The Impact of Technology on the Labor Procurement Process

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Abstract

We construct a mathematical model to explore why digitization of employee recruiting process so far has not resulted in employers reporting hiring better candidates faster. We model multidimensional impact of Internet technology with increases in the total number of applications, in the rate at which applications arrive, and in departure rates of applicants. We also assume that technology leads to a stochastic decrease in the quality of the applicants. We then model a firm’s recruiting process and investigate analytically and numerically the expected outcome. We show that the decrease in quality can be the dominant effect resulting in poorer outcome.

1. Introduction

When discussing a firm’s supply chain, most people think of the supply of physical goods that are inputs into the production process. They often overlook one of the key production inputs, labor, even though the ability to recruit and retain good employees is vital to a firm’s success. As with any other input, a firm needs a supply chain that delivers high-quality employees in a timely and cost-effective manner. The ultimate product of the labor supply chain is a trained worker fulfilling some internal function at the firm. Working backward from there are many steps in the chain, some of which are typically internal to the firm and some that are external. Before being assigned to a function, each employee receives function-specific training; before that, employees receive training in the general policies and procedures of the firm and are registered in the various administrative systems of the firm. Before that, they are screened (interviewed) and hired. All of these steps can be viewed as a quality inspection and production process, much like those used for other products. The creation or sourcing of the pool of applicants to interview is where the labor supply chain is most different from supply chains for other types of inputs.

Some firms are actively involved in training programs with external partners, both for-profit and nonprofit educational institutions, to develop a pool of potential employees. Some firms contract with labor providers, such as employment agencies and temporary staffing agencies, to procure labor by leasing workers from them or by partnering with them to identify candidates and do part of the screening. I.e., they outsource part of the human resource (HR) function.

![Figure 1. Process Map for Hiring](image_url)
not most, firms. This means that a firm’s HR department advertises positions, leading to applications that the HR department must process, screen, and then feed into the interview process, as is illustrated, for example, in Figure 1. It is this portion of the labor supply chain, from application to hiring, that we focus on in this paper.

We split this part of the process into two stages: Stage 1 is the initial screening of applications to decide which will receive more in-depth and costly evaluation in Stage 2. The outcome of Stage 2 is the selection and hiring of a candidate. While many employers have multiple steps in the evaluation, such as phone interviews and multiple rounds of in-person interviews, we consolidate this into one stage. The two stages can be distinguished by the degree of interaction with the applicant that they require.

When considering the recruitment process, we are particularly interested in developing a better understanding of how technology affects the labor procurement process. Prior to the widespread adoption of the Internet in the 1990s, firms needed to advertise in print media and at the employment offices of individual educational institutions or use “headhunter” agencies to find applicants for positions. Job seekers needed to peruse the job ads in their local newspapers, go to conferences or other events with employment recruiting activities, or sign up with the headhunters to find job openings. Applications were submitted by mail, and finding information about opportunities outside one’s local geographic area and social and professional networks was difficult and time-consuming. For both sides of the search, the process was very costly. With Internet-based services and communication, the costs to widely advertise a position, find a position, and apply for a position have all been dramatically reduced. Sites like Monster.com are based upon playing the role of market-maker. At the same time, it is not clear that the screening part of the hiring process has been similarly made more efficient. There are mixed opinions about whether the labor supply chain has improved as a result of the technological improvements.

When Internet job boards appeared, it was widely thought that firms would be able to downsize their HR recruiting departments and headhunters would be put out of business. Yet it appears that neither happened. While newspaper revenues from job advertisements fell significantly (see Figure 2) and the spending by U.S. companies on online recruitment was expected to reach $5.75 billion in 2012 [22], in 2011 52 percent of U.S. employers reported difficulty filling vacancies [4].

One anecdotal explanation is that the Internet makes the job application process easier for job seekers, which in turn leads to increased workload on the HR personnel, who have to spend more time weeding out many unqualified applicants[3, 12, 15]. The resulting congestion leads to a longer (or more labor-intensive) hiring process than pre-Internet. Sullivan [20] cautioned of two consequences of a large number of applications: slower hiring process, which means top performers drop out, and increased likelihood of legal action, which grows with every accepted applicant. To deal with an increasing number of applicants, many employers have resorted to using resume-filtering software—which may be filtering out qualified applicants [22, 23].

In this paper, our approach is to start from the point in time that a firm advertises a position (Figure 1) and analyze a situation in which Stage 2 is non-sequential in manner. This means that, as applications arrive, the firm determines if the applicant should enter the candidate pool. When the candidate pool has been created, the in-depth evaluation takes place for the entire pool or batch. The review may have stages that lead to elimination of many of the applications from consideration, but all applications go through some evaluation before a hiring decision is made. This is a common approach. For example, a firm might do an initial screening of resumes to narrow down to a smaller group that is interviewed by phone; next, a smaller group of those interviewed by phone are selected for in-person interviews. Only after all the interviews have been conducted is an offer made. The reason many hiring processes are non-sequential is that it facilitates comparisons between candidates, which makes it easier to derive preferences. Van Ommeren and Russo [21] present empirical evidence that many firms conduct their searches non-sequentially.
A negative consequence of non-sequential or batch evaluation of applicants is that early applicants have to wait longer than later applicants. During this delay, they may lose interest or find another opportunity. Therefore, while a larger batch size may increase the likelihood of finding a high-quality employee, it can also reduce the likelihood—because the added delay in the process can cause high-quality applicants to drop out. Technology has a role in this tension. The easier it is to apply for positions, the bigger the applicant pool will be. At the same time, these applicants will be applying to more positions and will be more time-sensitive. The quality of the applicant pool will also be different.

The remainder of the paper is organized as follows: We give a brief summary of related literature in Section 2. We formulate and analyze a benchmark analytical model in Section 3. In Section 4, we do a numerical study of a more complex and realistic model, and we conclude in Section 5.

2. Literature Review

There is a vast literature that is relevant to this problem from several different streams of research. We do not attempt to survey these here but rather cite the papers that help us illustrate the key elements of our work.

Several researchers have explored the influence of electronic intermediaries on labor supply chain. Autor [1] discussed the wired labor market and suggested that the Internet made the application process easy and lowered the cost of collecting “low bandwidth,” easily verifiable information about applicants. The Internet was not equally effective in lowering the cost of obtaining “high bandwidth” information about candidates: attributes such as quality, motivation, and fit. Autor posited that new entities will emerge that will lower the cost of collecting data about “high bandwidth” attributes.

The majority of academic papers considering the effects of a wired labor market take the perspective of a job seeker. For example, Kuhn and Skuterud [13] examine empirically the types of job seekers who incorporated the Internet into their job-search strategies and investigated whether searching for work online helped these workers find new jobs faster. Similarly, in [6], Fountain uses data on job searches by the unemployed to assess whether searching online increases the short-term probability of finding a job. Yakubovich and Lup in [24] analyze data from an Internet-based recruiting process to examine the influence of the quality of a referring employee on the firm’s decision to hire a candidate.

Taking the employer perspective, in an exploratory study Lee [14] studies the content of e-recruiting websites of Fortune 100 corporations and develops an evolution model of the corporate e-recruiting system. Hadass in [11] examines how the introduction of Internet technology affected employment duration of hired applicants, using that as a proxy for employee quality. The theoretical model in [11] includes two effects of technology: reduced application costs for job seekers, which reduces match quality; and improvements to a firm’s screening technology, which increases matched quality. The net impact depends on the relative magnitudes of these two effects.

Similar to Hadass, we created a mathematical model to examine the impact of Internet technology on a firm’s recruiting process. Our model gives a more detailed representation of the process and accounts not only for the difference in the quality of the applicants but also for the effect of increasing arrival of applications and of delay in the processing of applications. We use a queuing model to examine how the delay in processing affects a hiring process. Gautier in [9] uses a queuing model in a labor economics application. The modeling is different from ours, and its purpose is to explain unemployment by selection delays of employers. In our model, we not only consider the delay caused by the congestion of larger numbers of applicants but also how these delays affect the quality, cost, and timing outcomes of the hiring process.

Hiring of employees involves searching for employees, and candidate search for employment, so literature on search for information is relevant. Early economic papers in search theory discussed the advantages of the sequential search [16] algorithm in looking for a job over a fixed sample search [19]. Stigler’s model [19] suggested that in deciding how many price samples to obtain in looking for the lowest price, buyers trade off the marginal cost of search and the marginal benefit additional samples. Since the expected value of the minimum of a random sample of n observations decreases at a decreasing rate, search costs that are convex in the number of samples lead to an optimal fixed sample size for risk-neutral buyers. With the sequential search approach, the firm sets a minimum acceptable competence level and searches through applicants sequentially until it identifies the first applicant who is at or above the minimum acceptable level. Sequential search models have been studied extensively as various versions of the classic optimal stopping problem, known as the “Secretary Problem”[5, 7, 8, 18]. In several recent studies, researchers conducted experiments to examine the
choices of human decision makers presented with a “Secretary Problem” [2].

Beyond the search literature, literature on matching, two-sided markets, technology intermediation, contracting, and procurement are all relevant. Much work in labor economics relies on search theory to develop equilibrium models capable of explaining, for instance, simultaneous existence of unemployed workers and unfilled vacancies. What determines aggregate unemployment and vacancies? How can homogeneous workers earn different wages? What are the tradeoffs firms face from different wages? The importance of this research and its recommendations for government policies was recognized in the award of the 2010 Nobel Prize in Economics to three economists specializing in search theory and labor economics: Diamond, Mortenson, and Pissarides. [17] provides a recent survey of related economic literature.

3. Model

The outputs we care about are the quality of the person hired, the cost of the hiring process, and the duration of the process. All things being equal, the more applicants that are reviewed, the higher the quality of the hire, the costlier the process, and the longer the process. The duration of the process has two major effects. The direct effect is that the longer the duration, the longer until the new employee can make a productive contribution to the firm. The indirect effect is that the duration of the process influences the pool of applicants who are actually available to be hired, because applicants can get competing offers during the hiring process.

We start with a simple model in which applications arrive according to a homogeneous Poisson process. We assume that there are two kinds of applications arriving: those that meet the minimum requirements of the position and those that do not. Every application that arrives must be processed and identified as meeting the minimum requirements or not in the Stage 1 screening. We denote with $\lambda$ the arrival rate of applications from candidates who meet the minimum “low bandwidth” Stage 1 requirements, and let $\bar{N}(t)$ denote the stochastic counting process for these applicants.

We assume that each applicant $i$ has patience level $\bar{S}_i$ that is the amount of time the applicant is willing to wait for an offer. We assume that $\bar{S}_i$ follows an exponential distribution with rate $\mu$ and denote with $\bar{D}(t)$ the counting process for departures of the applicants. We use the patience level as a simplified way to capture many factors that influence whether an applicant would take a job if offered. One factor is the demand in the labor market. I.e., if unemployment rates are low, we expect $\mu$ to be high, thus a long recruitment process increases the likelihood that the candidate will have received other, possibly more attractive, offers. Another factor is the average interest that members of applicant pool attracted to this job actually has in such a job. If a job is easy to apply for, that may also mean that $\mu$ is high because many of the people applying are not very interested in it. Our assumption is that people who are generally less interested in a job need to be contacted sooner than people who are highly interested in the job, or they are more likely to drop out of the pool. Thus parameter $\mu$ can also be viewed as representing the likelihood an applicant would take the job if offered.

To keep the model simple, we assume that the time of Stage 2 evaluation is negligible. With these assumptions, we can model the hiring process as a single-stage queue. Arrivals are new applications, and services are when applicants decide to drop out of the process. The number of applicants in service at time $t$, $\bar{N}(t) - \bar{D}(t)$ is the state of the system and the pool of potential hires is our candidates. Let $N(t) = E[\bar{N}(t) - \bar{D}(t)]$ denote the expected number of candidates in the evaluation pool at time $t$; these candidates are considered in Stage 2.

If an $M/M/\infty$ queue operates for $t$ time units, starting with no candidates in it, then the probability that at time $t$ there are $n$ candidates in the pool is given on page 101 of [10] as

$$p_n(t) = \frac{x(t)^n}{n!} e^{-x(t)}, \quad (1)$$

where

$$x(t) = (1 - e^{-\mu t}) \frac{\lambda}{\mu}. \quad (2)$$

It turns out that $N(t) = x(t)$.

A candidate’s quality is unknown to the firm until the interview process is completed. We assume that after the firm interviews the candidates, it selects the best one. We model $Z_i$, the quality of candidate $i$ as random, drawn from a known distribution with support on $[0,1]$. We use $Q(t)$ to denote the expected quality of the best candidate available after $t$ time units.

Let $q(n)$ be the expected value of the maximum of a sample of $n$ from the quality distribution. Then,

$$Q(t) = \sum_{n=0}^{\infty} q(n)p_n(t) \quad (3)$$

We initially assume that each applicant has a quality from the uniform distribution on $[0,1]$. In that case we have that $q(n) = \frac{n}{n+1}$ and,
\[ Q(t) = \sum_{n=0}^{\infty} \left( \frac{n}{n+1} \right) \frac{x(t)^n}{n!} e^{-x(t)} \]  
(4)

which can be simplified to:

\[ Q(x(t)) = 1 - \frac{1}{x(t)} + \frac{e^{-x(t)}}{x(t)} \]  
(5)

It is easily shown that \( Q(t) \) is increasing in \( x \), and because \( x(t) \) is itself increasing in \( t \) we have that \( Q(t) \) is as well. This implies that the longer the search, the greater the quality, even if there are dropouts. We can also see that the expected quality will level off because \( x(t) \) asymptotically goes to \( \lambda/\mu \) as \( t \) increases. Similarly, the expected candidate pool size \( N(t) \) will converge to \( \lambda/\mu \).

The firm must decide when to start the evaluation of the pool of candidates. There are different ways to define this decision. It could be in terms of number of applicants, i.e., start the evaluation of the pool once \( A \) applications have been received, or it could be defined in terms of time, i.e., start the evaluation a time \( T \) after the job was announced. We use the evaluation time \( T \) in the following.

For simplicity, we assume a linear value structure for quality with \( a \) representing the relative weight we place on quality of the employee hired and \( b(T) \) is the time-related cost of the search process. We assume that there is a linear cost \( c \) for each candidate who goes through the more careful evaluation in the second stage. The firm also incurs the cost \( c_a \) for each Stage 1-passing (legitimate) applicant—whether or not the applicant becomes a candidate. In this, we assume that the arrival rate of applications not meeting a minimum requirement is proportional to \( \lambda \). We model Stage 1 screening as bearing a linear cost of \( c_a \) per legitimate applicant. Thus \( c_a \) is higher than the actual cost of processing a legitimate applicant, since it includes the cost of processing the unqualified applicants as well. Then our objective is:

\[ \max_{T} aQ(T) - b(T) - c_aE[\lambda(T)] - c N(T) \]  
(6)

Without loss of generality, we can assume \( a=1 \) and rescale \( a \) and \( c_a \) appropriately.

To focus on the candidate pool size tradeoffs, we assume that the time-related cost \( b(T) \) is a non-linear function with

\[ b(T) = \begin{cases} 
0, & T \leq T_{\text{max}} \\
\infty, & T > T_{\text{max}} 
\end{cases} \]  
(7)

reflecting the need of the firm to get the new employee in place before some deadline. Thus we can view \( T_{\text{max}} \) as a constraint. The implication is that, ignoring \( c_a \), past a certain amount of time, the value received by the hiring firm becomes constant as the application process achieves steady state.

However, value may be optimal before this point, especially if there is a cost for every application handled. From Eq. (2) and the fact that \( N(t) = x(t) \), we can reinterpret the objective (6) as selecting the optimal candidate pool size. Ignoring the time parameter for the moment, there is an unconstrained optimal expected pool size \( x^* \) (Figure 3). Given the application arrival and dropout rates, this \( x^* \) may or may not be attainable. If the steady state expected pool size \( \lambda/\mu \) is larger than \( x^* \) then the \( t \) such that \( x(t) = x^* \) is optimal. Otherwise, it is optimal to continue the search as long as possible, subject to the constraint \( T_{\text{max}} \).

We next consider the impact of technology on the application process. One effect firms observe is an increase in the number of applicants received, i.e., an increase in \( \lambda \). Technology can also be used to do the initial screening using automated systems, thus driving \( c_a \) to zero and reducing the burden of processing all electronically received applications. Setting \( c_a = 0 \) and following the discussion above regarding \( x^* \), we find that, ignoring the time constraint, increasing \( \lambda \) will reduce the search time but will not change the expected quality or the expected number of candidates. While \( t^* \) decreases with \( \lambda \), \( x(t^*) \) stays constant. The implication is that, if the firm is in a situation in which the time constraint is binding, more applications will improve the outcome of the search, but otherwise more applications will achieve essentially the same outcome but sooner. If \( c_a > 0 \), the firm will shorten searches for any value of \( \lambda \) to reduce the volume of applications that must go through the initial screening.

Another effect of technology is that applicants are exposed to more outside options, so \( \mu \) is higher. We first look at this effect holding \( \lambda \) fixed. Here, \( x(t) \) is the expected number of candidates available at time \( t \) in this transient system. The parameter \( \mu \) serves the purpose of determining how quickly the system approaches steady state. At the same time, it affects the number of candidates in the system. The higher \( \mu \) is, the faster we reach steady state and thus the point in time in which it makes little difference how much longer the search goes. A higher \( \mu \) will \emph{ceteris paribus} decrease the candidate pool because applicants drop out at a faster rate, thus reducing quality and the overall outcome. Interestingly, we find that the optimal search duration is not monotonic in \( \mu \) (see Figure 4), while it is monotonically decreasing in \( \lambda \).

In practice, we expect that the effect of technology in the recruitment process is to simultaneously increase the volume of applications and the dropout rate both because the applicants will
be applying to many more positions and because the low cost of applying will attract applicants who are less interested in the position. We find, in numerical experiments, that increasing $\lambda$ and $\mu$ but holding their ratio constant leads to no improvement in performance. Clearly this stability is not a law of nature but an artifact of the specific modeling assumptions we have made. On the other hand, it points to the inherent tradeoff reduced application cost creates between more applications and fewer interested applicants.

In this section, we build a deterministic continuous-time approximation of application arrival and dropout processes. With this approximation we are able to add more features to our model while still keeping the model tractable. In particular, we introduce a time varying application arrival process and use the Beta distribution to model the applicant quality. These changes allow us to explore the consequences of lowering the costs of the job search and application process in a richer way.

We model the arrival process as having an expected number of applications by time $t \geq 0$,

$$\Lambda(t) = \kappa(1 - e^{-\delta t})$$

and instantaneous rate

$$\frac{d\Lambda(t)}{dt} = \lambda(t) = \kappa\delta e^{-\delta t}$$

This model provides a good fit to the data we obtained from the human resources management system of our university for several secretarial positions (Figure 5). The fitted values of the parameter $\delta$ varied between 0.07 and 0.18, corresponding to 80 percent of all applications arriving within 9 ($\delta = 0.18$) to 23 ($\delta = 0.07$) days of the job first being posted.

With passage of time from the application, the applicants lose interest in the job. Using a differential equation, we define $N(t)$, the mean number of interested candidates in the system at time $t$:

$$\frac{dN(t)}{dt} = \lambda(t) - \mu N(t)$$

The rate of change in the number of interested candidates is the difference between the application arrival rate, given by (9), and the rate at which candidates lose interest, $\mu N(t)$. The latter is proportional to the number of candidates who are still interested in the position, which is analogous to the departure rate of an M/M/$\infty$ queue as described in the previous section. Combining (10) with the boundary condition $N(0) = 0$ leads to an analytic expression for $N(t)$:

$$N(t) = \frac{\kappa e^{-\mu t}(1 - e^{-(\delta - \mu)t})}{1 - \mu/\delta}$$

The expected maximum number of candidates is achieved at time $t$.
The quality of the hire increases in the number of candidates; hiring costs also increase in the number of candidates. Therefore, the optimal time for qualifying the candidates, $T^*$, has to be less than or equal to $t_{\text{Nmax}}$. The maximum expected number of candidates and the time when the maximum expected number of candidates is in the system are influenced by the ratio $\mu/\delta$. The larger the ratio, the faster the applicants are leaving the system relative to how quickly applications arrive. Both $N_{\text{max}}$ and $t_{\text{Nmax}}$ are decreasing in $\mu/\delta$ (Figure 6). We will assume that when technology is introduced, $\mu$ and $\delta$ both increase, moving in unison. While an increase in both $\mu$ and $\delta$ such that $\mu/\delta$ remains constant represents an effect of a cheaper application process, an increase in $\mu/\delta$ represents a more competitive job market.

With $N$ candidates available, the CDF for the quality of the best candidate is given by:

$$Pr\{\max(\tilde{Z}_1, \tilde{Z}_2, ..., \tilde{Z}_N) \leq z\} = (Pr(\tilde{Z}_1 \leq z))^N$$

(15)

and for the beta distribution with parameter $\alpha = 1$, $\beta = 1$:

$$\Phi(N) = \int_0^z \beta N (1 - z)^{-\beta - 1} (1 - z)^{N-1} \, dz$$

(16)

Using information technology in the labor procurement process has the potential to affect all of the main parameters in the model. Generally it will reduce application costs and increase parameters $\kappa$, $\delta$, and $\beta$. An increase in $\kappa$ models an increase in the total number of applications; an increase in $\delta$ models a decrease in the time it takes to receive a certain percentage of all applications that will arrive; an increase in $\beta$ models an increase in the percentage of lower-quality applicants in the applicant pool. The technology choices a firm makes will determine which of these parameters will change and by how much.

$$t_{\text{Nmax}}(\delta, \mu/\delta) = -\frac{\ln(\mu/\delta)}{\delta(1 - \mu/\delta)}$$

(12)

corresponding to

$$N_{\text{max}}(\kappa, \mu/\delta) = \kappa \left(\frac{\mu}{\delta}\right)^{\frac{1}{\delta - 1 - \mu}}$$

(13)

Figure 5: Arrival of Applications for a Secretarial Position at a University

An arrival rate that is decreasing in time causes some significant differences in the dynamics of the system. In the previous section, with a time-homogeneous arrival process, we discussed how the queuing system could achieve a steady state of candidates in the pool. In this case, with arrivals decreasing with time, the “steady state” is $0$. In addition, because more of the applications come earlier, the effect of delays in terms of increasing dropouts is also non-uniform in time. Therefore, there is greater pressure to finish the process sooner.

We model the applicant quality using beta distribution on $[0, 1]$ with parameters $\alpha$ and $\beta$. We consider as the reference distribution, the uniform distribution which is the same as beta distribution with parameters $\alpha = 1$ and $\beta = 1$. The beta distribution is convenient for modeling heterogeneity of the candidate pool. To model a decrease in the percentage of high-quality candidates, we keep $\alpha = 1$ and increase $\beta$. With these parameters, the percentage of candidates whose quality exceeds some level $z$, $0 \leq z \leq 1$ is equal to

$$Pr(\tilde{Z}_i \geq z) = (1 - z)\beta$$

(14)

decreasing exponentially with $\beta$. Figure 7 helps visualize what would be a reasonable range for $\beta$ values in a numerical simulation. Suppose an employer considers suitable candidates to be of quality 0.9 and above. Using $\beta = 1$ parameter as a benchmark, 10 percent of applicants would fall in the [0.9, 1] range. As an example, let us consider a technology that increases the total pool of applicants by a factor of 2, but the pool of applicants of suitable quality only by a factor of 1.8, so the percentage of suitable applicants in the pool decreases from 10 percent to 9 percent, or 0.9 of the benchmark value. The implied $\beta$ can be calculated as

$$1 + \log(2/1.8) = 1 + \log(1/0.9) = 1.1.$$

Figure 6: Maximum Expected Number Of Candidates in the System and the Time when the Number of Candidates is Maximum as a Function of $\mu/\delta$
We conducted numerical experiments to examine how the change in the parameters affects a hiring firm. For our numerical experiments, we set as the base case parameters $\kappa = 6, \delta = 0.06, \mu/\delta = 0.1, \beta = 1, c_d = 0.1$. These values imply $N_{\text{max}} = 4.65$ and $T_{\text{max}} = 41.91$. We then consider changes in the parameters to model the effects of technology on the hiring process. The set of parameters for each experiment is shown in Table 1. Table 2 lists the results of experiments in terms of the objective and intermediate outputs $T^*, Q(T^*), N(T^*)$ and $\Lambda(T^*)$ under the assumption that $T_{\text{max}}$ is large and $a = 100$.

![Figure 7: Using the $\beta$ Parameter to Model a Change in the Percentage of Applicants of Quality 0.9 and Above](image)

One of the effects of technology is an increase in the number of applicants by reducing application costs and disseminating job openings more widely. We model this with an increase in $\kappa$ shown as Case 1. Looking at the outputs for Case 1, we see that increasing $\kappa$ improves the firm’s objective, because it increases $N_{\text{max}}$, thus allowing an increase in $N(T^*)$ past the level corresponding to the lower $\kappa$. However, with an increase in $N(T^*)$ and $\Lambda(T^*)$, processing costs increase. An increase in $\kappa$ also leads to a decrease in $T^*$, and even though more candidates are considered, candidates can be considered sooner, which benefits the firm.

Table 1: List of Parameters for the Numerical Experiments

<table>
<thead>
<tr>
<th>Case</th>
<th>Parameters</th>
</tr>
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<tbody>
<tr>
<td>0</td>
<td>Base case: $\kappa = 6, \delta = 0.06, \mu = 0.006, \mu/\delta = 0.1, \beta = 1, c_d = 0.1</td>
</tr>
<tr>
<td>1</td>
<td>Increase in $\kappa$ : $\kappa = 12$</td>
</tr>
<tr>
<td>2</td>
<td>Decrease in $c_d$ : $\kappa = 12, c_d = 0.01$</td>
</tr>
<tr>
<td>3</td>
<td>Increase in $\delta$ : $\kappa = 12, c_d = 0.01, \delta = 0.12, \mu = 0.006</td>
</tr>
<tr>
<td>4</td>
<td>Increase in $\mu$ : $\kappa = 12, c_d = 0.01, \delta = 0.12, \mu = 0.012</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Case</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Increase in $\mu/\delta : \kappa = 12, c_d = 0.01, $\delta = 0.12, \mu = 0.006</td>
</tr>
<tr>
<td>6</td>
<td>Increase in $\beta$ : $\kappa = 12, c_d = 0.01, \delta = 0.12, \mu = 0.012, \beta = 1.2</td>
</tr>
<tr>
<td>7</td>
<td>Further increase in $\beta$ : $\kappa = 12, c_d = 0.01, \delta = 0.12, \mu = 0.012, \beta = 1.25</td>
</tr>
</tbody>
</table>

Another possible effect of technology is to decrease the application processing costs; we model that with a decrease in $c_d$. This decrease is examined as Case 2. We observe that decreasing $c_d$, in addition to increasing $\kappa$, improves the objective further. The increase is due to the improvement in quality: lower $c_d$ allows the firm to examine more candidates, which results in higher expected quality. Waiting for more candidates increases $T^*$ relative to Case 1.

Technology can also be used to change the time profile of applications, for example, automatic emails alerting job seekers to new postings are not uncommon. This could be modeled with an increase in $\delta$, which parameterizes the time profile of the applications. Increasing $\delta$ means that more of the applications arrive early. An increase in $\delta$ is shown in Case 3—we see that the value of the objective is improved only slightly relative to Case 2. We further observe that at optimality the quality and the number of candidates is the same as in Case 2; the increase in the objective is due to $\Lambda(T^*)$: with larger $\delta$, it takes fewer applicants to reach the same $N(T^*)$. Relative to Case 2, in Case 3 the same objective is achieved in a shorter time. That would appear to be a benefit for the company.

The above positive impacts of technology can also engender a market reaction. Lower application costs could mean that applicants are less serious about the position; we model that effect with an increase in $\mu$. In Case 4, we consider an increase in $\mu$ such that the ratio $\mu/\delta$ is the same as in the base case and higher than in Case 3. Comparing Cases 3 and 4, we see that an increase in $\mu$ results in lower payoff, due to having to process more applications to obtain the same quality. The results for Case 4 differ from the results for Case 2 only in the value of $T^*$: the higher $\delta$ of Case 4 means that the arrivals happen faster. With Case 5, we explore the situation where $\mu/\delta$ increases, which means fewer of the applicants are serious about their application. We observe that the objective value decreases relative to Case 4, the resulting quality decreases, while the time $T^*$ increases.

Finally, we consider how the distribution of applicants in terms of their quality affects the outcome. In addition to increasing $\mu$, another possible market effect of the technology is to change the mix of the applicants as discussed earlier, with a larger percentage of the applicants being of lower quality.
We model that with an increase in $\beta$. For Case 6, we used the same parameters as for Case 4, changing only $\beta$ from 1 to 1.2. Similar to the comparisons of Case 5 to Case 4, an increase in $\beta$ is bad for the employer: it leads to a lower value of the objective and later response time. In Case 7, we increase $\beta$ even further to 1.25; here our point is to demonstrate that overall, the employer could even be worse off with technology. A large enough increase in $\beta$ would require the employer to screen more candidates to get an acceptable quality level. The increased screening leads to a lengthier and a more expensive hiring process.

Table 2: Results of Numerical Experiments, $a = 100$

<table>
<thead>
<tr>
<th>Case</th>
<th>Objective</th>
<th>$T^*$</th>
<th>$Q(T^*)$</th>
<th>$\Lambda(T^*)$</th>
<th>$N(T^*)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>76.95</td>
<td>41.91</td>
<td>0.82</td>
<td>5.51</td>
<td>4.65</td>
</tr>
<tr>
<td>1</td>
<td>80.03</td>
<td>21.18</td>
<td>0.89</td>
<td>8.63</td>
<td>8.00</td>
</tr>
<tr>
<td>2</td>
<td>80.90</td>
<td>31.09</td>
<td>0.90</td>
<td>10.14</td>
<td>9.00</td>
</tr>
<tr>
<td>3</td>
<td>80.91</td>
<td>12.88</td>
<td>0.90</td>
<td>9.44</td>
<td>9.00</td>
</tr>
<tr>
<td>4</td>
<td>80.90</td>
<td>15.55</td>
<td>0.90</td>
<td>10.14</td>
<td>9.00</td>
</tr>
<tr>
<td>5</td>
<td>80.79</td>
<td>15.99</td>
<td>0.89</td>
<td>10.24</td>
<td>8.02</td>
</tr>
<tr>
<td>6</td>
<td>77.98</td>
<td>18.46</td>
<td>0.87</td>
<td>10.69</td>
<td>9.23</td>
</tr>
<tr>
<td>7</td>
<td>76.04</td>
<td>20.47</td>
<td>0.85</td>
<td>10.97</td>
<td>9.29</td>
</tr>
</tbody>
</table>

In selecting a recruiting technology, companies need to try to estimate the potential improvement in the number of applications, the timing of their arrival, and the cost of processing and then to quantify the resulting financial benefit. In Table 2, we observe that different levers could have different value to a hiring company investing in a recruiting technology. With our sample objective function, we observe that doubling the number of applications increases the value of the objective by 4 percent, while reducing the marginal cost of processing applications by a factor of 10 increases the objective only by 1.13 percent. Doubling $\delta$, so that the applications arrive earlier, has an even smaller effect, increasing the objective by a mere 0.01 percent. At the same time, comparing Cases 2 and 3 we observe that doubling of $\delta$ has a significant effect on $T^*$. So if the time to fill the position is important to the firm, it may be particularly important to invest in technology that increases $\delta$. Looking across Cases 1-5, we see that quality stays fairly constant, as does the objective, but there are large changes in $T^*$.

In order to endogenize the importance of search time to the firm, in Table 3 we investigate an alternative objective function, replacing $b(T)$ of (7) with $b \cdot T$, assuming the time to hire generates a linear cost to the firm. Repeating the numerical experiments for cases 0-7, we observe that the objective moves in the same direction as in Table 2 when we change the parameters. However, because time is now more important to the firm, we see that the search is stopped sooner, fewer candidates are considered, and the expected quality of the hired candidate is lower. We also observe that a decrease in applicant quality does not affect the objective as much because it is compensated for by time savings. When cost of time is a part of the objective, larger numbers of applicants and their earlier arrival are more valuable to a firm, and such improvements may be more important than an increase in the applicant departure rate.

Table 3: Results of Numerical Experiments, $a = 100, b(T) = 0.02T$

<table>
<thead>
<tr>
<th>Case</th>
<th>Objective</th>
<th>$T^*$</th>
<th>$Q(T^*)$</th>
<th>$\Lambda(T^*)$</th>
<th>$N(T^*)$</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.80</td>
<td>4.32</td>
<td>4.00</td>
</tr>
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<td>12.80</td>
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<td>6.16</td>
</tr>
<tr>
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<td>0.87</td>
<td>7.03</td>
<td>6.68</td>
</tr>
<tr>
<td>3</td>
<td>78.91</td>
<td>7.70</td>
<td>0.88</td>
<td>7.24</td>
<td>7.05</td>
</tr>
<tr>
<td>4</td>
<td>78.83</td>
<td>7.98</td>
<td>0.88</td>
<td>7.40</td>
<td>7.00</td>
</tr>
<tr>
<td>5</td>
<td>78.62</td>
<td>9.02</td>
<td>0.87</td>
<td>7.94</td>
<td>7.00</td>
</tr>
<tr>
<td>6</td>
<td>75.65</td>
<td>9.34</td>
<td>0.85</td>
<td>8.09</td>
<td>7.57</td>
</tr>
<tr>
<td>7</td>
<td>73.60</td>
<td>10.19</td>
<td>0.84</td>
<td>8.47</td>
<td>7.87</td>
</tr>
</tbody>
</table>

In any case, the managers need to be mindful of the unintended consequences of technology adoption. An easier application process may generate more applicants but result in the same number of quality applicants, thus only increasing processing costs for the organization.

5. Conclusion

We investigate the impact of technology on the process or hiring employees. We develop mathematical models of the application arrival and screening process that capture the tradeoffs between cost, quality, and delay in the process. We use the models to illustrate the effect on outcomes when technology increases the total number of applicants, the rate at which the applicants apply, the rate at which they lose interest in the job, and the likelihood that an applicant is not suitable for the advertised position. With numerical experiments we show that adoption of such technology may not be optimal for a firm and that any positive effect from larger pool of applications can be negated by the deterioration in quality. The effect may be ameliorated if the
technology is capable of lowering the cost of the screening process for the employer in addition to lowering the cost of an application for a job seeker. Comparing Cases 0 and 7 in Table 2, we see that the objective values are very close but the nature of search is very different. Compared to Case 0, in Case 7, the search is about half as long, twice as many applications are received, and twice as many candidates evaluated. Yet the resulting increase in quality is too small to overcome the extra costs incurred in the search. This illustrates how changes in technology can have a big impact on what happens in a search, while at the same time having little impact on the ultimate outcome.

In our model, we assume that a decrease in the quality of applications causes a decrease in the quality of candidates considered in Stage 2. But recruiting firms also use IT systems for electronic screening of the applications and for administering skills tests. Thus firms could use application screening software to set higher minimum requirements, possibly avoiding deterioration of the quality of the candidate pool. However, anecdotal evidence indicates that determining which “low bandwidth” qualities correlate with better employees is not a trivial task, and much of the existing software is not yet up to the task. To explain the difficulty faced by the developers, Weber [22] cites human-resources-technology consultant Elaine Orler: “Cultural and behavioral fit is a stronger indicator of success and business performance [than keywords].” We plan to investigate the benefits and limitations of electronic screening in our future models.

The challenge for the recruiting firm is to find a way to adapt its search to the new technological environment in a way that captures more of the benefits and less of the costs. Based upon our analysis, we see that it is easy for the benefits of faster application arrivals to be canceled out by the higher dropout rate (or lower commitment). The benefit of more total applications is canceled out by the reduction in quality in the applicant pool. Our suggestion is that the firm narrowcast its advertising of a position to specialized websites, so that more effort is required of an applicant to find it. This will lead to self-selection of applicants who are more interested and better fit the position. At the same time, the firm will still have a broader pool of applicants than using geographically limited advertising methods.

6. References