The Effect of Internet Recruiting on the Matching of Workers and Employers*

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Abstract

More then 25% of unemployed job seekers report using the Internet to look for jobs. This paper examines the impact of the spread of online recruiting on the matching of workers and firms. I develop a model of recruitment in which job seekers have private information about their qualification for different jobs and firms possess imperfect screening technologies. The adoption of Internet recruiting is modeled as reducing application costs to workers and improving screening technology for firms. The reduction in application costs to workers is shown to induce applications from candidates who are relatively less qualified and to decrease the proportion of qualified new hires; however, the improvement in firms' screening technology may offset this effect. Firms may adopt Internet recruiting strategies because of the direct reduction in recruiting costs and because of competition among employers for qualified hires. The implications of the model are empirically examined using personnel data from a large multinational manufacturing firm. Job duration is used as a proxy for match quality. Estimates from Cox duration models indicate that Internet recruits have shorter job duration than observationally equivalent workers hired through employee referrals but similar durations to those hired through print advertising. Propensity score methods show that the types of jobs (occupations) with a larger growth of the use of Internet recruiting show larger declines in expected job durations compared with jobs with less growth of Internet recruiting. This finding is consistent with a key prediction of the model.

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1 Introduction

The Internet has dramatically changed the nature of the job search. Survey results show that as early as August 2000, 25% of unemployed job-seekers reported regularly using the Internet to look for jobs. One in ten employed persons said that they regularly looked for other jobs online. *Monster.com,* a leading online job board, draws millions of unique visitors each month and boasts almost 30 million members, a resume database containing more than 20 million unique resumes, more than 130,000 member companies, and more than one million unique job opportunities.[1] The population of users of this website is constantly growing: in June 2001 there were 6.5 million unique visitors, up from 4.4 million in June 2000.[2]

The widespread usage of online recruiting tools prompts a question: do improvements in job search technology produce better firm-to-worker matches? On the one hand, better technology and easier access to information may produce more initial encounters between workers and firms, increasing the probability of finding the best match for a given opening (Freeman 2002, Autor 2002). On the other hand, reduced application costs may encourage increased applications from under-qualified job seekers. In the absences of perfect screening mechanisms firms will be more likely to hire under-qualified candidates out of an adversely selected pool (Autor 2002). Which of these two competing effects is more likely to influence the quality of matches between workers and firms?

I offer a theoretical model that studies the effects of online recruiting on the matching process of workers and firms and suggests implications for empirical testing. The model relies on the following assumptions: (1) for any given job there are two types of candidates, *qualified* and *non-qualified*; (2) each candidate has private information about the probability that she is qualified for the job; (3) each firm receives a signal, *bad* or *good*, about the

[1] Kuhn and Skuterud, 2002.

[2] Numbers are from "Monster.com strengthens lead in career category." *Business Wire*, July 12, 2001. Quoted in "Monster.com: Success Beyond the Bubble." *Harvard Business School Case* 9-802-024. Revised: January 7, 2002.

qualification of each candidate, and randomly chooses the number of candidates it needs out of all those who generate a *good* signal. The firm observes the right signal of the worker's type with a positive probability.

I show that the new recruiting technology has an adverse effect on the applicant pool for a given job. I assume that job seekers submit applications only if a job's expected value is higher than its cost of application. New recruiting technology reduces application costs and thus induces applications from candidates who are relatively less qualified for the job. For a given screening technology, an adversely-selected applicant pool decreases the proportion of qualified new hires- a finding consistent with the view of many employers that resumes posted to job boards represent an adversely selected pool (Autor, 2002; Li, 2000; iLogos, 1999). The beneficial effect of the new recruiting technology on the screening ability of the firm may offset the adverse effect of reduced application costs on the average quality of hires. The effect of improved recruiting technology on the proportion of qualified hires may be zero, negative or positive, depending on the relative magnitude of the effects of improved recruiting technology on the firm and the worker. The model implies that the magnitude of these effects should differ systematically across professions.

Why would firms use the Internet if it lowers match quality? I offer two explanations. First, recruiting via the Internet is much less costly than other recruiting methods. Even if Internet hires are more likely to be replaced, the benefits of Internet recruiting may still outweigh the costs. Moreover, in the long run, the Internet may allow firms to test more workers on the job and thereby identify superior candidates in the long run. Second, one must consider the effects of inter-firm competition. In a two-firm setting, I show that competition leads to a Nash equilibrium in which both firms choose to adopt the new technology without imposing application costs on the candidates.

I provide empirical evidence to illustrate the effects of Internet recruiting using data from a US-based multinational manufacturing firm with more than 15,000 employees. My sample contains employees' start and end dates, education, age, and occupation from 1995 to 2002.

Online recruiting at this firm increased from 0.2% of total hires in 1996 to 20% of total hires in 2002. Using employment duration as a measure of match quality, I estimate a Cox duration model that shows that Internet recruits are significantly more likely to leave the firm relative to recruits hired through employee referrals. Employment duration for Internet recruits does not differ significantly from that of hires made through newspaper advertising or agency.

I use propensity score methods to show that the average quality of the hires declined with the expansion of the Internet, with a significant decline in quality occurring in 2002 (the year with the highest level of online hires). This finding suggests the Internet may have a negative effect on the quality of the recruits- a result that is consistent with the predictions of my theoretical model.

2 Who Is Recruited Through the Internet?

Due to the novelty of the online recruiting technology, there is almost no empirical evidence about the type of workers that are recruited through the Internet. There have been a few recent attempts to identify the types of individuals who use the Internet to find jobs.[3] But to date, no study about workers who were actually recruited through the Internet is available. In this section I use a unique dataset obtained from a large US multinational to analyze the characteristics of employees who were recruited through the Internet, and compare them to the characteristics of employees recruited through other recruiting channels.

2.1 Data

This paper uses data supplied by a US-based multinational manufacturing employer of more than 15,000 employees to study the types of workers actually recruited via the Internet. The

[3] Kuhn and Skuterud 2000a, 2000b, 2000c, 2002.

firm has existed since the late 1970s and has been collecting information on the source of employee recruitment since 1995. My data set begins on 1 January 1995 and ends February 10, 2003. Fewer than 5% of the firm's employees work outside of the US. The sample used in my analysis includes all new hires with a known recruiting source excluding (1) workers entering the firm from mergers and acquisitions and (2) workers hired as interns who did not continue with the firm beyond their internship. The treatment of those of unknown recruiting origins does not affect any of the paper's substantive conclusions.

Recruiting is tracked with specialized computer software that maintains a record of each application submitted. For example, if a job applicant applied once through an employee referral and once through the *Monster.com* job board, the software establishes a file for the applicant indicating the date of application through referral, and the date of application via the Internet. Given the fact that there is an employee referral program in this firm, and that employees are compensated for hires made through their referrals, the firm must maintain accurate records of the recruitment channel.

2.2 Descriptive Statistics

The percentage of workers hired by each recruiting channel is shown in Table 1.[4] From 1995 to 1998 the number of employees recruited via the Internet was fewer than 15 (only 1.24% of total recruits in that year), but the year 1999 brought a major shift to recruiting via online tools, with 108 employees (4.67% of that year's recruits) hired. The number of workers recruited via the Internet continued to rise in the following years, with 277 employees (6.02%) recruited in 2000, 130 employees (8.02%) recruited in 2001, and 95 employees (20.34%) recruited in 2002. Graph 1 shows that print advertising is declining as online advertising has risen, suggesting a strong substitution effect.

[4]Number of observations (less than 20% in any given year) are missing the crucial recruiting channel information. However the data appear to be missing at random. Percentage computed using the total employee population appear to be very close to the percentages using only non missing data. Table 1 presents the percentages excluding the observations that lack recruiting channel information.

The average age and education of workers by recruitment source is shown in Table 2. The average education of employees recruited via the Internet (15.7 years of schooling) is not significantly different from hires through other channels. The average age of Internet recruits is lower than the average age of newspaper and agency recruits (38 years compared with 40 years and up), and higher than the average age of college recruits (38 years compared with 29 years).

Internet hires as a share of total hires within each occupation are shown in Table 3.[5] The share of engineers recruited via the Internet was fairly low until 2001 (1.58% in 1998, 4.45% in 1999, 5.71% 2000). By 2002, 25% of all engineer and technician recruits were via the Internet. During the period 1995-2001 the professions that were most heavily recruited via the Internet were human resources (26.47% in 1999, 18.07% in 2000) and marketing (14.94% in 1999, 10.90% in 2000).

There is ample evidence to suggest that in the not-too-distant future, the majority employment applications will be submitted online. The increasing use of online tools requires our understanding of this mechanism and its implications. The model described below illustrates the forces affecting the dynamics of this complex strategic interaction.

3 The Model

3.1 Description of the Environment

This section offers a model of the effect of improved recruiting technology on the quality of the match between workers and firms. I assume that the workers have private information about the degree of their qualifications for the job. Workers submit applications only if their expected utility from getting the job exceeds application costs. Improved recruiting

[5] This table excludes missing data.

technology is assumed to lower application costs and results in applications from candidates that are less likely to be qualified for the job. Firms receive an imperfect signal about the match quality for each applicant. A better recruiting technology is modeled as an improved screening process for the firm (that is, a higher probability of observing the right signal), and reduced application costs for the worker. The quality of the recruiting technology is captured by the parameter τ.

3.2 Workers

A prospective worker decides whether to submit an application for a given job opening. Every prospective worker is either qualified or unqualified for the job. Denote a prospective worker i's ability $m_i = 1$ if she is qualified for the job and $m_i = 0$ if she is not qualified. A prospective worker does not know whether she is qualified or not qualified for a given job. However, she receives a signal about the probability that she is qualified. Specifically, prospective worker i receives a signal θ_i drawn from a uniform distribution, which is the probability that she is qualified, equal to:

$$\theta_i = P(m_i = 1 | \theta = \theta_i) \tag{1}$$

3.3 Firms

Assume that the firm's production function exhibits constant returns to scale and that labor is the only factor of production. The productivity of each worker is $y_i = m_i$. However, the firm does not know the worker's productivity prior to the hire. I assume that the firm observes this productivity only after the worker has been employed in the firm for a certain period.

Similar to Gibbons and Katz (1992), for each applicant the firm observes a signal $S \in \{0, 1\}$ which represents the quality of the match between the applicant and the job, where:

$$P(S = 1|m_i = 1) > P(S = 1|m_i = 0) \tag{2}$$

More specifically, the firm observes each applicant's S with the following probabilities:

$$\begin{array}{lll} & S = 1 & S = 0 \\ m_i = 1 & \psi(\tau) & 1 - \psi(\tau) \\ m_i = 0 & 1 - \psi(\tau) & \psi(\tau) \end{array} \tag{3}$$

where $\psi(\tau) > \frac{1}{2}$.

I model the adoption of Internet recruiting technology as an increase in the firm's probability of observing the right signal of the workers' type. I assume that $\frac{\partial \psi(\tau)}{\partial \tau} > 0$. This assumption reflects the idea that when a candidate applies online, her resume is stored in the firm's database and is easier to screen using keyword search (also, since $\psi(\tau)$ is a probability, $\lim_{\tau \Longrightarrow \infty} \psi(\tau) = 1$). The probability of observing the right signal, $\psi(\tau)$, is known to the worker.

The firm maximizes profits, and hence offers the worker a wage equal to her expected productivity: $w_i = \psi(\tau) * 1 + (1 - \psi(\tau)) * 0 = \psi(\tau)$.

The firm decides how many workers it needs for every position by profit maximization. I denote by D the number of workers that the firm decides to hire out of the total applicant pool for a given position. I assume that recruiting costs do not affect the number of positions filled, since they are negligible relative to the cost of employing the worker (i.e. wages, benefits etc.).

The firm randomly selects D candidates from the group of those candidates with signal $S = 1$. Denote Z the number of applicants for which the firm observes $S = 1$. I assume that $Z \geq D$.

3.4 When Will a Worker Apply for A Position?

I assume that a prospective worker applies to a given position when the expected utility from submitting an application is higher than the cost of submitting an application. In this section I will derive the expected utility from submitting an application and the conditions under which a prospective worker decides to submit an application.

Assume that:

$$\begin{aligned} U(\text{getting the job}) &= w_i \\ U(\text{not getting the job}) &= 0 \end{aligned} \tag{4}$$

$$\begin{aligned} E(u(\textit{submit application})|\theta) &= [\Pr(\text{getting the job}) * U(\text{getting the job}) \\ &\quad + \Pr(\text{not getting the job}) * U(\text{ not getting the job})] \end{aligned}$$

$$E(u(\textit{submit application})|\theta) = \left[\frac{D}{Z} * P(S=1|\theta) * w_i + P(S=0|\theta) * 0\right] \tag{5}$$

The calculation of $E(u(\textit{submit application})|\theta)$ is in appendix 7.1.

Proposition 1 *The expected utility from a job opening is increasing in* θ

Proof: appendix 7.2.

I assume that the worker incurs a cost $K(\tau)$ when she submits an application for a job opening ($K(\tau)$ is constant for all types of jobs and workers). The *marginal prospective worker* is indifferent between applying and not applying when the expected utility from applying equals the cost of application. θ^* is the value that solves:

$$E(u(submit\ application)|\theta = \theta^*) = K(\tau) \tag{6}$$

Proposition 1 and equation 6 imply that workers with $\theta < \theta^*$ will not apply, since their expected utility from being hired is lower than the cost of application. Only workers with $\theta \geq \theta^*$ will apply. Higher θ^* implies that the applicant pool will include prospective workers with higher probabilities of being qualified. If in response to improved technology, θ^* decreases, then the applicant pool will contain more candidates that are less likely to be qualified. Appendix 7.3 defines the conditions under which θ^* increases, decreases or does not change with improved recruiting technology.

3.5 The Effect of Improved Recruiting Technology on the Expected Proportion of Qualified Hires

The firm and the worker have information about the probability that the worker is qualified for the job (i.e. $m_i = 1$), but they do not know at the time of the hire whether the worker is actually qualified or not.[6] However, we can form an expectation about the ratio of qualified hires to total hires.

Denote $Q(\tau)$ as the expected ratio of qualified hires to all those actually hired (the mathematical equation is given in appendix 7.4). This is the probability that the hire is

[6] We can assume that information about the real qualification of the worker is revealed only after some time t has passed. Therefore at the time of the hire we can only form expectations about the number of qualified hires out of the total hires.

qualified, conditional on both signals observed by the worker and the firm, multiplied by the probability of being hired out of all the applicants that received a signal $S = 1$. Summing the probability that a worker is both hired and qualified over all those who applied and dividing it by the number of hires will give us the expected ratio of qualified hires to total hires.

Denote $B = \left[\frac{d\theta^*}{d\tau} / \frac{d\psi}{d\tau}\right]$. This is the effect of improved recruiting technology on the marginal prospective worker, relative to the effect of improved recruiting technology on the screening ability of the firm.

Proposition 2 *There exist a value B^* such that improved recruiting technology does not change the expected proportion of qualified hires. For $B < B^*$, improved recruiting technology will increase the expected proportion of qualified hires. For $B > B^*$, improved recruiting technology will reduce the expected proportion of qualified hires. The value of B^* rises with θ^* and $\psi(\tau)$.*

Proof: see appendix 7.5.

Improved technology has two effects. First, for a given screening technology, improved recruiting technology reduces application costs and hence induces less qualified workers to apply. These candidates do not internalize the effects of their behavior on the welfare of the total applicant population. The firm, lacking a perfect signal of candidates' qualifications, sometimes chooses non-qualified candidates, and as a result the expected proportion of qualified hires decreases. Second, improved technology increases the firm's probability of observing the right signal. The net impact of the new technology depends on the relative magnitude of these two effects.

One can argue that the effect of the new recruiting technology should be of different magnitudes for different types of jobs. There are positions in which the firm is more likely to screen out unqualified candidates. For example, positions that require certain degrees, experience, or specific knowledge lend themselves to easier screening. On the other hand, positions highly dependent on candidates' soft skills (which are not obvious and not easily verifiable) may present firms with more difficulty. The parameter $\psi(\tau)$ in the model captures this tendency. Thus, $\psi(\tau)$ will be higher when the required skills are more easily observed. If different professions and positions have different $\psi(\tau)$, they may also differ in their $\frac{d\psi}{d\tau}$, that is, they skill observability may be differentially affected by improvement in technology.

Why would a firm adopt Internet recruiting if it reduces the quality of the applicant pool?

Recruiting via the Internet is one of the cheapest recruiting methods. The average cost per hire by recruiting method is:

Recruiting Method	Average Cost Per Hire[7]
Agency	\$15,000
Print Ad	\$12,000
Employee Referrals	\$2000
Internet Recruiting	\$500-\$800

These costs are mainly direct costs: the cost paid to an agency, the price of a newspaper ad until the position is filled, the cost of Internet advertising per year divided by the number of people recruited via the Internet, and the cost paid to the referee if the worker has arrived through employee referral. These costs do not include the indirect cost of training employees, or the cost of leaving a position vacant. The firm does not have a record of the indirect costs.

The cost-saving argument is that even if Internet workers are less qualified on average, they are also less costly to replace. Therefore, a firm's benefits from Internet recruiting may still outweigh the costs. Indeed, the firm that provided the data for this research gave this cost-saving argument as the reason they use online recruitment.

[7] Data given by the company who supplied the data for this research.

Suppose firms know that Internet recruiting leads to lower quality hires. Why wouldn't they just impose application fees? In talking with recruiters, I found that many suspect that application fees could be grounds for a lawsuit under Equal Employment Opportunity laws. In general, the law does not allow discrimination based on race or sex, and since some ethnic groups are poorer than others, charging application fees may be seen as discriminatory.[8] Even so, firms could impose non-monetary applications costs, such as requiring written essays. Recruiters I spoke with reported that these non-monetary costs are uncommon because firms do not have time for complex applications and do not want to discourage qualified workers from submitting applications, especially given inter-firm competition for qualified workers. Below I present a simple model to illustrate this point.

3.5.1 The Effect of Competition

Firms operate in competitive markets where they compete to hire qualified applicants. Assuming that applicants face budget constraints, they choose to apply first to less costly positions, *ceteris paribus*, and hence a preference will be given to firms that use Internet recruiting. I also assume that applicants accept the offer of the firm that responds the soonest.

Suppose there are two identical firms in the market, competing for good job candidates. The probability that a candidate will accept an offer from firm 1 depends only on the response time of firm 1 relative to the response time of firm 2. A firm that uses the Internet has a faster response time than one that does not. The candidate accepts the offer of the firm that respond first, with probability 1. If both respond at the same time, the candidate accepts the offer of firm i with probability 0.5. The following Table describes this game (the firm's payoffs represent the probability that the applicant will accept the offer):

[8] In my conversation with Harvard law Professor. Christine Jolls, I learned that the law itself is ambiguous on this point.

		Firm 2	
		Adopt	*Do Not Adopt*
Firm 1	*Adopt*	$(0.5, 0.5)$	$(1, 0)$
	Do Not Adopt	$(0, 1)$	$(0.5, 0.5)$

The dominant strategy for each firm is to adopt Internet recruiting. The Nash equilibrium is for both firms to adopt Internet recruiting. If the firm does not adopt Internet recruiting, the probability of finding the best candidate decreases even more, since candidates will accept offers from the firm that responds first. Therefore, the firm secures the opportunity to make an offer to the best candidate, at the risk of making a mistake and offering the job to the less qualified candidate.

3.6 Extension: What if People Have Different Online Skills?

Suppose that the use of the Internet does not reduce application costs in a uniform way to all users. The idea that different people have different online skills has been studied by several researchers. In a large field study, Hargiatti (2001) measures the time needed by subjects to complete 17 tasks online. She finds that the amount of time needed ranges from 20 minutes to over 100 minutes, indicating wide variation in online skills. In a related paper, Hargiatti and Field (2003) study the amount of time subjects needed to complete an online job search.[9] Using a discrete-time logit model predicting the hazard rate for completion of job search tasks across time periods (10 second intervals), Hargiatti and Field find that the probability of completing the task during the time period decreases with age and increases with education. African Americans also tend to have a lower probability of task completion within allotted time.[10]

What are the implications of heterogenous cost reduction in the context of the suggested model? If online recruiting effectively reduces application costs only to qualified candidates,

[9] Based on calculations that Harigiatti sent my via e-mail in a personal correspondence.
[10] Albeit this result is problematic since there are only 7 African Americans in the sample.

then even though θ^* is reduced, more people with matching quality $m_i = 1$ apply than before, *increasing* the expected number of qualified hires. If, on the other hand, Internet recruiting effectively reduces application costs only to non-qualified hires, then of course the expected number of qualified hires will drop even more. However, only in certain occupations is there a reason to believe that the skill of using the Internet is highly correlated with quality. These may be occupations that are intensive in computer use, such as programmers, engineers and technicians. On the other hand, there is no reason to believe that a kindergarten teacher's online skills have much to do with her qualifications for the job.

4 Testable Implications and Empirical Strategy

The model suggests that improvements in recruiting technology may lead to inferior matches between workers and firms if the screening effect is outweighed by the application cost effect. I measure match quality by the worker's employment duration (in months) at the firm. The idea that a good match yields a lengthy job duration is due to Jovanovic (1979), who treats a job match as a pure experience good; the quality of the match is not known ex ante, but must be experienced. Workers remain in jobs that are revealed as high quality matches, while workers with low-quality matches separate. Using job tenure as an indicator of match quality is also supported by Akerlof, Rose and Yellen's (1988) evidence that nonpecuniary match characteristics have a negative impact on the probability that an individual quits (Bowlus 1995).

I investigate whether the model's implications are supported by the data in two steps. First, I explore whether Internet recruits are more likely to have shorter employment durations with the firm compared with employees recruited by other channels. A finding that Internet recruits have shorter employment duration would support the idea that Internet hires are selected from an adversely selected pool. Second, I suggest a strategy that investigates whether online recruiting led to lower match quality between workers and firms.

This strategy compares the expected duration of observationally equivalent workers that differ only in the availability of Internet recruiting. A finding that workers for whom online recruiting was available have shorter employment durations compared with similar workers for whom it was not available supports the idea that the Introduction of the Internet led to hires of lower match quality.

A distinguishing feature of duration data is the possibility that some of the durations observed will be censored. My sample includes all the employees that were hired until February 10, 2003. An employee that was hired prior to that date but is still actively employed will display a duration spell that may be shorter than the actual time that she will be employed. The data consist of a measured spell length (number of months at the firm until February 10, 2003) together with the information that the spell was censored (or not).[11]

I use a Cox duration model to study my data. The advantage of the duration model is that it takes care of censoring issues.[12] The duration model estimates the probability of employment termination in a given month, conditional on the number of months that one has already been employed with the firm. In particular, I estimate the equation:

$$\lambda(t) = \lambda_0(t)e^{\beta_1 x_1 + \ldots + \beta_k x_k} \tag{7}$$

Where $\lambda(t)$, the hazard function, describes the rate at which employment spells will be completed at duration t, given that they last until t.[13] The exponentiated coefficients, e^{β_i},

[11] My dataset includes a variable that receives the value "Active" if the employee is employed at the firm on February 10, 2003, and the value "Terminated" if the employee is no longer working at the firm at that date. An employee that was hired prior to February 10, 2003 and is "active" at that date is a censored observation, since we don't have information about the full duration of this employee at the firm.

[12] For a detailed explanation about how duration models allow to deal with censoring issues see Kiefer (1988).

[13] The hazard function is defined as follows. The probability distribution of a duration spell can be specified by the distribution function $F(t) = \Pr(T < t)$ which specifies the probability that the random variable T is less than some value t. The corresponding density function is $f(t) = \frac{dF(t)}{dt}$. The hazard function is:

give the proportional change in the hazard rate (and expected job duration). A positive value of the coefficient β_i implies a higher hazard rate but a lower employment duration. A negative value of the coefficient β_i implies a lower hazard rate and therefore a higher employment duration.

The model is estimated using a limited sample of the data, after dropping observations missing any of the following: education, recruiting source, occupation, race or sex.[14] Table 4 provides descriptive statistics of the data. The limited sample contains 11,479 observations, consisting of 46% engineers and technicians, 32% sales workers, and approximately 7% administrative workers; Fifty three percent of the total employees in the sample were recruited through employee referral, 15% were recruited through an agency, 11% were unsolicited and 5% were recruited via the Internet.

4.1 Are Internet Recruits Likely to have Shorter Employment Duration than Recruits from Other Channels?

In this section I use the Cox duration model described above to explore whether Internet recruits are likely to have shorter employment durations than those recruited through other channels.

The control variables are education, age, occupation, hire year, race, sex and recruiting method,[15] and the results of the Cox duration model are presented in Table 5.[16] I run

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$\lambda(t) = \frac{f(t)}{1-F(t)}$. This function describes the rate at which spells will be completed at duration t, given that they last until t. The probability that a spell ends between 3 and $3 + \Delta$ conditional on having lasted 3 periods is $\lambda * \Delta$.

[14] I do not have any information about those who worked in the company and left before 1995, and therefore I exclude from my data set the 56 observations associated with employees hired prior to 1995 and still working in 2002. My sample includes only those hired between 1/1/1995 and 31/12/2002.

[15] I use years of schooling as a measure for education, a dummy variable for each recruiting source, a dummy variable for each occupation group and dummy variables for year of hire.

[16] All regressions presented in this paper were run using the sample which includes observations for which the recruiting channel is unknown. I include a dummy variable for "unknown recruiting channel". The results were not significantly different than the results of regressions run using a sub-sample that does not

the duration model on several sub-samples. Column (1) displays the results of the whole sample. The omitted recruiting channel is print advertising. The coefficient on Internet is not significantly different from zero, which means that the hazard rate of employment termination of Internet recruits is not significantly different from that of print advertising recruits. Similarly, the coefficient on agency recruits is not significantly different from zero. Employee referrals and college recruits have a hazard rate that is 0.6 of print advertising recruits and thus expected job durations that are 1.7 times longer. Unsolicited recruits have a hazard rate of 0.7, and thus expected job durations that are 1.4 times longer than that of print advertising. These results indicate that Internet recruits are not significantly different from print advertising recruits, but are more likely to have shorter employment duration than workers recruited through employee referrals or college recruiting as well as unsolicited hires.

Columns (2)-(6) exhibit the same model fit to sub-samples of occupation groups. I look at the five largest occupation groups: Engineers and Technicians, Sales, Administrative, Operational and Marketing. As before, the coefficient of interest is the coefficient on Internet. I find that hazard rates of Internet recruits are not significantly different than those of print advertising recruits. Within any of these occupations comparing the coefficient on Internet to the coefficients on other channels, I find that workers recruited through employee referrals are likely to stay longer with the firm (relative to print advertising recruits) in the case of engineers and technicians (hazard rate which is 0.5 of print advertising), administrative (hazard rate which is 0.6 of print advertising) and marketing (hazard rate which is 0.4 of print advertising). For sales and operational occupations employee-referral recruits do not seem to be significantly different from print advertising recruits (and hence from Internet recruits). Agency recruits are significantly different from print advertising recruits only among engineers and technicians (hazard rate which is 0.8 of print advertising). College

include employees with unknown recruiting source. For brevity, only the latter results are presented.

recruits are significantly different from print advertising recruits only in the case of engineers and technicians (hazard rate which is 0.5 of print advertising), and marketing workers (hazard rate which is 0.4of print advertising). For both of these occupation groups, college recruits are likely to have longer employment durations than print advertising recruits. Among the other professions, college recruits are not significantly different from print advertising recruits.

4.2 Did the Introduction of the Internet Lead to Lower Quality Matches?

In this section I consider the effect of the introduction of Internet recruiting quality of match between workers and firms. Job seekers hired during 2001-2002 are considered "treated," in the sense that low-cost Internet job search technology was widely available to them, whereas job seekers hired during 1995-2000 (years with limited recruitment via the Internet) are considered "untreated" since online recruiting technologies were not widely used in this period.[17] I use a quasi-experimental method in which the availability of Internet job search technologies during the period 2001-2002 is treated as an exogenous addition to the possible set of recruiting methods.[18]

I use a propensity score method,[19] which involves calculating the conditional probability that a candidate used the Internet for a job search given the available pretreatment covariates.[20] This conditional probability is called a propensity score: it is simply the probability of having used the Internet as a function of education, race, sex, and job category.

I interact the propensity score with the year of hire; these interactions are used as explanatory variables in a Cox duration model. The objective is to determine whether workers

[17] See Table 1.

[18] For a similar use of this method to study a related question, see Field (2003).

[19] The strategy to obtain propensity scores is described in Dehejia and Wahba (1999).

[20] Recall that these covariates are the attributes of the job candidate and the categorical type of the job itself.

with similar likelihoods of using the Internet have different hiring outcomes, depending on whether or not they received the "treatment."[21] The key identifying assumption that underlies this method is that it is the additional recruitment method (the Internet) alone that is responsible for such interactions and that there are no other underlying reasons for changes in employment prospects. This firm has grown steadily during the years included in the sample. There were no significant changes in the firm's policy or growth that might have it more attractive to certain groups of workers than to other groups of workers.

If the coefficients on propensity score*hire year are significant and become more positive (or less negative) as hire year (and thus Internet use) increases, then workers who were similarly likely to use the Internet but were hired in more recent years will be employed for shorter durations, and hence will be considered of lower match quality.

5 Empirical Results

Table 6 presents the results of the propensity score regression. Ideally, I would use a binary dependent variable indicating whether or not the applicant applied online, however, data were not available at this level of specificity.[22] I therefore use a dependent variable that takes on a value of 1 if the worker was *hired* through the Internet, and 0 otherwise. Since the biggest Internet expansion was during 2001-2002, I use a restricted sample (2084 observations) that includes only the last two years of new hires to calculate the likelihood of being hired via the Internet. The explanatory variables are education, occupation group, race and sex. The coefficients display the effect of the individual characteristics on the probability that an individual will be hired through the Internet. Due to reduced sample size, I group the ten occupation groups into four main groups: (1) executives, engineers and technicians (2)

[21] As mentioned above, the treatment here is having applied for a job in 2001-2002, the years when online recruiting technology was first prevalent.

[22] My sample contains only those that were actually hired, as I don't have data about those who applied and were not hired.

operational (3) administrative, human resources, finance, law, marketing (4) sales and quality control (dropped group).

I use the results of the propensity score's logit specification over the sub-sample of the last two years to predict the propensity scores for the whole sample. Higher propensity scores imply that a worker is more likely to use (be hired via) the Internet if Internet job search technology is available to her. Individuals with similar propensity scores are comparable in their probability of being hired through the Internet (Dehejia and Wahba 1999, Field 2003).

The propensity score multiplied by each hire-year dummy is then added to the duration model with the usual controls. The results are presented in Table 7. Column (1) shows the effect of the propensity score hire year interactions on the hazard rate. The coefficients on these interaction terms are significant for all the years 1998-2002. Point estimates of the coefficient become less negative with each hire year (implying that the employment duration of workers who are likely to use the Internet is shorter in later years). However, Wald test results do not allow for rejection of the null hypothesis that the interaction term coefficients are the same for 1998-2001.[23] This implies that during the years 1998-2001, there is no evidence of a decline in quality among people who were likely to use the Internet if it was available to them. Therefore, there is no strong evidence that Internet recruiting reduced the quality of Internet hires during these years. The coefficient on the interaction term for hire year 2002 is positive and significant, which implies that the quality of people who were likely to use the Internet at the time of the biggest Internet expansion did indeed decline (as measured by the likelihood of shorter survival at the firm).

Column (2) shows the effect of the propensity score multiplied by hire year on the hazard rate, while controlling for recruiting channel. The coefficients on the interaction terms are similar to those in column (1). The coefficient on Internet is positive and significant, indicating that those who were actually hired via the Internet fared less well with the firm

[23] Wald test statistic is 0.7874 (whereas chi2(2) = 0.48).

than those recruited via print advertising.

These results do reveal one puzzle: the coefficient on the interaction term for hire year 1995-1997 is insignificant, which suggests that people who would have been likely to use the Internet but were hired in 1995-1997 did not experience different employment durations compared to similar recruits in other years. This is a puzzle, since the type of people likely to be recruited online appear to have more stable job durations (lower hazard rates from 1998 to 2001) relative to the pre-Internet period of 1995-97. One possible explanation can be that in this particular firm, the screening technology improved prior to the reduction in application costs attributed to online recruiting. Thus during 1998-2001, when Internet application tools were not widely used, improved screening technology in this firm allowed it to select better workers from those who were likely to be Internet hires, compared with similar hires made during the period 1995-1997.

6 Conclusion

This paper has proposed and tested a model in which the adoption of Internet recruiting technology can, under certain conditions, lead to lower-quality matches between workers and firms. I show that Internet recruiting has two offsetting effects: it reduces application costs for job seekers–thereby reducing match quality–and improves firms' screening technology–thereby increasing match quality. The net impact depends on the relative magnitudes of these two effects. Using a unique data set from a large multinational employer, I show that employment durations of Internet hires are not significantly different from those of print advertising hires, but are shorter than those of hires made through employee referrals or college recruiting. I also find that the occupations that exhibited the most rapid growth in Internet recruiting show the largest declines in expected job durations over the sample period, consistent with a key prediction of the model.

The broad implication of these findings is that, as a result of informational asymmetries, improved technology may have perverse effects on labor market outcomes. If indeed the new technology leads to lower-quality matches between workers and firms, employers may increasingly turn to "internal" or referred candidate pools,[24], disadvantaging individuals with less extensive networks.[25] However, the adverse effect will be offset to the extent that firms improve their screening technologies. Until then, firms may explore ways to overcome the adverse effects of improved technology using mechanisms to induce self selection among applicants. For example, they can create a time consuming online application process, that will discourage applications from candidates who know they have low probability to be hired.

One promising direction for future research relates to the lower recruiting costs incurred by firms who use online recruiting. Although online recruiting may lead firms to hire workers of lower match quality, it might nonetheless make them better off by reducing the cost of replacing poor matches. In that case, turnover should increase in the short run but not in the long run, once firms have found good matches through trial and error. To test this hypothesis, we will need to wait until the use of Internet recruiting has been prevalent for more than a few years.

References

[1] Akerlof, George, Andrew Rose and Janet Yellen. "Job Switching and Job Satisfaction in the US Labor Market." *Brooking Papers on Economic Activity* 2(1988):495-582.

[2] Autor, David. "Wiring the Labor Market." *Journal of Economic Perspectives.* 15.1(2001) 25-40.

[3] Autor, David, Frank Levy and Richard J. Murname. "Skill Demand, Inequality and Computerization: Connecting the dots." Mimeograph Preprared for the Federal Reserve

[24] Literature about referral as a sources to overcome information asymmetries in the labor market includes Rees (1966), Greenwald (1986), Holzer (1987), Montgomery (1991), Stigler (1962) and many others.

[25] See for example Holzer (1987).

Bank of Atlanta and Andrew Young School of Policy Studies Conference on Technology, Growth and the Labor Market, December 2001.

[4] Bowlus, Audra J. "Matching Workers and Jobs: Cyclical Fluctuations in Match Quality." *Journal of Labor Economics*, 13.2(1995):335-350.

[5] Dehejia, Rajeev H. and Sadek Wahba. "Casual Effects in Nonexperimental Studies: Reevaluating the Evaluation of Training Programs." *Journal of the American Statistical Association.* 94.448 (1999):1053-1061.

[6] Field, Erica. "The Effect of Internet Job Search on Rates of Job-to-Job Transitions, Employed Search Durations and Returns to Mobility." Final Proposal. Unpublished Manuscript (received through personal correspondence).

[7] Fernandez, Roberto M. and Nancy Weinberg. "Sifting and Sorting: Personal Contacts and Hiring in a Retail Bank." *The American Sociological Review.* 62(1997): 883-902.

[8] Freeman, Richard. "The Labor Market in the New Information Economy." NBER Working Paper 9254. 2002.

[9] Gibbons, Robert, and Lawrence Katz. "Does Unmeasured Ability Explain Inter-Industry Wage Differentials." *The Review of Economic Studies.* 59.3(1992): 515-535.

[10] Greenwald, Bruce C. "Adverse Selection in the Labour Market." *The Review of Economic Studies* 53.3 (1986), 325-347.

[11] Hargiatti, Eszter. "Beyond Logs and Surveys: In-Depth Measures of People's Web Use Skills." *Journal of the American Society for Information Science and Technology* 53.14(2002):1239-1244.

[12] Hargiatti, Eszter and Erica Field. Results communicated in personal correspondence.

[13] Holzer, Harry and David Neumark. "Are Affirmative Action Hires Less Qualified? Evidence from Employer-Employee Data on New Hires." *Journal of Labor Economics* 17.3 (1999), 534-569.

[14] Holzer, Harry J. "Informal Job Search and Black Youth Unemployment." *The American Economic Review* 77.3(1987), 446-452.

[15] Holzer, Harry J. "Search Method Use by Unemployed Youth." *Journal of Labor Economics* 6.1(1988), 1-20.

[16] Internet Recruiting News (July 15, 1998). <http://www.interbiznet.com/ern/archives/ern>.

[17] Jovanovic, Boyan. "Job Matching and the Theory of Turnover." *Journal of Political Economy* 87(1979):972-90.

[18] Ilogos. "Internet Recruiting: Lessons from the Global 500." May 1999.

[19] Interbiznet.com. "The 2001 Electronic Recruiting Index: The Human Capital Market Place, Executive Summary."

[20] Kiefer, Nicholas M. "Economic Duration Data and Hazard Functions." *Journal of Economic Literature* 26.2 (1988): 646-679.

[21] Kuhn, Peter and Mikal Skuterud. "Internet Job Search and Unemployment Durations." Mimeo. 2002.

[22] Kuhn, Peter. "The Internet and the Labor Market." Mimeo University of California Santa Barbara. 2000a.

[23] Kuhn, Peter and Mikal Skuterud. "Job Search Methods: Internet versus Traditional." *Monthly Labor Review*. (October 2000b): 3-11.

[24] Kuhn, Peter and Mikal Skuterud. "Internet and Traditional Job Search Methods, 1994-1999." Mimeo University of California Santa Barbara. 2000c.

[25] Li, Charlene, Chris Charron and Amy Dash. "The Career Networks." Forrester Research. February 2000.

[26] Hallowell, Roger and Cate Reavis. "Monster.com: Success Beyond the Bubble." *Harvard Business School Case* 9-802-024. 2001.

[27] Montgomery, James D. "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis." *The American Economic Review 81.5(1991), 1408-1418.*

[28] Mortensen, D. T. and C.A. Pissarides. "New Developments in Models of Search in the Labor Market" in Orley Ashenfelter and David Card eds. *Handbook of Labor Economics.* Amsterdam: Elsevier Science Pub. Co. 1999. pp. 2568-2627.

[29] Mortensen, Dale T. "Job Search and Labor Market Analysis." in ed. *Handbook of Labor Economics*. Vol II. Ashenfelter and R. Layard. Amsterdam: Elsevier Science Publishers, 1986. pp. 849-919.

[30] Osberg, Lars. "Fishing in Different Pools: Job-Search Strategies and Job-Finding Success in Canada in the Early 1980s." *Journal of Labor Economics*. 11.2(1993), 348-386.

[31] Rees, Albert. "Information Networks in Labor Markets." *The American Economic Review* 56.1/2 (1996), 559-566.

[32] Saloner, Garth. "Old Boys Networks as Screening Mechanisms." *Journal of Labor Economics* 3.3(1985):255-267.

[33] Stigler, George J. "Information in the Labor Market." *Journal of Political Economy* (1962) Sup.

[34] University of California at Los Angeles Center for Communication Policy (2001). The UCLA Internet Report 2001: Surveying the future. Los Angeles, CA. <http://www.ccp.ucla.edu/pages/internet-report.asp>.

7 Appendix

7.1 Calculating $E(u(submit\ application)|\theta)$:

$$\begin{aligned} E(u(submit\ application)|\theta) &= [\Pr(\text{getting the job}) * U(\text{getting the job}) \\ &\quad + \Pr(\text{not getting the job}) * U(\text{ not getting the job})] \end{aligned}$$

Plugging in the probability of getting the job and the utilities from getting/not getting the job:

$$E(u(submit\ application)|\theta) = \left[\frac{D}{Z} * P(S=1|\theta) * w_i + P(S=0|\theta) * 0\right] \tag{8}$$

$$E(u(submit\ application)|\theta) = \left[\frac{D}{Z} * P(S=1|\theta) * \psi(\tau) + P(S=0|\theta) * 0\right]$$

$$P(S=1|\theta=\theta) = \theta * P(S=1|m_i=1) + (1-\theta) * P(S=0|m_i=1) \tag{9}$$

Substituting the firm's probabilities of observing the correct applicant's signal (equation 3) we get:

$$P(S=1|\theta=\theta) = \theta * \psi(\tau) + (1-\theta) * (1-\psi(\tau)) \tag{10a}$$

Rearranging terms, we get:

$$P(S = 1|\theta = \theta) = (1 - \psi(\tau)) + \theta\,(2\psi(\tau) - 1) \tag{11}$$

7.1.1 Calculating the Number of Applicants that Receive a Good Signal

Let $\theta^*(\tau)$ be the lowest value of θ for which a prospective worker will still apply for a job. Then $\theta \geq \theta^*(\tau)$ for all those who submit an application. Therefore, the total number of people with signal $S = 1$ who submit an application is:

$$Z = \int\limits_{\hat{\theta}=\theta^*(\tau)}^{1} P(S = 1|\theta = \hat{\theta}) f(\hat{\theta}) d\hat{\theta} \tag{12a}$$

Substituting (6) we get:

$$Z = \int\limits_{\hat{\theta}>\theta^*(\tau)}^{1} \Big[(1 - \psi(\tau)) + \hat{\theta}\,(2\psi(\tau) - 1)\Big]\, f(\hat{\theta}) d\hat{\theta} \tag{13}$$

if $f(\hat{\theta}) = 1$ (i.e. a uniform distribution) then:

$$\begin{aligned} Z &= \int\limits_{\hat{\theta}=\theta^*(\tau)}^{1} \Big[(1 - \psi(\tau)) + \hat{\theta}\,(2\psi(\tau) - 1)\Big]\, d\hat{\theta} = \Big[\hat{\theta}(1 - \psi(\tau)) + \hat{\theta}^2(\psi(\tau) - \frac{1}{2})\Big]_{\theta^*(\tau)}^{1} = (14) \\ Z &= -\theta^{*2}(\tau)(\psi(\tau) - \frac{1}{2}) - \theta^*(\tau)(1 - \psi(\tau)) + \frac{1}{2} \end{aligned}$$

Therefore,

$$E(u(job)|\theta) = \frac{D * [(1-\psi(\tau)) + \theta\,(2\psi(\tau)-1)]\,\psi(\tau)}{\left[-\theta^{*2}(\tau)(\psi(\tau)-\frac{1}{2}) - \theta^{*}(\tau)(1-\psi(\tau)) + \frac{1}{2}\right]} \tag{15}$$

7.2 Comparative Statics: The Effect of θ on the Expected Utility from Getting a Job:

$$\begin{aligned} E(u(submit\ application)|\theta) &= \frac{D * [1-\psi(\tau) + \theta(2\psi(\tau)-1)]\,\psi(\tau)}{-\theta^{*2}(\tau)(\psi(\tau)-\frac{1}{2}) - \theta^{*}(\tau)(1-\psi(\tau)) + \frac{1}{2}} \\ \frac{\partial E(u(submit\ application)|\theta)}{\partial\theta} &= \frac{D(2\psi(\tau)-1)\psi(\tau)}{-\theta^{*2}(\tau)(\psi(\tau)-\frac{1}{2}) - \theta^{*}(\tau)(1-\psi(\tau)) + \frac{1}{2}} \end{aligned} \tag{16}$$

The numerator is always positive, since $0 < \psi(\tau) < 1$. Let d be the denominator. Then:

$$d = -\theta^{*2}(\tau)(\psi(\tau) - \frac{1}{2}) - \theta^{*}(\tau)(1-\psi(\tau)) + \frac{1}{2} \geq 0 \tag{17}$$

Therefore d is positive when:

$$-1 \leq \theta^{*} \leq \frac{1}{2\psi(\tau)-1} \tag{18}$$

Since by definition, $\psi(\tau) > \frac{1}{2}$ (and thus $\frac{1}{2\psi(\tau)-1} > 1$), and since $0 \leq \theta^{*}(\tau) \leq 1$, then $d > 0$ for all $\theta^{*}(\tau)$.

7.3 Comparative Statics: The effect of τ on θ^{*} :

The following equation describes the condition under which the utility from submitting a job application exactly equals $K(\tau)$, the cost of submitting an application. θ^{*} is the signal observed by the worker whose utility from submitting an application equals his application cost. τ is the technology parameter.

$$K(\tau) = \frac{D * [(1-\psi(\tau)) + \theta^* (2\psi(\tau) - 1)] \psi(\tau)}{-\theta^{*2}(\psi(\tau) - \frac{1}{2}) - \theta^*(1-\psi(\tau)) + \frac{1}{2}}$$

I assume that: $\frac{d\psi}{d\tau} > 0$ (when technology improves, the screening mechanism of the firm improves) and $\frac{\partial K(\tau)}{\partial \tau} < 0$ (when technology improves, the application cost declines).

The comparative statics of the derivative $\frac{\partial \theta^*}{\partial \tau}$ will indicate the impact of technological change on the applicant pool.

Rewriting the previous equation, we have:

$$K(\tau)\left[-\theta^{*2}(\psi(\tau) - \frac{1}{2}) - \theta^*(1-\psi(\tau)) + \frac{1}{2}\right] = D\psi(\tau)\left[(1-\psi(\tau)) + \theta^* (2\psi(\tau) - 1)\right]$$

Taking the full derivative gives us the following:

$$K f_{\theta^*} \frac{\partial \theta^*}{\partial \tau} + K f_\psi \frac{d\psi}{d\tau} + \frac{dK(\tau)}{d\tau} F = g_{\theta^*} \frac{\partial \theta^*}{\partial \tau} + g_\psi \frac{d\psi}{d\tau}$$

Now substituting to get $\frac{\partial \theta^*}{\partial \tau}$, we have:

$$
\begin{aligned}
Kf_{\theta^*}\frac{\partial\theta^*}{\partial\tau} + Kf_\psi\frac{d\psi}{d\tau} + \frac{dK(\tau)}{d\tau}F &= g_{\theta^*}\frac{\partial\theta^*}{\partial\tau} + g_\psi\frac{d\psi}{d\tau} \\
\frac{\partial\theta^*}{\partial\tau}\left[Kf_{\theta^*} - g_{\theta^*}\right] &= g_\psi\frac{d\psi}{d\tau} - Kf_\psi\frac{d\psi}{d\tau} - \frac{dK(\tau)}{d\tau}F \\
\frac{\partial\theta^*}{\partial\tau}\left[Kf_{\theta^*} - g_{\theta^*}\right] &= \left(g_\psi - Kf_\psi\right)\frac{d\psi}{d\tau} - \frac{dK(\tau)}{d\tau}F \\
\frac{\partial\theta^*}{\partial\tau} &= \frac{\left(g_\psi - Kf_\psi\right)\frac{d\psi}{d\tau} - \frac{dK(\tau)}{d\tau}F}{\left[Kf_{\theta^*} - g_{\theta^*}\right]}
\end{aligned}
$$

Therefore:

$$
\frac{\partial\theta^*}{\partial\tau} = \frac{\left(g_\psi - Kf_\psi\right)}{\left[Kf_{\theta^*} - g_{\theta^*}\right]}\frac{d\psi}{d\tau} - \frac{F}{\left[Kf_{\theta^*} - g_{\theta^*}\right]}\frac{dK(\tau)}{d\tau} \tag{19}
$$

Calculating the derivatives:

$$
\begin{aligned}
f_{\theta^*} &= -2\theta^*(\psi(\tau) - \frac{1}{2}) - (1 - \psi(\tau)) = -2\theta^*\psi(\tau) + \theta^* - 1 + \psi(\tau) \\
&= \theta^*\left(1 - 2\psi(\tau)\right) - 1 + \psi(\tau) \\
f_\psi &= -\theta^{*2} + \theta^* = \theta^*(1 - \theta^*) \\
g_{\theta^*} &= D\psi(\tau)\left(2\psi(\tau) - 1\right) \\
g_\psi &= D\left[(1 - \psi(\tau)) + \theta^*\left(2\psi(\tau) - 1\right)\right] + D\psi(\tau)\left[-1 + 2\theta^*\right] = \\
g_\psi &= D\left[\theta^*\left(4\psi(\tau) - 1\right) + 1 - 2\psi(\tau)\right]
\end{aligned}
$$

Plugging into 19:

$$\frac{\partial\theta^*}{\partial\tau} = \frac{\left[D\left[\theta^*\left(4\psi(\tau)-1\right)+1-2\psi(\tau)\right]-K\theta^*(1-\theta^*)\right]}{K\left[\theta^*\left(1-2\psi(\tau)\right)-1+\psi(\tau)\right]-D\psi(\tau)\left(2\psi(\tau)-1\right)}\frac{d\psi}{d\tau} - \frac{\left[-\theta^{*2}(\psi(\tau)-\frac{1}{2})-\theta^*(1-\psi(\tau))+\frac{1}{2}\right]}{K\left[\theta^*\left(1-2\psi(\tau)\right)-1+\psi(\tau)\right]-D\psi(\tau)\left(2\psi(\tau)-1\right)}\frac{dK(\tau)}{d\tau}$$

so:

$$\begin{aligned}
\frac{\partial\theta^*}{\partial\tau} &> 0 \text{ iff } \frac{\left[D\left[\theta^*\left(4\psi(\tau)-1\right)+1-2\psi(\tau)\right]-K\theta^*(1-\theta^*)\right]}{\left[-\theta^{*2}(\psi(\tau)-\frac{1}{2})-\theta^*(1-\psi(\tau))+\frac{1}{2}\right]} > \frac{\frac{dK(\tau)}{d\tau}}{\frac{d\psi}{d\tau}} \\
\frac{\partial\theta^*}{\partial\tau} &= 0 \text{ iff } \frac{\left[D\left[\theta^*\left(4\psi(\tau)-1\right)+1-2\psi(\tau)\right]-K\theta^*(1-\theta^*)\right]}{\left[-\theta^{*2}(\psi(\tau)-\frac{1}{2})-\theta^*(1-\psi(\tau))+\frac{1}{2}\right]} = \frac{\frac{dK(\tau)}{d\tau}}{\frac{d\psi}{d\tau}} \\
\frac{\partial\theta^*}{\partial\tau} &< 0 \text{ iff } \frac{\left[D\left[\theta^*\left(4\psi(\tau)-1\right)+1-2\psi(\tau)\right]-K\theta^*(1-\theta^*)\right]}{\left[-\theta^{*2}(\psi(\tau)-\frac{1}{2})-\theta^*(1-\psi(\tau))+\frac{1}{2}\right]} < \frac{\frac{dK(\tau)}{d\tau}}{\frac{d\psi}{d\tau}}
\end{aligned}$$

Improved recruiting technology will affect the identity of the marginal prospective worker. Let $A = \left[\frac{\frac{dK(\tau)}{d\tau}}{\frac{d\psi}{d\tau}}\right]$. This is the effect of improved recruiting technology on the worker's application cost relative to the effect of improved recruiting technology on the screening ability of the firm.

Proposition 3 *There exists a value $A^* < 0$ such that improved recruiting technology does not change the identity of the marginal prospective worker. For $A < A^*$, improved recruiting technology will induce prospective marginal worker with higher probability to be qualified for the job (i.e. higher θ^*). For $A > A^*$ improved recruiting technology will induce a prospective marginal worker with lower probability to be qualified for the job (i.e. lower θ^*). The value of A^* rises with D and falls with K.*

7.4 Calculating Q, the Expected Proportion of Qualified Hires out of Total Hires.

The expected proportion of qualified hires out of the total hires is:

$$Q = \frac{\int_{\hat{\theta}=\theta^*(\tau)}^{1} \frac{D}{Z} \cdot P(S=1|\theta=\hat{\theta}) \cdot P(m_i=1|\theta=\hat{\theta}, S=1) d\hat{\theta}}{D}$$

I now calculate the probability that the worker is of high quality given his private signal and the firm's observed signal, assuming that the firm observe that he is qualified:

$$\begin{aligned} P(m_i &= 1|\theta=\hat{\theta}, S=1) = \frac{P(m_i = 1 \ \& \ \theta = \hat{\theta} \ \& \ S=1)}{P(\ \theta = \hat{\theta} \ \& \ S=1)} = \\ &= \frac{f(\hat{\theta}) \cdot \hat{\theta} \cdot \psi(\tau)}{f(\hat{\theta}) \cdot \left[\hat{\theta} \cdot \psi(\tau) + (1-\hat{\theta}) \cdot (1-\psi(\tau))\right]} = \frac{\hat{\theta} \cdot \psi(\tau)}{\left[(1-\psi v) + \hat{\theta}\,(2\psi(\tau)-1)\right]} \end{aligned} \tag{20}$$

Plugging in all the probabilities, we get:

$$\begin{aligned} Q &= \frac{1}{D} \int_{\hat{\theta}=\theta^*(\tau)}^{1} \frac{D}{\left[-\theta^{*2}(\tau)(\psi(\tau)-\frac{1}{2}) - \theta^*(1-\psi(\tau)) + \frac{1}{2}\right]} \cdot \hat{\theta} * \psi(\tau) d\hat{\theta} \\ Q &= \frac{\psi(\tau) \cdot \left(1-\theta^{*2}(\tau)\right)}{-\theta^{*2}(\tau)(2\psi(\tau)-1) - 2\theta^*(\tau)(1-\psi(\tau)) + 1} \end{aligned}$$

7.5 Comparative Statics: the Effect of τ on the Proportion of High Quality Types Chosen

I showed that:

$$Q(\tau) = \frac{\psi(\tau) \cdot \left(1 - \theta^{*2}(\tau)\right)}{-\theta^{*2}(\tau)(2\psi(\tau) - 1) - 2\theta^{*}(\tau)(1 - \psi(\tau)) + 1} \tag{29x}$$

Hence:

$$Q(\tau)\left[-\theta^{*2}(\tau)(2\psi(\tau) - 1) - 2\theta^{*}(\tau)(1 - \psi(\tau)) + 1\right] = \psi(\tau)\left(1 - \theta^{*2}(\tau)\right) \tag{21}$$

Denote:
$F = \left[-\theta^{*2}(\tau)(2\psi(\tau) - 1) - 2\theta^{*}(\tau)(1 - \psi(\tau)) + 1\right]$,
$G = \psi(\tau)\left(1 - \theta^{*2}(\tau)\right)$

Differentiating (21) with respect to τ:

$$\begin{aligned} Q(\tau) f_{\theta^*}\frac{d\theta^*}{d\tau} + Q(\tau) f_{\psi}\frac{d\psi}{d\tau} + \frac{\partial Q(\tau)}{\partial \tau}F &= g_{\theta^*}\frac{d\theta^*}{d\tau} + g_{\psi}\frac{d\psi}{d\tau} \\ \frac{\partial Q(\tau)}{\partial \tau} &= \frac{g_{\theta^*}\frac{d\theta^*}{d\tau} + g_{\psi}\frac{d\psi}{d\tau} - Q(\tau) f_{\theta^*}\frac{d\theta^*}{d\tau} - Q(\tau) f_{\psi}\frac{d\psi}{d\tau}}{F} \end{aligned}$$

$$\frac{\partial Q(\tau)}{\partial \tau} = \frac{\frac{d\theta^*}{d\tau}\left(g_{\theta^*} - Q(\tau) f_{\theta^*}\right) + \left(g_{\psi} - Q(\tau) f_{\psi}\right)\frac{d\psi}{d\tau}}{F} \tag{22}$$

$$
\begin{aligned}
g_{\theta^*} &= -2\theta^*(\tau)\psi(\tau) \\
f_{\theta^*} &= -2\theta^*(\tau)(2\psi(\tau)-1)-2(1-\psi(\tau)) \\
g_{\psi} &= \left(1-\theta^{*2}(\tau)\right) \\
f_{\psi} &= -2\theta^{*2}(\tau)+2\theta^*(\tau) = 2\theta^*(\tau)\left(1-\theta^*(\tau)\right)
\end{aligned}
$$

We know from appendix 7.2 that $F > 0$. We therefore have to find the sign of the numerator of equation (22) to do the comparative statics.

Plugging in:

$$
\left(g_{\theta^*}-Q(\tau)f_{\theta^*}\right)\frac{d\theta^*}{d\tau} = \left(-2\theta^*(\tau)\psi(\tau) - \frac{\left(1-\theta^{*2}(\tau)\right)\psi(\tau)[-2\theta^*(\tau)(2\psi(\tau)-1)-2(1-\psi(\tau))]}{-\theta^{*2}(\tau)(2\psi(\tau)-1)-2\theta^*(\tau)(1-\psi(\tau))+1}\right)\frac{d\theta^*}{d\tau}
$$

$$
\left(g_{\psi}-Q(\tau)f_{\psi}\right)\frac{d\psi}{d\tau} = \left(\left(1-\theta^{*2}(\tau)\right) - \frac{2\left(1-\theta^{*2}(\tau)\right)\theta^*(\tau)(1-\theta^*(\tau))\psi(\tau)}{-\theta^{*2}(\tau)(2\psi(\tau)-1)-2\theta^*(\tau)(1-\psi(\tau))+1}\right)\frac{d\psi}{d\tau}
$$

Comparative Statics:

$\frac{\partial Q(\tau)}{\partial \tau} = 0$ iff:

$$
\left(\frac{(\theta^*(\tau)-1)^2}{-\theta^{*2}(\tau)(2\psi(\tau)-1)-2\theta^*(\tau)(1-\psi(\tau))+1}\right)2\psi(\tau)(1-\psi(\tau))\frac{d\theta^*}{d\tau}+
$$

$$
\left(\frac{\theta^*(\tau)-1}{-\theta^{*2}(\tau)(2\psi(\tau)-1)-2\theta^*(\tau)(1-\psi(\tau))+1}\right)\left(1-\theta^{*2}(\tau)\right)\frac{d\psi}{d\tau} = 0
$$

Simplifying:

$$
\left(\theta^*(\tau)-1\right)^2 2\psi(\tau)(1-\psi(\tau))\frac{d\theta^*}{d\tau} = -\left(\theta^*(\tau)-1\right)\left(1-\theta^{*2}(\tau)\right)\frac{d\psi}{d\tau}
$$

$$
\frac{d\theta^*}{d\tau} = \frac{(1+\theta^*(\tau))}{2\psi(\tau)(1-\psi(\tau))}\frac{d\psi}{d\tau}
$$

Hence:

$$
\begin{aligned}
\frac{\partial Q(\tau)}{\partial \tau} &= 0 \text{ iff } \frac{d\theta^*}{d\tau} = \frac{(1+\theta^*(\tau))}{2\psi(\tau)(1-\psi(\tau))}\frac{d\psi}{d\tau} \\
\frac{\partial Q(\tau)}{\partial \tau} &> 0 \text{ iff } \frac{d\theta^*}{d\tau} > \frac{(1+\theta^*(\tau))}{2\psi(\tau)(1-\psi(\tau))}\frac{d\psi}{d\tau} \\
\frac{\partial Q(\tau)}{\partial \tau} &< 0 \text{ iff } \frac{d\theta^*}{d\tau} < \frac{(1+\theta^*(\tau))}{2\psi(\tau)(1-\psi(\tau))}\frac{d\psi}{d\tau}
\end{aligned}
$$

The net impact of the new technology on the ratio of qualified hires out of the total hires depends on the relative magnitudes of the change in the prospective marginal worker and the change in the screening ability of the firm due to improved technology.

Table 1: Percentage of Employees Hired by Recruiting Channel

Recruiting Channel	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
Number of Total Recruits	14	507	1034	888	2333	4616	1620	467
Advertisement		6.11%	2.61%	1.91%	1.67%	2.77%	0.68%	1.28%
Agency	7.14%	22.68%	17.31%	24.77%	17.87%	12.95%	11.54%	1.50%
Internet		**0.20%**	**0.19%**	**1.24%**	**4.67%**	**6.02%**	**8.02%**	**20.34%**
Total Employee Referrals*	50%	35.11%	42.56%	49.78%	57.05%	58.84%	53.46%	44.32%
College Recruiting	7.14%	3.55%	7.06%	7.88%	6.04%	5.24%	8.64%	4.07%
Client Referral		0.20%				0.02%		
Executive Search						0.26%	0.19%	1.93%
Internal Recruiter	7.14%	0.20%	0.19%	0.11%	0.04%	0.91%	5.06%	14.78%
Internal Transfer					0.09%			
Job Fair		1.97%	0.97%	1.35%	1.07%	1.36%	1.36%	0.21%
Open House			0.39%	0.23%	0.34%	0.11%	0.19%	
Other Source		0.79%	0.39%	0.79%	0.30%	0.50%	0.43%	1.71%
State/Federal Agency							0.06%	
Temp to Perm		0.39%		0.11%	0.69%	3.47%	2.22%	6.00%
Unsolicited	28.57%	28.80%	28.34%	11.82%	10.16%	7.54%	8.09%	3.85%
Walk In							0.06%	
Total Recruits	100%	100%	100%	100%	100%	100%	100%	100%

- Total employee referral includes employee referrals + executive referrals + former employee
- Employees of unknown hiring channel were dropped from the sample.

Graph 1:

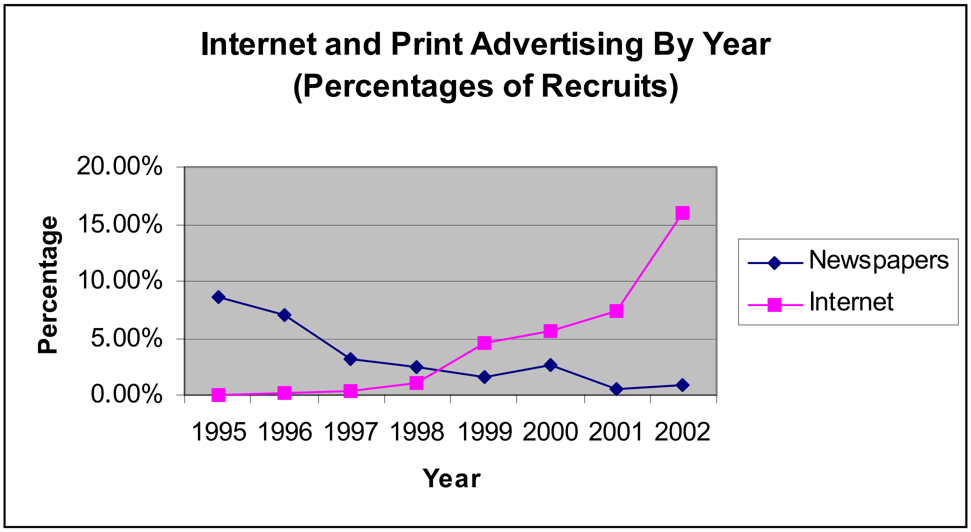

Table 2: Education and Age By Main Recruiting Channels

(Std. Deviations in Parentheses)

	Education	Age	Number of Observations
Newspaper	15.7	40.8	259
	(2.0)	(8.9)	
Internet	15.7	38.8	626
	(1.9)	(8.5)	
Agency	15.7	40.9	1724
	(1.9)	(8.3)	
Employee referral	15.2	39.6	6187
	(2.0)	(8.5)	
College recruiting	15.9	29.0	704
	(1.9)	(5.6)	
Unsolicited	15.2	39.7	1282
	(2.0)	(9.2)	
All other recruiting methods	15.3	38.0	697
	(2.2)	(9.3)	

"All other recruiting methods" includes: client referral, internal recruiter, executive search, internal transfer, job fair, open house, other, state/federal agency, temp to permanent, walk in.
Note: college recruiting average age is high because it contains all the workers that were hired through college recruiting but are still employed at the firm. This means that you can find older employees that were hired several years ago through college recruiting.

Table 3: Internet Recruits As a Percentage of Total Recruits per Occupation

Occupation	1995	1996	1997	1998	1999	2000	2001	2002
Executives	0%	0%	0%	0%	0%	0%	0%	0%
Engineers and Tech	0%	0.37%	0.38%	1.58%	4.45%	5.71%	9.54%	24.81%
Administrative	0%	0%	0%	1.32%	7.02%	5.33%	8.70%	12.12%
Finance	0%	0%	0%	9.09%	10.91%	15.74%	10.42%	5%
Human Resources	0%	0%	0%	0%	26.47%	18.07%	23.68%	14.29%
Law	0%	0%	0%	0%	11.11%	0%	0%	0%
Marketing	0%	0%	0%	0%	14.94%	10.90%	13.33%	42.11%
Operational	0%	0%	0%	5.88%	4.62%	11.74%	4.11%	0%
Quality Control	0%	0%	0%	0%	10%	18.75%	20%	0%
Sales	0%	0%	0%	0.51%	1.80%	3.72%	4.36%	15.32%

- Employee of unknown recruiting channel were dropped from the sample.

Table 4: Distribution of Occupation and Reference Source

Reference Source		Occupation	
Total	11,479	**Total**	11,479
Advertisement	2.26%	Executives	0.34%
Internet	5.45%	Engineers and Technicians	46.22%
Agency	15.02%	Administrative	7.18%
Employee Referral	53.90%	Finance	2.54%
College Recruiting	6.13%	Human Resource	1.74%
Executive Search	0.21%	Law	0.27%
Internal Recruiter	1.73%	Marketing	3.85%
Internal Transfer	0.02%	Operational	5.29%
Client Referral	0.02%	Quality control	0.51%
Job Fair	1.25%	Sales	32.07%
Open House	0.19%		
Other	0.52%		
State/Federal Agency	0.01%		
Temp to Perm	2.12%		
Unsolicited	11.17%		
Walk In	0.01%		
Total	100%	Total	100%

Table 5: Duration Model for Different Groups of Workers
Dependent Variable: The hazard rate of employment termination

	(1) Full Sample	(2) Engineers and Technicians	(3) Sales	(4) Administrative	(5) Operational	(6) Marketing
Internet	-0.06	-0.24	0.24	-0.13	0.30	-0.23
	(0.50)	(1.40)	(0.80)	(0.40)	(0.64)	(0.45)
Employee Referral	-0.52	-0.62	-0.22	-0.47	-0.49	-0.86
	(5.27)**	(4.46)**	(0.80)	(1.99)*	(1.23)	(1.76)*
Agency	-0.14	-0.26	0.14	-0.13	0.38	-0.36
	(1.33)	(1.68)*	(0.52)	(0.50)	(0.91)	(0.72)
College Recruiting	-0.45	-0.74	-0.34	0.37	0.07	-0.90
	(3.73)**	(4.39)**	(0.86)	(1.09)	(0.13)	(1.66)*
Unsolicited	-0.32	-0.43	-0.13	-0.38	0.03	-0.50
	(3.03)**	(2.73)**	(0.45)	(1.51)	(0.07)	(1.01)
Other	-0.45	-0.42	-0.16	-0.85	-0.31	-0.98
	(3.79)**	(2.53)**	(0.49)	(2.49)**	(0.67)	(1.74)*
Education	-0.02	0.00	-0.03	-0.01	-0.06	0.03
	(1.93)*	(0.30)	(2.20)*	(0.23)	(1.40)	(0.83)
Age	-0.07	-0.09	-0.05	-0.13	-0.05	-0.06
	(5.29)**	(4.20)**	(2.07)*	(3.45)**	(0.70)	(0.92)
Age Squared	0.00	0.00	0.00	0.00	0.00	0.00
	(5.78)**	(4.25)**	(2.76)**	(3.28)**	(0.88)	(1.00)
Executives	-1.65					
	(4.03)**					
Engineers and technicians including customer support	-1.21					
	(31.97)**					
Administrative	-0.45					
	(7.23)**					
Finance	-0.65					
	(6.70)**					
Human Resource	-0.92					
	(7.60)**					
Law	-0.99					
	(3.25)**					
Marketing	-0.32					
	(4.53)**					
Operational	-0.99					
	(12.64)**					
Quality control	-1.75					
	(5.24)**					
Hire Year 1997	-0.04	-0.19	0.45	0.01	-0.28	-0.43
	(0.43)	(1.34)	(2.55)**	(0.06)	(0.77)	(1.37)
Hire Year 1998	0.24	-0.06	0.75	0.23	-0.31	0.22

	(2.70)**	(0.36)	(4.36)**	(0.96)	(0.70)	(0.65)
Hire Year 1999	0.50	0.32	0.99	0.20	0.16	0.55
	(6.12)**	(2.32)*	(5.84)**	(0.91)	(0.57)	(1.79)*
Hire Year 2000	0.78	0.64	1.33	0.09	0.06	1.18
	(9.75)**	(4.84)**	(7.97)**	(0.43)	(0.19)	(4.00)**
Hire Year 2001	0.93	0.87	1.47	0.35	-0.12	1.04
	(10.45)**	(5.78)**	(8.35)**	(1.35)	(0.30)	(2.74)**
Hire Year 2002	0.99	1.45	1.09	-0.33	-36.29	0.63
	(6.29)**	(6.24)**	(3.69)**	(0.53)	0.00	(0.78)
Observations	11479	5306	3681	824	607	442

Dropped Variables: (1) Print Advertising (2) hire year 1995-1996 (3) Sales, Sex and Race controls included. Absolute value of z-statistics in parentheses. * significant at 5% level; ** significant at 1% level

Table 6: Propensity Scores Logit Model

Dependent Variable: Internet Hire

	Internet
Education	0.76
	(1.90)*
Education Squared	-0.02
	(1.88)*
Executives, Engineers and Technicians	0.84
	(4.42)**
Operational	-0.49
	-0.80
All Other Occupations Except Sales and Quality Control	0.97
	(3.86)**
Constant	-8.70
	(2.74)**
Observations	2084

The dependent variable equals 1 if the worker applied through the Internet and zero otherwise. The occupation groups are: (1) executives, engineers and technicians (2) operational (3) administrative, human resources, finance, law, marketing (4) sales and quality control (dropped group). I run this logit on a sub-sample that includes only the last two years of hire. I include control for sex, and race. Absolute value of z-statistics in parentheses.
* significant at 5% level; ** significant at 1% level

Table 7: Duration Model with Propensity Scores Multiplied by Time Dummies
Dependent Variable: The hazard rate of employment termination

	(1)	(2)
Propensity Score * 1995-1997 hires dummy	-2.331	-2.487
	(1.51)	(1.60)
Propensity Score * 1998 hires dummy	-4.634	-4.919
	(2.57)**	(2.72)**
Propensity Score * 1999-2000 hires dummy	-3.692	-4.327
	(2.91)**	(3.40)**
Propensity Score * 2001 hires dummy	-3.562	-4.067
	(2.27)*	(2.58)**
Propensity Score * 2002 hires dummy	9.451	8.3
	(2.94)**	(2.59)**
Education	-0.002	-0.008
	(0.27)	(0.98)
Age	-0.068	-0.072
	(5.20)**	(5.33)**
Age Squared	0.001	0.001
	(5.71)**	(5.79)**
Executives	-1.488	-1.469
	(3.59)**	(3.54)**
Engineers and Technicians including customer support	-0.984	-0.938
	(11.08)**	(10.48)**
Administrative	-0.178	-0.15
	(1.63)	(1.36)
Finance	-0.339	-0.319
	(2.43)**	(2.28)*
Human Resource	-0.577	-0.587
	(3.65)**	(3.71)**
Law	-0.679	-0.739
	(2.16)*	(2.35)**
Marketing	-0.052	-0.007
	(0.43)	(0.06)
Operational	-1.059	-1.079
	(12.82)**	(12.97)**
Quality control	-1.678	-1.72
	(5.02)**	(5.14)**
Hire Year 1997	-0.077	-0.05
	(0.89)	(0.58)
Hire Year 1998	0.412	0.469
	(2.25)*	(2.56)**
Hire Year 1999	0.571	0.675

	(4.04)**	(4.77)**
Hire Year 2000	0.837	0.962
	(5.96)**	(6.81)**
Hire Year 2001	0.97	1.08
	(5.64)**	(6.26)**
Hire Year 2002	-0.357	-0.19
	(0.88)	(0.47)
Agency		0.136
		(2.60)**
College Recruiting		-0.179
		(2.07)*
Employee Referral		-0.248
		(5.45)**
Internet		0.211
		(2.76)**
Other		-0.196
		(2.34)**
Observations	11479	11479

Dropped Variables (1) Print Advertising, (2) Sales (3) Hire Year 95-96. Sex and Race controls included. Absolute value of z-statistics in parentheses. * significant at 5% level; ** significant at 1% level