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

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Abstract

How does online recruiting affect the matching of workers and firms? I offer a model in which the Internet generates effects which raise or lower match quality. Job seekers have private information about their quality, and firms have imperfect screening technology. The Internet reduces application costs, which induces applications from less-qualified job-seekers, decreasing the proportion of qualified hires. Firms adopt Internet technology despite its potentially adverse effects because of its lower costs and inter-firm competition for qualified candidates. Measuring quality by duration at the firm, a Cox duration model fit to real data from a multinational firm shows online recruiting increased dramatically from 1996 to 2002, with consequences consistent with this model. Internet recruits were not significantly different in quality from print advertising recruits, but were less likely to retain their jobs than employee-referral recruits. Propensity score methods suggest that workers hired in 2002 who had characteristics making them relatively likely to be recruited via the Internet had shorter job durations than comparable workers in prior years.

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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] This site drew 6.5 million unique visitors in June 2001, up from 4.4 million in June 2000[2].

Will improvements in job search technology produce better firm-to-worker matches? On 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, triggering increased effort by firms to improve screening mechanisms, or else firms will be more likely to hire under-qualified candidates out of 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 only 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 qualification of each candidate and randomly chooses the number of candidates it needs out of all those who generate a *good* signal.

Candidates apply only if a job's expected value is higher than its cost of application. Lower application costs (due to new technology) induce applications from candidates who are relatively less qualified. Since the firm's ability to identify a qualified candidate is less than perfect, I show that reduced application costs decrease the expected proportion of qualified hires

[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.

from the population of total hires, a finding consistent with the view of many employers who believe that resumes posted to job boards represent an adversely selected pool (Autor, 2002; Li, 2000; iLogos, 1999). The model allows one to estimate the magnitude of these effects across different 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 perhaps this process will ultimately identify superior candidates. Second, one must consider the effects of inter-firm competition. In a two-firm setting, I show that competition leads firms 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 1995-2002. Online recruiting at this firm increased from 0.15% of total hires in 1996 to 15.9% of total hires in 2002. Measuring quality of the match by employment duration, I estimate a Cox duration model that shows Internet recruits are significantly less likely to survive at the firm relative to employee referrals. Employment duration for Internet recruits does not differ significantly from that of hires made through newspaper advertising, agency or college recruiting.

I also use propensity score methods to show that the average quality of the hires declines 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?

There have been a few recent attempts to identify the types of people who use the Internet to find jobs (Kuhn and Skuterud (2000a,2000b,2000c,2002)). This paper represents the first systematic study of the types of workers actually recruited via the Internet, with data supplied by a US-based multinational employer of more than 15,000 employees. The 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, 2002. Less than 5% of the firm's employees work outside the US.

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 referrees are compensated, the firm must maintain accurate records of the recruitment channel.

2.1 How Many People Are Hired Through the Internet?

Table 1 shows the percentage of workers hired by recruiting channel[3]. From 1995-1998 the number of employees recruited via the Internet was lower than 20 (only 0.99% of total recruits at 1998), but the year 1999 brought a major shift to recruiting via online tools, with 122 employees (4.48% of that year's recruits) hired. The number of workers recruited via the Internet continued to rise in the following years, with 307 employees (5.64%) recruited in 2000, 147 employees (7.42%) recruited in 2001, and 94 employees (15.93% of total recruits) recruited until the end of 2002. Graph 1 shows that print advertising is declining as online advertising has risen, suggesting a strong substitution effect.

2.2 What Types of Workers Are Hired Through the Internet?

Table 2 presents the average age and education of workers by recruitment source. The average education of employees recruited via the Internet (15.6

[3]There is a portion of the population (less than 20% in any given year) that is missing corresponding reference information. This data appears to be missing-at-random: when the table is produced with and without the unknowns, percentages do not change significantly. I therefore present the table without the unknowns.

years of schooling) is somewhat higher than the average education of employees recruited through other channels, yet the differences in average education of employees are not large. The average age of Internet recruits is lower than the average age of newspaper, agency and employee-referred recruits (38 years compared with 40 years and up), and higher than the average age of college recruiting (38 years compared with 29 years).

Table 3 presents the share of hires via the Internet out of total hires per occupation[4] (i.e. 0.55% of total engineers hired in 1997 were recruited via the Internet). The share of engineers recruited via the Internet was fairly low until 2001 (0.55% at 1997, 4.25% in 1999, 5.65% 2000). At 2002, on the other hand, 21% of total engineers and technician recruits were via the Internet. At the years 1995-2001 the professions that were heavily recruited via the Internet were human resource (25% in 1999, 16.85% in 2000) and marketing (14.3% in 1999, 10.9% in 2000).

There is ample evidence to suggest that in the not-too-distant future, almost all 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 Model

3.1 Workers

Suppose that a prospective worker has to decide whether to submit an application for a given job opening. Assume every prospective worker is either qualified or not qualified 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 for the job. 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 $\theta_i \tilde{} U[0,1]$ about her match quality. This signal is the probability that she is qualified and therefore has $m_i = 1$:

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

[4] This table excludes missing data.

3.2 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 that quality of the match of 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:

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

where $\psi > \frac{1}{2}$.

The probability to observe the right signal, ψ, is exogenous and known to the worker. I will discuss below the implications of endogenizing ψ. The firm maximizes profits, and hence offers the worker the wage equal to its expected productivity: $w_i = \psi * 1 + (1 - \psi) * 0 = \psi$.

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 recruiting costs should not affect the number of position filled, since they are negligible relative to the cost of the worker (i.e. wages, benefits etc.).

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

3.3 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.

3.3.1 Expected Utility from Submitting an Application:

Assume that:

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

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

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

The calculation of $E(u(\mathit{submit\ application})|\theta)$ is in appendix 6.1.

Definition 1 *let $\theta = \theta^*$ be the signal observed by the applicant that is indifferent between submitting an application and not submitting an application. I call this applicant the* ***marginal prospective worker****.*

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

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

Proposition 2 *The expected utility from a job opening is increasing in θ*

Proof: appendix 6.2 .

This result implies that $\forall\theta^*$ such that prospective worker who observes $\theta \geq \theta^*$ will apply for the job whereas prospective workers with $\theta < \theta^*$ will not apply for the job. 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.

3.4 The Effect of Application Costs on the Marginal Prospective Worker

As I argued in the introduction, one effect of the Internet on the recruiting process is a decrease in application costs. In this section I study how application costs affect the quality of the applicant pool.

Proposition 3 *θ^* is increasing with the cost of application*

Proof: appendix 6.2.1:

Therefore, when K increases, θ^* increases as well. Since the applicant pool will include only $\theta \geq \theta^*$, higher θ^* implies that the applicant pool will include only prospective workers with higher probability of being qualified. When application costs are relatively low, applicants with lower probability of being qualified will still submit applications. Increasing application costs will cause workers with low probability of being qualified to refrain from submitting an application, and therefore the applicant pool will be composed of prospective workers with higher probability of being qualified.

3.5 What is the Expected Proportion of Qualified Hires out of All the People that are Hired?

The firm and the worker have information about the probability that the worker is qualified for the job (i.e. having $m_i = 1$), but they do not know at the time of the hire whether the worker is actually qualified or not[5]. Using

[5] 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.

the probabilities that we already know, we can form an expectation about the proportion of the qualified hires out of the total number of hires.

Denote Q as the expected proportion of qualified hires out of the all those that were actually hired (the mathematical equation is given in appendix 6.3). This is the probability that the hire is 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 numbers of hires will give us the expected proportion of the qualified hires out of the total hires.

Proposition 4 *Q, the expected proportion of qualified hires, is increasing with θ^*, the signal observed by the marginal prospective worker.*

Proof: appendix 6.4.

The firm benefits from having a marginal prospective worker with higher θ^*, because it means a higher expected proportion of qualified hires out of the total number of hires. Using proposition 3, θ^* is an increasing function of application costs, K. Therefore, reducing application costs will reduce θ^* and in turn will reduce Q, the expected proportion of qualified hires out of the total hires.

We can also see that when the firm is fully capable of identifying those with $m_i = 1$ (i.e. $\psi = 1$), then $\frac{dQ}{d\theta^*} = 0$ which means the applicant pool does not affect the expected proportion of qualified hires (appendix 6.4, equation 24). $Q = 1$ when $\psi = 1$ (appendix 6.4,equation 23). Hence when the firm is able to identify the qualified candidate, all the hired workers will be qualified. In this case, the Internet will have no effect on the quality of the match of the workers and firms.

An intuitive explanation of this effect is that candidates do not internalize the effects of their behavior on the welfare of the total applicant population. Motivated by reduced application costs, applicants submit applications despite knowing they are likely under-qualified. The firm, lacking a perfect signal of candidates' qualifications, sometimes chooses non-qualified candidates, and as the expected quality of the hires decreases.

One can argue that this effect should be of different magnitudes for different types of jobs. There are positions in which the firm is more likely to screen away non-qualified candidates. For example, positions that require certain degrees and certain experience or specific knowledge lend themselves to easier screening mechanisms. Nevertheless, positions highly dependent on candidates' soft skills (which are not obvious and not easily verifiable) may present firms with more difficulty. The parameter ψ in the model captures this tendency. We can argue that ψ will be higher when the required skills are more easily observed. Different professions and positions are likely to have different ψ. The negative impact of the reduced application costs will be present in all jobs, but the magnitude of this effect will be dependent on the job's ψ.

What will be the general equilibrium implications for all the firms? It seems that as long as the screening technology is not perfect, the expected quality of the match will be reduced in all the firms that use Internet recruiting. However the recruiting costs through this method, as I show below, are significantly lower. So the ultimate result of reduced recruiting costs would be a lower expected quality of matches. Long run effects of improved application technology may be different: if firms will improve their screening technologies, the adverse effect of the Internet can be significantly reduced, and the benefits can be used (information to wider group of potential employees, fast response time).

3.6 If Internet Leads to Workers of Lower Quality, Why do Firms Adopt the Internet As a Recruiting Method? And Why Don't They Charge Application Fees?

Why would firm adopt the Internet if they receive workers of lower quality through this channel?

3.6.1 Cost Considerations

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[6]
Agency	\$15,000
Print Ad	\$12,000
Employee Referrals	\$2000
Internet Recruiting	\$500-\$800

These costs are mainly the 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 number of people recruited via the Internet, and the cost paid to the referree if the worker has arrived through Employee referral. These costs do not include indirect costs of training employees, or the cost of leaving a position vacant. The firm does not have record of the indirect costs.

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

Still the question remains: are firms ultimately better off using the Internet? They may have to replace more workers, but it might be less costly to test more workers on the job. Assume that firms know Internet recruiting lead to lower quality hires. Why wouldn't they just impose a cost on hiring? While talking with recruiters I found that many of them suspect that requiring application fees could be grounds for a lawsuit under Equal Employment Opportunity laws. In general, the law does not allow discrimination between employees based on race and sex, and since some ethnic groups are poorer then others, charging application fees may be discriminatory.[7] Even so, firms could impose non-monetary applications costs, such as requiring written essays etc. 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 good workers from submitting applications, especially given inter-firm competition for qualified workers. Below I present a simple model to illustrate this point.

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

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

3.6.2 The Effect of Competition

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

Suppose that there are two identical firms in the market competing over good candidates. The probability that a candidate will accept an offer from firm 1 depends only on the response time of the 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 then 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):

		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 the Internet. The Nash equilibrium is for both firms to adopt the Internet as an online recruiting tool. If the firm does not adopt the Internet, the probability of finding the best candidate decreases even more, since candidates will accept offers from the firm responding faster. 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.

3.7 Extension: Endogenizing ψ

Suppose that given the fact that the firm is aware of the problems induced by the Internet, it responds with enhancing its screening technology. By improving the screening technology the firm affects ψ, the probability to observe the right signal about the candidates' quality.

Can the firm totally offset the adverse impact of the reduction in application costs? Its clear that the adverse impact of the reduction in application cost falls with an increase in ψ (equation 24 in appendix 6.4). Only when the firm has a perfect screening technology ($\psi = 1$) then the adverse impact of reduced application costs disappears. I expect that in the long run firm and job matching sites will improve their screening technology to allow the benefit of the Internet recruiting tools without the costs that are described at this paper[8].

3.8 Extension: What if People Have Different Online Skills?

Suppose that the use of the Internet does not reduce the cost of job application in a uniform way to all users. The idea that different people have different online skills is currently studied by various researchers. In a large field study, Hargiatti (2001) measures the time needed to complete 17 tasks online. She finds that online skills vary widely, ranging from 20 minutes to over 100 minutes needed to complete all 17 tasks. In a related research, Hargiatti and Field (2003) study the time needed for a person to complete an online job search[9]. Using a discrete time logit model predicting the hazard for completion of job search task across time periods (10 sec. time intervals), Hargiatti and Field find that the probability to complete the task across the time period decreases with age, and increases with education. African Americans tend to have lower probability of task completion across time periods[10].

What are the implications of heterogenous cost reduction by the Internet in the context of the suggested model? If the Internet reduces the application costs effectively only to the qualified candidates, than even when the θ^* is reduced, it induces more people with matching quality $m_i = 1$ to apply than before, and this will in fact *increase* the expected number of qualified hires. If on the other hand, the Internet reduces the application costs effectively only to the non-qualified hires, then of course the expected number of qualified hires will drop even more. However, only in certain jobs is there a reason to believe that the skill of using the Internet is highly correlated with the matching quality for the job. These may be occupations that are intensive in computer use, such as programmers, engineers and technicians. On the other hand, if we are considering the context of a kindergarten teacher, than

[8] According to a conversation with the VP of research at *Monster.com* and a director of employment in a major financial firm in Boston, firms are currently working on improving screening facilities for resumes that arrive through the Internet.

[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.

there is no reason to believe that her online skills have much to do with her teaching skills.

One implication of the model presented in this paper is that when the cost and difficulty of screening job applications increases, the company may prefer "internal" or referred candidates (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). Autor (2002) notes that "if on-line job application exacerbates adverse selection, one perverse consequence may be that personal referrals become more important in a wired labor market" (p.31). This is in contrast to Freeman (2002), who thinks that the Internet's biggest contribution to the labor market is to help break down old boy's networks and traditional geographic barriers by diffusing information about jobs widely. Whether Internet use increases referral reliance is an empirical question. But if inefficiencies caused by the new technology indeed increase usage of referrals, it means lesser job prospects to those who have smaller informal networks. An example of such a case can be found in Holzer (1987), who suggests that low employment for young blacks can be due to the low quality of network of contacts available to them.

4 Empirical Evidence

4.1 Data

Table 4 exhibits descriptive statistics about the data underlying the regressions. This is a limited sample, after dropping observations with one of the following missing: information about education, recruiting source, occupation, race or sex[11]. After eliminating the missing data, 11,998 observations remains, consisting of 45% engineers and technicians, 31% sales workers, and approximately 10% administrative workers; 51% of the total employees in the sample were recruited through employee referral, 14% were recruited through an agency, 11% were unsolicited and 5% were recruited via the Internet.

The measure for the quality of the match is the duration of employment

[11] 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 data includes only those hired between 1995-2002.

with the firm in months. The idea that a good match is represented by a lengthy duration comes from Jovanovic (1979), where a job match is treated as a pure experience good: the quality of the match is not known ex ante, but must be experienced. Workers remain in matches that are revealed as high quality, while workers with low-quality match separate. Using job tenure as match indicator is also supported by Akerlof, Rose and Yellen's (1988) evidence of nonpecuniary match characteristics having a negative impact on the probability that an individual quits (Bowlus (1995)).

As independent variables I use years of schooling as a measure for education, a dummy variable for each recruiting source (i.e. dummy for employee referral receives the value *one* if the workers was referred by an employee and *zero* otherwise. The dummy for Internet receives 1 if the worker was recruited through the internet and zero otherwise, etc.) I use a series of dummy variables for each occupation group (i.e. the dummy for engineers and technicians receives the value 1 if the worker is an engineer or technician, and 0 otherwise, etc.) Dummy variables for year of hire were also included.

4.2 Empirical Evidence: Are Internet Recruits Less Likely to Stay with the Firm Compared with Recruits from Other Channels?

4.2.1 Duration Model

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 (for a description of the duration model, hazard function and the Cox specification, as well as treatment of specific censoring issues see appendix 7). Due to the form of the hazard function, the coefficients' values do not give the marginal contribution to the dependent variable, as in a regular regression model. Positive values of the coefficient imply a higher probability of employment termination given the time spent in the firm. Negative values of the coefficient imply a lower probability of termination given the time already spent.

Explanatory variables are education, age, occupation, hire year, race, sex and recruiting method, and results of the Cox duration model are presented in Table 5[12]. The omitted recruiting channel is print advertising. Includ-

[12] All the regression presented in this paper were run over the sample which includes

ing all the controls (column (1)), the coefficient for Internet recruits is not significantly different from zero, which means that Internet recruits are not significantly different from Print Advertising recruits. Agency and College recruits are also not significantly different from Print Advertising recruits. Employee referrals[13], unsolicited and "other[14]" recruiting channels are all significantly different from Print Advertising, and are negative, which means that workers recruited through these channels are more likely to stay longer with the firm relative to workers that were recruited through print advertising. Thus, the duration model suggests that Internet recruits are not significantly different from Print Advertising recruits, but are more likely to leave the firm compared with employee referrals.

Table 6 exhibits the same model fit to a sub-sample of occupation groups. I look at the five largest occupation groups: Engineers and Technicians, Sales, Administrative, Operational and Marketing. The coefficient of interest is the coefficient of the Internet channel. I find that in all these groups Internet recruits are not significantly different then print advertising recruits. Comparing the coefficient of the Internet channel to the coefficients of the rest of the 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, Administrative and Marketing. For Sales and operational employee referrals recruits do not seem to be significantly different from print advertising recruits (and hence from Internet recruits). Agency recruits are significantly different then print advertising recruits only at the group of engineers and technician. At this group they are likely to stay longer with the firm compared with print advertising. College recruits are significantly different from print advertising recruits only in the case of Engineers and Technicians, and Administrative workers. For Engineers and Technicians college recruits are likely to survive longer at the firm relative to print advertising, yet administrative which are college recruits are likely to

observation to which the recruiting channel is unknown. The results were not significantly different then running the regressions on a sub-sample that does not include the employees with unknown recruiting source. For brevity, only the results on the restricted sample which does not include employee with unknown recruiting source are presented.

[13]The employee referral variable includes (1) employee referral (2) executive referral (3) former employee

[14]The Other Channel in my regression include 10 recruiting channels: (1) aquired company (2) client referral (3) internal recruiter (4) executive search (5) internal transfer (6) other (7) state/federal agency (8) temp to perm (9) walk in (10) vocational

survive less at the firm relative to print advertising recruits. This is logical since an administrative position can be only a short term employment for a college recruit until he decides the next step in his career, whereas for engineers and technicians employment at this firm is more often a longer-term component of their careers. In other profession groups, college recruits are not significantly different then print advertising.

The theoretical model presented above suggests that the Internet's lower costs should induce more applications from less qualified candidates, and since the firm has a screening technology that is less then perfect, it is more likely to make mistakes and hire less qualified candidates on average. As a result, we expect Internet hires to be of lower quality than the hires made prior to the introduction of the Internet. The empirical findings are consistent with the model—Internet hires do seem to be of lower quality relative to referrals, yet this is not a proof the Internet technology is the reason for the lower value. It may be just that people who use the Internet are those who previously used the newspaper and they are consistently of lower quality relative to employee referrals. A better test, discussed below, evaluates whether the quality of job seekers likely to use the Internet is decreasing over time.

4.3 What is the Effect of the Internet on Overall Hiring Quality?

Does exogenous change in the cost of Internet recruiting lead to different hiring outcomes for similar workers? 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.[15] 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.[16]

The analysis compares similar workers that differ only by the fact that some had the availability of the Internet while the others did not. I therefore

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

[16] See Table 1.

use a propensity score method[17], which involves calculating the conditional probability that a candidate used the Internet for a job search given the available pretreatment covariates.[18] This conditional probability is called a propensity score: it is defined as the propensity (probability) of having used the Internet, as a function of education, age, race, sex, and job category.

I interact the propensity score with the year of hire and use these variables as explanatory variables in a Cox duration model. The objective is to determine whether workers with similar likelihoods of using the Internet have different hiring outcomes, depending on whether or not they received the "treatment"[19]. The key identifying assumption of this model is that it is only the recruitment method change (the Internet) that leads to such an interaction effect and that there are no other underlying reasons for interactions of hire year with education or occupation.[20] If the coefficients of the `propensity score*hire year` are significant and become more positive (or less negative) with the increase in hire year (and the use of the Internet), workers which were similarly likely to use the Internet but were hired in more recent years were employed for shorter durations, and hence are considered to be of lower match quality.

Table 7 presents the results of the propensity score regression. While in theory I would like to use a dependent variable which receives the value 1 if the worker *applied* through the Internet and 0 otherwise, data was not available at this level of specificity. I therefore use a dependent variable that receives the value 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 that includes only the last 2 years of new hires to calculate the likelihood of submitting a job application via the Internet. 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. People with similar propensity scores are comparable in their probability to be hired through the Internet (Dehejia and Wahba, 1999, Field (2003)).

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

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

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

[20] See next section for discussion of this assumption.

The propensity score multiplied by hire-year dummy is then added to the duration model with the usual controls. The result of the duration model with the propensity score are presented in Table 8. Column (1) shows the effect of the propensity score multiplied by hire year on the hazard rate, and the coefficient of propensity score interacted with the hire year dummy is significant for all the years 1999-2002. Point estimates of the coefficient of the interaction term `propensity score*hire year` become less negative with hire year. However, Wald test results do not allow for rejection of the null hypothesis that the interaction term coefficients are the same for 1998-2001. This implies that during the years 1998-2001, there is no evidence of the decline in quality of people that were likely to use the Internet if it was available to them. Therefore, there is not strong evidence that the effect of Internet recruiting is indeed a decrease in the quality of Internet hires during these years. The coefficient of 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 has indeed declined (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, while controlling for recruiting channel. The coefficients of `propensity score*hire year` variables are similar to those in column (1). The coefficient on the Internet recruiting method is positive and significant, which means that those who were actually hired via the Internet fared less well with the firm relative to applicants recruited via print advertising.

These results do prompt one puzzle: the coefficient for propensity score multiplied by hire year 1995-1997 is insignificant, which suggest that people who were more likely to use the Internet according to 2001-2002 standards did not have specific effect on the duration at the firm if they were hired in 1995-1997. This is a puzzle, since the type of people likely to be hired from the Internet appear to have more stable job durations (lower hazard rates from 1998 to 2001) relative to the pre-Internet period of 1995-97. Only similar people hired in 2002 show reduction in job duration.

4.3.1 Discussion of the Key Identifying Assumption for Using The Propensity Score Method

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 change in employment prospects for different groups of workers. Field (2003) suggests that the relevant concern is whether increases in Internet-assisted job search proxy for computer skill among certain population subgroups who might also benefit from skilled biased technological change (SBTC) in the workforce. If this is the case, the correlation between on-line job search and search outcomes could simply reflect the fact that the return to computer skill has risen during the period in question.

Field (2003) presents two pieces of evidence that suggest that this is not an important concern. Data about the use of online job search and recruiting (Field (2003, p.9)) suggests that the acceleration in online job search activity was rapid enough to be plausibly exogenous from other changes in technology and educational investment which potentially altered patterns of employment demand or the skill composition of supply. Compared with the pattern of online job search, Field (2003) suggests that there is little evidence of large changes in labor demand or supply during the same period. In particular, she cites the *CPS Computer Use Supplement,* between October 1993 and October 1997- the aggregate rate of computer use at work increased only slightly, from 46.6% to 49.8%. Field (2003) cites other studies of skill-biased technological change in the 1990s also indicate a deceleration in the demand for college graduates relative to less skilled workers in the 1990s (Autor, et. al., 2001). Field (2003) concludes that all pieces of evidence suggest a limited role of skill-biased technological change affecting the composition of labor demand in the late 1990s.

Field (2003) also offers an array of evidence that suggests that Internet search is not a strong skill proxy. According the *UCLA Internet Study*, unlike all other web activities, the amount of time spent on Internet job search is identical for users with limited Web experience and those with extensive web experience (UCLA). She therefore infers that if Internet users of varying experience levels invest the same amount of time in online job search, this suggests that the propensity to use the Internet to search for a job is not closely correlated with computer or Internet skill.

As an additional control for unobserved factors which could be biasing measures of the return to Internet search, Field makes use of the fact that much of the growth in the number of positions advertised online has taken place in non-technological industries and sectors, such as the health care sector, in which, conditional on observable levels of human capital investment, computer use is unlikely to be a critical skill differential (Internet Recruiting

News, 1998).

4.4 Other evidence and suggestions for further research

Graph 4 describes the hiring channels according to the main recruiting sources by year of hire [21]. While in 1995 the total hires through referrals are 28.45%, during the years 1999-2000 referrals peaked to 57%. At 2002 hires through referrals accounted for only 35.7%. It seems that part of the decline in the use of referrals is offset by an increase in the Internet recruiting. It is interesting to study the change in use of various recruiting method over the business cycle. This trend may suggests that referrals are more effective during economic booms (when people come to new jobs out being employed elsewhere), whereas the Internet is more effective in economic downturn. To verify this hypothesis one would have to examine the whole economy rather than at a single firm[22]

5 Conclusion

One of the prominent effects of the Internet on job search is the reduction in application costs. The model presented in this paper studies the effect of reduced application costs attributed to Internet technology on the matching process of workers and firms. The model assumes that a prospective worker has private information about the probability that she is qualified to do the job. The firm has less accurate information about the probability that a prospective worker is qualified. Using private information, prospective workers form expectations about the expected utility of submitting an application, and choose to apply when this expected utility exceeds the application costs.

The reduction in application costs associated with the Internet induce applications from prospective workers who know that they have lower probability of being qualified. The firm is not able to identify the quality of the applicant perfectly, and therefore is likely to make mistakes. Since the Internet induces a larger applicant pool that includes a larger proportion of non-qualified applicants, the expected proportion of qualified hires is lower. This analysis leads to the conclusion that the new technology, (i.e. the Internet) can have an adverse effect on the matching process of workers and firms.

[21] Based on the numbers in Table 1.

[22] Will be explored in another paper.

The effect is not equal in magnitude in all types of jobs and the magnitude of this adverse effect is defined by the model parameters.

Why would firms adopt Internet recruiting if it leads to adverse results? I offer two explanations. First, recruiting via the Internet is cheaper than other methods, in terms of recruiting costs for the firm. Even if workers recruited via the Internet are more likely to be replaced, the benefits of Internet recruiting may still outweigh the costs. Second, firms compete over qualified hires. I show that competition considerations result in a single Nash equilibrium in which both firms choose to adopt the new technology without imposing application costs on the candidates.

This paper uses a unique data set from a large multinational employer to study the trends in recruiting and their effect on the duration of workers at the firm. The data shows that while in 1996 only 0.15% of the workers were hired through online recruiting, by 2002 15.93% of the worker were hired through online recruiting. The data also shows that the increase of online advertising and recruiting has been associated with a corresponding decrease in print advertising. I first ask whether Internet recruits are less successful in terms of duration in the firm then those hired through other recruiting channels. I then ask whether exogenous change in the cost of internet recruiting leads to different hiring outcomes for similar workers.

To answer the first question, I estimate a Cox duration model that estimates the probability of leaving the firm given duration of employment, conditional on a set of controls. The controls include education, age, occupation, race, sex and hire year, and of course recruiting source—the main variable of interest. Results of the duration model show that on average and when controlling for workers' characteristics, workers recruited via the Internet are not significantly different from workers recruited through print advertising. Internet recruits are more likely to have a shorter survival time with the firm, relative to workers recruited through employee referrals. This implies that Internet recruits are of lower quality only relative to employee referrals, but the result does not prove that Internet recruits are consistently of lower quality compared with other recruiting channels.

To answer the second question, I use the propensity score method, estimating the propensity to be hired via the Internet in the years that Internet was widely used. I then predict the probability of being hired via the Internet for the entire sample, which allows me to compare similar workers, before and after the Internet emerged on the scene. Interacting the propensity score variable with the hire year variable in the duration model allows me to study the effect of the hire year on the duration at the firm for people with similar propensity to be hired via the Internet. I find some evidence that the quality of those likely to be hired via the Internet declines from 1998-2001. During 2002 there is a significant decline in the quality of those who are likely to be hired via the Internet. Since 2002 is the year with the highest percentage of recruits via the Internet, this result is consistent with the model predictions. I could not find similar evidence during the years 1999-2000, but this may be due to the fact that Internet recruiting was less widely used during these years, and hence firms could effectively screen the right candidate even from a pool of candidates that contain many non qualified candidates.

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6 Appendix

6.1 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 to get the job and the utilities from getting/not getting the job:

$$E(u(submit\ application)|\theta) = \left[\frac{D}{Z} * P(S=1|\theta) * w_i + P(S=0|\theta) * 0\right] \quad (7)$$

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

$$P(S=1|\theta=\theta) = \theta * P(S=1|m_i=1) + (1-\theta) * P(S=0|m_i=1) \quad (8)$$

Substituting the firm's probabilities for signal (equation 3) we get:

$$P(S=1|\theta=\theta) = \theta * \psi + (1-\theta) * (1-\psi) \quad \text{(9a)}$$

Reorganizing we get:

$$P(S=1|\theta=\theta)=(1-\psi)+\theta\,(2\psi-1) \qquad (10)$$

6.1.1 Calculating the Number of Applicants that Receive a Good Signal

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

$$Z=\int\limits_{\hat{\theta}=\theta^*}^{1} P(S=1|\theta=\hat{\theta})f(\hat{\theta})d\hat{\theta} \qquad (11a)$$

Substituting (6) we get:

$$Z=\int\limits_{\hat{\theta}>\theta^*}^{1} \left[(1-\psi)+\hat{\theta}\,(2\psi-1)\right] f(\hat{\theta})d\hat{\theta} \qquad (12)$$

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

$$\begin{aligned}
Z &= \int\limits_{\hat{\theta}=\theta^*}^{1} \left[(1-\psi)+\hat{\theta}\,(2\psi-1)\right] d\hat{\theta}=\left[\hat{\theta}(1-\psi)+\hat{\theta}^2(\psi-\frac{1}{2})\right]_{\theta^*}^{1} = \qquad (13)\\
Z &= \left[(1-\psi)+(\psi-\frac{1}{2})\right]-\left[\theta^*(1-\psi)+\theta^{*2}(\psi-\frac{1}{2})\right]\\
Z &= \frac{1}{2}-\left[\theta^*(1-\psi)+\theta^{*2}(\psi-\frac{1}{2})\right]=-\theta^{*2}(\psi-\frac{1}{2})-\theta^*(1-\psi)+\frac{1}{2}\\
Z &= \int\limits_{\hat{\theta}=\theta^*}^{1} \left[(1-\psi)+\theta^*\,(2\psi-1)\right] d\hat{\theta}=-\theta^{*2}(\psi-\frac{1}{2})-\theta^*(1-\psi)+\frac{1}{2}
\end{aligned}$$

Therefore,

$$E(u(job)|\theta) = \frac{D * \left[(1-\psi) + \theta\left(2\psi - 1\right)\right]\psi}{\left[-\theta^{*2}(\psi - \frac{1}{2}) - \theta^{*}(1-\psi) + \frac{1}{2}\right]} \tag{14}$$

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

$$\begin{aligned} E(u(submit\ application)|\theta) &= \frac{D * \left[1-\psi + \theta(2\psi - 1)\right]\psi}{-\theta^{*2}(\psi - \frac{1}{2}) - \theta^{*}(1-\psi) + \frac{1}{2}} \\ \frac{\partial E(u(submit\ application)|\theta)}{\partial\theta} &= \frac{D(2\psi - 1)\psi}{-\theta^{*2}(\psi - \frac{1}{2}) - \theta^{*}(1-\psi) + \frac{1}{2}} \end{aligned} \tag{15}$$

The numerator is always positive. Denote the denominator d and see when it is positive:

$$d = -\theta^{*2}(\psi - \frac{1}{2}) - \theta^{*}(1-\psi) + \frac{1}{2} \geq 0 \tag{16}$$

$$\begin{aligned} -\theta^{*2}(\psi - \frac{1}{2}) - \theta^{*}(1-\psi) + \frac{1}{2} &> 0 \\ -\theta^{*2}(2\psi - 1) - 2\theta^{*}(1-\psi) + 1 &> 0 \end{aligned} \tag{17}$$

Solving this quadratic equation we get:

$$\frac{(1-\psi) \pm \sqrt[2]{(1-\psi)^2 + 4(\psi - \frac{1}{2})\frac{1}{2}}}{2(\psi - \frac{1}{2})} = \frac{(1-\psi) \pm \sqrt[2]{1 - 2\psi + \psi^2 + 2\psi - 1}}{2\psi - 1} = \frac{(1-\psi) \pm \psi}{2\psi - 1}$$

So:

$$\theta_1^* = \frac{(1-\psi)+\psi}{2\psi-1} = \frac{1}{2\psi-1} \tag{18}$$
$$\theta_2^* = \frac{(1-\psi)-\psi}{2\psi-1} = -1$$

Therefore, d is positive when:

$$-1 \leq \theta^* \leq \frac{1}{2\psi-1} \tag{19}$$

Since by definition, $\psi > \frac{1}{2}$ (hence $\frac{1}{2\psi-1} > 1$), it means that since $0 \leq \theta^* \leq 1$ then $d > 0$ for all θ^*.

6.2.1 Comparative Statics: the effect of K on θ^* :

$$K = \frac{D * [(1-\psi) + \theta^* (2\psi - 1)] \psi}{-\theta^{*2}(\psi - \frac{1}{2}) - \theta^*(1-\psi) + \frac{1}{2}} \tag{20}$$
$$K = \frac{D * [(1-\psi) + \theta^* (2\psi - 1)] \psi}{\frac{1}{2}\left[1 - \theta^{*2}(2\psi - 1) - \theta^*(1-\psi)\right]} \tag{21}$$
$$K = \frac{2D * [(1-\psi) + \theta^* (2\psi - 1)] \psi}{\left[1 - \theta^{*2}(2\psi - 1) - \theta^*(1-\psi)\right]}$$

I want to find: $\frac{d\theta^*}{dK}$. I will find $\frac{dK}{d\theta^*}$ and then will take the inverse: $\frac{1}{\frac{dK}{d\theta^*}}$.

First, lets find the derivative of:

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

$$\frac{dK}{d\theta^*} = 2D\psi \frac{dh}{d\theta^*}$$

$$
\begin{aligned}
f' &= (2\psi - 1) \\
g' &= -2\theta^*(2\psi - 1) - (1 - \psi)
\end{aligned}
$$

$$
\begin{aligned}
f'g - g'f &= (2\psi - 1)\left[1 - \theta^{*2}(2\psi - 1) - \theta^*(1 - \psi)\right] + \\
&\quad [2\theta^*(2\psi - 1) + (1 - \psi)]\,[(1 - \psi) + \theta^*(2\psi - 1)] \\
&= (2\psi - 1) - \theta^{*2}(2\psi - 1)^2 - \theta^*(1 - \psi)(2\psi - 1) + \\
&\quad 2\theta^*(2\psi - 1)(1 - \psi) + 2\theta^{*2}(2\psi - 1)^2 + (1 - \psi)^2 + \theta^*(2\psi - 1)(1 - \psi) \\
&= \theta^{*2}(2\psi - 1)^2 + 2\theta^*(2\psi - 1)(1 - \psi) + (1 - \psi)^2 + (2\psi - 1) \\
&= [\theta^*(2\psi - 1) + (1 - \psi)]^2 + (2\psi - 1)
\end{aligned}
$$

So:

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

Which means that:

$$
\frac{d\theta^*}{dK} = \frac{1}{2D\psi} * \frac{\left[-\theta^{*2}(\psi - \frac{1}{2}) - \theta^*(1 - \psi) + \frac{1}{2}\right]^2}{[\theta^*(2\psi - 1) + (1 - \psi)]^2 + (2\psi - 1)} > 0 \tag{22}
$$

This term is always positive, except for one incidence, where the numerator is 0:

$$
-\theta^{*2}(2\psi - 1) - 2\theta^*(1 - \psi) + 1 = 0
$$

For the values $\theta^* = -1$ and $\theta^* = \frac{-1}{2\psi - 1}$, a change in the application cost will not change the trheshold θ^*. However, these values are not within the possible range of θ and therefore $\frac{d\theta^*}{dK} > 0$ always. The denominator gets the value of zero only to $\theta^* = \frac{2(1-\psi)}{2\psi - 1}$. For this value of θ^* the derivative is not define.

6.3 Calculating Q, the Expected Proportion of Qualified Hires out of Total Hires:

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

Since we already calculated Z and $P(S = 1|\theta = \hat{\theta})$, I now calculate $P(m_i = 1|\theta = \hat{\theta}, S = 1)$:

$$\begin{aligned} P(m_i &= 1|\theta=\hat{\theta}, S=1) = \frac{P(m_i = 1 \ \& \ \theta=\hat{\theta} \ \& \ S=1)}{P(\ \theta=\hat{\theta} \ \& \ S=1)} = \\ &= \frac{f(\hat{\theta}) * \hat{\theta} * \psi}{f(\hat{\theta}) * \left[\hat{\theta} * \psi + (1-\hat{\theta}) * (1-\psi)\right]} = \frac{\hat{\theta} * \psi}{\left[(1-\psi) + \hat{\theta}\,(2\psi - 1)\right]} \end{aligned} \tag{23}$$

Plugging in all the probabilities we get:

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

6.4 Comparative Statics: the Effect of θ^* on the Proportion of High Quality Types Chosen:

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

Differentiating Q with respect to θ^*:

$$\begin{aligned}
f &= \left(1-\theta^{*2}\right) \\
f' &= -2\theta^* \\
g &= -\theta^{*2}(2\psi-1)-2\theta^*(1-\psi)+1 \\
g' &= -2\theta^*(2\psi-1)-2(1-\psi)
\end{aligned}$$

$$\begin{aligned}
f'g-g'f &= -2\theta^*\left[-\theta^{*2}(2\psi-1)-2\theta^*(1-\psi)+1\right]- \\
&\quad \left[-2\theta^*(2\psi-1)-2(1-\psi)\right]\left(1-\theta^{*2}\right) \\
&= 2\theta^{*3}(2\psi-1)+4\theta^{*2}(1-\psi)-2\theta^*+ \\
&\quad \left[2\theta^*(2\psi-1)+2(1-\psi)\right]\left(1-\theta^{*2}\right) \\
&= 2(1-\psi)\left[\theta^{*2}+2\theta^*+1\right] \\
&= 2(1-\psi)\left[1+\theta^*\right]^2
\end{aligned}$$

$$\frac{dQ}{d\theta^*} = \frac{2(1-\psi)\left[1+\theta^*\right]^2}{\left[-\theta^{*2}(2\psi-1)-2\theta^*(1-\psi)+1\right]^2} > 0 \tag{24}$$

7 Duration Model

Duration models allow for the estimation of the probability that a process (in this case, employment) will end, conditional on surviving t periods. This duration model estimates the effect of explanatory variables on the duration of employment, taking into account censoring issues.

The hazard function[23]

The probability distribution of duration 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:

$$\lambda(t) = \frac{f(t)}{1 - F(t)}$$

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 $\lambda * \Delta$. *Positive duration dependence* exists at the point t^* if $\frac{d\lambda(t)}{dt} > 0$ at $t = t^*$. *Negative duration dependence* exists at the point t^* if $\frac{d\lambda(t)}{dt} < 0$ at $t = t^*$.

I use the Cox proportional hazard model. In the Cox proportional hazards model, the hazard is assumed to be

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

The Cox model provides estimates for $\beta_1, ..., \beta_k$. It doesn't provide a direct estimation of $\lambda_0(t)$ although it allows one to estimate it. However, we are not interested in $\lambda_0(t)$ but in the value of the βs. In the proportional hazard specification the effect of regressors is to multiply the hazard function itself by a scale factor. The interpretation of the coefficients of the explanatory variables depends on the specification. In the general case, the coefficient does not have a clean interpretation as a partial derivative analogous to the interpretation of coefficients in the linear regression model. The sign of the

[23] This review is taken from Kiefer (1988).

coefficient indicates the direction of the effect of the explanatory variable on the conditional probability of completing a spell. The numerical value of this effect, which is the partial derivative, depends on duration and in general on other included variables. In my setup, the sign of the coefficient indicates the direction of the effect of the explanatory variable (i.e. recruiting channel) on the probability of employment termination given the time already spent in the firm.

Censoring Issues

A distinguishing feature of duration data is the possibility that some of the duration observed will be censored. Censoring is an event that occurs at some time, so our data consist of a measured spell length together with the information that the spell was censored (or not). Let T^*, a random variable, be a spell length for an individual in the absence of censoring, and let c be the censoring time measured from the time origin for the spell. Then the random variable which will be observed is the smaller of T^* and c, or $T = \min(T^*, c)$. We also observe an indicator variable $d = 1$ if the observation is censored ($T = c$), $d = 0$ if uncensored ($T = T^*$). Often the censoring times are known constants (given the time origin), for example, the end of the fixed-length panel survey. It is crucial to assume that individuals whose spells are censored at time c are representative of all the individuals whose spells lengths at least equal to c, perhaps after allowance for explanatory variable. Thus, if we regard the censoring time c as a random variable, it must be independent of T^*, after taking account of other factors. This is a maintained assumption in most applications.

In my sample, an employee that is hired within a short time before 10 February 2003 but is still actively employed with the firm will have a short duration spell, while in fact she may end up staying with the firm for much longer than the current data indicates. How one deals with estimating this setup is explained below.

Estimation

I write the density of a duration of length t as $f(t, \theta)$. If a sample of n completed spells were available and each individual's spell was independent of the others, the likelihood function is:

$$L^*(\theta) = \Pi_{i=1}^{n} f(t_i, \theta)$$

The likelihood function is the joint probability distribution of the sample as a function of parameters θ. When a spell is censored, at duration t_j for example, the only information available is that the duration was at least t_j. Consequently the distribution to likelihood from that observation is the value of the survivor function, $S(t_j, \theta)$, the probability that the duration is longer than t_k. Let $d_k = 1$ if the k^{th} spell is uncensored, $d_k = 0$ if censored. Then the likelihood function $L(\theta) = \ln L^*(\theta)$ is[24]

$$L(\theta) = \sum_{i=1}^{n} d_i \ln f(t_i, \theta) + \sum_{i=1}^{n} (1 - d_i) \ln S(t_i, \theta)$$

which has completed spells contributing a density term $f(t_i, \theta)$ and censored spells contributing a probability $S(t_i, \theta)$. Using the fact that the density is the product of the hazard and survivor function, $f(t, \theta) = \lambda(t, \theta) S(t, \theta)$, and the fact that the log of the survivor function is minus the integrated hazard $\ln S(t, \theta) = -\Lambda(t, \theta)$, the log-likelihood function can be written in terms of the hazard function:

$$L(\theta) = \sum_{i=1}^{n} d_i \ln \lambda(t, \theta) - \sum_{i=1}^{n} \Lambda(t_i, \theta)$$

In practice it is usual to estimate the parameters by maximum likelihood. Under a variety of well-known sets of sufficient conditions the maximum-likelihood estimator $\hat{\theta}$ is consistent for θ and $\sqrt{n(\hat{\theta} - \theta)}$ is asymptotically normally distributed with mean zero and a variance which can be consistently estimated by $V\left[\sqrt{n(\hat{\theta} - \theta)}\right] = -\left[n^{-1} \partial^2 L(\theta) / \partial\theta \partial\theta'\right]^{-1}$.

8 Probit Analysis

The first stage of my empirical work uses probit regressions in which the dependent variable is the time spent at the firm measured in months, and the independent variables are employee characteristics and recruiting channels. Since it is less inclusive then the duration model, I include the results only in the appendix.

[24]In writing this likelihood function we have used the assumption of independent censoring. In general, we would write down the joint distribution of the failure times and the censoring times and base the likelihood on that distribution. With independent censoring or fixed censoring times, the result is the likelihood function in the text.

I am interested in learning whether Internet recruits have shorter durations than employees hired through other channels. Table 9 displays the result of a probit regression[25]. The dependent variable receives the value 1 if the worker has left within 12 months (column 1), 3 months (column 2), 6 months (column 3) or 9 months (column 4) and zero otherwise. Regressions include controls for recruiting channel, education, age, occupation groups, race, sex and year of hire. I use a series of dummy variables for the recruiting channel. Each dummy receives 1 if the employee was recruited through that channel (i.e. referrals) and zero otherwise. The omitted variable in the recruiting source category is the dummy for print advertising.

Censoring issues: employees that were hired towards the end of the time observed (i.e. were hired within a year before 10 February 2003 may receive the value *1* even though they may end up staying with the firm longer than a year. This is because the sample is censored from above. A way to solve this problem is to run the regression over a sub sample of employees that were hired at least a year before the end date of the sample. The dependent variable for employees in this group will get the value 1 if and only if they left the firm within 12 month.

The coefficient of the Internet recruiting dummy is negative and significant in explaining the probability to leave the firm within 12 months (column 1). Compared with print advertising, Internet hires are significantly less likely to leave the firm within a year. A Wald test shows that Internet hires are not significantly different from agency hires or college hires. Employee referrals are much less likely to leave the firm within a year compared both with Internet Recruits and with Print Advertising ($\frac{\partial F}{\partial Internet} = -0.047, \frac{\partial F}{\partial Employee} = -0.137$). Unsolicited recruits are less likely to leave the firm within a year compared both with Internet recruits ($\frac{\partial F}{\partial Internet} = -0.047, \frac{\partial F}{\partial Unsolicited} = -0.089$).

Column (2)-(4) at Table 6 display different definitions of the dependent variable over the same set of controls. When defining failure to stay with the firm over shorter duration, Internet hires are not significantly different from Print Advertising hires in explaining the probability to leave the firm. Employee referrals are significantly less likely to leave the firm within 3,6,

[25] All the regression presented in this paper were run over the sample which includes observation to which the recruiting channel is unknown. The results were not significantly different then running the regressions on a sub-sample that does not include the employees with unknown recruiting source. For brevity, only the results on the restricted sample which does not include employee with unknown recruiting source are presented.

and 9 months than Print Advertising Recruits. When the dependent variable measures the probability to leave the firm within 9 months the Agency hires seem to do significantly better then Internet hires in terms of duration at the firm.

These results imply that Internet hires are of lower quality compared with employee referrals, they are not significantly different then hires through channels such as agency and college recruiting, and they are of higher quality compared with newspaper hires. While this evidence is consistent with the theoretical model (i.e. Internet hires are not of the top quality), it does not prove the model's prediction. Since Internet, agency, print advertising and college hires are similar, it may be that firms simply replaced one low quality recruitment source for a cheaper one without much impact.

Table 10 presents the result of running the specification presented in Table 6, column (1) over sub-samples of five of the largest occupation groups. The dependent variable is 1 if the worker leaves the firm within a year, and zero otherwise. This table allows for the comparison of Internet recruits over different occupational groups. Column (1) shows that for the group of Engineers and Technicians, Internet recruits are less likely to leave the firm within a year compared with print advertising recruits, but Internet recruits are not significantly different from recruits by any other channel, including employee referrals. This result is very interesting, since it implies that the adverse effect of the Internet recruiting is nonexistent in the group of engineers and technicians. Engineers and technicians are professions which are easily screened since they contain very specific skills. In the terms of the model above, it means that ψ is very high, and therefore we should not expect a reduction in the quality of hires due to the Internet for this group. For the other groups: sales, administrative, operational and marketing , on the other hand, Internet hires appear to be not significantly different from Print Advertising hires. Other recruiting channels such as employee referrals and agency seem to be less likely to leave the firm within a year compared to Internet hires.

Table 1: Number of People Hired by Recruiting Channel
(Percentages, Dropping Unknowns)

	1995	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**2002**
Total Recruits	116	651	1493	2017	2711	5429	1982	590
Acquired Company							2.57%	12.03%
Advertisement	8.62%	7.07%	3.22%	2.53%	1.62%	2.71%	0.61%	0.85%
Agency	14.66%	20.43%	15.54%	17.95%	16.93%	11.83%	10.19%	1.02%
Client Referral		0.15%				0.02%		
College Recruiting	8.62%	6.61%	7.03%	13.24%	6.09%	8.71%	14.58%	13.90%
Employee Referral	25.00%	33.33%	42.73%	48.24%	56.03%	56.05%	48.94%	33.56%
Executive Referral			0.13%	0.59%	0.66%	0.50%	0.96%	1.02%
Former Employee	3.45%	0.61%	0.54%	0.40%	0.18%	0.22%	0.25%	
Total Employee Referrals*	**28.45%**	**34.71%**	**43.47%**	**49.33%**	**56.91%**	**57.01%**	**50.30%**	**35.77%**
Executive Search		0.77%	0.07%	0.10%	0.04%	0.24%	0.15%	1.19%
Internal Recruiter	27.59%	1.08%	1.47%	0.15%	0.04%	0.52%	2.93%	11.36%
Internal Transfer					0.11%			
Internet		**0.15%**	**0.33%**	**0.99%**	**4.50%**	**5.64%**	**7.42%**	**15.93%**
Job Fair		1.54%	0.87%	1.49%	1.00%	1.34%	1.16%	0.17%
Open House			0.33%	0.45%	0.33%	0.13%	0.15%	1.36%
Other Source	7.76%	1.38%	2.28%	2.28%	0.33%	0.74%	0.30%	
State/Federal Agency							0.05%	
Temp to Perm		0.31%		0.10%	0.81%	4.29%	2.12%	4.41%
Unsolicited	4.31%	26.52%	25.45%	11.50%	11.32%	7.07%	7.57%	3.22%
Walk In							0.05%	
Total Recruits	100%	100%	100%	100%	100%	100%	100%	100%

* Total employee referral includes Employee Referrals + Executive Referrals + Former Employee

Graph 1:

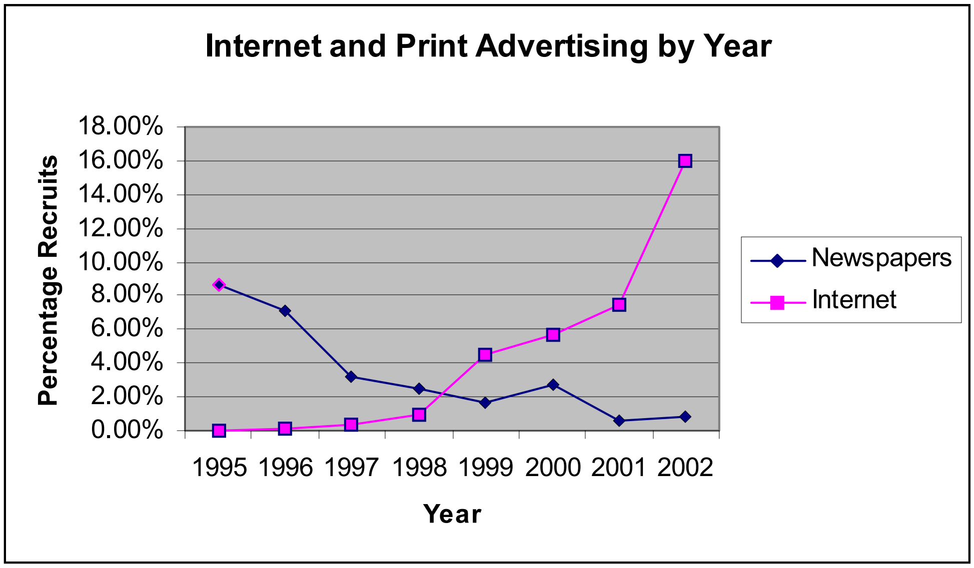


Table 2: Education and Age By Main Recruiting Channels

(Std. Deviations in Parenthesis)

	Education	Age	Number of Observations
Newspaper	15.587 (1.931)	43.708 (9.460)	523
Internet	15.634 (1.939)	38.639 (8.565)	694
Agency	15.668 (1.931)	41.424 (8.579)	2152
Employee Referral	15.109 (2.011)	40.151 (8.942)	7972
College Recruiting	14.904 (2.050)	29.248 (7.075)	1563
All other Recruiting Methods	15.294 (2.067)	43.431 (9.789)	3749

Table 3: The Share of Internet Recruits As Percentage of Total Recruits per Occupation (Unknowns Dropped)

Occupation	1995	1996	1997	1998	1999	2000	2001	2002
Executives	0	0	0	0	0	0	0	0
Engineers and Tech	0	0.32	0.55	0.6	4.25	5.65	9	21.36
Administrative	0	0	0	0.5	7	3.52	4.55	5.38
Finance	0	0	0	2.78	9.84	15.32	10	4.55
Human Resources	0	0	0	10	25	16.85	23.68	8.33
Law	0	0	0	9.09	0	0	0	0
Marketing	0	0	0	2.6	14.29	10.91	12.5	32
Operational	0	0	1.92	4.65	4.92	11.55	4.05	0
Quality Control	0	0	0	0	6.67	22.22	27.27	0
Sales	0	0	0	0.65	1.87	3.78	4.11	13.71
Total	0	0.15	0.34	0.95	4.48	5.65	7.31	16.12

Table 4: Distribution of Occupation and Reference Source

Reference Source	Percentages	Occupation	Percentages
Total	11,998	**Total**	11,998
Acquired Company	0.95%	Executives	0.36%
Advertisement	2.16%	Engineers and Technicians	44.86%
Agency	14.37%	Administrative	10.27%
Client Referral	0.02%	Finance	2.45%
College Recruiting	9.08%	Human Resource	1.71%
Employee Referral	50.71%	Law	0.26%
Executive Referral	0.62%	Marketing	3.74%
Executive Search	0.20%	Operational	5.08%
Former Employee	0.32%	Quality control	0.49%
Internal Recruiter	1.68%	Sales	30.78%
Internal Transfer	0.02%		
Internet	5.24%		
Job Fair	1.19%		
Open House	0.18%		
Other	0.50%		
State/Federal Agency	0.01%		
Temp to Perm	2.03%		
Unsolicited	10.74%		
Walk In	0.01%		
Total	100%	Total	100%

Table 5: Duration Model
Dependent Variable: Employment in the Firm (time to termination, given time spent)

	(1)	(2)	(3)
Internet	-0.071	0.208	0.159
	(0.63)	(1.84)*	(1.40)
Employee Referral	-0.517	-0.149	-0.415
	(5.30)**	(1.55)	(4.27)**
Agency	-0.134	0.268	-0.127
	(1.33)	(2.69)**	(1.26)
College Recruiting	0.136	0.192	0.128
	(1.25)	(1.80)*	(1.18)
Unsolicited	-0.318	-0.158	-0.367
	(3.06)**	(1.53)	(3.55)**
Other	-0.486	-0.304	-0.264
	(4.12)**	(2.60)**	(2.26)*
Education	-0.030	-0.002	-0.022
	(3.66)**	(0.28)	(2.75)**
Age	-0.077	-0.089	-0.094
	(6.08)**	(7.27)**	(7.52)**
Age Squared	0.001	0.001	0.001
	(6.58)**	(6.87)**	(7.58)**
Executives	-1.643		-1.657
	(4.01)**		(4.04)**
Engineers and technicians including customer support	-1.280		-1.270
	(33.94)**		(34.36)**
Administrative	-0.085		-0.040
	(1.62)		(0.85)
Finance	-0.687		-0.702
	(7.12)**		(7.39)**
Human Resource	-0.907		-0.875
	(7.47)**		(7.30)**
Law	-0.992		-0.894
	(3.26)**		(2.95)**
Marketing	-0.349		-0.405
	(4.92)**		(5.77)**
Operational	-1.016		-1.016
	(13.03)**		(13.10)**
Quality control	-1.835		-1.849
	(5.48)**		(5.53)**
Hire Year 1997	-0.083		
	(1.00)		
Hire Year 1998	0.193		
	(2.27)*		
Hire Year 1999	0.444		
	(5.71)**		
Hire Year 2000	0.763		
	(10.06)**		
Hire Year 2001	0.912		
	(10.90)**		
Hire Year 2002	1.097		
	(8.52)**		
Observations	11998	11998	11998

Absolute value of z-statistics in parentheses

* significant at 5% level; ** significant at 1% level
Dropped Variables: (1) Print Advertising (2) hire year 1995-1996 (3)Sales
Sex and Race controls included.

Table 6: Duration Model on a Sub Sample of Worker Groups

	(1) Engineers and Technicians	(2) Sales	(3) Administrative	(4) Operational	(5) Marketing
Internet	-0.234	0.238	-0.252	0.295	-0.276
	(1.35)	(0.81)	(0.81)	(0.64)	(0.54)
Employee Referral	-0.623	-0.214	-0.432	-0.493	-0.836
	(4.47)**	(0.79)	(1.88)*	(1.23)	(1.72)*
Agency	-0.258	0.145	-0.124	0.378	-0.344
	(1.69)*	(0.53)	(0.50)	(0.92)	(0.68)
College Recruiting	-0.736	-0.290	1.048	0.066	-0.827
	(4.36)**	(0.75)	(4.14)**	(0.14)	(1.54)
Unsolicited	-0.436	-0.122	-0.262	0.027	-0.496
	(2.75)**	(0.44)	(1.05)	(0.07)	(1.01)
Other	-0.457	-0.107	-0.884	-0.319	-0.767
	(2.76)**	(0.33)	(2.74)**	(0.68)	(1.40)
Education	-0.004	-0.030	0.011	-0.057	0.035
	(0.30)	(2.24)*	(0.48)	(1.40)	(0.93)
Age	-0.094	-0.047	-0.002	-0.048	-0.034
	(4.21)**	(2.03)*	(0.08)	(0.70)	(0.58)
Age Squared	0.001	0.001	0.000	0.001	0.000
	(4.24)**	(2.73)**	(0.03)	(0.89)	(0.68)
Hire Year 1997	-0.190	0.454	0.005	-0.278	-0.448
	(1.34)	(2.55)**	(0.02)	(0.77)	(1.41)
Hire Year 1998	-0.064	0.754	0.160	-0.307	0.204
	(0.38)	(4.37)**	(0.86)	(0.70)	(0.60)
Hire Year 1999	0.316	0.987	0.305	0.163	0.545
	(2.30)*	(5.86)**	(1.75)*	(0.57)	(1.78)*
Hire Year 2000	0.645	1.335	0.355	0.056	1.179
	(4.85)**	(7.98)**	(2.24)*	(0.19)	(4.00)**
Hire Year 2001	0.857	1.475	0.478	-0.129	1.030
	(5.70)**	(8.42)**	(2.72)**	(0.32)	(2.72)**
Hire Year 2002	1.363	1.064	0.467	-32.169	1.513
	(5.86)**	(3.60)**	(2.08)*	(0.00)	(2.61)**
Observations	5382	3693	1232	610	449

Absolute value of z-statistics in parentheses
* significant at 5% level; ** significant at 1% level
Dropped Variables: (1) Print Advertising (2) Hire Year 1995-1996
Race and Gender Controls included.

Table 7: Propensity Scores Logit Model

	Internet
Education	0.828
	(2.06)*
edu_y2	-0.025
	(1.95)*
Executives, Engineers and Technicians	0.796
	(4.22)**
All Other Occupations Except Sales	0.403
	(1.71)*
	(2.98)**
Observations	2335

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

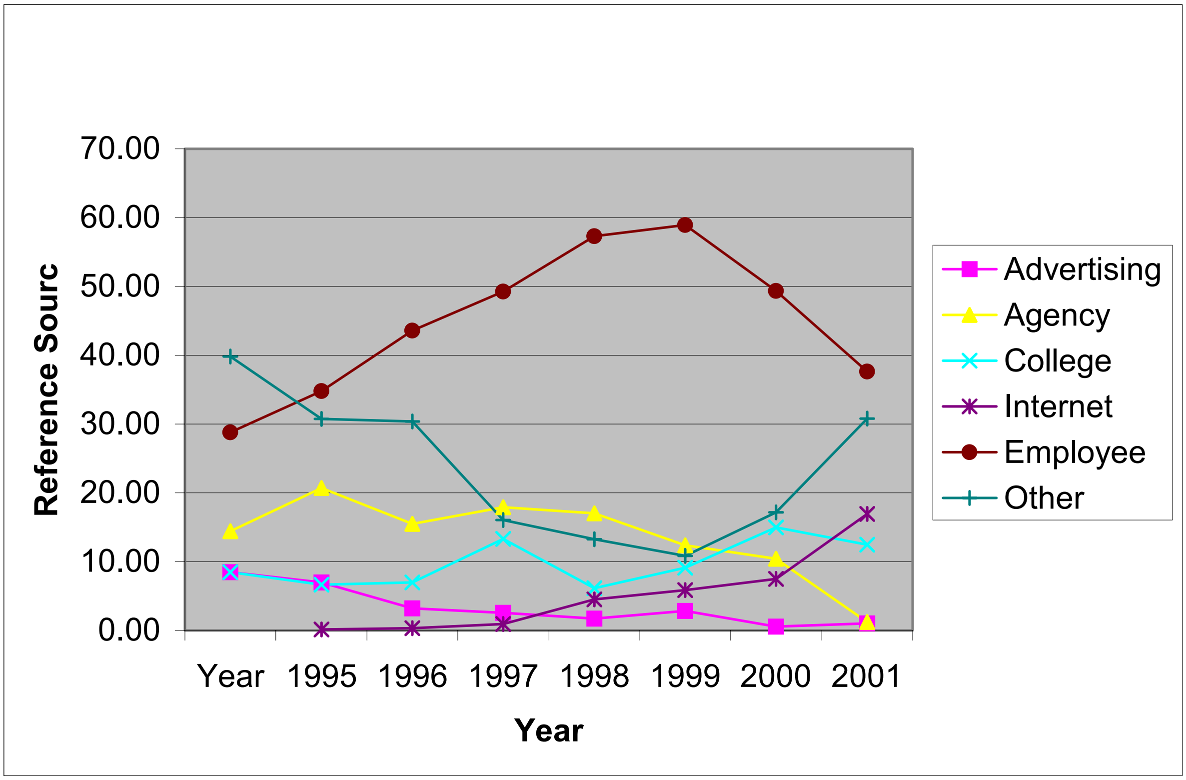
Table 8: Duration Model with Propensity Scores Multiplied by Time Dummies

	(1)	(2)
Internet		0.203
		(2.67)**
Employee Referral		-0.244
		(5.38)**
Agency		0.146
		(2.80)**
College Recruiting		0.425
		(6.31)**
Other		-0.222
		(2.71)**
Propensity Score for 1995-1997 hires	-1.108	-0.901
	(0.62)	(0.51)
Propensity Score for 1998 hire	-8.222	-8.847
	(3.65)**	(3.94)**
Propensity Score for 1999-2000 hires	-4.873	-5.673
	(3.61)**	(4.18)**
Propensity Score for 2001 hire	-4.490	-5.155
	(2.54)**	(2.91)**

Propensity Score for 2002 hire	6.118	5.816
	(1.86)*	(1.79)*
Education	-0.002	-0.009
	(0.17)	(0.92)
Age	-0.121	-0.077
	(10.63)**	(6.10)**
Age Squared	0.001	0.001
	(10.57)**	(6.56)**
Executives	-1.452	-1.435
	(3.51)**	(3.47)**
Engineers and technicians including customer support	-0.981	-0.977
	(11.75)**	(11.56)**
Administrative	0.101	0.033
	(1.74)*	(0.55)
Finance	-0.499	-0.539
	(4.91)**	(5.26)**
Human Resource	-0.692	-0.757
	(5.51)**	(5.99)**
Law	-0.771	-0.924
	(2.53)**	(3.04)**
Marketing	-0.175	-0.218
	(2.26)*	(2.78)**
Operational	-0.873	-0.875
	(10.41)**	(10.35)**
Quality control	-1.743	-1.805
	(5.21)**	(5.39)**
Hire Year 1997	-0.118	-0.095
	(1.42)	(1.14)
Hire Year 1998	0.740	0.835
	(3.58)**	(4.07)**
Hire Year 1999	0.692	0.848
	(4.55)**	(5.63)**
Hire Year 2000	0.986	1.171
	(6.52)**	(7.80)**
Hire Year 2001	1.106	1.274
	(6.03)**	(6.99)**
Hire Year 2002	0.395	0.514
	(1.19)	(1.57)
Observations	11998	11998

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

Graph 2: The Percentage of Hires Per Year by Recruiting Source (Unknown Dropped)



Appendix Tables:

Table 9: Probit Regressions with Recruiting Source

	(1)	(2)	(3)	(4)
	Dummy that gets the value 1 if the worker survived **1 year** or less	Dummy that gets the value 1 if the worker survived **3 months** or less	Dummy that gets the value 1 if the worker survived **6 months** or less	Dummy that gets the value 1 if the worker survived **9 months** or less
Internet	-0.228	0.047	-0.061	-0.132
	(2.03)*	(0.26)	(0.43)	(1.08)
Employee Referral	-0.586	-0.282	-0.384	-0.467
	(6.19)**	(1.84)*	(3.22)**	(4.50)**
Agency	-0.259	-0.054	-0.155	-0.179
	(2.62)**	(0.34)	(1.25)	(1.66)*
College Recruiting	-0.122	0.242	0.284	0.130
	(1.13)	(1.44)	(2.15)*	(1.12)
Unsolicited	-0.472	-0.196	-0.327	-0.336
	(4.61)**	(1.18)	(2.54)**	(3.01)**
Other	-0.477	-0.292	-0.254	-0.380
	(4.25)**	(1.55)	(1.79)*	(3.07)**
Education	-0.045	-0.045	-0.048	-0.040
	(5.50)**	(3.40)**	(4.67)**	(4.41)**
Age	-0.036	-0.002	-0.004	-0.018
	(2.79)**	(0.12)	(0.23)	(1.24)
Age Squared	0.000	0.000	0.000	0.000
	(3.03)**	(0.09)	(0.27)	(1.44)
Engineers and technicians including customer support	-0.844	-0.363	-0.591	-0.756
	(22.59)**	(5.72)**	(12.28)**	(18.24)**
Administrative	0.019	0.552	0.295	0.169
	(0.34)	(6.70)**	(4.45)**	(2.82)**
Finance	-0.442	0.055	-0.262	-0.394
	(4.50)**	(0.38)	(2.16)*	(3.65)**
Human Resource	-0.578	-0.222	-0.512	-0.512
	(4.79)**	(1.05)	(3.07)**	(3.83)**
Law	-0.510	-0.003	-0.619	-0.642
	(1.78)*	(0.01)	(1.40)	(1.84)*
Marketing	-0.369	-0.168	-0.307	-0.379
	(4.64)**	(1.18)	(2.93)**	(4.25)**
Operational	-0.550	-0.223	-0.332	-0.436
	(7.73)**	(1.82)*	(3.71)**	(5.66)**
Quality control	-1.351		-1.002	-1.381
	(3.97)**		(2.28)*	(3.13)**
Hire Year 1997	-0.159	-0.217	-0.239	-0.215

	(1.82)*	(1.65)*	(2.33)**	(2.32)*
Hire Year 1998	-0.152	-0.159	-0.280	-0.209
	(1.71)*	(1.21)	(2.68)**	(2.23)*
Hire Year 1999	-0.084	-0.136	-0.186	-0.153
	(1.07)	(1.18)	(2.05)*	(1.85)*
Hire Year 2000	0.152	-0.058	-0.125	0.015
	(2.05)*	(0.53)	(1.46)	(0.20)
Hire Year 2001	0.367	-0.106	-0.009	0.160
	(4.63)**	(0.88)	(0.10)	(1.90)*
Hire Year 2002	0.035	-0.393	-0.163	-0.142
	(0.13)	(0.75)	(0.49)	(0.47)
Constant	1.129	-0.761	-0.071	0.366
	(3.61)**	(1.55)	(0.18)	(1.08)
Observations	11413	11361	11413	11413

Absolute value of z-statistics in parentheses
* significant at 5% level; ** significant at 1% level
Dropped category: (1) Newspaper advertising (2) Hire Year 1995-1996, (3) Sales
There are controls for sex and race.

Table 10:

Dependent Variable: Dummy that Gets the Value 1 if the Worker Survived Less than a Year with the Firm.

	(1)	(2)	(3)	(4)	(5)
	Engineers and Technicians	Sales	Administrative	Operational	Marketing
Internet	-0.495	-0.098	-0.377	-0.260	-0.015
	(2.94)**	(0.31)	(1.16)	(0.69)	(0.02)
Employee Referral	-0.574	-0.600	-0.642	-0.844	-0.487
	(4.47)**	(2.07)*	(2.59)**	(2.60)**	(0.83)
Agency	-0.308	-0.230	-0.307	-0.229	-0.571
	(2.17)*	(0.79)	(1.16)	(0.67)	(0.93)
College Recruiting	-0.618	-1.431	0.772	-1.014	-1.192
	(3.94)**	(2.47)**	(2.83)**	(2.18)*	(1.78)*
Unsolicited	-0.488	-0.523	-0.460	-0.595	-0.736
	(3.28)**	(1.76)*	(1.72)*	(1.78)*	(1.22)
Other	-0.330	-0.417	-0.979	-0.930	-0.655
	(2.22)*	(1.23)	(3.03)**	(2.30)*	(0.98)
Constant	1.045	0.065	-1.130	-0.008	-0.390
	(2.17)*	(0.10)	(1.49)	(0.01)	(0.22)
Observations	5090	3587	1145	605	423

Absolute value of z-statistics in parentheses
* significant at 5% level; ** significant at 1% level
Control for sex, controls for race.
Dependent Variable: gets the value 1 if the worker has worked less than a year in the firm, and zero otherwise.
These regressions are run over sub-sample that does not include observations that were hired after 2/10/2002. This is because my last date of observation is 2/10/2003. By restricting the sample in this manner I don't include observation of people that are employed less than a year but are still working with the firm. Each column represents a regression that is run over different dependent variable:
Omitted groups: Newspaper advertising for Recruiting method, Hire Year 95-96 for hire year. Sales for occupation group.
Control variables that are included but their coefficient is not presented: Education, Age, Age Squared, Hire Year 1997, Hire Year 1998, Hire Year 1999, Hire Year 2000, Hire Year 2001, Hire Year 2002.