at random for each respondent.
A report results for the length of the unemployment spell, total work experience, and tenure at previous job, respectively. For these cases, we define the respondent as correctly recalling the information if the response is within a given window around the “actual” value, where the window varies by characteristic (and roughly scales with the average value of the characteristic across the resumes used in the survey). Using this definition, respondents correctly recall length of unemployment spell 52% of the time, total work experience 64% of the time, and tenure at previous job 47% of the time. The second column of Panel A reports analogous results for the subsample of respondents who report “high experience” in reviewing resumes (corresponding to a 4 or a 5 on a 5-point scale, which comprises roughly 19% of the full sample). The results are broadly similar for this subsample, with more respondents in this subsample correctly recalling the length of unemployment spell and whether job applicant was currently employed.

Next, in Panel B we report an alternative measure of salience: the correlation between the “recalled” information and the “actual” resume characteristic. This correlation is based on the variation across resumes in the values of these characteristics. Across all of the rows in the table, the two values are strongly and significantly correlated, suggesting that the respondents were able to recall information. Additionally, the correlations are generally higher among the subsample of respondents with “high experience”. Consistent with the results in Panel A, the correlation for length of unemployment spell is similar in magnitude to the correlations for the other variables. We also report the “mean % error” (defined as the average percentage difference between the “recalled” and “actual” values across all survey responses). This number is similar across characteristics, confirming that the respondents are not substantially biased on average in recalling specific information. We interpret the results in Panel A and Panel B as being broadly consistent with students being aware of employment status and length of unemployment spell, in addition to the other resume characteristics that they were asked to recall.

Lastly, in Panel C we report results from the subjective survey question which asked respondents to list the two most important attributes in evaluating the job applicant’s resume. Interestingly, there is overwhelming preference for the resumes to have “relevant work experience”, with very few respondents indicating employment status or length of unemployment spell as being one of the two most important attributes. These results may shed light on why resume audit studies typically explain so little variation in callback rates: if employers are primarily trying to gauge whether the work experience is specifically relevant for the job, and this information is not being measured or manipulated by researchers, then the ability of the other covariates to explain variation in callback rates will be limited.

Overall, the results of this survey are consistent with our assumption that employers in our experiment are aware of the employment status and the length of the unemployment spell, at least to the extent that they are aware of other information on the resume, such level of education, total work experience, and tenure at last job. While there is an important caveat that the survey respondents are not a representative sample of the individuals evaluating resumes in our field experiment, we are reassured that our results persist in the subsample of MBA students with high levels of experience actually reviewing resumes.

Appendix G: Covariance Between City Fixed Effects and City-Specific Effect of Unemployment Duration

Recall the following estimating equation from the main text:

33 The resumes in the survey have 84 months of work experience on average (std. dev. 18 months). For job tenure, the mean is 51 months (std. dev. 20 months). Finally, for length of unemployment spell, the mean (conditional on not being currently employed) is 20 months (std. dev. 9 months). The unemployment spells are chosen from set \{8, 14, 20, 27, 36\}. One reason why we choose the 4-month window for the length of unemployment spell is that there is a clear mass of respondents who respond with 12 and 24 months when true value of unemployment spell is 8 and 20, respectively. More than half of the survey respondents only provide year (and no month) for experience, job tenure, and unemployment spell. This could be consistent with a memory-based “heuristic” that rounds to the nearest year, or alternatively the respondents wanted to complete the survey more quickly and did not bother to guess the exact month for these characteristics.

44 In pilot survey, we did not have “relevant work experience”, and every student taking pilot survey responded that this would have been their first choice.
\[ y_{i,c} = \delta^c + \gamma^c \log(1 + d_{i,c}) + X_{i,c} \Gamma + \varepsilon_{i,c} \]

where \( \delta^c \) is city fixed effects and \( \gamma^c \) is a city-specific estimate of the effect of unemployment duration. We test for whether duration dependence varies with labor market conditions by treating \( \gamma^c \) as a proxy measure of labor market tightness and then estimating the covariance between \( \delta^c \) and \( \gamma^c \); i.e., \( E[(\delta^c - \tilde{\delta}^c)\gamma^c] \). We compute this by first computing the covariance between the estimates; i.e., \( E[\gamma^c \bar{\gamma}^c] \). Defining \( \bar{\gamma}^c \) as estimation error for \( \gamma^c \) (i.e., \( \bar{\gamma}^c = \gamma^c + \tilde{\gamma}^c \)) and \( \bar{\gamma}^c \) as estimation error for \( \bar{\gamma}^c \), then we can compute \( E[\gamma^c \bar{\gamma}^c] \) as follows:

\[
E[\gamma^c \bar{\gamma}^c] = \frac{1}{C} \sum_{c=1}^{C} \gamma^c \bar{\gamma}^c = \frac{1}{C} \sum_{c=1}^{C} (\delta^c + \hat{\delta}^c)(\gamma^c + \hat{\gamma}^c)
\]

\[
= \frac{1}{C} \sum_{c=1}^{C} \delta^c \gamma^c + \frac{1}{C} \sum_{c=1}^{C} \delta^c \bar{\gamma}^c + \frac{1}{C} \sum_{c=1}^{C} \bar{\gamma}^c \gamma^c + \frac{1}{C} \sum_{c=1}^{C} \bar{\gamma}^c \bar{\gamma}^c
\]

where \( C \) is the total number of cities in the sample. We can re-write this using expectations as follows (using the fact that \( E_c[\gamma^c] = 0 \) and \( E_c[\bar{\gamma}^c] = 0 \)):

\[
E[\gamma^c \bar{\gamma}^c] = E[\delta^c \gamma^c] + \frac{1}{C} \sum_{c=1}^{C} E_c[\bar{\gamma}^c \bar{\gamma}^c]
\]

Next, we can compute \( E_c[\bar{\gamma}^c \bar{\gamma}^c] \) using standard statistical results:

\[
E_c[\bar{\gamma}^c \bar{\gamma}^c] = -\frac{\sigma^2}{N^c} Var(\log(1 + d))
\]

where \( \sigma^2 \) is the residual variance for city \( c \), and \( N^c \) is the number of observations in the city. Combining the above gives us the following expression for the unbiased estimate of \( E[\delta^c \gamma^c] \):

\[
E[(\delta^c - \tilde{\delta}^c)\gamma^c] = \frac{1}{C} \sum_{c=1}^{C} \delta^c (\gamma^c - \bar{\gamma}^c) + \frac{1}{C} \sum_{c=1}^{C} \bar{\delta}^c \gamma^c + \frac{1}{C} \sum_{c=1}^{C} \bar{\gamma}^c \bar{\gamma}^c
\]

In other words, there is a negative bias in estimated covariance if one simply computes empirical covariance based on the regression estimates \( \delta^c \) and \( \bar{\gamma}^c \). Intuitively, this bias comes from the fact that the sampling errors in the estimates for these two parameters for a given city are negatively correlated. While this bias goes away asymptotically, it requires both that \( C \to \infty \) and \( N^C \to \infty \). In Monte Carlo simulations resembling our experimental data, we find substantial bias unless we use the bias correction above.

We conduct inference on the estimated covariance by computing the following standard error estimate, and we have verified that these standard errors are reliable using Monte Carlo simulations:

\[
se(E[\delta^c \gamma^c]) = \sqrt{\frac{1}{C} \left( \frac{1}{C} \sum_{c=1}^{C} (\delta^c)^2 (\gamma^c)^2 \right)}
\]
### Table 1
Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Received callback for interview</td>
<td>6866</td>
<td>0.040</td>
<td>0.196</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Received any phone call from employer</td>
<td>6866</td>
<td>0.116</td>
<td>0.320</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Employed</td>
<td>6866</td>
<td>0.224</td>
<td>0.417</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>**Months unemployed</td>
<td>Unemployed**</td>
<td><strong>5325</strong></td>
<td><strong>17.761</strong></td>
<td><strong>10.317</strong></td>
<td><strong>1</strong></td>
</tr>
<tr>
<td>Some college</td>
<td>6866</td>
<td>0.430</td>
<td>0.495</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>College degree</td>
<td>6866</td>
<td>0.362</td>
<td>0.481</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Years of experience</td>
<td>6866</td>
<td>5.292</td>
<td>2.042</td>
<td>1</td>
<td>15</td>
</tr>
<tr>
<td>Female</td>
<td>6866</td>
<td>0.636</td>
<td>0.481</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>6866</td>
<td>9.365</td>
<td>2.567</td>
<td>4.8</td>
<td>17.1</td>
</tr>
<tr>
<td>Administrative/Clerical job</td>
<td>6866</td>
<td>0.279</td>
<td>0.448</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Customer Service job</td>
<td>6866</td>
<td>0.313</td>
<td>0.464</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Sales job</td>
<td>6866</td>
<td>0.408</td>
<td>0.491</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

**Notes:** The first row reports the primary dependent variable which is whether or not the resume received a callback from the employer explicitly asking to set up an interview. The experimental sample is split into resumes where the worker reports currently being employed and resumes where the worker does not report currently being employed (with the gap between when the worker last reported working and when the resume was submitted being uniformly distributed between 1 and 36 months, inclusive).
Table 2  
Randomization Tests

<table>
<thead>
<tr>
<th></th>
<th>Employed</th>
<th>Unemployed</th>
<th>p-value of difference in means</th>
<th>Sample means</th>
<th>p-value of difference in means</th>
<th>Sample means</th>
<th>p-value of difference in means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Employed</td>
<td>Unemployed ≥18 months</td>
<td>Unemployed &lt;18 months</td>
<td></td>
</tr>
<tr>
<td>Some college</td>
<td>0.427</td>
<td>0.430</td>
<td>0.757</td>
<td>0.433</td>
<td>0.428</td>
<td>0.740</td>
<td></td>
</tr>
<tr>
<td>College degree</td>
<td>0.380</td>
<td>0.356</td>
<td>0.727</td>
<td>0.370</td>
<td>0.343</td>
<td>0.471</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.629</td>
<td>0.638</td>
<td>0.478</td>
<td>0.627</td>
<td>0.648</td>
<td>0.102</td>
<td></td>
</tr>
<tr>
<td>Unemployment rate</td>
<td>9.440</td>
<td>9.344</td>
<td>0.458</td>
<td>9.360</td>
<td>9.328</td>
<td>0.746</td>
<td></td>
</tr>
<tr>
<td>Administrative/Clerical job opening</td>
<td>0.291</td>
<td>0.275</td>
<td>0.384</td>
<td>0.276</td>
<td>0.275</td>
<td>0.988</td>
<td></td>
</tr>
<tr>
<td>Customer Service job opening</td>
<td>0.311</td>
<td>0.314</td>
<td>0.768</td>
<td>0.317</td>
<td>0.311</td>
<td>0.680</td>
<td></td>
</tr>
<tr>
<td>Sales job opening</td>
<td>0.397</td>
<td>0.411</td>
<td>0.605</td>
<td>0.408</td>
<td>0.414</td>
<td>0.706</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1541</td>
<td>5325</td>
<td>2612</td>
<td>2713</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The first row reports the primary dependent variable which is whether or not the resume received a callback from the employer explicitly asking to set up an interview. The experimental sample is split into resumes where the worker reports currently being employed and resumes where the worker does not report currently being employed (with the gap between when the worker last reported working and when the resume was submitted being uniformly distributed between 1 and 36 months, inclusive).
Table 3
The Effect of Unemployment Duration on Probability of Callback

<table>
<thead>
<tr>
<th>Dependent variable: Received callback for interview</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(1 + Months unemployed)</td>
<td>-0.010</td>
<td>-0.010</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.017]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>1 {Employed}</td>
<td>-0.028</td>
<td>-0.024</td>
<td>-0.024</td>
<td>(0.014)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.044]</td>
<td>[0.025]</td>
</tr>
<tr>
<td>6 ≤ Months unemployed ≤ 36</td>
<td>Unemployed</td>
<td></td>
<td>-0.027</td>
<td>(0.010)</td>
</tr>
<tr>
<td>6 ≤ Months unemployed &lt; 12</td>
<td>Unemployed</td>
<td></td>
<td>-0.032</td>
<td>(0.011)</td>
</tr>
<tr>
<td>12 ≤ Months unemployed &lt; 24</td>
<td>Unemployed</td>
<td></td>
<td>-0.024</td>
<td>(0.011)</td>
</tr>
<tr>
<td>24 ≤ Months unemployed ≤ 36</td>
<td>Unemployed</td>
<td></td>
<td>-0.027</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Joint significance of piecewise coefficients (p-value)</td>
<td></td>
<td></td>
<td></td>
<td>[0.031]</td>
</tr>
<tr>
<td>F-test of equality across piecewise coefficients (p-value)</td>
<td></td>
<td></td>
<td></td>
<td>[0.501]</td>
</tr>
<tr>
<td>Average callback rate in estimation sample</td>
<td>0.041</td>
<td>0.040</td>
<td>0.040</td>
<td>0.040</td>
</tr>
<tr>
<td>N</td>
<td>5325</td>
<td>6866</td>
<td>6866</td>
<td>6866</td>
</tr>
<tr>
<td>R²</td>
<td>0.084</td>
<td>0.074</td>
<td>0.075</td>
<td>0.075</td>
</tr>
<tr>
<td>Full sample</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Restrict sample to unemployed</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Include controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Notes: All columns report OLS linear probability model estimates. Data are resume-level submissions matched to callbacks from employers to request an interview. The controls included are the following: Some college, College degree, Quadratic in years of experience, Female dummy, metropolitan area fixed effects, resume template dummies, resume font dummies, and job category dummies. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets.
<table>
<thead>
<tr>
<th>Covariate $X = \ldots$</th>
<th>Customer Service job</th>
<th>Sales job</th>
<th>Female</th>
<th>College</th>
<th>Years of Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>log(1+d)</strong></td>
<td>0.010</td>
<td>0.033</td>
<td>0.047</td>
<td>0.005</td>
<td>0.002</td>
</tr>
<tr>
<td>(From model without interactions)</td>
<td>(0.004)</td>
<td>(0.009)</td>
<td>(0.006)</td>
<td>(0.010)</td>
<td>(0.002)</td>
</tr>
<tr>
<td></td>
<td>[0.017]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.373]</td>
<td>[0.827]</td>
</tr>
<tr>
<td><strong>F-test of equality for interaction terms (p-value)</strong></td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.308]</td>
<td>[0.225]</td>
</tr>
<tr>
<td>(City fixed effect $\times X$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Correlation between city fixed effect and</strong></td>
<td>-0.730</td>
<td>0.096</td>
<td>0.188</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>City-specific interaction term (bias-corrected)</td>
<td>(0.331)</td>
<td>(0.120)</td>
<td>(0.158)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.028]</td>
<td>[0.424]</td>
<td>[0.234]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>5325</td>
<td>5325</td>
<td>5325</td>
<td>5325</td>
<td>5325</td>
</tr>
<tr>
<td>R²</td>
<td>0.122</td>
<td>0.122</td>
<td>0.122</td>
<td>0.122</td>
<td>0.122</td>
</tr>
</tbody>
</table>

**Notes:** All columns report OLS linear probability model estimates. Data are resume-level submissions matched to callbacks from employers to request an interview, restricting sample to unemployed workers. Each column reports results from two separate regressions. The first row reports the point estimate on the covariate included in the column heading, when the effect is constrained to be the same across all cities. The second and third row report results from an alternative regression; specifically, it estimates a full set of interaction terms formed by multiplying indicator variable for each city with the variable listed in the column heading. The second row reports p-value from a test of equality across all of the estimated interaction terms, while the third row reports a bias-corrected estimate of the correlation between the estimated interaction terms and the city fixed effects. All regression include same controls listed in Table 3. If a cell entry has "0" with no standard error or p-value, then this implies that the model does not reject the null that the effect of the variable in the column is the same in all cities. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets.
Table 5
Heterogeneity by Local Labor Market: Correlated Random Effects Estimates

<table>
<thead>
<tr>
<th>Covariate $X = \cdots$</th>
<th>Customer Service job $d$</th>
<th>Sales job</th>
<th>Female</th>
<th>College</th>
<th>Years of Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(1+d)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>Mean of random coefficients for $X$</td>
<td>-0.011</td>
<td>0.048</td>
<td>0.047</td>
<td>0.005</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.012)</td>
<td>(0.010)</td>
<td>(0.006)</td>
<td>(0.008)</td>
</tr>
<tr>
<td></td>
<td>[0.019]</td>
<td>[0.000]</td>
<td>[0.000]</td>
<td>[0.432]</td>
<td>[0.694]</td>
</tr>
<tr>
<td>Standard deviation of random coefficient estimates</td>
<td>0.024</td>
<td>0.075</td>
<td>0.052</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.026)</td>
<td>(0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.008]</td>
<td>[0.004]</td>
<td>[0.019]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation between random coefficients for $X$ and city-specific random effects</td>
<td>-0.911</td>
<td>0.333</td>
<td>0.590</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(0.155)</td>
<td>(0.299)</td>
<td>(0.415)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.000]</td>
<td>[0.266]</td>
<td>[0.155]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: All columns report correlated random effects estimates, where a random coefficient on the variable listed in the column is allowed to be flexibly correlated with a city-specific random effect parameter. The random coefficients are allowed to vary across cities but are constant within a city. Data are resume-level submissions matched to callbacks from employers to request an interview, restricting sample to unemployed workers. Each column reports results from separate regression. The first row reports the mean of the random coefficients estimated on the variable in column heading. The second row reports the standard deviation across the random coefficient estimates. The final row reports the correlation between the random coefficient estimates and the city-specific random effect estimates. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets. If a cell entry has "0" with no standard error or p-value, then this implies that the model does not reject the null that the effect of the variable in the column is the same in all cities. In the case, the model does not estimate city-specific random coefficients for variable in column, and instead only estimates city-specific random effects.
Table 6
How Does Duration Dependence Vary With the Unemployment Rate?

<table>
<thead>
<tr>
<th>Dependent variable: Received callback for interview</th>
<th>Interaction term formed using $U = \ldots$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u \geq 8%$</td>
<td>$u$</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>log(1 + Months unemployed)</td>
<td>-0.015</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>[0.011]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>log(1 + Months unemployed) $\times U$</td>
<td>0.007</td>
</tr>
<tr>
<td>(0.005)</td>
<td>(0.081)</td>
</tr>
<tr>
<td>[0.156]</td>
<td>[0.654]</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.074</td>
</tr>
</tbody>
</table>

Panel A: Log unemployment duration

| Months unemployed $\geq 6$ | $-$0.046 | $-$0.027 | $-$0.027 | $-$0.031 | $-$0.027 | $-$0.027 |
| (0.015) | (0.010) | (0.010) | (0.011) | (0.010) | (0.010) | (0.010) |
| [0.003] | [0.007] | [0.007] | [0.004] | [0.007] | [0.007] | [0.007] |
| (Months unemployed $\geq 6$) $\times U$ | 0.028 | 0.262 | 0.034 | 0.014 | 0.681 | 0.128 |
| (0.014) | (0.231) | (0.024) | (0.011) | (0.408) | (0.053) | (0.053) |
| [0.049] | [0.257] | [0.164] | [0.187] | [0.095] | [0.016] | [0.016] |
| $R^2$ | 0.076 | 0.075 | 0.075 | 0.075 | 0.075 | 0.076 |

Panel B: High unemployment duration dummy

Notes: All columns report OLS linear probability model estimates. Data are resume-level submissions matched to callbacks from employers to request an interview. The controls included are the following: Some college, College, Quadratic in years of experience, Female dummy, city fixed effects, resume template dummies, resume font dummies, and job category dummies. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets.
Notes: These figures are generated by computing the average callback rate for each two-month bin in the range [1,36]. Figure 1 reports the average callback rate in each bin, while Figure 2 divides the average callback rate by the average callback rate in the first (lowest) unemployment duration bin [1,2].
Notes: This figure is generated by estimating a local linear regression on the experimental data. The nonparametric regression results are constrained to be monotonic following the rearrangement procedure described in the main text. The confidence intervals are bootstrapped 95% uniform confidence intervals based on 1000 replications.
Notes: These figures are generated by computing the average callback rate for each two-month bin in the range [1,36] for two sub-samples of the experimental data: data from cities with low unemployment rates (8%), and cities with high unemployment rates. Figure 4 reports the average callback rate in each bin for each sub-sample, while Figure 5 divides the average callback rate by the average callback rate in the first (lowest) unemployment duration bin [1,2].
Notes: These figures are generated by computing the average callback rate for each two-month bin in the range [1,36] for two sub-samples of the experimental data: data from cities with low unemployment rate growth (less than 4 percentage points between 2008 and 2011), and cities with high unemployment rate growth. Figure 6 reports the average callback rate in each bin for each sub-sample, while Figure 7 divides the average callback rate by the average callback rate in the first (lowest) unemployment duration bin [1,2].
### Appendix Table A1
Measuring salience of resume characteristics: MBA student survey

<table>
<thead>
<tr>
<th>What is the level of education of the applicant?</th>
<th>% answering correctly</th>
<th>% answering correctly</th>
</tr>
</thead>
<tbody>
<tr>
<td>[Bachelors, Associate Degree, GED, High School Grad]</td>
<td>65% correct</td>
<td>65% correct</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Is the job applicant currently employed?</th>
<th>% answering correctly</th>
<th>% answering correctly</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>66% correct</td>
<td>82% correct</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>How many jobs has the applicant held?</th>
<th>% answering correctly</th>
<th>% answering correctly</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>85% correct</td>
<td>86% correct</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>How long is the applicant currently unemployed?</th>
<th>% answering correctly</th>
<th>% answering correctly</th>
</tr>
</thead>
<tbody>
<tr>
<td>[Sample limited to not currently employed]</td>
<td>52% correct</td>
<td>74% correct</td>
</tr>
<tr>
<td>(within 4 months)</td>
<td>(0.054) (1.5%)</td>
<td>(0.135) (3.8%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>What is the applicant's total work experience?</th>
<th>% answering correctly</th>
<th>% answering correctly</th>
</tr>
</thead>
<tbody>
<tr>
<td>(within 24 months)</td>
<td>64% correct</td>
<td>71% correct</td>
</tr>
<tr>
<td>(within 24 months)</td>
<td>(0.070) (2.3%)</td>
<td>(0.132) (3.8%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>How long did the applicant hold his/her last job?</th>
<th>% answering correctly</th>
<th>% answering correctly</th>
</tr>
</thead>
<tbody>
<tr>
<td>(within 12 months)</td>
<td>47% correct</td>
<td>50% correct</td>
</tr>
</tbody>
</table>

### PANEL B: CORRELATION AND MEAN % ERROR
Comparing "RECALLED" AND "ACTUAL" RESUME CHARACTERISTICS

<table>
<thead>
<tr>
<th>How many jobs has the applicant held?</th>
<th>Correlation</th>
<th>Mean % error</th>
<th>Correlation</th>
<th>Mean % error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.710</td>
<td>3.4%</td>
<td>0.647</td>
<td>5.9%</td>
</tr>
<tr>
<td></td>
<td>(0.054)</td>
<td>(1.5%)</td>
<td>(0.135)</td>
<td>(3.8%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>How long is the applicant currently unemployed?</th>
<th>Correlation</th>
<th>Mean % error</th>
<th>Correlation</th>
<th>Mean % error</th>
</tr>
</thead>
<tbody>
<tr>
<td>[Sample limited to not currently employed]</td>
<td>0.499</td>
<td>-13.3%</td>
<td>0.757</td>
<td>-14.3%</td>
</tr>
<tr>
<td>(within 4 months)</td>
<td>(0.067)</td>
<td>(-6.0%)</td>
<td>(0.115)</td>
<td>(7.5%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>What is the applicant's total work experience?</th>
<th>Correlation</th>
<th>Mean % error</th>
<th>Correlation</th>
<th>Mean % error</th>
</tr>
</thead>
<tbody>
<tr>
<td>(within 24 months)</td>
<td>0.419</td>
<td>-13.0%</td>
<td>0.664</td>
<td>-11.4%</td>
</tr>
<tr>
<td>(within 24 months)</td>
<td>(0.070)</td>
<td>(2.3%)</td>
<td>(0.132)</td>
<td>(3.8%)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>How long did the applicant hold his/her last job?</th>
<th>Correlation</th>
<th>Mean % error</th>
<th>Correlation</th>
<th>Mean % error</th>
</tr>
</thead>
<tbody>
<tr>
<td>(within 12 months)</td>
<td>0.447</td>
<td>-11.1%</td>
<td>0.771</td>
<td>-9.7%</td>
</tr>
<tr>
<td>(within 12 months)</td>
<td>(0.069)</td>
<td>(5.2%)</td>
<td>(0.113)</td>
<td>(9.3%)</td>
</tr>
</tbody>
</table>

### PANEL C: RANKING RESUME ATTRIBUTES BY IMPORTANCE
Which two attributes were most important in evaluating the job applicant's resume?

<table>
<thead>
<tr>
<th>Years of work experience</th>
<th>1st choice</th>
<th>2nd choice</th>
<th>1st choice</th>
<th>2nd choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>4%</td>
<td>29%</td>
<td>11%</td>
<td>28%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Length of time at most recent job</th>
<th>1st choice</th>
<th>2nd choice</th>
<th>1st choice</th>
<th>2nd choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
<td>13%</td>
<td>0%</td>
<td>17%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Level of education</th>
<th>1st choice</th>
<th>2nd choice</th>
<th>1st choice</th>
<th>2nd choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>9%</td>
<td>28%</td>
<td>11%</td>
<td>39%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of jobs held by applicant</th>
<th>1st choice</th>
<th>2nd choice</th>
<th>1st choice</th>
<th>2nd choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
<td>12%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Relevant work experience</th>
<th>1st choice</th>
<th>2nd choice</th>
<th>1st choice</th>
<th>2nd choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>84%</td>
<td>8%</td>
<td>74%</td>
<td>6%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Current employment status</th>
<th>1st choice</th>
<th>2nd choice</th>
<th>1st choice</th>
<th>2nd choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1%</td>
<td>2%</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Length of time out of work</th>
<th>1st choice</th>
<th>2nd choice</th>
<th>1st choice</th>
<th>2nd choice</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2%</td>
<td>7%</td>
<td>5%</td>
<td>11%</td>
</tr>
</tbody>
</table>

Notes: This table reports results from a web-based survey administered to first-year MBA students at the University of Chicago Booth School of Business. Details of the survey are given in the Appendix. The table reports results for entire sample as well as a subsample of survey respondents who reported high experience in reviewing resumes (either a 4 or 5 on a 5-point scale). Standard errors are reported in parentheses in Panel B.
Appendix Table A2
The Effect of Unemployment Duration on Probability of Callback

<table>
<thead>
<tr>
<th>Dependent variable: Received callback for interview</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \log(1 + \text{Months unemployed}) )</td>
<td>-0.010</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td></td>
<td>[0.017]</td>
<td>[0.024]</td>
</tr>
<tr>
<td>( 1 {\text{Employed}} )</td>
<td>-0.028</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.044]</td>
<td></td>
</tr>
<tr>
<td>Some college</td>
<td>-0.001</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.006)</td>
</tr>
<tr>
<td></td>
<td>[0.839]</td>
<td>[0.943]</td>
</tr>
<tr>
<td>College degree</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.008)</td>
</tr>
<tr>
<td></td>
<td>[0.827]</td>
<td>[0.795]</td>
</tr>
<tr>
<td>Female</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.005)</td>
</tr>
<tr>
<td></td>
<td>[0.373]</td>
<td>[0.258]</td>
</tr>
<tr>
<td>Years of experience</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td></td>
<td>[0.365]</td>
<td>[0.224]</td>
</tr>
<tr>
<td>( (\text{Years of experience})^2 )</td>
<td>0.000</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>[0.545]</td>
<td>[0.098]</td>
</tr>
<tr>
<td>Customer service job</td>
<td>0.033</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.008)</td>
</tr>
<tr>
<td></td>
<td>[0.000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Sales job</td>
<td>0.047</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td></td>
<td>[0.000]</td>
<td>[0.000]</td>
</tr>
<tr>
<td>Average callback rate in estimation sample</td>
<td>0.041</td>
<td>0.040</td>
</tr>
<tr>
<td>N</td>
<td>5325</td>
<td>6866</td>
</tr>
<tr>
<td>R²</td>
<td>0.084</td>
<td>0.074</td>
</tr>
</tbody>
</table>

Notes: All columns report OLS linear probability model estimates. Data are resume-level submissions matched to callbacks from employers to request an interview. The controls included are the following: Some college, College, Quadratic in years of experience, Female dummy, metropolitan area fixed effects, resume template dummies, and resume font dummies. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets.
Appendix Table A3
Robustness to Alternative Controls

<table>
<thead>
<tr>
<th>Dependent variable: Received callback for interview</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>\log(1 + \text{Months unemployed})</td>
<td>-0.010</td>
<td>-0.010</td>
<td>-0.010</td>
<td>-0.010</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td></td>
<td>[0.024]</td>
<td>[0.017]</td>
<td>[0.022]</td>
<td>[0.013]</td>
</tr>
<tr>
<td>1 {\text{Employed}}</td>
<td>-0.028</td>
<td>-0.031</td>
<td>-0.028</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.013)</td>
<td>(0.013)</td>
</tr>
<tr>
<td></td>
<td>[0.044]</td>
<td>[0.024]</td>
<td>[0.038]</td>
<td>[0.040]</td>
</tr>
<tr>
<td>R^2</td>
<td>0.074</td>
<td>0.011</td>
<td>0.084</td>
<td>0.143</td>
</tr>
</tbody>
</table>

Full sample X X X X
Metropolitan area fixed effects X X X
Resume template and resume font fixed effects X X X
Demographic controls X X X
Year x week fixed effects X X
Metropolitan area × job type fixed effects X
Year x week × job type fixed effects X

Notes: All columns report OLS linear probability model estimates. Data are resume-level submissions matched to callbacks from employers to request an interview. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets.
Table A4
The Effect of Unemployment Duration on Probability of Callback

<table>
<thead>
<tr>
<th>Dependent variable: Received any callback from employer</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(1 + Months unemployed)</td>
<td>-0.014</td>
<td>-0.014</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.018]</td>
<td>[0.018]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1(employed)</td>
<td>-0.023</td>
<td>-0.003</td>
<td>-0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.232]</td>
<td>[0.835]</td>
<td>[0.844]</td>
<td></td>
</tr>
<tr>
<td>6 ≤ Months unemployed ≤ 36</td>
<td>Unemployed</td>
<td></td>
<td>-0.021</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.089]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6 ≤ Months unemployed &lt; 12</td>
<td>Unemployed</td>
<td></td>
<td>-0.019</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.239]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>12 ≤ Months unemployed &lt; 24</td>
<td>Unemployed</td>
<td></td>
<td>-0.015</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.014)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.263]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>24 ≤ Months unemployed ≤ 36</td>
<td>Unemployed</td>
<td></td>
<td>-0.030</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.014)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.031]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Joint significance of piecewise coefficients (p-value)</td>
<td></td>
<td></td>
<td>[0.159]</td>
<td></td>
</tr>
<tr>
<td>F-test of equality across piecewise coefficients (p-value)</td>
<td></td>
<td></td>
<td>[0.309]</td>
<td></td>
</tr>
<tr>
<td>Average callback rate in estimation sample</td>
<td>0.114</td>
<td>0.116</td>
<td>0.116</td>
<td>0.116</td>
</tr>
<tr>
<td>N</td>
<td>5325</td>
<td>6866</td>
<td>6866</td>
<td>6866</td>
</tr>
<tr>
<td>R^2</td>
<td>0.107</td>
<td>0.097</td>
<td>0.097</td>
<td>0.097</td>
</tr>
<tr>
<td>Full sample</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Restrict sample to unemployed</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Include controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Notes: All columns report OLS linear probability model estimates. Data are resume-level submissions matched to callbacks from employers to request an interview. The controls included are the following: Some college, College degree, Quadratic in years of experience, Female dummy, metropolitan area fixed effects, resume template dummies, resume font dummies, and job category dummies. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets.
## Appendix Table A5
### The Effect of Unemployment Duration Across Subsamples

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Women Only</th>
<th>Men Only</th>
<th>College Degree Only</th>
<th>Non-College Only</th>
<th>High-skill Only</th>
<th>Low-skill Only</th>
<th>Customer Service Jobs</th>
<th>Sales Jobs</th>
<th>Admin / Clerical Jobs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>log(d = Months unemployed)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(1)</td>
<td>-0.010</td>
<td>-0.012</td>
<td>-0.008</td>
<td>-0.012</td>
<td>-0.007</td>
<td>-0.012</td>
<td>-0.007</td>
<td>-0.004</td>
<td>-0.021</td>
<td>-0.001</td>
</tr>
<tr>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.007)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.008)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>[0.024]</td>
<td>[0.006]</td>
<td>[0.289]</td>
<td>[0.045]</td>
<td>[0.259]</td>
<td>[0.045]</td>
<td>[0.259]</td>
<td>[0.554]</td>
<td>[0.013]</td>
<td>[0.832]</td>
<td></td>
</tr>
<tr>
<td><strong>1 {Employed}</strong></td>
<td>-0.028</td>
<td>-0.032</td>
<td>-0.020</td>
<td>-0.033</td>
<td>-0.019</td>
<td>-0.033</td>
<td>-0.019</td>
<td>-0.018</td>
<td>-0.048</td>
<td>-0.007</td>
</tr>
<tr>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.023)</td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.020)</td>
<td>(0.027)</td>
<td>(0.010)</td>
<td></td>
</tr>
<tr>
<td>[0.044]</td>
<td>[0.022]</td>
<td>[0.380]</td>
<td>[0.081]</td>
<td>[0.288]</td>
<td>[0.081]</td>
<td>[0.288]</td>
<td>[0.370]</td>
<td>[0.074]</td>
<td>[0.511]</td>
<td></td>
</tr>
<tr>
<td><strong>p-value of test log(d) equal across cols.</strong></td>
<td>[0.366]</td>
<td>[0.617]</td>
<td>[0.543]</td>
<td>[0.190]</td>
<td>[0.190]</td>
<td>[0.190]</td>
<td>[0.190]</td>
<td>[0.190]</td>
<td>[0.190]</td>
<td></td>
</tr>
<tr>
<td><strong>Average callback rate in sample</strong></td>
<td>0.040</td>
<td>0.035</td>
<td>0.048</td>
<td>0.043</td>
<td>0.037</td>
<td>0.043</td>
<td>0.037</td>
<td>0.042</td>
<td>0.059</td>
<td>0.011</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>6866</td>
<td>4364</td>
<td>2502</td>
<td>3434</td>
<td>3432</td>
<td>3434</td>
<td>3432</td>
<td>2152</td>
<td>2800</td>
<td>1914</td>
</tr>
<tr>
<td><strong>R^2</strong></td>
<td>0.074</td>
<td>0.080</td>
<td>0.101</td>
<td>0.081</td>
<td>0.088</td>
<td>0.081</td>
<td>0.088</td>
<td>0.131</td>
<td>0.107</td>
<td>0.089</td>
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<tr>
<td><strong>Metropolitan area FEs</strong></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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<td></td>
</tr>
<tr>
<td><strong>Resume template and resume font FEs</strong></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
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<tr>
<td><strong>Demographic controls</strong></td>
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</tr>
</tbody>
</table>

**Notes:** All columns report OLS linear probability model estimates. Data are resume-level submissions matched to callbacks from employers to request an interview. The controls included are the following: Some college, College degree, Quadratic in years of experience, Female dummy, metropolitan area fixed effects, resume template dummies, resume font dummies, and job category dummies. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses and p-values are in brackets.
Appendix Figure A1

Chicago Booth Web-Based Resume Survey

Survey Instructions
We would like you to put yourself in the hypothetical situation of a Human Resources Manager who is currently trying to fill an opening for a job as a Customer Service Representative. You are considering two resumes that were submitted earlier today.

Please spend a few minutes reading the job description and the two resumes below, and then evaluate (in your capacity as the HR Manager) which of the two applicants you would contact to set up an in-person interview for the job.

Once you have finished evaluating the resume, you will then be asked several questions about the job applicant on the next page.

Job Description

Description:
Home Buyers Warranty, the leader in the home warranty industry, is seeking an Internet Dispatcher in a high paced call center environment.

Exempt or just some of the day-to-day duties include:
- Places outbound calls to homeowners for contract service requests
- Receives inbound calls with regard to network enrollment
- Sets up claims and dispatch service requests to contractors
- Enters contractor information into the company database for GNA

Resume #1: Jennifer Moore

Jennifer Moore

Objective
Seeking position with a reputable organization where I can utilize my experience in customer service.

Summary of Qualifications
I am a very motivated, responsible, and ambitious individual. I enjoy the challenges of working with others. I am looking for an organization that values its employees while providing a workplace that suits both the needs of the company and the needs of its employees.

Education

Experience
GREAT WEST FURNITURE DISTRIBUTION Denver, CO 1999-2003
- Answered telephones
- Maintained and entered inventory
- Assisted with customer service issues
- Provided customer service for service pick-ups

7/2000 - 4/2008
GREAT WEST FURNITURE DISTRIBUTION Denver, CO 1999-2003
- Responsible for daily sales
- Provided customer service to store patrons
- Managed inventory and maintained assistants
- Responsible for balancing cash register drawer
- Completed sales reports and bank deposits

1/2004 - 4/2005
NEW YORK & COMPANY - MILLER & MERRICK FURNITURE Denver, CO 2004-2005
- Responsible for daily sales
- Provided customer service to store patrons
- Managed inventory and displayed
- Responsible for daily cash

SKILLS
Over six years of excellent customer service experience; Computer proficient in Excel, Word, Outlook, and Internet; Skilled in sales and adapted well in many different sales environments.

Resume #2: Timothy Collins

TIMOTHY COLLINS
942 Revere Street, Thornton, Arvada, Colorado 80229
(303) 457-8005
timothycollins89@gmail.com

Summary
Customer service professional with the ability to build strong relationships with customers, establish and maintain personal customer service\n
Professional Experience
Customer Service Representative
January 2003 - May 2004
- Maintained and organized returns and exchanges
- Answered customer inquiries in a positive manner
- Managed customer's orders and interactions
- Answered telephone inquiries

Teak Stone Furniture
Denver, Colorado

Experience
Customer Service Manager
May 2006 - August 2010
- Recognized for excellent customer service
- Trained new hires in the aspects of customer service
- Developed and maintained customer relationships
- Answered telephone inquiries

SKILLS
Over ten years of exceptional sales experience; Computer proficient in Excel, Word, Outlook, and Internet; Skilled in sales and adapted well in many different sales environments.

Please select which applicant should be contacted for an interview:
- Resume #1: Jennifer Moore
- Resume #2: Timothy Collins

Continue
Appendix Figure A2

Chicago Booth Web-Based Resume Survey

Resume Characteristics
For all of the questions below, you should provide your BEST GUESS if you are not able to remember something exactly. You should NOT click the BACK button, doing so will invalidate your survey response.

Q1: How many jobs has the applicant held? (Please provide your BEST GUESS) [NOTE: Including the current job, if applicable]
   Jobs

Q2: How long is the applicant currently unemployed? (Please provide your BEST GUESS) [NOTE: If the applicant is currently employed, please select ’0’]
   Years, Months

Q3: What is the applicant’s total work experience? (Please provide your BEST GUESS) [NOTE: Include years at current job, if applicable]
   Years, Months

Q4: What is the level of education of the applicant? (Please provide your BEST GUESS)
   • High School Degree
   • GED
   • Associate Degree
   • Bachelors Degree

Q5: How long did the applicant hold his/her last job? (Please provide your BEST GUESS) [NOTE: Use months at current job, if applicable]
   Years, Months

Q6: Is the job applicant currently employed? (Please provide your BEST GUESS)
   • Yes
   • No

Ranking Attributes
Among the list of attributes below, please select the two that were the most important in evaluating the job applicant’s resume. Please place a ’1’ to indicate the most important attribute and a ’2’ to indicate the second-most important attribute.

- Current employment status
- Number of jobs held by applicant
- Years of work experience
- Length of time out of work
- Level of education
- Relevant work experience
- Length of time at most recent job

Continue
Appendix Figure A3

Chicago Booth Web-Based Resume Survey

Wrap-Up Questions

To complete the survey, please answer the following background questions.

Please indicate your overall level of experience in reviewing resumes for recruiting new hires, interns, etc.? (no experience) 1 2 3 4 5 (very experienced)

Have you worked in Human Resources before?
Yes  No

What is your gender?
Male  Female