



TO BE OR NOT TO BE LINKED ON LINKEDIN: ONLINE SOCIAL NETWORKS AND JOB SEARCH

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ABSTRACT

Prior research suggests that social connections like friends and family – usually categorized as strong- and weak-ties – are valuable in a job search process. Nevertheless, the size of an average job seeker’s network was limited because of constraints posed by the available modes of communication and costs associated with maintaining those connections. The recent growth of online social networks has enabled job seekers to stay connected with all of their acquaintances, peers, friends, and family. Thus the number of online connections – weak or strong – that an individual is able to manage has increased significantly. In this paper, we first examine if an individual’s social network still plays a role in driving his/her job search behavior not only on the social network but also on other modes. Second, we examine how the ties (weak and strong) and search intensity affect the job outcomes (which we model sequentially as job leads, interviews and offers) from online social networks and compare it to job outcomes from traditional job search modes like career fairs and employment agencies, newspaper and magazine ads, Internet postings, and close friends and family (offline). We first built an economic model of search behavior with cost and benefit functions and then estimated the model to recover some key estimates and structural parameters using a survey data of 109 users. We found that users with more weak-ties search more and users with more strong-ties search less. We also find that weak-ties are especially helpful in generating job leads, but it is the strong-ties that play an important role in generating job interviews and job offers.

1 INTRODUCTION

“How to effectively search for jobs?” is an enormously important question for individuals, firms and policy makers. Over the past four decades job seekers have modified their search efforts as the technology has shaped this process. According to Monthly Labor Review of 1973 (Bradshaw 1973), 71% of job seekers reached out to employers directly, 40% reached out to agencies (public or private), and only 14% used their formal and information social connections to search for jobs. This changed slightly in 1991 (Bortnick and Ports 1992) when 22% of job seekers reached out to friends and family. Growth of Internet use since the late 90’s reshaped this again with the rise of Internet-based firms (like Monster.com) that specialize in matching job seeking individuals with potential employers.

A key element in the process has been the role of job seekers’ social connections. There is significant literature that suggests that “who you know” plays a very important role in finding a job. (Granovetter 2005) argues that social networks are valuable because they affect the flow and quality of information, reward or punish connections, and improve the trust and confidence in the information. These factors are especially important as online platforms have enabled every job post to be available to every job seeker across the globe. According to a survey conducted by CareerBuilder.com¹ in 2009, each job post received more than 75 resumes on average. Social connections could potentially help job seekers in reaching directly to hiring managers, thus improving the probability of visibility because of trust in the quality of information shared by the common connection.

Increase in Internet penetration has led to a meteoric rise in use of online social networking sites (SNS) like Facebook. However, most SNS have unique characteristics and thus all are not used for job search. SNS like LinkedIn have grabbed the lion’s share in professional networking space. A recent cover story article in Fortune magazine (Hempel 2010) suggested that connecting on LinkedIn is more useful than exchanging business cards or churning resumes.

¹ <http://www.theworkbuzz.com/get-the-job/job-search/companies-receive-more-than-75-resumes-on-average-for-open-positions/>

Online social networks are gaining popularity because of their extensive reach and simplified usability by Internet users. Based on statistics from Alexa.com (November 2010), the more popular job search boards (like monster.com or indeed.com) are visited by approximately 0.25% of Internet users, with each person spending four minutes on average on these websites. Online social (or professional) networks surpass these numbers by a factor of 10. Similar information from Alexa (November 2010) shows that LinkedIn is consumed by 3.4% of daily Internet users, each spending 7.4 minutes/day on average. According to LinkedIn (November 2011), one new member is joining the portal every second, with a current user-base of more than 100 million people spanning 200 countries. Employers are responding to this growth by positioning, advertising and using their employees' social network as a way to recruit potential employees.

A fundamental difference in online social networks, compared to users' formal and information networks, is the ability of individuals to maintain and manage many more online connections – the average number of friends on facebook.com² is 130 – albeit most users' networks consist of “weak-ties” (Granovetter 1973). It is useful to highlight an individual's job search process on a SNS like LinkedIn to provide full context.

1.1 Using LinkedIn for Job Search

A typical LinkedIn user can search for a job in any of four ways: 1) searching for jobs posted and advertised on the network, 2) contacting friends or family in his/her network for leads and/or referrals, 3) finding and contacting recruiters and hiring managers, and 4) being contacted by an employer regarding a potential job opportunity.

All these modes are heavily influenced by one's social network. In the case of 1), for example, when a user is searching for jobs, the results presented will show if he/she has connections that are directly related to a job opening. In the cases of 2), 3) and 4), the role of the network is self-evident. Additionally, an employer may opt to share a job posting only within her network and

² <http://www.facebook.com/press/info.php?statistics>

thus the job may not be visible in the search results seen by a potential employee. Thus a large and diverse network plays an important role in finding an insider who can help in the discovery of a potential job lead and convert that lead to an interview or an offer.

If a user does not have any connection to the recruiters advertising the job, s/he cannot directly contact them. However, job seekers can contact recruiters and hiring managers through a limited email service called “inMail” that requires a paid LinkedIn account. A \$19.99/month account gets enough inMail options to directly contact three individuals per month and a \$74.99/month account gets inMail options to contact 25 individuals. However, the most economical and common approach would be to get introduced by a common friend. This could be visualized as a professional meeting where a common contact introduces any two strangers at the meeting. Thus the number of introductions received by a job seeker will be positively correlated with the network size.

While the role of network seems to be important, it is not clear how effective this network is in the actual job outcome. Many connections may be helpful, but they may also make it harder for a user to search for jobs effectively. Similarly, employers may also realize that a large number of irrelevant connections are not useful in measuring the social capital of an individual. It is also not clear if unemployed users actually consider online social networks a great tool for job search as unemployment information is not something users may wish to share widely.

In summary, while there is a lot of press surrounding online social networks, there is little empirical work that has examined this issue in detail. This paper seeks to examine two major questions:

(i) How do people allocate their job search efforts across different modes, especially online social networks? How does a user’s online social network (including weak-ties) affect these search efforts?

(ii) Are online networks effective in generating job offers? How do strong and weak-ties influence outcomes classified as job leads, interviews or offers?

Answers to these questions require having access to detailed data on users' job search behavior. To get this data, we administered a survey to unemployed users asking them detailed questions on their job search methods, their online and offline social capital, and job outcomes. Using survey responses of 109 users, we find that job seekers with relatively more connections on online social network (LinkedIn in this case) spend more time searching for jobs on that platform. We also find that "strength of weak-ties" (Granovetter 1973) and "strength of strong-ties" (Krackhardt 1992) arguments hold for online social networks but under different job outcomes. Weak-ties continue to help job seekers find new job leads while strong-ties help in converting these job leads to offers. One interesting finding is that a large number of weak-ties tend to reduce the strength of strong-ties, implying that job seekers should not be driven by the popularity of online social networks to grow their network beyond a manageable state. In other words, while a much larger network size may help a job seeker find new leads, it may be a disadvantage when seeking help from his/her strong connections in converting those leads to offers.

Our paper addresses several important aspects of using the SNS to find a job. First, the whole domain of online social networks and job outcomes is ripe for serious empirical work. How new online platforms are reshaping job search process and its effectiveness is enormously important information for labor economists, sociologists and technologists. Even policy makers (especially at the Department of Labor) who spend significant resources on training users and employers on how to efficiently find a match would find our research useful. Despite some limitations of our survey, we believe our paper will be able shed some light on questions largely unanswered due to data unavailability.

This paper is organized as follows. We provide a literature review in Section 2. In Section 3, we provide details on our data and survey, including summary statistics. We build a simple model of user job search that provides a way for empirical estimation in Section 4. We present our results and analysis in Section 5. We conclude with a discussion of the implications and limitations of our results and possibilities for future research in Section 6.

2 LITERATURE

We draw from two major literature pools. First is the job search literature in labor economics. Most job search models use the framework of income-leisure utility models (Burdett 1977; Mortensen 1986; Holzer 1988). These models have been extensively studied and applied in different settings and estimate different structural parameters like the impact of benefits on unemployment, reservation wages, employed vs. unemployed users and so on (Bloeman 2005). In the context of job search method, different papers have looked at how a “social network” (in particular friends and family) affects the search and outcomes. (Holzer 1988) studies unemployed youth and shows how friends and families increase significantly the probability of finding a job. (Blau and Robins 1990) differentiate between different job outcomes (offer probability, acceptance probability, contact probability). They also differentiate between unemployed vs. employed individuals and unveil that the offer probability while being employed is higher than when unemployed.

Another stream of literature has studied the role of social networks in job search. Scholars have studied labor market and the role of social ties on job outcomes (Granovetter 1983; Holzer 1988), wages (Montgomery 1992), and job information diffusion (Granovetter 1995). It has been shown that the number of job leads converting to job offers is highest for search through friends and family and direct job applications (Holzer 1988). In a study of recruitment process of a bank, the role of social networks was found to be positive and significant (Petersen, Saporta, and Seidel 2000). At the same time the role of social ties was found to be positive and significant on wage over time (Rosenbaum et al. 1999). An analytical work using the diffusion of job lead information through network structure suggests duration dependence of unemployment (Calvó-Armengol and Jackson 2004).

The second literature we explore is that of sociology that examines the role of social capital. Seminal work in this area was done in the mid-twentieth century (Katz and Lazarsfeld 1955; Coleman, Katz, and Menzel 1957; Mansfield 1961; Merton 1968; Van den Bulte and Lilien 2001; Valente 2003). During the same time the origination of strength-of-weak-ties theory (Granovetter 1973) changed the perspective of social capital. Granovetter suggested that close

friends and family do not contribute to the discovery of newer content (job leads in his study) but the weak-ties (people who we know but do not communicate with on a regular basis) provide a larger volume of novel information. It was later shown that both strong and weak-ties play a role in product and information diffusion (Goldenberg, Libai, and Muller 2001) but may have a different impacts based on the interaction between the ties and the network size. It was also shown that strong-ties are important (Krackhardt 1992) in causing actual changes and weak-ties may lead to more diffusion of information, suggesting that weak-ties may be useful in generating job leads but strong-ties help more in getting job offers. Other studies (Burt 1995) showed that the position in network matters more than the tie-strength. Overall, the idea is that networks cause an increased effect on the diffusion of information (Economides and Himmelberg 1995), but the true role of peer influence may be hard to estimate from the observational data because of reflection problem (Manski 1993).

With the rise of the Internet as a channel for job search, it has been used increasingly both by unemployed and employed workers and is expected to be an effective platform because of low costs. This allows job seekers to collect more information about potential opportunities and selectively submit their job applications (Stevenson 2008). But the Internet is also shown to have a negative effect on the unemployment duration of job seekers (Kuhn and Skuterud 2004). Also, the Internet may be more effective than newspaper ads or direct applications but less effective than social networks (Feldman and Klaas 2002), thus creating a need for investigation of various job search modes including online social networks.

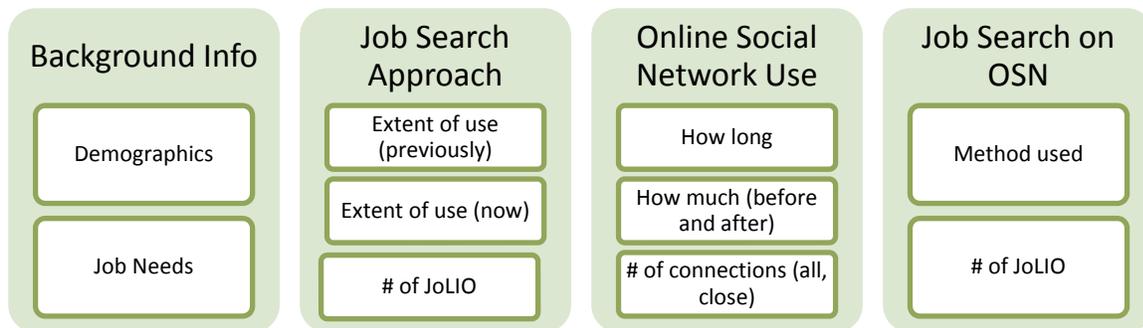
Some studies have tried to address the challenges of identifying the peer influence and information diffusion on online networks using randomized experiments (Aral, Muchnik, and Sundararajan 2009) and dissection of archival data (Garg, Smith, and Telang 2011).

The role of increasing the number of weak- or strong-ties on job outcomes is still novel to the field. Through this paper we try to take the first step at understanding the role of online social networks on job search by unemployed workers using survey data collected from these workers.

3 DATA

Traditionally labor economists have relied on the National Longitudinal Survey (NLS) or Current Population Survey (CPS) to examine how users are searching for jobs and in some cases how their friends and family networks are helping them (Holzer 1988). While these are large datasets, most lack details such as network composition (strong- or weak- ties), or information about job leads, interviews and job offers specific to a search mode.

To better understand the role of online social networks on job outcomes, we designed an IRB-approved survey and administered it to individuals who had lost their jobs at large (revenue in excess of \$100 million) organizations across the United States during 2010. An outplacement consulting firm facilitated the survey by allowing us to administer the survey to people it had helped with their job search. The survey contained questions about the individual's current employment status, motivations for job search, past and present job search strategies, job outcomes (leads, interviews, or offers: JoLIO), familiarity and use of online social networks, and knowledge of using online social networks for job search. The survey was detailed and required more than 20 minutes of each subject's time to answer all the questions. The survey comprised the following:



To test if users would respond favorably to the survey, we created a pilot survey that was made available on the Internet; the link was shared with our peers and friends. The goal of the pilot was to gain feedback to improve the questions in order to maintain the attention of job seekers over the questionnaire. Based on the feedback, we made adjustments to the questions, but the data from this sample was ignored for the study.

The outplacement firm had access to the email addresses of 288 individuals. We sent the questionnaire to all 288, of whom 163 individuals opened the email and 109 took the survey. Eight surveys were not fully complete or did not meet the data validation tests, leaving us with 101 completed surveys. We paid \$10 in Amazon.com gift cards to each individual who completed the survey; in addition we provided a job search strategy report³ created with the help of professionals in the field. It should be noted that our survey was sent to mostly educated, white collar workers, so the sample is neither representative of the general population nor perfectly random. However, given that educated and white collar workers are the people most likely to use online social networks, our survey targeted those who can provide the most useful insight into the phenomenon of interest. Summary demographics are presented in Table 1.

Completed Surveys	109
Currently Unemployed	57
Married	53
Age (Average)	39 (8.97)
Total Work Experience (Average)	14.2 (6.3)
Approximate Salary (Average)	\$78.7k (28.1)
Race = White	62
Race = Black	6
Race = Hispanic	7
Race = Asian	14

Table 1: Demographic summary for survey takers

We asked users about five major search modes they used in job search: (i) Internet sites (like monster.com), (ii) online social networks (like LinkedIn), (iii) offline close friends and family, (iv) newspapers and other print media, (v) job agencies and career fairs. Of 101 people, 89 individuals used the Internet as a job search mode, 77 used online social networks for job search, 81 used their offline network of close friends and family, 56 used print media, and 43 used agencies (including career fairs and placement services).

Table 2 shows how the job search behavior changed conditional on the search mode being selected during the current or the previous time period. The increase in the number of

³ http://bit.ly/ttg_linkedin

individuals using each job search mode reflects either the reduced search costs or the impact of unemployment. Change in use of online social networks could be attributed to the newness of the mode, with large majority still adopting the platform.

Job Search Mode	Count	Search Intensity (hrs/week)	Search Intensity -Sticky (condition of use in past) (hrs/week)
Agencies (AG)	43	4.79 (2.69)	2.76 (2.74)
Print Media (PM)	56	4.45 (3.13)	3.39 (3.46)
Internet Posts (IN)	89	14.39 (11.61)	13.27 (12.22)
Online Social Networks (SN)	77	8.79 (7.42)	6.85 (6.49)
Friends and Family (FF)	81	5.54 (4.13)	4.87 (4.37)

Table 2: Search intensity on each job search mode - conditional on using the search mode (mean values with std. dev.)

Interestingly we note that the share of time spent (conditional on the job search mode being used) on online social network for job search (31%) is slightly smaller than the share of time spent with close friends and family (33%). The share of search effort is largest for the Internet (49% on average), with print media (29%) and agencies (25%) being the lowest. We explicitly asked users how many job leads, job interviews and job offers they found via each mode. The summary of search effort distribution across job search mode, the search intensity on that mode; the summary of results is presented in Table 3.

Job Search Mode	N	Effort	Leads	Interviews	Offers
Agencies (AG)	43	0.16 (0.1)	0.08 (0.12)	0.19 (0.2)	0.15 (0.2)
Print Media (PM)	56	0.16 (0.15)	0.17 (0.14)	0.17 (0.21)	0.18 (0.38)
Internet Posts (IN)	89	0.41 (0.2)	0.43 (0.25)	0.49 (0.29)	0.26 (0.39)
Online Social Networks (SN)	77	0.24 (0.12)	0.19 (0.2)	0.21 (0.23)	0.54 (0.39)
Friends and Family (FF)	81	0.19 (0.11)	0.23 (0.24)	0.32 (0.3)	0.49 (0.43)
N		96	96	83	43

Table 3: Search intensity & job outcome share (%) on each job search mode

Table 4 below presents the number of individuals that used a specific search mode and number of those that found a job outcome from each of the modes.

	Searched	Job Leads	Job Interviews	Job Offers
Internet	89	82	62	12
Online Social Networks	77	55	34	17
Close Friends & Family	81	70	49	18
Print Media	56	45	22	3
Agencies	43	19	12	3

Table 4: Count of job seekers on various job search modes conditional on search or job outcome

Next, we asked users to specify how many connections they have and how many they consider as weak and strong respectively. Our definition of strong connections is derived from philo (Krackhardt 1992). We allowed survey takers to pick a range for the number of strong connections that are close friends and family members whom they communicate with at least once a month. The phrase “close friends and family” was also used to classify those individuals that a job seeker would interact with offline when searching for a job. Thus, these strong-ties (or philos) would generate trust and serve as a valuable asset when searching for a job. Because of the overlap of offline and online close friends and family, we expect the strong-ties on LinkedIn to serve as a proxy of professional strong-ties on an offline network. Thus, it gives us an opportunity to explore how job seekers utilized the strong connections for their job search both online and offline.

Weak-ties, on the other hand, allow a channel for flow of novel information and thus provide a measure of the number of sources available to gain job related information. It is believed that online platforms enable development of a much larger weak-tie network because of the low cost to create and maintain a tie (Pénard and Poussing 2009)⁴. As a result online network provides a measure of the number of channels a job seeker can explore outside of online social networks to find a new job. For example, if John is weakly connected to Mike, then he can potentially gain some job leads through Mike or by looking for advertised jobs at Mike’s workplace using any of the search modes. Thus, weak-ties open channels for discovery of new information.

From our dataset, we observed that individuals have 120 connections an average on personal social platforms like Facebook and 150 connections on average on professional social platforms like LinkedIn (See Figure 1).

⁴ Pénard, Thierry and Poussing, Nicolas, Internet Use and Social Capital: The Strength of Virtual Ties (October 12, 9). Available at SSRN: <http://ssrn.com/abstract=760084>

Contrary to what might be expected, individuals have much larger share of strong-ties on Facebook yet a much larger share of weak-ties on LinkedIn. For individuals who did not use online social networks as a job search mode, we asked about their distrust in that platform. All these individuals cited privacy concerns as the most important reason for not using online social networks (like Facebook) and lack of relevant job leads for not using online professional networks (like LinkedIn). It has also been shown (Calvó-Armengol and Zenou 2005) that a large number of connections tends to have a negative effect on job outcomes (leads) when they exceed a threshold. Since online social platforms enable such large network formations, it becomes more important to understand if online social connections are indeed helpful in job search.

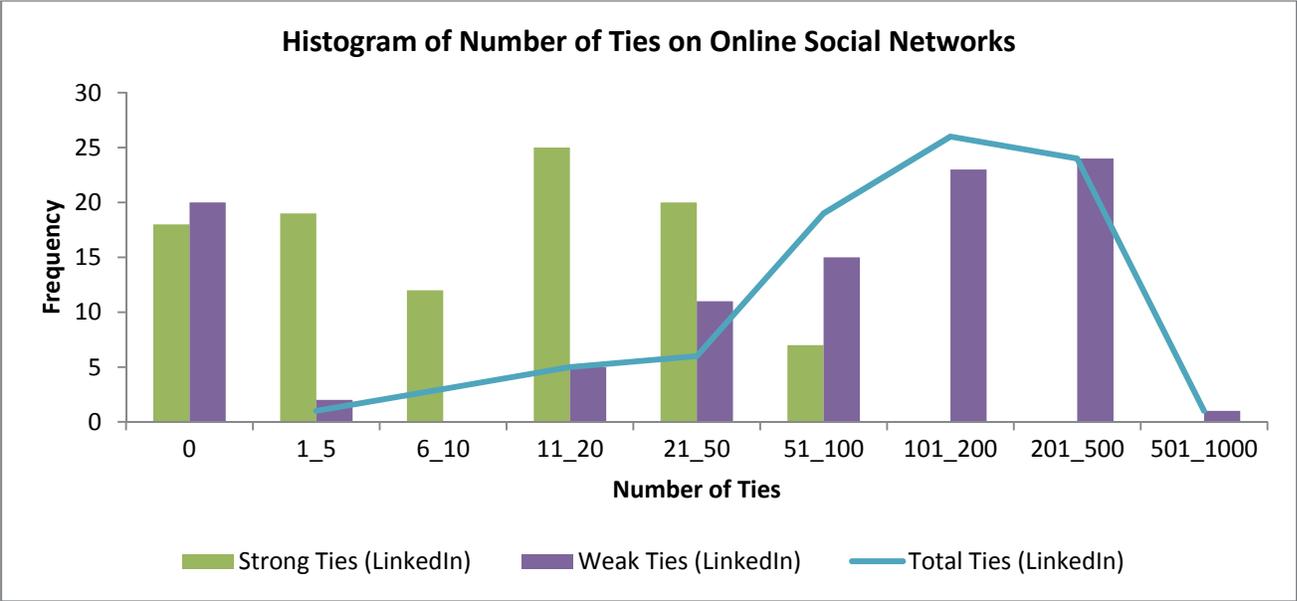


Figure 1: Distribution of number of online social ties on LinkedIn

3.1 Survey Data Validation & Reliability

We used three approaches to build confidence in the response data: 1) we verified accuracy of conditional responses, 2) we matched answers with actual publicly available data, and 3) we built redundancies into the survey. For example, we found that one job seeker reported that the number of interviews received from print media ads were higher than number of job

applications submitted. Though this could just be a typographical error, we dropped that individual from the data.

We asked individuals about the number of connections they had on social networks like LinkedIn, Facebook, and Twitter, and encouraged users to visit their online social network platform so they could provide accurate information. To validate their responses, we used publicly available data from LinkedIn. Of the 77 job seekers who used online social networks for job search, we were able to access the profiles of 71 job seekers and the answers selected by 69 survey takers matched the observed data. The two responses that did not match the actual data were off by an average of six total connections. We dropped these individuals from the dataset to ensure accuracy.

We additionally asked users about “how” they searched for jobs within the online social networks (OSN). We identified four modes of job search on LinkedIn based on a separate set of responses from LinkedIn users. These four modes were 1) searching for job posts and ads on LinkedIn, 2) contacting close friends and family (strong-ties) on the online network for leads and/or references, 3) contacting other connections (weak-ties) on the online network for leads and/or references, and 4) finding and contacting recruiters for potential job opportunities.

We asked users to identify how many leads, interviews and offers they got from each of these modes. We added these numbers and compared them to the aggregate number of JoLIO from online social networks to verify if they provided consistent answers. While not everyone responded to these questions, we found three users whose answers were not consistent and dropped them from the sample.

In summary, despite some limitations, many validations seem to confirm the overall robustness of the numbers provided by end users.

4 THEORY

We are interested in exploring the main questions that we outlined in the introduction. How do people allocate their time across different modes, how do online connections affect those choices, and do online connections affect job outcomes? Unfortunately, job outcomes are also affected by how diligently users search for jobs on a particular mode. Moreover, the job search decision itself will be driven by how likely the user thinks s/he will find a job. In short, the relationship between social connection, job outcomes and search effort is complex and requires a formal treatment to carry out a convincing empirical analysis.

Intuitively, the decision to allocate time across different search modes depends on a user's expected benefits and cost calculation. Thus, we present a simple model that provides the basis for our empirical analysis. In the process, we will also outline some challenges in identification.

We consider the following five job search channels: 1) agencies [AG], such as libraries, employment agencies and career fairs; 2) print media [PM], mainly newspapers and magazines; 3) Internet job boards [IN], such as monster.com and hotjobs.com; 4) online social networks [SN]; and 5) close friends and family [FF].

4.1 JOB SEARCH ALLOCATION

We use and modify widely used income-leisure utility models (Burdett 1977; Mortensen 1986; Holzer 1988) to set up our empirical strategy. These models assume that there is certain baseline utility from being unemployed. Searching for a job increases the probability of being employed but it also has associated costs. Job seekers are rational and are trading costs of search vs. benefits of being employed. In particular, we modify the search models to include social connections affecting the job outcomes. More formally, we specify the utility of an unemployed individual who spends s_{ij} time searching for job on model j :

$$U_{i,j,t}(w_R, s_{ij}) = v_{i,j}(L_i - s_{ij}, Y_i - c_j(s_{ij})) + \pi_{j,t}(s_{ij}, X_i, E_i) * p_{j,t}(w_t \geq w_{R,t}) * E(U_{emp,(t+1)}) + (\pi_{ij}(s_{ij}, X_i, E_i)) * (1 - p(w_t \geq w_{R,t})) * U_{t+1} + (1 - \pi_{ij}(s_{ij}, X_i, E_i)) * U_{t+1} \quad \dots (1)$$

i indexes an individual, j indexes search mode and t indexes time. Here $v_{i,j}$ is the current period utility from leisure and outside income. Searching is costly: it reduces leisure time as well as incurs monetary cost c_j . L_i is the leisure time for individual i and Y_i is the non-wage income. The second term in the utility function is the expected utility of being employed if the probability of an offer is π and offered wage (w_t) is higher than reservation wage ($w_{R,t}$). Here X_i represents the user's characteristics (education, age, experience, salary during last job, race, etc.). E_{ij} represents the embeddedness or social capital of user i on mode j . The third term in (1) is simply the probability that user will remain unemployed because the offered wage is not higher than his/her reservation wage⁵, and the fourth term indicates that the user may not get any offer despite searching and hence remain unemployed in the next period.

Assuming that the wage offer distribution is given as $f(w)$, we can rewrite equation (1) as:

$$U_{i,j,t}(s_{ij}) - U_{i,j,t+1} = v_{i,j}(L_i - s_{ij}, Y_i - c_{ij}(s_{ij})) + \pi_{i,j,t}(s_{ij}, X_i, E_{ij}) * \int_{w_R}^{\infty} [E(U_{emp,(t+1)}) - U_{i,j,t+1}(w_R, s_{ij})] * f(w)dw \quad \dots (2)$$

The equation specifies expected change in utility due to search effort s . The first part is reduction in utility due to searching. The second part is increase in utility due to searching. Users invest in search intensity “ s ” to maximize this utility. So optimal search time s^* is given by taking the derivative and equating it with zero.

However, for empirical tractability, we need to assume functional forms for both cost and job offer rate. Here we rely on prior literature for these functions. v is assumed to be linear in its arguments (Holzer 1988). Given that these are unemployed users, the cost of search on leisure time is assumed to be minimal. Thus we can ignore the first argument in function v . The offer probability is a linear combination of the offer arrival rate (λ) and search effort allocated to a job search mode (Bloeman 2005). We will suppress subscript t :

⁵ We used past wage as reservation wage for unemployed workforce. For employed individuals, the reservation wage is indeed their current wage.

$$\pi_{ij}(s_{ij}, X_i, E_{ij}) = \lambda_{ij}(X_i, E_{ij}) * (\tau_0 + \tau_1 s_{ij}) \quad \dots (3)$$

$$\text{where } \lambda_{ij}(X_i, E_{ij}) = \exp(\varphi_{0j} + \varphi_{1j} X_i + \varphi_{2j} E_{ij})$$

Here λ is the offer arrival rate on a search mode during a given time period that is dependent on the user characteristics X and embeddedness E of a job seeker. We also include a dummy φ_{0j} to control for mode specific unobserved. E suggests that if a job seeker has higher social connections on a particular search mode, s/he is more likely to receive job offers. It is also clear from π that higher the efforts on search, more is the likelihood of receiving an offer. A constant τ_0 allows for the fact that even zero search effort could lead to some positive job outcomes.

Finally, we also assume a functional form for the search cost (Bloemen 2005) where cost is increasing and convex in search efforts:

$$c_{ij}(s_{ij}) = \gamma_j * \exp\left(-\frac{\delta_j * X_i}{\gamma_j}\right) * \left[\exp\left(\frac{s_{ij}}{\gamma_j}\right) - 1\right] \quad \dots (4)$$

Typically embeddedness will be a part of the cost function if the job seeker uses the available time for job search in building his/her social network, but we assume that the individuals have already built their network and are searching for jobs using that network. Given that the benefit of search is linear, an interior solution is guaranteed. Taking first order of (2) will yield:

$$-v_2 \alpha_1 \exp\left(\frac{s_{ij}}{\gamma_j}\right) + \tau_1 \lambda_{ij}(X_i, E_{ij}) * R_{ij} = 0$$

$$\text{where } R_{ij} = \int_{w_R}^{\infty} [E(U_{emp,(t+1)}) - U_{i,j,t+1}(w_R, s_j)] * f(w) dw$$

$$\text{and } \alpha_1 = \exp\left(-\frac{\delta_j * X_i}{\gamma_j}\right)$$

Since v is linear, v_2 (derivative of v with respect to its second argument) is simply a constant which we normalize to 1. Solving for optimal s and simplifying (3) leads to:

$$s_{ij}^* = (\gamma_j * \log \tau_1) + (\varphi_{j,0} * \gamma_j) + (\delta_j + \gamma_j * \varphi_1) * X_i + \varphi_{j,2} * \gamma_j * E_{ij} + \gamma_j * \log(R_{ij}) \quad (5)$$

Since we observe s_{ij} , the difference between observed and predicted s is simply the error component. Thus an estimable form would be

$$s_{ij} = s_{ij}^* + \varepsilon_{ij}^s \quad \dots (6)$$

One missing component in estimating this equation is that we do not directly observe R , which is the expected benefit of employment given the distribution of wages (w). We follow the approach suggested in prior literature (Mortensen 1986; Bloemen 2005) that assumes the difference in the utility from employment and the utility from the unemployed search to be equal to the difference in employed wage and reservation wage. This further simplifies the equation since we know the past wage of the user. If wage offer distribution is normal for a job search mode, then:

$$R_{ij} = \int_{w_{i,last}}^{\infty} [w_j - w_{i,last}] * N(w_j, \bar{w}_j, \sigma^2) dw_j$$

Since we know the past wage of a job seeker and distribution of wages available from a job search mode, we can recover the value of expected benefit of employment. From the data, we create a distribution for each job search mode. Thus, the wage information and distribution of wages allows us to estimate the value of R for each job seeker, which is summarized in Table 5.

	N	Mean (\$1000s)	Std. Dev.
Internet	24	74	30.06
Online Social Networks	14	88	22.82
Close Friends & Family	39	83	26.55
Print Media	10	52	19.89
Agencies	10	70	29.81

Table 5: Mean and std dev of wage on various job search modes

4.2 EFFECT OF EMBEDDEDNESS ON JOB OUTCOME

Our model of search allocation is derived from the expected benefits and cost calculations. If people perceive some modes to be more beneficial, they will search more. Thus their search allocation is a sufficient statistic to underscore the value of a search mode to them. We do not need to know the “actual” outcomes.

However, we do have data on actual outcomes – how many job leads, interviews and offers an individual actually received. This information allows us to examine three additional models of interest: (i) it allows us to estimate the cost of each search mode in Equation (4), (ii) it allows us to examine if users are disproportionately spending time searching on modes that are actually ineffective (this may be particularly true of OSN, which have been hyped but little is known of their effectiveness in actually finding a job), and (iii) it allows us to estimate the direct effect of connections on outcomes (i.e., we should be able to estimate the benefit function that allows us to measure the effect of social ties in the absence of actual search effort).

Our job offer model is straight-forward.

$$\pi_{ij}(s_{ij}, X_i, E_i) = (\tau_{0j} + \tau_{1j}s_{ij}) * \exp(\varphi_{0j} + \varphi_{1j}X_i + \varphi_{2j}E_{ij})$$

Embeddedness can affect job outcomes in two ways. First, as our model in equation (4) shows, more connections may lead to more search effort by users. Second, more connections would lead to more job outcomes independent of search effort. Formally, the effect of embeddedness on job outcome could then be written using the chain rule as follows:

$$\frac{d\pi_{ij}}{dE_i} = \frac{\partial\pi_{ij}}{\partial E_i} + \frac{\partial\pi_{ij}}{\partial s_j} * \frac{ds_j}{dE_i}$$

Many empirical papers do not have details on search efforts. That is, the second term in the equation above is not estimable. It is clear that without measuring “s,” the effect of embeddedness on job outcomes will be under (or over) estimated. In our paper, by directly observing s and E, and writing down the structure of search effort, we can estimate how social capital affects search outcomes cleanly by estimating all components of the above equation.

An even more interesting aspect of our data is the granularity in job outcomes. Most papers measure only job offers as an outcome. However, the actual job offer process is more complex. Usually job search efforts generate relevant job leads, which convert to interviews and then to offers. The effect of social capital would be different on these outcomes. For example, we would expect weak-ties to have a strong effect on job leads. Weak-ties may be able to provide a

user with potentially relevant job leads. The cost of diffusing information across weak links is low. However, weak-ties may not influence interviews or offer probabilities. Strong-ties can potentially play a bigger role. Interviews and offers depend on people willing to make phone calls, or writing recommendation letter on behalf of a user, or pressing for a user's prospect. This is costly, and only strong-ties may be willing to make these investments.

In short, if we get access to more granular outcomes we can get better insights into how social connections affect job outcomes. In this paper, we build on the productivity model (Blau and Robins 1990), such that there is a sequential process of search leading to job leads to job interviews and eventually to job offers. Thus, we can write the job offer as a function of outcomes (interviews, which is a function of search). Or,

$$JO_{ij}(s_{ij}, X_i, E_{ij}) = f\left(JI_{ij}\left(JL_{ij}\left(s_{ij}(X_i, E_{ij})\right)\right)\right)$$

Here JO is the number of job offers received from the search mode j, when a job seeker received JI interviews and JL job leads from search effort s. This brings us back to the job outcome function with the modification of dependent variable being the job outcome in the sequential process.

$$JL_{ij}(s_{ij}, X_i, E_{ij}) = (\tau_{0,j}^3 + \tau_{1,j}^3 s_{ij}) * \exp(\varphi_{0,j}^3 + \varphi_1^3 X_i + \varphi_{2,j}^3 E_{ij}) + \varepsilon_{ij}^1 \quad (7a)$$

$$JI_{ij}(JL_{ij}, X_i, E_{ij}) = (\tau_{0,j}^2 + \tau_{1,j}^2 JI_{ij}) * \exp(\varphi_{0,j}^2 + \varphi_1^2 X_i + \varphi_{2,j}^2 E_{ij}) + \varepsilon_{ij}^1 \quad (7b)$$

$$JO_{ij}(JI_{ij}, X_i, E_{ij}) = (\tau_{0,j}^1 + \tau_{1,j}^1 JI_{ij}) * \exp(\varphi_{0,j}^1 + \varphi_1^1 X_i + \varphi_{2,j}^1 E_{ij}) + \varepsilon_{ij}^0 \quad (7c)$$

Using the chain rule, the effect of embeddedness on job outcomes could be readily calculated as follows:

$$\frac{dJO_{ij}}{dE_{i,j}} = \frac{\partial JO_{ij}}{\partial E_{ij}} + \frac{\partial JO_{ij}}{\partial JI_{ij}} * \frac{dJI_{ij}}{dE_{ij}}$$

$$\frac{dJL_{ij}}{dE_{ij}} = \frac{\partial JL_{ij}}{\partial E_{ij}} + \frac{\partial JL_{ij}}{\partial JL_{ij}} * \frac{dJL_{ij}}{dE_{ij}}$$

$$\frac{dJL_{ij}}{dE_{ij}} = \frac{\partial JL_{ij}}{\partial E_{ij}} + \frac{\partial JL_{ij}}{\partial s_{ij}} * \frac{ds_{ij}}{dE_{ij}}$$

In addition to estimating the effect of embeddedness on various job outcome classifications, the above model also allows us to estimate the effectiveness of each job search mode in converting search effort to job leads, job leads to interviews, or job interviews to offers.

5 EMPIRICAL ANALYSIS & RESULTS

5.1 Joint Models of Search Effort and Job Outcomes

Our models from the previous section provide a clear empirical strategy. If we believe social capital increases the value of a search mode, a rational user would also allocate more time. Similarly, allocation of more time would potentially lead to more job leads. In theory, we can separately estimate (6) and (7a, b, c) readily. However, our model indicates that search effort and job outcomes are highly correlated and a shock is likely to affect both equations. Thus, a joint model represents the data better. Therefore, we assume that job outcomes and search efforts are distributed bivariate normal. In other words, equation (6) and (7) would be jointly estimated to recover structural parameters. Since we are assuming ε_{ij}^S from (6) and ε_{ij}^I from (7a) are bivariate normal, we also estimate the correlation coefficient.

Before we present our results, we provide some details into the precise regression we run and potential challenges to estimation. Our search effort regression is (as in 6):

$$s_{i,j} = (\gamma_j * \log \tau_1) + (\varphi_{j,0} * \gamma_j) + (\delta_j + \gamma_j * \varphi_{j,1}) * X_i + \varphi_{j,2} * \gamma_j * E_i + \gamma_j * \log(R_{i,j}) + \varepsilon_{ij}^S$$

First notice that E (or social connections) in our case is specific to OSN (strong and weak-ties on online social networks). However, we test whether more OSN connections affect search across other modes as well. For example, OSN ties may be a reflection of a user's large social network and affect overall search effort. In the equation above, the first two terms are simply constants,

while the other terms are readily identified. As we will show, we can recover structural parameters for cost (γ_j, δ_j) .

Even though we do not observe users' choices repeatedly, we do observe the same user over five modes. Thus we have a dataset that allows us to control for user specific and search mode specific unobserved by including mode specific dummies and user specific random effects.

One may still worry that some unobserved may be correlated with embeddedness. For example, more social users may search more on online social networks and also have more connections. Though we use user specific random effects to control for unobserved effects, we also use Facebook connections as a potential control since social users are likely to have more connections on Facebook as well. We also control for duration of unemployment since this controls for its effect on search intensity. It also potentially controls for the fact that users' social connections may increase over time. However, the fact remains that more search time may also lead to increase in their social ties. Although, building strong-ties is non-trivial and takes time, the causal interpretation of the effect of social connections on search intensity requires some caution. Still, the effect of ties on job outcomes is still cleanly identified.

After adding all controls, our search regression takes the form:

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij}^S \quad (8)$$

Here ω_i is user specific random effects and θ_j is mode specific fixed effect dummy. Notice that by controlling for user and mode specific heterogeneity, we control for significant unobserved variations across modes and users. $\alpha_1 = \delta_j + \gamma_j * \varphi_{j,1}$ and $\alpha_2 = \varphi_{j,2} * \gamma_j$ directly identified. E_i^F is the number of Facebook connections for user i and duration Dur_i is the length of unemployment. We also split E_i into strong and weak-ties separately to explore how these ties affect search time. The key variable of interest is the estimate on social embeddedness (α_2). A positive estimate suggests that users with higher online connections, on average, search more.

While equation (7) estimates the overall search efforts across all modes, we are also interested in understanding how the OSN connections affect search effort on OSN relative to other modes. If a user has larger number of weak and strong-ties on OSN, does s/he proportionally search more on OSN? If yes, it suggests that people perceive OSN ties to be less portable and more relevant for outcomes received from OSN. Thus, the regression is

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_{2a} * E_i * D_s + \alpha_{2b} * E_i * D_o + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij}^S \quad (9)$$

D_s is dummy for online social network search mode while D_o is a dummy for other search modes. Thus, we estimate if online social ties affect search allocation differently for OSN mode than the other modes. In equation (9) we normalize search time by controlling for total search intensity.

Notice from 7a and 8 that many parameters appear in both regressions, indicating computational constraints. Thus we jointly estimate (7a and 8; search effort and job leads) to recover structural parameters for cost. We then estimate interviews and offers as individual regressions.⁶ We first report the estimates from joint estimation of (7a and 8) and (7a and 9) in the two columns of Table 6. The left out dummy (in θ_j) is the search mode “agencies.” Since our sample size is limited, we do not jointly estimate search effort regression in equation (8) with job leads, interviews and offer model in equations (7a, b and c).

From the table below, notice that the coefficients for all dummies are positive. This suggests that, relative to agencies, people devote more time to online social networks, the Internet, print media and friends and family when searching for jobs. Statistically, job seekers allocate most time searching for jobs on the Internet followed by the online social networks, which reflects the low cost of search and ease of submitting a job application online.

⁶ One can jointly estimate interviews and leads, and offers and interviews as well. But they yield almost identical results.

We see that people with more strong-ties search less on all modes. In terms of economic significance, an estimate of -0.26 indicates that a 10% increase in number of strong-ties decreases the search effort by about 1.6 minutes per week. An implication of this result is that strong-ties, in general, suggest a social capital that is not specific to a mode and may suggest the multiplexed (Verbrugge 1979) nature of those relationships. Thus users with larger number of strong-ties spend less time in searching for job because of two potential explanations: one, strong-ties are more willing to help and thus a job seeker doesn't need to repeatedly contact those connections to seek help with job search; two, unemployed job seekers are more conservative (possibly because of a concern about their social reputation) in their search approach and prefer not to disclose their unemployment status to close friends and family.

Facebook connections, a measure of social behavior of an individual, have a positive and significant effect on the search intensity. We believe this to be true because online connections on Facebook (like LinkedIn) have a large share of weak-ties, which have positive effect on search intensity. Prior employment wage has a positive and significant effect on search intensity, which is intuitive as a higher financial loss may drive higher search intensity.

Search Effort (hours/week)	Coeff (Std Dev)	Coeff (Std Dev)
Dummy (Online Social Networks)	6.136 (1.853)***	5.737 (1.873)***
Dummy (Offline Friends & Family)	2.281 (1.832)	2.246 (1.843)
Dummy (Internet)	11.75 (1.739)***	11.77 (1.751)***
Dummy (Print Media)	4.082 (2.019)**	4.229 (2.03)**
Log (LinkedIn Strong-Ties)	-0.263 (0.06)***	
Log (LinkedIn Weak-Ties)	0.153 (0.039)***	
SN * Log (LinkedIn Strong-Ties)		-0.053 (0.059)
SN * Log (LinkedIn Weak-Ties)		0.113 (0.057)**
OT * Log (LinkedIn Strong-Ties)		-0.358 (0.075)***
OT * Log (LinkedIn Weak-Ties)		0.197 (0.046)***
Log (Total Facebook Ties)	0.058 (0.02)***	0.062 (0.022)***
Log (Unemployment Spell)	0.518 (0.379)	0.551 (0.381)
Log (Salary)	5.165 (2.449)**	5.414 (2.467)**
Experience	-0.021 (0.064)	-0.024 (0.064)
Married (yes = 1)	0.347 (0.744)	0.316 (0.75)
Sex (female = 1)	-0.497 (0.657)	-0.506 (0.66)
Education (College Graduate)	-0.5 (0.952)	-0.581 (0.958)

Education (Graduate Degree)	-0.867 (1.107)	-0.962 (1.115)
Race (White)	1.458 (1.007)	1.462 (1.011)
Race (Black)	1.404 (1.474)	1.423 (1.479)
Race (Hispanic)	2.276 (1.459)	2.281 (1.466)
Employment Value (Online Social Networks)	0.575 (0.858)	0.644 (0.864)
Employment Value (Offline Friends & Family)	1.392 (0.918)	1.463 (0.924)
Employment Value (Internet)	1.334 (0.933)	1.391 (0.941)
Employment Value (Print Media)	0.648 (0.375)*	0.677 (0.377)*
Employment Value (Agencies & Career Fairs)	1.568 (0.855)*	1.635 (0.86)*
Total Search Intensity	0.192 (0.015)***	0.193 (0.015)***
_cons	-26.031 (11.831)**	-27.223 (11.911)**
N = 480, bivariate joint likelihood estimates User (96 groups) random effect Standard deviation in parenthesis Significance: *(p<0.1), **(p<0.05), ***(p<0.01) Omitted dummies: Race(Asian & Other), Education(Diploma & Other), Search Mode (Agencies)		

Table 6: Time spent on job search using various job search modes

In the first column we tested the aggregate effect of online ties on job search, now we examine the effect of these ties on search behavior on online social network relative to other modes. To accomplish this we created two dummies and interacted online ties with those dummies. The results are presented in column 3 of Table 6. We see that the estimates of strong-ties and weak-ties interacted with online social networks and are not significantly different; i.e., it is the weak-ties that stimulate higher search intensity. An increase in the number of online strong-ties, which serve as a proxy for social capital offline or online, reduces the search intensity by an unemployed job seeker on traditional job search modes. The effect of strong-ties is not significant on online social networks.

5.1.1 Sequential Model (Search Intensity Affecting Job Leads)

As discussed earlier, job search delivers outcomes that are sequential in nature. Since we collected information from job seekers about each of the job outcomes, we are able to understand the role of search on job leads and subsequently on other outcomes. Thus we could estimate which search mode is more effective in converting search to leads, leads to interviews, and interviews to offers

Here we consider the following three non-linear models:

$$JO_{i,j}(II_{i,j}, X_i, E_i) = (\tau_{0,j}^1 + \tau_{1,j}^1 II_{i,j}) * \exp(\varphi_{0,j}^1 + \varphi_1^1 X_i + \varphi_{2,j}^1 E_i) + \varepsilon_j^1$$

$$II_{i,j}(IL_{i,j}, X_i, E_i) = (\tau_{0,j}^2 + \tau_{1,j}^2 IL_{i,j}) * \exp(\varphi_{0,j}^2 + \varphi_1^2 X_i + \varphi_{2,j}^2 E_i) + \varepsilon_j^2$$

$$IL_{i,j}(s_{i,j}, X_i, E_i) = (\tau_{0,j}^3 + \tau_{1,j}^3 s_{i,j}) * \exp(\varphi_{0,j}^3 + \varphi_1^3 X_i + \varphi_{2,j}^3 E_i) + \varepsilon_j^3$$

As before, we control for mode specific unobserved effect by using a mode specific dummy. We allow the errors to be correlated for the same user using different modes. This controls for user specific unobserved. And, as before, we estimate two models. In the first we estimate the effect of online ties (strong and weak) on job leads, interviews, and offers from all search modes. In the second, we estimate the marginal effects of ties on leads, interviews, and offers from online social network search mode vs. all other models.

Since we are estimating nonlinear regression, we report the marginal effects in Table 7 below. First we look at the job leads model that is estimated jointly with the search. Notice that search increases job leads significantly: an unemployed job seeker is submitting a new job application every three hours of search. As discussed earlier, the effect of ties on job outcomes is not straightforward. More ties affect search which in turn affects job leads. However, ties also have a direct effect on job leads. From the results in column (1), the effect of strong-ties is negative on leads across all modes but the effect of weak-ties is positive. Increasing the number of weak-ties by 10% increases the number of job leads by 0.07. Although the effect is small, it is worth noting that the cost to increase the number of weak-ties on SNS is very low and the effect is non-linear.

The effect of strong-ties on job leads is surprising. Higher number of strong online ties seems to reduce the number of leads. It may be that more strong-ties alone are not very useful in generating leads possibly because strong-ties tend to provide little or no new information to a job seeker. By definition most job leads are new pieces of information that serve as potential job opportunities matching a user's skills for which a job seeker submits a job application. A large number of weak-ties are thus needed for new job lead generation.

	Job Leads		Job Interviews		Job Offers	
	Effect of ties on all modes	Effect of ties on OSN vs other modes	Effect of ties on all modes	Effect of ties on OSN vs other modes	Effect of ties on all modes	Effect of ties on OSN vs other modes
	(1)	(2)	(3)	(4)	(5)	(6)
Search Intensity	0.336 (0.064)***	0.332 (0.066)***				
Job Leads			0.11 (0.027)***	0.111 (0.027)***		
Job Interviews					0.11 (0.023)***	0.09 (0.022)***
Dummy (OSN)	0.469 (1.294)	-3.405 (1.648)**	-0.557 (0.291)*	1.373 (1.276)	0.354 (0.265)	-0.107 (0.119)
Dummy (FF)	1.222 (1.427)	1.101 (1.411)	-0.324 (0.339)	-0.32 (0.346)	0.159 (0.195)	0.056 (0.129)
Dummy (Internet)	2.156 (1.471)	1.984 (1.475)	0.242 (0.39)	0.242 (0.394)	0.021 (0.126)	-0.002 (0.089)
Dummy (Print Media)	0.821 (1.388)	0.62 (1.362)	-0.505 (0.277)*	-0.501 (0.278)*	-0.002 (0.182)	-0.086 (0.114)
Log (Strong-Ties)	-1.054 (0.405)***		0.386 (0.141)***		0.112 (0.027)***	
Log (Weak-Ties)	0.741 (0.251)***		-0.083 (0.09)		0.019 (0.015)	
SN * Log (Strong-Ties)		-0.303 (0.596)		0.096 (0.026)**		0.093 (0.041)**
SN * Log (Weak-Ties)		1.234 (0.453)***		-0.228 (0.118)*		-0.043 (0.023)*
OT * Log (Strong-Ties)		-1.224 (0.4)***		0.425 (0.148)***		0.117 (0.026)***
OT * Log (Weak-Ties)		0.767 (0.246)***		-0.082 (0.097)		0.011 (0.018)
Log (Facebook Ties)	0.125 (0.16)	0.126 (0.155)	0.098 (0.066)	0.102 (0.065)	0.031 (0.011)***	0.022 (0.01)**
Log (Unemployment Spell)	0.103 (0.323)	0.078 (0.317)	0.003 (0.132)	-0.015 (0.125)	0.009 (0.034)	-0.027 (0.024)
Log (Salary)	0.487 (1.041)	0.272 (1.081)	0.643 (0.369)*	0.627 (0.376)*	-0.164 (0.063)**	-0.163 (0.058)***
Experience	0.034 (0.059)	0.033 (0.059)	-0.021 (0.023)	-0.022 (0.024)	-0.032 (0.006)***	-0.028 (0.006)***
Married (yes = 1)	0.747 (0.773)	1.001 (0.742)	-0.392 (0.321)	-0.392 (0.323)	0.405 (0.093)***	0.312 (0.095)***
Sex (female = 1)	-1.835 (0.578)***	-1.72 (0.554)***	0.128 (0.214)	0.104 (0.218)	-0.026 (0.054)	-0.073 (0.048)
Education (College Graduate)	-3.213 (0.78)***	-3.258 (0.753)***	-0.068 (0.334)	-0.025 (0.35)	-0.048 (0.111)	-0.023 (0.1)
Education (Graduate Degree)	-2.377 (0.979)**	-2.464 (0.924)***	-0.489 (0.391)	-0.419 (0.407)	0.028 (0.109)	0.095 (0.099)
Race (White)	-1.485 (2.485)	-1.819 (2.377)	-0.254 (0.337)	-0.19 (0.336)	0.086 (0.051)*	0.089 (0.044)**
Race (Black)	-2.042 (1.594)	-2.195 (1.393)	-0.45 (0.275)*	-0.47 (0.278)*	0.02 (0.085)	-0.06 (0.056)
Race (Hispanic)	-0.059 (2.156)	-0.521 (1.891)	-0.933 (0.174)***	-0.939 (0.166)***	0.747 (0.502)	0.155 (0.224)
R2	0.663	0.667	0.615	0.617	0.660	0.684
N	338	338	268	268	179	179
Clusters	96	96	95	95	81	81
Conditional on	Search		Job Leads		Job Interviews	

Non-linear least square regression average marginal effects; standard deviation in parenthesis
Significance: *(p<0.1), **(p<0.05), ***(p<0.01)
Omitted dummies: Race(Asian & Other), Education(Diploma & Other), Search Mode (Agencies)

Table 7: Job outcomes (leads, interviews, and offers) received as dependent variable for non-linear estimation

In column (2) we examine the effect of ties on outcomes from OSN vs. other modes. Here strong-ties have no effect on job leads from social networks. However, weak-ties are highly significant and a 10% increase in the weak-ties increases the number of job leads received by 0.12. While the effect of weak-ties on other modes is also positive, the estimate is smaller than

for OSN (both Wald test and t-test confirm this). The effect of strong-ties is still negative and significant for other modes.

In column (3) we estimate the probability of interviews conditional on job leads. Notice that the effect of strong-ties is now highly significant but that of weak-ties is not. This suggests strong-ties do a much better job of converting leads into interviews. When we interact ties with search modes, the effects persist (see column 4). Note the negative and significant effect of weak-ties on OSN; more weak-ties are not necessarily useful in converting leads into interviews. It may be that for leads to convert into interviews, ties have to make phone calls or write recommendation letters. These are costly activities and only strong-ties may be willing to undertake them. So while weak-ties may help to obtain a lead, they do not necessarily help in converting these leads into interviews.

Analyzing job offers (column 5 and 6), we see results consistent with those of the job interview regression: strong-ties play a significant positive role in job offers and weak-ties suggest a negative effect on online social networks and no effect on job offers from traditional search modes.

The counterintuitive negative marginal effect of weak-ties on job interviews and offers supports the principle of reflected exclusivity⁷ (Krackhardt 1998), suggesting that a large number of weak-ties may reduce the strength of strong-ties that are more valuable in converting job leads to interviews and offers. This incongruity may result from the communication overhead associated with connections. If a job seeker allocates more time to communicate with weaker connections and thus less time to strong connections, then s/he might not be able to receive optimum level of benefits from the strong-ties. Although we see these negative coefficients to be marginal effects of social connections on job outcome, the true impact still needs to be evaluated.

⁷ "a friend of the world is no friend of mine" - Krackhardt paraphrased Jean-Baptiste Poquelin (Moliere) *The Misanthrope* (1966) Act I, Scene I "L'ami du genre humain n'est point du tout mon fait" ("friend of the whole human race is not to my liking")

5.1.2 Role of Social Connections on Job Outcomes

As we explained earlier, more ties affect search intensity, however the effect of ties on job outcome is complex. Our estimates from Table 6 confirm that users with more ties are more likely to search. To estimate the effect of social capital on job outcomes, we use the equation discussed in section 4.2:

Role of Strong-Ties on Job Outcomes (j= Online Social Network - LinkedIn)

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = -0.303 - 0.332 * 0.053 \approx -0.321$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = 0.096 - 0.111 * 0.321 \approx 0.061$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = 0.093 + 0.09 * 0.061 \approx 0.099$$

Role of Weak-Ties on Job Outcomes (j= Online Social Network - LinkedIn)

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = 1.234 + 0.332 * 0.113 \approx 1.272$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = -0.228 + 0.111 * 1.272 \approx -0.087$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = -0.043 - 0.09 * 0.087 \approx -0.051$$

Thus, an increase in weak-ties on LinkedIn will result in more job leads but will decrease the number of job interviews and offers received from LinkedIn. Similarly, an increase in strong connections on LinkedIn will decrease the job leads but will increase the number of job interviews and offers received by an unemployed individual.

In summary, the effect of change in strong- and weak- ties on job outcomes from online social network could be expressed as:

$$\Delta JL_{i,j} = 1.272 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} - 0.321 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}}$$

$$\Delta JI_{i,j} = -0.087 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.061 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}}$$

$$\Delta JO_{i,j} = -0.051 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.099 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}}$$

These three equations could be used to optimize the number of connections on online social networks to maximize the job outcomes. Although it may appear that strong-ties are most useful, a job seeker needs to search more to get leads and more leads will convert to more interviews, which will give more offers. Thus one needs to find an optimal allocation of ties on online social networks like LinkedIn.

A major limitation here is that the marginal effect of strong-ties on search effort and on job leads is not statistically significant at 95% level. To better understand the net effect of search allocation and social network on job outcomes we will need to understand the confidence interval around each coefficient, which we leave for future extension of this work.

5.1.3 Estimating Structural Parameters

We see from equation 5 that there are constraints added on to the estimated parameters of equation 7a because job leads is a function of search, which requires the two models (search as dependent variable and job leads as a function of search) to be estimated jointly. Thus we have maximized the following bivariate likelihood model to recover the structural parameters in both the cost (equation 4) and benefit (equation 3) functions:

$$L = \prod_i \prod_j \Phi(JL_{i,j}(s_{i,j}, X_i, E_i)) * \Phi(s_{i,j}(X_i, E_i, R_{i,j}))$$

Estimates for the parameters in the cost function are given in the table below:

Cost Function	OSN	FF	IN	PM	AG
γ_j	0.64	1.46	1.39	0.68	1.63
δ_j / γ_j (Log(FB_Connections))	0.04	-0.01	-0.01	0.04	-0.01
δ_j / γ_j (Log(Unemployment_Spell))	0.9	0.42	0.44	0.86	0.38
δ_j / γ_j (Log(Salary))	8.51	3.8	4	8.1	3.41
δ_j / γ_j (Experience)	-0.06	-0.04	-0.04	-0.06	-0.04
δ_j / γ_j (Married)	0.43	0.15	0.16	0.4	0.13
δ_j / γ_j (Sex_Female)	-0.32	0.12	0.1	-0.29	0.15

From the cost function (equation 4) estimates, we see that scale coefficient (γ) is smallest for online social networks, which reflects the low overall search costs of the platform. We believe that it is intuitive that online social networks have the lowest cost because they tend to combine the strengths of online platform for almost costless communication with social ties that individuals are comfortable communicating with. On the other hand, we believe that the cost of search is high for offline friends and family because it takes significant effort and time to update those connections about job loss and seek help in finding a new job. The Internet seems to be a platform with surprising results for cost coefficient, and we believe this is the case of information overload. Unemployed job seekers may find numerous opportunities on the Internet and may find it hard to choose the ones worth the time it takes to submit a job application.

The coefficients for print media and agencies are somewhat intuitive as magazines and newspapers are available ubiquitously and provide only limited information that could be processed by a job seeker in a given time frame. The cost for agencies is highest because of the need for interpersonal communication with an agency or additional service costs.

The estimates of structural parameters for benefit function are presented below:

$$JL_{i,j}(s_{i,j}, X_i, E_i) = (\tau_{0,j}^3 + \tau_{1,j}^3 s_{i,j}) * \exp(\varphi_{0,j}^3 + \varphi_1^3 X_i + \varphi_{2,j}^3 E_i) + \varepsilon_j^3$$

$$JL_{i,j}(JL_{i,j}, X_i, E_i) = (\tau_{0,j}^2 + \tau_{1,j}^2 JL_{i,j}) * \exp(\varphi_{0,j}^2 + \varphi_1^2 X_i + \varphi_{2,j}^2 E_i) + \varepsilon_j^2$$

$$JO_{i,j}(JI_{i,j}, X_i, E_i) = (\tau_{0,j}^1 + \tau_{1,j}^1 JI_{i,j}) * \exp(\varphi_{0,j}^1 + \varphi_1^1 X_i + \varphi_{2,j}^1 E_i) + \varepsilon_j^1$$

Benefit Function Structural Parameter	Job Leads		Job Interviews		Job Offers	
	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)
τ_0	0.03	0.03	0.08	0.08	-10.05	-10.05
τ_1	1.22	1.22	0.02	0.02	28.49	28.49
ϕ_{0j}	-0.69	0.57	0.82	-0.13	-0.68	-0.07
ϕ_{2j} (Log(LinkedIn Strong-Ties))	-0.08	-0.28	0.08	0.33	0.48	0.61
ϕ_{2j} (Log(LinkedIn Weak-Ties))	0.17	0.15	-0.18	-0.06	-0.23	-0.06
ϕ_1 (Log(FB_Connections))	0.05	0.05	0.08	0.08	0.11	0.11
ϕ_1 (Log(Unemployment_Spell))	-0.04	-0.04	-0.01	-0.01	-0.14	-0.14
ϕ_1 (Log(Salary))	-0.10	-0.10	0.49	0.49	-0.85	-0.85
ϕ_1 (Experience)	0.03	0.03	-0.02	-0.02	-0.15	-0.15
ϕ_1 (Married)	0.06	0.06	-0.30	-0.30	1.67	1.67
ϕ_1 (Sex_Female)	-0.46	-0.46	0.08	0.08	-0.40	-0.40

From the estimate of mode specific constant (ϕ_{0j}) we see that the number of job leads received from online social networks is lower when compared to the average from all other job search modes. This is because the number of job posts, although steadily growing, is still low when compared to the job posts advertised in print media or Internet job boards. This coefficient for job interviews is larger for online social networks, suggesting that the conversion rate of job leads to interviews is higher for online social networks when compared to the average of other traditional job search modes. We believe this is the case because many recruiters are moving towards online social networks to screen candidates.

As previously discussed, we see a negative effect of strong online connections and a positive effect of weak online connections on job leads, which suggests that strong-ties contribute less new information whereas weak-ties provide more new information. The roles of strong-ties and weak-ties reverse when it comes to job interviews or offers.

The positive coefficient for strong-ties suggests that strong connections play a more significant role in converting the job leads to interviews or offers whereas the weak-ties have a smaller rate of conversion to job interviews or offers. The effect of online weak-ties is negative when it

comes to interviews or offers as the trust placed on weak-ties is likely lower, thus impacting the conversion rate from job applications to interviews to offers.

These results are also evident from the summary statistics seen in section 3.2 on job search using online social networks, where we find that users spend the most time on online social networks searching for jobs posted on the network and are able to submit applications to direct postings. It is worth noting that as the number of ties increases, the number of potential job posts increases exponentially. The conversion rate for leads to interviews is highest for jobs found through recruiters and the rate for interviews to offers is highest for strong-ties. This supports our findings that compare the job search and outcomes from online social networks to traditional job search modes.

In summary, the estimated structural parameter allows us to build both cost and benefit functions for all five job search modes, which should help the job seekers allocate their job search effort effectively on various modes and improve the probability of outcomes.

6 CONCLUSION & DISCUSSION

This study, like most survey-based studies, faces the limitation of not representing the entire population accurately. The survey responses received from the unemployed job seekers represent individuals that are more educated and earn a higher income. Still, this is the first study – to our knowledge – that investigates the role of online social networks in the labor market. We have found that the continuously expanding social capital plays an important role in the job search. But since the effects of weak-ties and strong-ties are different in the job market, the results presented here could be used to strategically build a social capital to maximize the job offer probability.

In this study, we have developed an empirical structural job search model to describe the behavior of job seekers and to find the optimal search effort allocation. This approach was useful to address the rising concern about homophily when estimating the role of social capital in the labor market. Unfortunately this study does not conduct a controlled random experiment

that would minimize the effect of homophily, but it does a reasonable job of suggesting that online social capital has a positive effect on time spent by job seekers on online social networks.

This study also echoes the argument (Kuhn and Skuterud 2004) suggesting that Internet-enabled searches or low-cost job search platforms could reduce the perceived value of a job seeker. This could also be assumed to exist because Internet-enabled platforms result in many job applications for every job posting, whereas the print media requires more effort for each application and thus results in fewer applications leading to a higher number of job interviews. Many career transition experts suggest that job seekers find leads from various search modes and then apply for positions like job seekers did a decade ago – mailing a resume and cover letter. This could improve the ratio of interviews vs. applications.

Furthermore, we used the productivity model for understanding the role of social capital on job offers and intermediate job outcomes. This is important because it allows us to estimate the effect of effort on a more direct outcome. This allows a job seeker to maximize the offer probability if information from one search mode could be ported to another mode. For example, a job seeker could find job leads through the Internet and then tap into his/her social capital to convert those leads into interviews and offers.

6.1 LIMITATIONS & FUTURE WORK

One limitation of our approach is that we use multiple non-linear models for analysis that caused the burden of jointly estimating the productivity model and the search model with the added challenge of simultaneous estimation across all job search modes. Both joint and simultaneous estimation of job outcomes requires more sophisticated econometric modeling and is left for future extension of this work.

It has been shown that individuals are impatient while being unemployed and are assumed to be willing to work at lower wage (DellaVigna and Paserman 2004), but for simplicity we assumed the reservation wage to be equal to the wage received during the last employment

term. This would reduce the computed utility from employment for all individuals but we believe that the user random effect should account for this difference because the difference should be dependent on various user characteristics.

To extend and strengthen the current findings we need to collect more data and possibly longitudinal data to use lag as an instrument and to account for various endogeneity issues. Additionally, we plan to jointly estimate the job outcomes across each search mode and use the nonlinear offer probability function to estimate the individual productivities. Search allocation and job outcomes from search approaches within online social networks could use further analysis. In summary, this study shows that the online social networks play a significant role in the job search by unemployed professionals.

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