Online Appendix for "Duration Dependence and Labor Market Conditions: Evidence from a Field Experiment"

February 2013

Online Appendix A: Mechanical Model

This section describes a mechanical model of unemployment. We purposely label the model "mechanical" since it is not explicitly based on microfoundations; it does not specify an information structure, firm or worker objectives, or a wage setting process. The question we address is the following: What properties on the job-finding process lead to duration dependence and how does duration dependence vary with labor market conditions? By considering a reduced-form approach to this problem, we simplify the analysis considerably. More importantly, this approach demonstrates that the predictions of the model are general: we show in Appendix B that a class of employer screening models, including a generalized version of the screening model in Lockwood (1991), map into the reduced-form of this mechanical model and therefore generate the same comparative statics. Thus, the approach pursued here can be thought of as identifying the pivotal assumptions in screening models that feature duration dependence in unemployment. Those interested in the structural screening model can go directly to Appendix B.

Population Flows

We consider economies in steady state such that inflows into unemployment are equal to outflows out of unemployment. A population of mass 1 is born continuously into unemployment. There are two possible types: either "high" ($y = h$) or "low" ($y = l$). The fraction of these two types are fixed at π_0 and $1 - \pi_0$, respectively. In the screening model below, worker type will correspond to unobserved worker productivity.

In the unemployed population, we allow the share of high types to depend on unemployment duration, which we denote by d. Formally, we define:

$$\pi(d) \equiv \Pr(y = h | d) \tag{1}$$

In terms of outflows, we assume that individuals transition out of unemployment either by finding a job or by retiring. We assume that the job-finding rate depends on worker type and the share of high types, and we denote this rate by $h_y(\pi(d))$.

We assume that individuals retire at an exogenous rate δ which does not depend on worker type or labor market status. The decision to assume away job separations is primarily to keep the analysis simple. Employer screening models that feature job separations are more complicated since this provides another source of information to potential employers to learn about worker productivity. Our interest is characterizing the adverse effects of a current spell of unemployment. While characterizing the effects of a worker's entire work history is interesting, it is beyond the scope of our study. We therefore follow Lockwood (1991) and assume that a worker is employed with at most a single firm in his lifetime.

The individual exit rate out of unemployment is the sum of the individual job-finding rate and retirement rate:

$$h_y(\pi(d)) + \delta \tag{2}$$

Given the escape rate in equation (2), $\pi(d)$ satisfies:

$$\pi(d) = \frac{\pi_0 \exp(-\int_0^d (h_h(\pi(\tau)) + \delta)\, d\tau)}{\pi_0 \exp(-\int_0^d (h_h(\pi(\tau)) + \delta)\, d\tau) + (1 - \pi_0) \exp(-\int_0^d (h_l(\pi(\tau)) + \delta)\, d\tau)} \tag{3}$$

To interpret equation (3), recall that the unemployed population at $d = 0$ is normalized to 1, so π_0 gives the number of newly unemployed high types and the term $\exp(-\int_0^d (h_h(\pi(\tau)) + \delta)\, d\tau)$ is the survival function for high types. Thus, the numerator exactly represents the number of high types that are unemployed after d periods. By similar logic, the denominator is the total number of individuals that are unemployed at duration d. Thus, their ratio pins down $\pi(d)$.

Finally, given the individual job-finding rate and the share of high types, we can define the population job-finding rate at a given duration as a mixture of the type-specific job-finding rates:

$$h(\pi(d)) = \pi(d)\, h_h(\pi(d)) + (1 - \pi(d))\, h_l(\pi(d)) \tag{4}$$

Expression (4) shows that the population job-finding rate varies with unemployment duration through two channels. First, it varies directly with duration through the share of high type workers. This source of variation represents "unobserved heterogeneity". Intuitively, the composition of types at risk of leaving unemployment shifts over time. Second, it varies indirectly with duration through the individual job finding rates. This source of variation captures "true duration dependence" and represents how the population job-finding rate varies over the spell, holding the share of high types constant. Ultimately, both sources depend on how the share of high types varies over the unemployment spell, so that the two sources of duration dependence interact and reinforce each other. This calls into question the standard practice of trying to separately identify true duration dependence from unobserved heterogeneity.

Duration Dependence

To operationalize the model, we impose two key assumptions on the individual job-finding rate. The first assumption states that there is heterogeneity in job-finding rates across types, so that one type finds jobs at higher rates than the other. Without loss of generality, we assume that the "high" type finds a job at a higher rate.

Assumption 1 *At a given unemployment duration, high types find jobs at higher rates than low types:*

$$h_h(\pi(d)) > h_l(\pi(d)) \tag{5}$$

The second assumption restricts how the type-specific job-finding rates vary with the share of high types in the unemployed population.

Assumption 2 *The individual job-finding rates increase in the share of high types:*

$$\frac{\partial h_y(\pi(d))}{\partial \pi} \geq 0 \tag{6}$$

Assumptions 1 and 2 are intuitively explained in the context of employer screening models (Vishwanath 1989; Lockwood 1991). In such models, worker types differ in productivity, firms draw signals on worker productivity, and firms set a hiring threshold for signals. Since the signals are informative on worker productivity, high types are more likely to draw high signals and be hired. Assumption 2 is satisfied since the

hiring threshold decreases in the firm's prior that a worker is productive. Under rational expectations, this threshold equals the share of high types in the unemployed population.

The next proposition states that the proportion of high types among the unemployed and, as a result, the job-finding rates decline with duration.

Proposition 1 *The proportion of high types in the unemployed population* (3) *and the population job-finding rate* (4) *decline strictly with duration. The individual job-finding rate declines weakly with duration d. Thus, the model features negative duration dependence in unemployment.*

The proof is straightforward. First, by Assumption 1, high types find jobs more frequently than low types. As a result, the composition of the unemployed shifts to low types at longer durations. Since the share of high types declines over the spell and since individual job-finding rates are increasing in the share of high types (Assumption 2), individual job-finding rates decline over the spell. Finally, the population job-finding rate declines due to true negative duration dependence and unobserved heterogeneity.[1]

To study how duration dependence interacts with market tightness, we impose more structure on individual job-finding rates. First, 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. Defining $x = \frac{V}{U}$ as labor market tightness, the CRS assumption implies that the rate at which unemployed individuals are matched with vacancies depends only on labor market tightness. Under this assumption, worker type does not influence the arrival rate of jobs offers. This is useful since it allows us to isolate the consequences of employer behavior.

Once a firm and worker have matched, we assume that the conditional hiring rate depends on worker type and the share of high types in the population. We denote this rate by $l_y(\pi(d; x))$ and assume that $l_h(\pi) > l_l(\pi)$ and $\frac{\partial l_y(\pi)}{\partial \pi} \geq 0$, which ensures that the individual job-finding rate continues to satisfy Assumptions 1 and 2. The third key assumption of the model governs how individual job-finding rates vary with market tightness.

Assumption 3 *In the individual job-finding rate, the type of the worker and the share of high types conditional on duration are weakly separable from market tightness:*

$$h_y(d; x) = m(x) \times l_y(\pi(d; x)) \tag{7}$$

We next define the following function:

$$r(d; x) = \frac{h(d; x)}{h(0; x)} \tag{8}$$

The function $r(d; x)$ is the ratio of the population job-finding rate evaluated at duration d to the population job-finding rate among the newly unemployed. This is an intuitive measure of the strength of duration dependence. If there is negative duration dependence, this ratio is below 1; conversely, if there is positive duration dependence, this ratio exceeds 1.[2] A key property of this ratio is that it depends on market

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[1]More formally, define $\theta(d) = \frac{\pi(d)}{1-\pi(d)}$. Differentiating $\theta(d)$ with respect to d and applying Assumption 1 gives $\pi'(d) < 0$. This combined with Assumption 2 delivers $\frac{\partial h_y(\pi(d))}{\partial d} \leq 0$. Finally, $\frac{\partial h(\pi(d))}{\partial d} = (1 - \pi(d)) \underbrace{\frac{\partial h_l(\pi(d))}{\partial d}}_{\leq 0} + \pi(d) \underbrace{\frac{\partial h_h(\pi(d))}{\partial d}}_{\leq 0} + \underbrace{\frac{\partial \pi(d)}{\partial d}}_{<0} \underbrace{(h_h(\pi(d)) - h_l(\pi(d)))}_{>0} < 0$.

[2]An alternative measure of how duration dependence varies with market tightness is 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.

tightness only through the share of high types.[3] The effect of market tightness on duration dependence occuring through the arrival rate is not operational since it affects the job-finding rate at all durations in a uniform way. This leads to the second proposition.

Proposition 2 *Duration dependence is stronger (more negative) when labor markets are tighter.*

Proof. Recall that $r(d;x)$ and $\theta(d;x)$ are defined as follows:

$$r(d;x) = \frac{h(d;x)}{h(0;x)}$$

$$\theta(d;x) = \frac{\pi(d;x)}{1-\pi(d;x)}$$

From the expressions above, it is clear that $r\left(\pi\left(d;x\right);x\right)$ 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 definition of $\theta(d,x)$, it is simple to show that

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

Since $m'(x) > 0$ and $l_h\left(\pi_0\right) > l_l\left(\pi_0\right)$, $\left|\frac{\partial\theta\left(0;x'\right)}{\partial d}\right| > \left|\frac{\partial\theta(0;x)}{\partial d}\right|$. 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^*, $\left|\frac{\partial\theta\left(d^*;x'\right)}{\partial d}\right| > \left|\frac{\partial\theta(d^*;x)}{\partial d}\right|$. 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 $\theta\left(d;x\right)$ and $\theta\left(d;x'\right)$. And, since $\theta\left(0;x\right) = \theta\left(0;x'\right)$, we have that $\theta\left(d;x\right) > \theta\left(d;x'\right)$ and consequently $r\left(d;x\right) > r\left(d;x'\right)$ for all $d > 0$. ∎

Formally, this proposition states that $r(d;x)$ for tight labor markets (large x) lies everywhere below the function $r(d;x)$ observed in loose labor markets (small x); i.e., $\partial r(d;x)/\partial x < 0$. Intuitively, in tight labor markets, workers are more likely to meet early on with firms. By Assumption 3, this rate of matching does not depend on worker type. Assumption 1 guarantees that high types are relatively more likely to exit unemployment when matched with a firm. This selection effect implies that the share of low types is relatively larger among the long-term unemployed. By Assumption 2, this strengthens duration dependence. By contrast, in loose labor markets, both worker types are less likely to meet open vacancies. Therefore, the share of high types will vary little over time, generating less duration dependence. As described in more detail in Appendix B, in employer screening models that are consistent with this mechanical model, market tightness affects the job-finding rate through two channels. First, it affects the rate at which workers meet firms. Second, it controls the precision of the information revealed by a worker's unemployment duration. In tight markets, a long unemployment spell reveals that the worker has likely been previously found unsuitable by prospective employers. Thus, the conditional hiring rate will implicitly depend on market tightness.

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[3]This requires that the composition of newly unemployed job seekers does not change over the business cycle.

Callbacks

Propositions 1 and 2 deliver testable predictions on job-finding rates. However, in our audit experiment, we do not observe hiring decisions, but rather whether applicants are called back for interviews. To align the theory more closely with our empirical application, we now adapt the model to incorporate an interview stage and callbacks. We define the callback rate as the probability that a worker gets invited for an interview. This is to be distinguished from the job-finding rate, the (joint) probability a worker receives a callback and gets hired.

The decision to interview a worker will depend on individual characteristics in addition to the duration of unemployment. We represent these characteristics by the vector ϕ and denote its distribution conditional on type y and duration d by $\Phi_y(.|d)$. The unconditional distribution is given by $\Phi(.|d)$.[4] We denote the share of high types in the population by $\pi(d; \phi)$.

We consider the case where the callback rate has the form $c(\pi(d; \phi); x)$ and we assume that it is weakly increasing in the high type share. When $d = 0$, the callback rate varies with market tightness only through the congestion channel; in particular, the information channel is absent. Intuitively, a newly unemployed worker reveals no information to firms that can be used to predict productivity. Thus, in our empirical work, we use the callback rate of a newly unemployed worker as a measure of market tightness. The population job-finding rate, conditional on ϕ, is obtained by replacing $\pi(d)$ with $\pi(d; \phi)$ and $h_y(\pi(d))$ with $h_y(\pi(d; \phi))$ in equation (4). This immediately implies the following corollary to Proposition 1:

Corollary 1 *Callback rates exhibit negative duration dependence.*

Intuitively, once all of a worker's characteristics (ϕ) are accounted for, bad luck that leads to a longer duration at the individual level will lead to a callback rate that declines at the individual level. Next, as an analog to the function $r(d; x)$, we define the relative ratio of callback rates:

$$r_c(d; x, \phi) = \frac{c(d; \phi; x)}{c(0; \phi; x)} \tag{9}$$

This delivers the following corollary to Proposition 2:

Corollary 2 *Duration dependence in the callback rate is stronger if markets are tighter.*

Formally, this corollary states that conditional on ϕ, $r_c(d; x, \phi) \geq r_c(d; x', \phi)$ if $x < x'$. The practical value of this corollary is that it implies we can use callback rates to test the implications on job-finding rates that we derived above. In practice, it is difficult to empirically test for true duration dependence in callback rates using observational data. If an econometrician cannot fully account for the impact of ϕ on callbacks, the estimate of $\frac{\partial c(\pi(d; \phi))}{\partial d}$ will be confounded by composition bias. For example, it is easy to account for some characteristics on a resume (such as gender, education and experience). However, resumes are complex and it is difficult to fully control for all characteristics. 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.

To illustrate this bias more formally, consider the extreme case where callbacks depend only on ϕ, 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 ϕ is unobserved by the econometrician. The population callback rate $c(d)$ is

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[4] $\Phi(.|d)$ is equal to $\pi(d)\Phi_h(.|d) + (1 - \pi(d))\Phi_l(.|d)$.

defined as follows:

$$c(d) \equiv \int c(\phi) \frac{d\Phi(\phi|d)}{d\phi} d\phi \tag{10}$$

Differentiating with respect to d yields:

$$c'(d) \equiv \int c(\phi) \frac{d^2\Phi(\phi|d)}{d\phi dd} d\phi \tag{11}$$

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 (11), we get

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

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

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

In our resume audit study, randomization of unemployment durations ensures that the distribution of unobserved characteristics ϕ is independent of the duration of unemployment, and so the composition bias described above will be absent. Since we randomize unemployment duration, our experiment recovers how the average callback rate evolves with unemployment duration. More formally, define the distribution $\widetilde{\Phi}(.)$ as the distribution of characteristics on our experimental set of CVs. Note that this distribution will not be the population distribution. Instead, we recover the following object:

$$\widetilde{c}(d) = E_{\widetilde{\Phi}}[c(\pi(d; \phi))|d] = \int_\phi c(\pi(d; \phi)) d\widetilde{\Phi}(\phi) \tag{12}$$

The function $\widetilde{c}(d)$ is an average over the callback rates for which the above corollary holds and the predictions of this corollary therefore also apply to $\widetilde{c}(d)$. This implies that we can use the callback rates elicited in our experiment to test the implications of the model. Finally, it is worth noting that even conditional on ϕ, the population job-finding rate, $h(\pi(d; \phi))$, will nevertheless decline in d due in part to unobserved heterogeneity. This occurs since $h_h(\pi(d; \phi)) > h_l(\pi(d; \phi))$ and because the share of high types conditional on ϕ increases with duration d. 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 ϕ. As we show formally in the screening model in Appendix B, 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 ϕ and low values of z. An econometrician who observes ϕ – but not the signal z at the hiring stage – may be led to conclude that there is duration dependence in job-finding rates when in fact the estimates are picking up a selection effect. In this sense, it is more straightforward to identify duration dependence in callback rates than in job-finding rates, since an econometrician only needs to condition on the information that a potential employer sees at the interview stage, not the hiring stage.

In the next three appendices, we present three leading behavioral models of employer-driven duration dependence. In doing so, we discuss whether the hiring rates in these models satisfy Assumptions 1-3 of the mechanical model. We find that the mechanical model is not so general so as to be vacuous: there are specific behavioral models which do and do not map into the structure of the mechanical model. These models therefore do not generate the same predictions regarding the interaction between hiring rates and the strength of duration dependence.

Online Appendix B: 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 in Appendix A. 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 ϕ on the worker's productivity ($y = h$ or l, with $h > l$) 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 firm is positive, then the individual is offered the 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 Appendix A since (i) a matching function of the required type is assumed to govern the rate at which firms and workers meet; (ii) high type applicants are more likely to be hired conditional on matching than low type applicants; and (iii) hiring rates conditional on matching decline with $\pi(d; \phi)$.

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 $w = b + \lambda\left(E[y|\pi(d; \phi), z] - b\right)$ where $\lambda \in [0, 1]$. In this case, firms would invite fewer individuals for interviews, since the expected surplus $(1 - \lambda)\left(E[y|\pi(d; \phi), z] - b\right)$ 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 Appendix A. 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.[5][6]

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.[7] 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 only high productivity workers.[8] We assume that firms hold rational expectations. Thus, firms' beliefs about the probability that a worker of duration d and signals ϕ 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 ϕ on the productivity of the worker - which we interpret to reflect the unobserved characteristics of the CV as described in Appendix A. Given this additional signal, the firm can decide whether or not to interview the worker at a fixed cost ξ. 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 the worker type that is orthogonal to the prior $\pi(d, \phi)$ that firms hold about worker productivity when they make callback 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 $F_y^z(.)$. Assume further that $F_l^z(.)$ and $F_h^z(.)$ satisfy a monotone likelihood ratio property. This captures the idea that z is informative about the underlying type.

Assumption 4 *[Monotone Likelihood Ratio]* $F_l^z(.)$ *and* $F_h^z(.)$ *satisfy the MLR property so that* $\frac{f_h^z(k)}{f_l^z(k)}$ *(strictly)*[9] *increases in* k.[10]

Implied in this assumption is first-order stochastic dominance ($F_l^z(k) - F_h^z(k) > 0$ for all k). Continuous distributions satisfying MLR include the exponential family and the normal distribution. This assumption

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[5] Type fully predicts productivity in this model. Another formulation would allow type to determine productivity probabilistically. See Gonzales and Shi (2009) for a learning model.

[6] Krueger 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).

[7] 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.

[8] 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.

[9] 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.

[10] WLOG, because we can always reassign the support of z.

implies that firms pursue a "reservation signal policy" for both callbacks 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 (13) says that the return on an unfilled 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 and signals ϕ: $G^D(d, \phi)$:

$$rJ_u = -c + m_v(x) \int\limits_d \int\limits_\phi J_m(d, \phi) dG^D(d, \phi) \tag{13}$$

The value of a match depends on the signal ϕ 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 ξ[11]:

$$J_m(d, \phi) = \max \left\{ J_u, \int_z J_I(d, z, \phi) dF(z|d, \phi) - \xi \right\} \tag{14}$$

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

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\begin{aligned}
F(z|d, \phi) &= \pi(d, \phi) F_h(z) + (1 - \pi(d, \phi)) F_l(z) \\
&= F(z|\pi(d, \phi))
\end{aligned}
$$

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 ϕ and the signal z.[12] With rate δ, individuals retire and the match is consequently dissolved. Thus, the flow return from a filled vacancy is discounted using both the interest rate r and the retirement rate δ.

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\begin{aligned}
J_I(d, z, \phi) &= \max \left\{ J_u, \frac{1}{r + \delta} (E[y|z, \pi(d, \phi)] - b) \right\} \tag{15} \\
&= J_I(z, \pi(d, \phi)) \tag{16}
\end{aligned}
$$

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 $\int_z J_I(z, \pi(d, \phi)) dF(z|\pi(d, \phi)) \geq \xi$.

2. Firms hire workers if and only if $E[y|\phi, d, z] \geq b$.

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[11] 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.

[12] To form this expectation, firms use the joint distribution of incomplete durations, signals, and productivity at time t: $G^D(D, Z, y; t)$.

3. Given x and implied $m_v(x)$, 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 ϕ. These properties of the hiring rates are maintained when we aggregate across ϕ.

1. **Conditional on π, 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 $E[y|\phi, d, z] = E[y|\pi(\phi, d), z]$ 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 π**
   By FOSD, we have that $F(z|\pi)$ increases in π and that $J_I(z, \pi)$ increases in z and π. Therefore, $\int_z J_I(z, \pi(d, \phi)) dF(z|\pi(d, \phi))$ increases in π. Thus, callback rates for any type of worker (high or low) increase in π, satisfying the conditions of corollary 1. Furthermore, we have again that $E[y|\pi, z]$ increases in π. Since the type-specific distribution $F_y(z)$ does not depend on π, hiring rates for a given type increase in π.

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 1 is satisfied. It follows that the model exhibits negative duration dependence and that the model implies that duration dependence worsens if markets are tighter.

Online Appendix C: Model of Human Capital Depreciation

An alternative interpretation of duration dependence in unemployment is that workers skills depreciate during unemployment. We present a simple model that captures this idea. Our main point is to illustrate 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, in human capital models, information about the general skills of workers are known to employers. We therefore assume that, conditional on ϕ, all individuals have the same market skills. Instead of introducing an additional variable, we will simply assume that ϕ equals the human capital / productivity of a worker. Let ϕ at $d = 0$ be given by ϕ_0 and use Φ to denote the distribution of $\phi_0 : \phi_0 \sim \Phi$. We assume that individual human capital depreciates exponentially at rate ρ 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 by $\phi + \varepsilon_{ij}$ where ε_{ij} is independent of ϕ and drawn from distribution F_ε. The independence assumption on ε 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 ϕ and d,[13] but needs to interview a worker in order to discover the match specific component ε. As before, we assume that interviews are costly and for simplicity we assume that firms cannot 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. (13) :

$$r J_u = -c + m_v(x) \int\limits_{d} \int\limits_{\phi_0} J_m(d, \phi_0) dG^D(d, \phi_0) \tag{17}$$

Upon meeting, the firm again has to choose whether to interview the worker with characteristics ϕ and pay the interview cost of ξ. The problem is similar to the one above, except that the expectation is taken over the match specific component ε:

$$J_m(d, \phi_0) = \max\left\{ J_u, \int_{\varepsilon} J_I(\phi_0, d, \varepsilon) dF(\varepsilon) - \xi \right\} \tag{18}$$

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

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

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

$$\varepsilon \geq b - \exp(-\rho d)\, \phi_0 \tag{19}$$

Thus, conditional on matching and interviewing, the rate at which interviewees with (ϕ_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 $J_I(d, \phi_0, \varepsilon)$ increases in ϕ_0 and decreases in d, we have that the callback rate $c(\phi_0, d)$ increases in ϕ_0 and decreases in d. We thus have that the hiring rate is given by $h(\phi_0, d) = m(x) c(\phi_0, d) l(\phi_0, d)$ and 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 callback rates $c(\phi_0, d)$. However, consider the functions $r(d, x) = \frac{h(d, x, \phi)}{h(0, x, \phi)}$ and $r^c(d, x) = \frac{c(d, x, \phi)}{c(0, x, \phi)}$ that we have used to generate a testable implication for models following the structure of the mechanical model described in Appendix A. For the model based on human capital depreciation, these two functions are:

$$
\begin{aligned}
r(d, x, \phi_0) &= \frac{c(\phi_0, d)\, l(\phi_0, d)}{c(\phi_0, 0)\, l(\phi_0, 0)} \\
r^c(d, x, \phi_0) &= \frac{c(\phi_0, d)}{c(\phi_0, 0)}
\end{aligned}
$$

Neither of them depend on market tightness x. Therefore, it is possible to distinguish the skill depreciation model from the screening model described above exploiting the function $r^c(d, x, \phi)$. Crucial however is again that the distribution of characteristics ϕ is adequately controlled for – and as we argue above, this requires experimental data of the type we exploit below.

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[13] We assume that the firm knows the relationship $\phi(d) = \phi_0 \exp(-\rho d)$ so, given ϕ and d, it can recover ϕ_0. Thus, observing ϕ and d is equivalent to observing ϕ_0 and d. We adopt this convention when defining the value functions below.

Online Appendix D: 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.[14] 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[15]:

$$h_R(d) = a \exp\left(\frac{-aU(d)}{V}\right) \tag{20}$$

In this model, the probability a worker matches with a firm, $m_u(x) = a$, does not depend on market tightness.[16] 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.

OA.0.1 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:

$$r_R(d) = \exp(-a\frac{U(d) - U(0)}{V}) = \exp(-a\frac{U(d)}{V}) \tag{21}$$

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

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[14] We do not fully develop the BD model here, but refer the reader to the original work.

[15] This is equation (15) in BD.

[16] 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.[17] 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.

Online Appendix E: Constructing Job-finding Rates from the CPS

Following the procedures outlined in Shimer (2008), we match observations across months and match on rotation group, household identifiers, individual line number, race, sex, and age. Furthermore, we restrict ourselves to matches originating in the first and fifth months in the sample, as in Shimer (2008), and scale weeks to months by multiplying weeks unemployed by 52/12.

We depart from Shimer (2008) and instead follow Rothstein (2011) by imposing the following requirement on exits from unemployment: an individual is defined to have exited from unemployment if and only if that individual is observed as employed in each of the successive to months/waves. This procedure therefore classifies U-E-U spells non-exits; only U-E-E spells are counted as exits from unemployment. See Rothstein (2011) for more discussion on this sample. Using these definitions, we compute the monthly exit rate from unemployment by month of duration of unemployment, grouping durations with fractional months using the floor function. The exit rates are computed using the final weights.

Online 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.[18] The students did not receive any compensation for participation, and they took roughly 5-10 minutes on average to complete the survey.[19]

The survey took place in three stages. In the first stage (Figure OA.I), 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 correponding 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 (Figure OA.II), 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

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[17]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, $\frac{U}{V}$.

[18]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.

[19]We measure time-to-completion by treating the IP address of the respondent as a unique identifier.

job, level of education, current employment status, and the length of unemployment spell.[20] 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.[21] In the third stage of the survey (Figure OA.III), 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 Table OA.I. 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 Table OA.I, 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 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).[22] 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.

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[20] The ordering of these questions was chosen at random for each respondent.

[21] The ordering of these attributes was chosen at random for each respondent.

[22] 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.

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.[23] 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.

Online Appendix G: Relating Poisson Model Estimates to Relative Callback Rate

Define the *arc* elasticity of a change in duration from d_0 to d_1 as follows:

$$\varepsilon_{ARC}(d_0, d_1; x) = \frac{(E[y|d_1; x] - E[y|d_0; x])/E[y|d_0; x]}{(d_1 - d_0)/d_0}$$

Define the *point* elasticity at d_0:

$$\varepsilon_{POINT}(d_0; x) = \frac{(E[y|d_0 + \Delta; x] - E[y|d_0; x])/E[y|d_0; x]}{\Delta/d_0}$$

Note that $\varepsilon_{POINT}(d_0; x) = \varepsilon_{ARC}(d_0, d_0 + \Delta; x)$. Let us assume that $\varepsilon_{ARC}(d_0, d_1; x) = \varepsilon_{ARC}(d_0; x)$. This implies that $\varepsilon_{POINT}(d_0; x) = \varepsilon_{ARC}(d_0; x)$ (i.e. the point and arc elasticities are equal at d_0). Suppose furthermore that $\varepsilon_{ARC}(d_0; x) = \varepsilon_{ARC}(x)$. This implies that $\varepsilon_{POINT}(x) = \varepsilon_{ARC}(x)$ (i.e. the point and arc elasticities are equal at all values of d). The Poisson Model assumes the following:

$$E[y|d_0; x] = e^{\theta(d_0; x)\log(d_0)}$$

Notice that

$$\theta(d_0; x) = \frac{dE[\log(y)|d_0; x]}{d\log(d_0)} = \varepsilon_{POINT}(d_0; x)$$

Under the assumption that $\varepsilon_{POINT}(d_0; x) = \varepsilon_{POINT}(x)$, $\theta(d_0; x) = \varepsilon_{ARC}(x)$. Thus, studying how θ varies with x sheds light on how the arc elasticity varies with x. This is useful since the relationship between $\varepsilon_{ARC}(1, d; x) \times (d - 1)$ and x pins down exactly how the relative callback rate varies with x:

$$\varepsilon_{ARC}(1, d; x) \times (d - 1) + 1 = \frac{E[y|d; x]}{E[y|1; x]}$$

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[23] 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.

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Online Appendix Table OA.I

Measuring salience of resume characteristics: MBA student survey

	All resumes (N = 180)		Only resumes reviewed by "High experience" students (N = 34)	

PANEL A: DESCRIPTIVE STATISTICS FROM SURVEY

	% answering correctly		% answering correctly	
What is the level of education of the applicant? [Bachelors, Associate Degree, GED, High School Grad]	65% correct		65% correct	
Is the job applicant currently employed?	66% correct		82% correct	
How many jobs has the applicant held?	85% correct		86% correct	
How long is the applicant currently unemployed? [Sample limited to not currently employed]	52% correct (within 4 months)		74% correct (within 4 months)	
What is the applicant's total work experience?	64% correct (within 24 months)		71% correct (within 24 months)	
How long did the applicant hold his/her last job?	47% correct (within 12 months)		50% correct (within 12 months)	

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

	Correlation	Mean % error	Correlation	Mean % error
How many jobs has the applicant held?	0.710 (0.054)	3.4% (1.5%)	0.647 (0.135)	5.9% (3.8%)
How long is the applicant currently unemployed? [Sample limited to not currently employed]	0.499 (0.067)	-13.3% (6.0%)	0.757 (0.115)	-14.3% (7.5%)
What is the applicant's total work experience?	0.419 (0.070)	-13.0% (2.3%)	0.664 (0.132)	-11.4% (3.8%)
How long did the applicant hold his/her last job?	0.447 (0.069)	-11.1% (5.2%)	0.771 (0.113)	-9.7% (9.3%)

PANEL C: RANKING RESUME ATTRIBUTES BY IMPORTANCE

Which two attributes were most important in evaluating the job applicant's resume?

	1st choice	2nd choice	1st choice	2nd choice
Years of work experience	4%	29%	11%	28%
Length of time at most recent job	0%	13%	0%	17%
Level of education	9%	28%	11%	39%
Number of jobs held by applicant	0%	12%	0%	0%
Relevant work experience	84%	8%	74%	6%
Current employment status	1%	2%	0%	0%
Length of time out of work	2%	7%	5%	11%

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 Online 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.

Online Appendix Table OA.II
The Effect of Unemployment Duration on Probability of Callback

Dependent variable: Received callback for interview
Sample: Full sample

	(1)	(2)
log(Months unemployed)	-0.011	-0.012
	(0.003)	(0.003)
	[0.000]	[0.000]
$\mathbf{1}$\{Employed\}	-0.020	-0.023
	(0.010)	(0.010)
	[0.040]	[0.019]
Metropolitan area unemployment rate		-0.003
		(0.001)
		[0.007]
Demographic variables and job characteristics		
Some college	-0.014	-0.016
	(0.006)	(0.006)
	[0.017]	[0.006]
College degree	-0.014	-0.018
	(0.008)	(0.008)
	[0.065]	[0.022]
High quality resume	0.011	0.012
	(0.004)	(0.004)
	[0.010]	[0.005]
Female	0.002	0.003
	(0.004)	(0.004)
	[0.529]	[0.502]
Customer service job	0.029	0.029
	(0.006)	(0.006)
	[0.000]	[0.000]
Sales job	0.057	0.057
	(0.007)	(0.007)
	[0.000]	[0.000]
Average callback rate in estimation sample	0.047	0.047
N	12054	12054
R^2	0.038	0.016
MSA fixed effects	X	
Baseline controls	X	X

Notes: All columns report OLS linear probability model estimates. The rows report the baseline controls that are included in most of the specifications reported in the main tables. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses, and p-values are in brackets.

Online Appendix Table OA.III
How Does Duration Dependence Vary With Labor Market Conditions?
[Using Alternative Labor Market Conditions Proxies in Table V]

Dependent variable: Received callback for interview
Sample: Unemployed only

Interaction term formed using proxy for local labor market conditions, $X = \ldots$	Baseline controls only		
	$\log(u_{2011})$	$-\log(V_{2011}/U_{2011})$	$\log(u_{2011}/u_{2008})$
	(1)	(2)	(3)
log(Months unemployed)	-0.012	-0.012	-0.012
	(0.003)	(0.003)	(0.003)
	[0.000]	[0.000]	[0.000]
log(Months unemployed) × X	0.048	0.020	0.054
	(0.014)	(0.009)	(0.026)
	[0.001]	[0.021]	[0.038]
X [Local labor market conditions proxy]	-0.154	-0.067	-0.144
	(0.043)	(0.026)	(0.077)
	[0.000]	[0.009]	[0.061]
Standardized effect of $\log(d)$ interaction term	0.012	0.009	0.006
Standardized effect of X	-0.040	-0.030	-0.015

Notes: N = 9236. All columns report OLS linear probability model estimates. All regressions include the same controls listed in Table III. See Table V for notes on the labor market conditions proxies. The standardized effects reported at the bottom are computed by multiplying the estimated coefficients by the (cross-MSA) standard deviation of the labor market conditions proxy. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each job posting, are in parentheses, and p-values are in brackets.

How Does Duration Dependence Vary With Labor Market Conditions?
[Replacing OLS with Probit in Table V]

Dependent variable: Received callback for interview
Sample: Unemployed only

Interaction term formed using proxy for local labor market conditions, X = …	Probit Specification		
	u_{2011}	$-V_{2011}/U_{2011}$	$u_{2011} - u_{2008}$
	(1)	(2)	(3)
log(Months unemployed)	-0.012	-0.013	-0.013
	(0.005)	(0.005)	(0.005)
	[0.014]	[0.011]	[0.012]
log(Months unemployed) × X	0.461	0.007	0.876
	(0.169)	(0.002)	(0.303)
	[0.006]	[0.003]	[0.004]
X [Local labor market conditions proxy]	-1.565	-0.022	-2.871
	(0.480)	(0.006)	(0.861)
	[0.001]	[0.000]	[0.001]
Standardized effect of interaction term	0.012	0.011	0.011
Standardized effect of X	-0.039	-0.036	-0.037
N	9236	9236	9236

Notes: All columns report models analogous to Table V, replacing the OLS linear probability model with a probit model. The columns report marginal effects evaluated at the means of all variables except log(Months unemployed), which is evaluated at 0. All regressions include same baseline controls listed in Table III. See Table V for notes on the labor market conditions proxies. The standardized effects reported at the bottom are computed by multiplying the estimated coefficients by the (cross-MSA) standard deviation of the labor market conditions proxy. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses, and p-values are in brackets.

Duration Dependence by Local Labor Market: Correlated Random Coefficients Estimates

Dependent variable: Received callback for interview
Sample: Unemployed only

	Covariate $X = \ldots$				
	$\log(d)$	Female	High quality resume	Customer service job	Sales job
	(1)	(2)	(3)	(4)	(5)
Mean of random coefficients for X	-0.012	0.002	0.012	0.035	0.057
	(0.004)	(0.003)	(0.004)	(0.006)	(0.006)
	[0.000]	[0.400]	[0.007]	[0.000]	[0.000]
Standard deviation of random coefficient estimates	0.013	0	0	0.042	0.043
	(0.003)			(0.007)	(0.007)
	[0.000]			[0.000]	[0.000]
Correlation between random coefficients on X and MSA-specific random effects; $corr(\delta^c, \gamma^c)$	-0.802	0	0	-0.495	0.272
	(0.092)			(0.171)	(0.342)
	[0.000]			[0.004]	[0.427]

Notes: N = 9236. Each column reports results from a single regression. This table reports results analogous to the main results in Table VI, except the fixed effects estimator is replaced with a correlated random coefficients model. In this model, a random coefficent for the variable listed in the column is allowed to be flexibly correlated with the MSA-specific random effect. These random coefficients are allowed to vary across MSAs but are constant within a MSA. 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 MSA-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 of constant effect of X across MSAs. In the case, the model does not estimate MSA-specific random coefficients for variable in column, and instead only estimates MSA-specific random effects.

Online Appendix Table OA.VI
Heterogeneity in Duration Dependence by Other Resume, Job, and Employer Characteristics

Dependent variable: Received callback for interview

	Full Sample	High Quality Resumes	Low Quality Resumes	Jobs in Construction or Manufact. Sectors	Jobs in Service Sectors	Jobs in Wholesale Trade or Retail Trade	Job Posting Mentions that Experience is Required Yes	No	Job Posting Mentions Equal Opportunity Employer Yes	No
	(1)	(2)	(3)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
log(d = Months unemployed)	-0.011	-0.013	-0.009	-0.023	0.000	-0.024	-0.011	-0.009	-0.019	-0.008
	(0.003)	(0.004)	(0.004)	(0.007)	(0.004)	(0.008)	(0.003)	(0.007)	(0.006)	(0.004)
	[0.000]	[0.003]	[0.024]	[0.001]	[0.933]	[0.004]	[0.001]	[0.194]	[0.001]	[0.046]
1{Employed}	-0.020	-0.022	-0.018	-0.043	0.004	-0.054	-0.016	-0.024	-0.040	-0.013
	(0.010)	(0.014)	(0.013)	(0.023)	(0.012)	(0.027)	(0.010)	(0.021)	(0.018)	(0.012)
	[0.040]	[0.115]	[0.164]	[0.059]	[0.712]	[0.044]	[0.118]	[0.244]	[0.021]	[0.278]
log(d) equal across columns [p-value]		[0.504]			[0.003]			[0.849]		[0.112]
Average callback rate in sample	0.047	0.050	0.044	0.032	0.053	0.049	0.030	0.085	0.032	0.053
N	12054	6049	6005	2336	6278	2367	7975	3663	3299	8339
R^2	0.038	0.045	0.044	0.077	0.081	0.067	0.040	0.123	0.074	0.051
MSA fixed effects	X	X	X	X	X	X	X	X	X	X
Baseline controls	X	X	X	X	X	X	X	X	X	X

Notes: All columns report OLS linear probability model estimates. All regressions include the same controls listed in Table III. The observations do not add up to 12054 across the groups of columns in columns (5) through (11) because of missing or incomplete data in the job postings. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses, and p-values are in brackets.

Online Appendix Table OA.VII
How Does Duration Dependence Vary With Labor Market Conditions?
[Replacing OLS with Fixed-Effects Poisson in Table V]

Dependent variable: Received callback for interview
Sample: Unemployed only

Interaction term formed using proxy for local labor market conditions, $X = \ldots$	Fixed-Effects Poisson Specification		
	u_{2011}	$-V_{2011}/U_{2011}$	$u_{2011} - u_{2008}$
	(4)	(5)	(6)
log(Months unemployed)	-0.182	-0.195	-0.186
	(0.055)	(0.054)	(0.055)
	[0.001]	[0.000]	[0.001]
log(Months unemployed) $\times$ X	6.710	0.085	0.142
	(2.232)	(0.030)	(0.045)
	[0.003]	[0.004]	[0.002]
Standardized effect of interaction term	0.173	0.138	0.187
N	8398	8398	8398

Notes: All columns report models analogous to Table V, replacing the OLS linear probability model with a fixed-effects Poisson model. All regressions include same controls listed in Table III as well as MSA fixed effects. See Table V for notes on the labor market conditions proxies. The standardized effects reported at the bottom are computed by multiplying the estimated coefficients by the (cross-MSA) standard deviation of the labor market conditions proxy. The sample size for fixed-effects Poisson model is smaller than in Table V because it is only identified off of cities with variation in the dependent variable. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses, and p-values are in brackets.

Callbacks for Currently Employed and Labor Market Conditions: Full Results and Sensitivity Analysis

	Dependent variable: Received callback for interview Sample: Unemployed only						Baseline controls + MSA fixed effects + MSA characteristics × { $\mathbf{1}$\{Employed\}, $\log(d)$ }		
	Baseline controls only			Baseline controls + MSA fixed effects					
Interaction term formed using proxy for local labor market conditions, $X = \ldots$	u_{2011}	$-V_{2011}/ U_{2011}$	$u_{2011} - u_{2008}$	u_{2011}	$-V_{2011}/ U_{2011}$	$u_{2011} - u_{2008}$	u_{2011}	$-V_{2011}/ U_{2011}$	$u_{2011} - u_{2008}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbf{1}$\{Employed\}	-0.023	-0.022	-0.023	-0.020	-0.020	-0.020	-0.018	-0.018	-0.018
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
	[0.019]	[0.024]	[0.018]	[0.039]	[0.043]	[0.039]	[0.061]	[0.063]	[0.062]
$\mathbf{1}$\{Employed\} × X	0.990	0.015	1.747	1.015	0.015	1.799	1.333	0.014	2.300
	(0.434)	(0.008)	(0.785)	(0.435)	(0.008)	(0.788)	(0.614)	(0.010)	(1.050)
	[0.023]	[0.052]	[0.026]	[0.020]	[0.044]	[0.023]	[0.030]	[0.185]	[0.029]
X [Local labor market conditions proxy]	-1.403	-0.024	-2.530						
	(0.415)	(0.007)	(0.744)						
	[0.001]	[0.001]	[0.001]						
$\log(d$ = Months unemployed)	-0.012	-0.011	-0.012	-0.011	-0.011	-0.011	-0.011	-0.011	-0.011
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\log$(Months unemployed) × X	0.432	0.007	0.794	0.429	0.007	0.792	0.458	0.006	0.883
	(0.142)	(0.002)	(0.252)	(0.142)	(0.002)	(0.252)	(0.201)	(0.003)	(0.332)
	[0.002]	[0.003]	[0.002]	[0.003]	[0.003]	[0.002]	[-0.003]	[0.079]	[0.008]
Standardized effect of Employed interaction term	0.025	0.024	0.022	0.025	0.022	0.023	0.033	0.022	0.029
Standardized effect of X	-0.035	-0.037	-0.032						
Standardized effect of $\log(d)$ interaction term	0.011	0.012	0.010	0.011	0.011	0.010	0.011	0.010	0.011
Joint sig. of the MSA vars. × $\mathbf{1}$\{Employed\} interactions [p-value]							[0.434]	[0.651]	[0.428]
Joint sig. of the MSA vars. × $\log(d)$ interactions [p-value]							[0.018]	[0.037]	[0.012]

Notes: N = 12054. All columns report OLS linear probability model estimates. All regressions include the same controls listed in Table III. See Table V for notes on the labor market conditions proxies.   In columns (7) through (9), the MSA characteristics include population, median income, fraction of population with a Bachelor's degree, and fraction of employed in information industries, professional occupations, service sectors, public administration, construction, manufacturing, wholesale/retail trade, and transportation. The standardized effects reported at the bottom are computed by multiplying the estimated coefficients by the (cross-MSA) standard deviation of the labor market conditions proxy. Standard errors, adjusted to allow for an arbitrary variance-covariance matrix for each employment advertisement, are in parentheses, and p-values are in brackets.

The University of Chicago Booth School of Business

Chicago Booth Web-Based Resume Survey

Survey Instructions

We would like you to put yourself in the hypothetical situation of a Human Resource 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.

Examples of just some of the day-to-day duties include:
• Makes outbound calls to non-enrolled contractors for service requests.
• Receives inbound/outbound calls with regard to network enrollment.
• Sets up claims and dispatch service requests to contractors.
• Enters contractor information into the company databases for SNA.

Resume #1: Jennifer Moore

(303) 223-5715   5872 Ruth Way, Denver, CO 80221   JenniferM.1221@yahoo.com

Jennifer Moore

OBJECTIVE

Seeking a 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 new challenges and value working with others. I am looking for an organization that values its excellence, while providing a workplace that seeks to both teach and learn from its employees.

EDUCATION

Aprahoe Ridge High School   Boulder, CO – G.E.D.

EXPERIENCE

5/2008 – 4/2009   **GEBHARDT BMW DEALERSHIP** Boulder, CO
Receptionist
o   Answered phones
o   Organized and maintained files
o   Sorted sales documents and contracts
o   Provided customer service for service pick-ups

7/2006 – 4/2008   **CHARLOTTE RUSSE – SHOPS AT NORTHFIELD STAPLETON** Denver , CO
Supervisor
o   Responsible for daily sales
o   Provide customer service to store patrons
o   Organized inventory and stocked products
o   Responsible for balancing cash register drawer
o   Completed sales records and bank deposits

1/2004 – 6/2005   **NEW YORK & COMPANY – SHOPS AT NORTHFIELD STAPLETON** Denver, CO
Sales Associate
o   Responsible for daily sales
o   Provide customer service to store patrons
o   Responsible for store displays

SKILLS

Over six years of impeccable customer service experience; Computer- Proficient in Word, Outlook, Win2data, MLS and Win Total; Skilled at sales and adapts well in many different sales environments.

Resume #2: Timothy Collins

TIMOTHY COLLINS
982 Rowena Street, Thornton, Adams, Colorado 80229
(720) 437-8005
timothycollins.8101@yahoo.com

SUMMARY

Customer Service professional with the ability to build strong relationships with customers, coworkers and potential clients. Professional and hardworking individual devoted to improving company's reputation through exceptional customer service.

PROFESSIONAL EXPERIENCE

Target   Littleton, Colorado
Customer Service Manager
May 2006 – August 2010

• Recommended, selected, and helped locate merchandise based on customer needs and desires.
• Resolved customer issues and inquiries; completed returns and exchanges as necessary.
• Examined merchandise to ensure that it is correctly priced and displayed.
• Conducted market research, identified emerging trends, and introduced marketing strategies.
• Operated cash register, handled money and performed daily check out procedures.

Tebo Store Fixtures   Denver, Colorado
Customer Service Representative
January 2003 – May 2006

• Trained new hires in a variety of warehouse departments.
• Made sure items were in good shape and that packages were received and shipped timely.
• Conducted and reported monthly inventory of warehouse items.
• Provided office support and administrative assistance for customer orders processing and computer tracking.

EDUCATION

Westwood College – Denver North Campus   Denver, Colorado
Associate Degree in Information Technology

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

[Continue]

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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.

	Resume #1: Jennifer Moore	**Resume #2: Timothy Collins**
Q1: How many jobs has the applicant held? (**Please provide your BEST GUESS**) [NOTE: Including the current job, if applicable]	▾ Jobs	▾ 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	▾ 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	▾ 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	○ 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	▾ Years, ▾ Months
Q6: Is the job applicant currently employed? (**Please provide your BEST GUESS**)	○ Yes ○ No	○ 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]

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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)
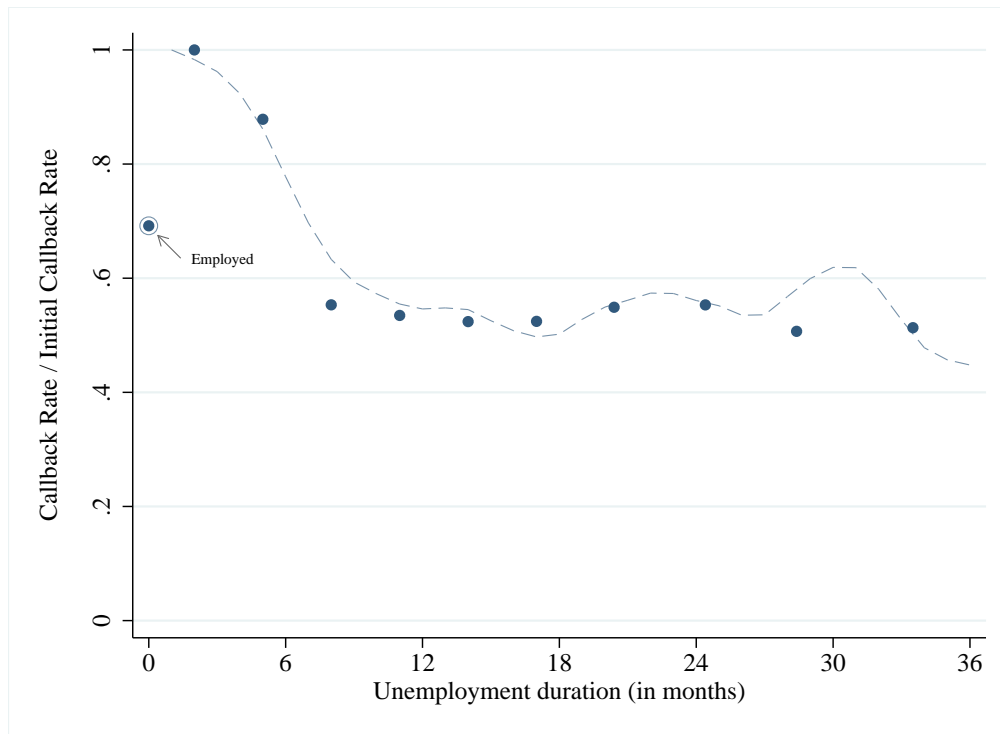
Have you worked in Human Resources before?
○ Yes   ○ No

What is your gender?
○ Male   ○ Female

Finish!

(RELATIVE) CALLBACK RATE VS. UNEMPLOYMENT DURATION
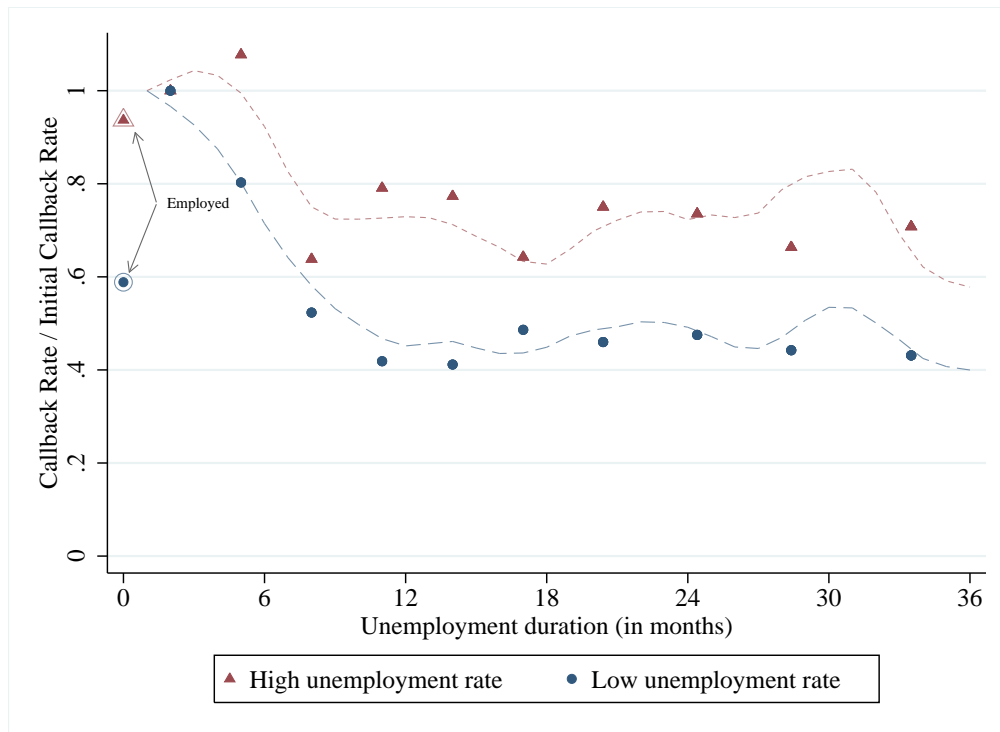
Notes: This figure reports the average callback rate by unemployment duration (in months); resumes where the individual was currently employed are assigned unemployment duration of 0. The data are grouped into 3-4 month bins before computing the average callback rate, and then the average is scaled by the average callback rate in the first unemployment duration 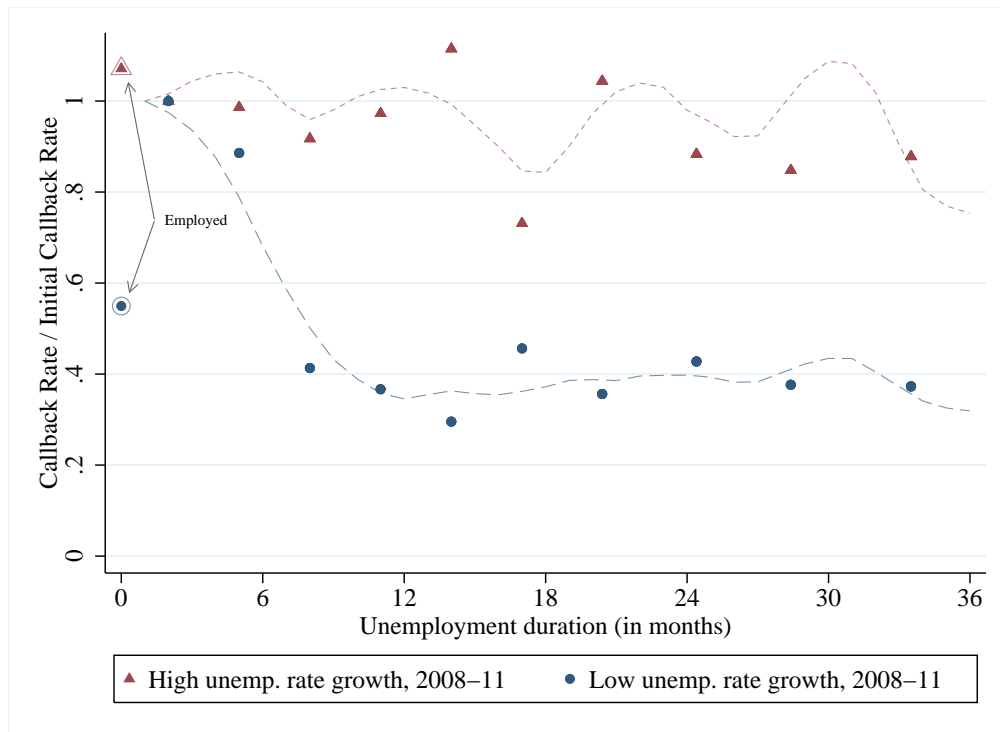bin [1,3] to convert into a *relative* callback rate. The dashed line is a (smoothed) local mean, which is generated using an Epanechnikov kernel and a bandwidth of 2 months.

Notes: This figure is generated by computing the average callback rate for each 3-4 month bin for two subsamples of the experimental data: data from cities with low unemployment rates in July 2011 ($u < 8.8\%$) and cities with high unemployment rates ($u \geq 8.8\%$). The dashed lines are (smoothed) local means, which are generated using an Epanechnikov kernel and a bandwidth of 2 months. For both subsamples, the average callback rate in each bin is scaled by the average callback rate in the first unemployment duration bin [1,3] to covert into a *relative* callback rate.
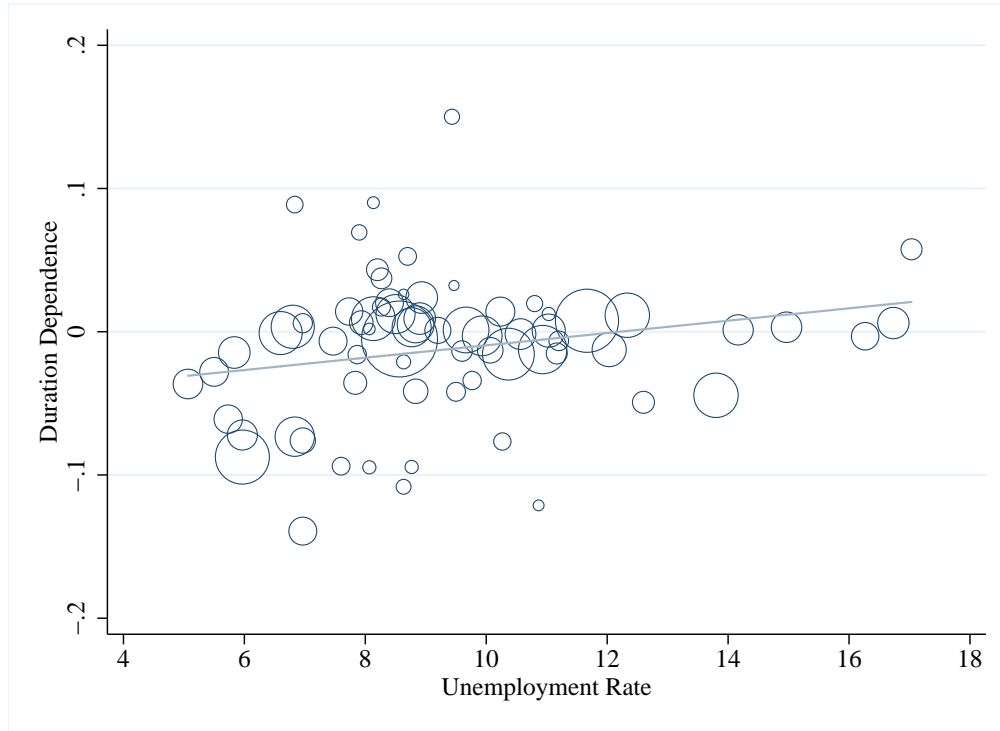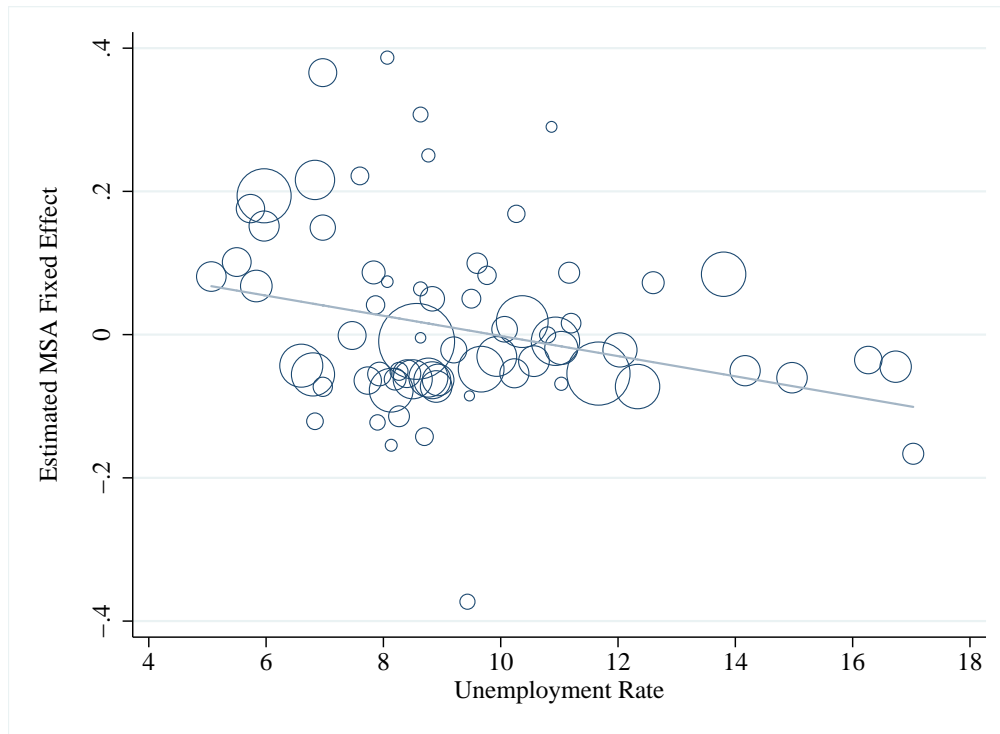
Notes: This figure is generated by computing the average callback rate for each 3-4 month bin for two subsamples of the experimental data: data from cities with high vacancy/unemployment ratios ($V/U > 3.25$), and cities with low V/U ratios ($V/U \leq 3.25$). The dashed lines are (smoothed) local means, which are generated using an Epanechnikov kernel and a bandwidth of 2 months. For both subsamples, the average callback rate in each bin is scaled by the average callback rate in the first unemployment duration bin [1,3] to covert into a *relative* callback rate.

Notes: This figure is generated by computing the average callback rate for each 3-4 month bin for two subsamples of the experimental data: data from cities with low unemployment rate growth ($<$ 3.6 percentage points between 2008 and 2011) and cities with high unemployment rate growth ($\geq$ 3.6 percentage points). The dashed lines are (smoothed) local means, which are generated using an Epanechnikov kernel and a bandwidth of 2 months. For both subsamples, the average callback rate in each bin is scaled by the average callback rate in the first unemployment duration bin [1,3] to covert into a *relative* callback rate.
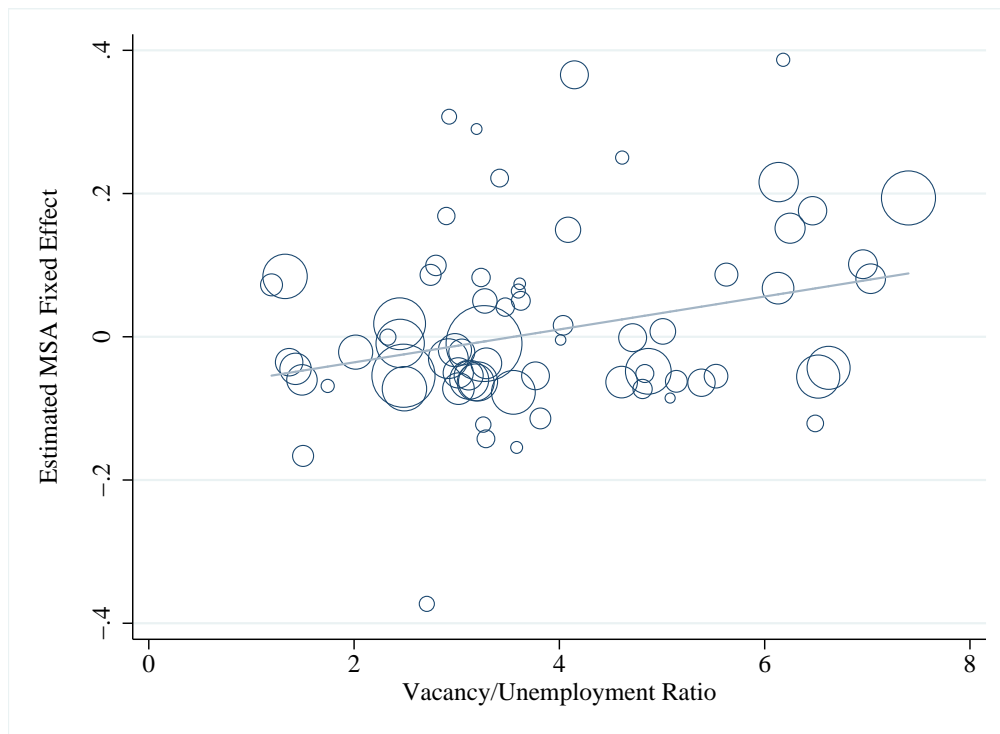
Notes: This figure shows the correlation between the MSA-specific estimated coefficient on unemployment duration (the duration dependence coefficient) and the MSA unemployment rate at the start of the experiment (July 2011). The solid line is the weighted OLS regression line using the number of observations in the MSA for the weights. The size of the circles are proportional to these weights.

Notes: These figures show the correlation between the estimated city-specific fixed effects and two alternative proxies for market tightness. The solid line is the weighted OLS regression line using the number of observations in the city for the weights. The size of the circles are proportional to these weights.