ROLE OF ONLINE SOCIAL NETWORKS IN JOB SEARCH BY UNEMPLOYED INDIVIDUALS

Completed Research Paper

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Abstract

The recent growth of online social networks has enabled job seekers to stay connected with all of their acquaintances. 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 online social network plays a role in driving her job search behavior. Secondly, we examine how the ties (weak and strong) and search intensity affect the job outcomes (job leads, interviews and offers) received from online social networks vs. those from other job search modes like career fairs & agencies, newspapers & magazines, internet, and close friends and family (offline). Using a survey data of 109 unemployed job seekers, we 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.

Keywords: online social networks, professional networks, strong ties, weak ties, job search, search intensity, job outcomes

Introduction

"How to effectively search for jobs?" is an enormously important question for individuals, firms and policy makers. Governments around the world spend millions in trying to train and find jobs for unemployed individuals. Over the last 4 decades job seekers have modified their job search efforts as the technology has shaped this process. According to Monthly Labor Review of 1973 (Bradshaw 1973) 71 percent job seekers reached out to the employers directly, 40 percent reached out to agencies (public or private), 14 percent used their formal and information social connections to search for jobs. This changed slightly in 1991 (Bortnick and Ports 1992) when 22 percent of job seekers reached out to their friends and family. Expansion of Internet since late 90's has reshaped this again because of the growth of Internet based firms (like Monster.com) who specialize in matching individuals with firms.

A key element in job search process has been the role of individuals' social connections; extant literature suggests that "who you know" plays a very important role in someone 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 on the information. These factors are especially important since online platforms have enabled greater competition amongst the job seekers as every job post is now accessible to every job seeker across the globe. According to a survey conducted by CareerBuilder.com[1] in 2009, each job post received over 75 resumes on average. Social connections could potentially help job seekers in reaching directly to hiring managers and improving their probability of visibility (from 1 in 75) because of trust on quality of information shared by the common connection.

Growth of Internet and broadband has led to a meteoric rise in online social networking firms like Facebook that allow users to connect with their friends. We are still grappling with the impact of Facebook on our society. There is a lot of work which examines different aspects of social networks and how it affects various individual and collective outcomes (Ellison et al. 2007; Valenzuela et al. 2009). However, most social networking sites (SNS) have unique characteristics and thus all are not used for job search. There are online social networking sites like LinkedIn which have grabbed a lion's share in this space. A cover-page article in Fortune magazine (Hempel 2010) suggested that connecting on LinkedIn is more useful than exchanging business cards or churning resumes. 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 used by approximately 0.25% of internet population with each spending 4 minutes on average on these websites. However, online social (or professional) networks surpass these numbers by a factor of 10. Similar statistics from Alexa (November 2010) show that LinkedIn is consumed by 3.4% of daily internet users each spending on an average 7.4 minutes/day. According to LinkedIn (November 2011), one new member is joining the portal every second with a current user-base of over 100 million people in 200 countries. Employers are responding to this growth by positioning, advertising and using their employees' social networks to recruit potential employees.

A fundamental difference in online social networks, compared to users' formal and information network is the ability of individuals to maintain and manage far more online connections - average number of friends on facebook.com[2] is 130. However, most of users' network consists of what one calls "weak ties" (Granovetter 1973). This raises the question about the effectiveness of these online professional networks in the job search process. Too many connections while helpful may 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 network of an individual. It is also not clear if unemployed users consider online social networks to be a great tool for job search. After all, unemployment information is not something a user may be willing to share with her network especially when the network consists of large number of weak ties. So users may be reluctant to conduct directed search on these networks.

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

[2] http://www.facebook.com/press/info.php?statistics

In summary, while there is a lot of hype and press surrounding online social networks, there is little empirical work that has examined this issue in any detail. This paper seeks to examine two major questions: 1) how are people allocating their job search efforts across different modes, especially, online social networks? 2) Are online networks effective in generating job offers?

Answers to these questions require having access to some detailed data on users' job search behavior. To do this, we administered a survey to unemployed users asking them detailed questions on their job search methods, their online and offline social networks, and job outcomes. Using completed survey of 109 users, we find that job seekers with larger number of connections on online social networks (LinkedIn in this case) spend more time searching for jobs on LinkedIn. We also find that "strength of weak-ties" and "strength of strong-ties" arguments hold for online social networks albeit under different job outcomes. Weak-ties continue to help job seekers find new job leads whereas the 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 hype around 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 hurt them when seeking help from their strong connections in converting those leads to offers.

We believe our paper is important on several dimensions. First, the whole domain of online social networks and job outcomes is ripe for serious empirical work. The answers to our research questions are important to individuals seeking jobs and firms like LinkedIn whose business models depend on answers to these questions. Even more importantly, policy makers (especially Department of Labor) who spend significant resources on training users and employers on how to efficiently find a match would find our research important and useful. Second, we collect a unique and detailed data set. Very little empirical work with particular focus on online networks has been possible due to lack of detailed data in the past. Despite some usual limitations of survey data, we believe our paper will be able shed some light on questions largely unanswered due to data unavailability. We hope that our work will pave the road for many promising future studies, which are undoubtedly needed to investigate this very important issue.

This paper is organized as follows. We first provide a literature review followed by details about the data including summary statistics. Then we present our empirical approach and results and finally conclude with a discussion and implications of results, followed by research limitations and future possibilities.

Literature

Granovetter's strength-of-weak-ties theory (Granovetter 1973) suggested that friends & family being close to an individual do not contribute to the discovery of a newer content (job leads in his study), but it is the weak-ties (people who we know but do not communicate with on a regular basis) that 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 et al. 2001) but may have different impacts based on the interaction between the ties and the size of the network. It was also shown (Krackhardt 1992) that strong-ties are important in causing actual changes whereas weak-ties may lead to more diffusion of information. This may suggest that weak ties may be useful in generating job leads but strong ties help more in getting the final job offers. At the same time studies on structural-holes (Burt 1995) showed that the position in network matters more than the tie-strength.

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 a bank's recruitment process the role of social networks was found to be positive and significant (Petersen et al. 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). 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). As pointed in a recent review (Mouw 2006), estimating the role of social capital has been increasingly challenging due to homophily (McPherson et al. 2001) and reflection (Manski 1993). (Mouw 2006) suggests that an investigation of

social capital on job search intensity was overlooked, which was an important component in determining if online social capital really helps in labor market. Additionally, extant literature is also found to be prone to endogeneity problems (Durlauf 2002). Some have also argued that there may be no significant value in informal social channels when compared to other channels (Lin 1999).

However, online social networks have enabled the formation of larger social networks while increasing the transparency of information shared between individuals. This openness in sharing the information and larger potential for influence has changed the traditional approaches of evaluating the role of social networks. Some recent studies have tried to address the challenges of identifying the peer influence on online networks (Garg, Smith, and Telang 2011) (Aral et al. 2009) and shown that peers do matter in diffusion and discovery of novel information. Online social networks allow users to maintain a large number of connections that are weak-ties that exist between acquaintances found through work, focus groups, affiliations, etc. Individuals are able to find information about potential job opportunities more quickly because of reduced search costs and large number of weak-ties. But the role of this increased number of weak- or strong-ties on job outcomes is still novel to the field.

Online social networks have been growing rapidly because of low cost associated with adding and maintaining connections. This low costs is true for most Internet enabled platforms and Internet has been used increasingly both by unemployed and employed workforce because of low search costs allowing job seekers to collect more information about potential opportunities and selectively submit their job applications (Stevenson 2008). Internet has negative effect on the unemployment duration of job seekers (Kuhn and Skuterud 2004) and is shown to be more effective when compared to newspaper ads or direct application but it is less effective compared to social networks (Feldman and Klaas 2002). Thus online social networks combine the strength of ties and low costs associated with Internet resulting in a powerful job search platform.

Job search by unemployed workforce is less effective when compared to the employed work force (Blau and Robins 1990) and diffusion of job lead information through network is dependent on duration of unemployment (Calvó-Armengol and Jackson 2004). Thus understanding the role of online social networks for unemployed job seekers is even more valuable for the workforce, which has become a victim of downsizing by large corporations in the current troubled economy. Through this paper we try to take a step forward at understanding the role of online social networks on job search by unemployed workforce using a survey data of unemployed individuals.

Data

Traditionally labor economists have relied on National Longitudinal Survey (NLS) or Current Population Survey (CPS) to examine how users search for jobs and in some cases how their social networks help them in job search (Holzer 1988). While these datasets have large number of observations, they do not contain enough details that are needed to answer the questions we outline in the introduction. For example, they do not have details on how many job leads, interviews and job offers a user has received. Additionally most of these surveys do not have any details on users' online social networks and search behavior.

To better understand the role of online social networks on job outcomes, we designed an institutional review board (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 was helping with job search. The survey contained questions about the individual's current employment status, motivations for job search, past and present job search strategies, familiarity and use of online social networks, and knowledge of using online social networks for job search. The survey was very detailed and required about 30 minutes of subject's time in answering all the questions regarding her job search approach. The survey asked unemployed individuals questions about their background (demographics, job search motivation), job search approach (prior to losing their job, after losing their job, and number of job outcomes), and use of online social networks (length of membership, frequency of use before and after job loss, and number

of strong- weak- and total- connections). Job outcomes refer to the number of job leads (job applications), interviews, or offers received.

To test if users would respond to the detailed questions asked in the survey and to check if the questions were clear, we created a pilot survey that was made available on the Internet and the link was shared with our peers and friends. The goal of the pilot was to gain any feedback to improve the questions in order to maintain the attention of the survey taker during the entire time. We made some adjustments to the questions based on the feedback received and the actual data from original survey was ignored for the study.

The outplacement firm had access to 288 individuals whose emails were available to the firm. Of the 288 emails sent, 163 individuals opened the email and 109 individuals took the survey. 8 surveys were not fully complete, 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 report created with help of professionals in the field. It should be noted that our survey was sent to mostly educated, white collared workers. Thus the sample is neither representative of general population nor is perfectly random. However, since we expect that educated and white collar workers are precisely the people likely to use online social networks. This implies that our survey targets users who can provide useful insight into the phenomenon of interest. Within the selected population set, we believe there is enough interesting variation that allows us to examine the question of job search and online social network reliably. Summary demographics for these individuals are presented in Table 1. We also believe that the limitations of our survey are not any different than other well published survey papers.

Table 1: Demographic Summary	
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

We asked users about five major search modes they used in job search (i) Internet (like monster.com), (ii) Online social networks (like LinkedIn), (iii) Offline close friends and family, (iv) Newspapers and print media, (v) job agencies and career fairs. Of 101 people, 89 individuals used internet as 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). Summary of the time spent on each of these modes and the time spent conditional on mode being used is given in Table 2.

Table 2: Search Intensity on Each Job Search Mode (mean values with std. dev.)		
Job Search Mode	**Count**	**Search Intensity (hrs./week)**
Agencies (AG)	43	4.79 (2.69)

Print Media (PM)	56	4.45 (3.13)
Internet Posts (IN)	89	14.39 (11.61)
Online Social Networks (SN)	77	8.79 (7.42)
Friends and Family (FF)	81	5.54 (4.13)

We explicitly ask users how many job leads, job interviews and job offers they found via each mode. The summary of search effort distribution across job search modes, search intensity on a mode, and job outcomes (number of leads, interviews, and offers) from each mode is presented in Table 3. The numbers are presented in terms of share (%). We see that job seekers allocated most time (41%) on Internet searching for jobs and submitted most applications (43%) through leads found on Internet. These large number of applications converted to a large share (49%) of interviews from jobs posted on the Internet but had a much smaller return in the share of offers received (26%). Job seekers spent relatively less time (19%) but found increasing share of leads, interviews and offers from their close friends – suggesting strength of strong-ties. Online social networks had a very consistent share of effort, leads, and interviews but jumped significantly in the share of offers (54%) received. We expect this is due to the transparency of information and availability of publicized recommendations for a job seeker on professional social networks like LinkedIn.

Table 3: Search Intensity & Job Outcome Share on Each Job Search Mode					
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

Next we asked users to specify how many connections they have and how many they consider to be weak and strong connections respectively. We defined strong connections as frequently communicated close friends or family members. Everyone else was considered a weak-tie so the sum of strong- and weak- ties equaled total connections. Distribution of total, strong, and weak connections on both Facebook and LinkedIn is presented in Figure 1. We observe that individuals have much larger share of strong-ties on Facebook yet a much larger share of weak-ties on LinkedIn. Individuals that did not use online social networks as a job search mode selected privacy concern as the most important reason for not using online social networks (like Facebook) and lack of sufficient job leads as the most important reason for not using online professional networks (like LinkedIn). It is also shown (Calvó-Armengol and Zenou 2005) that a large number of connections tend 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.

Histogram of Number of Ties on Online Social Networks
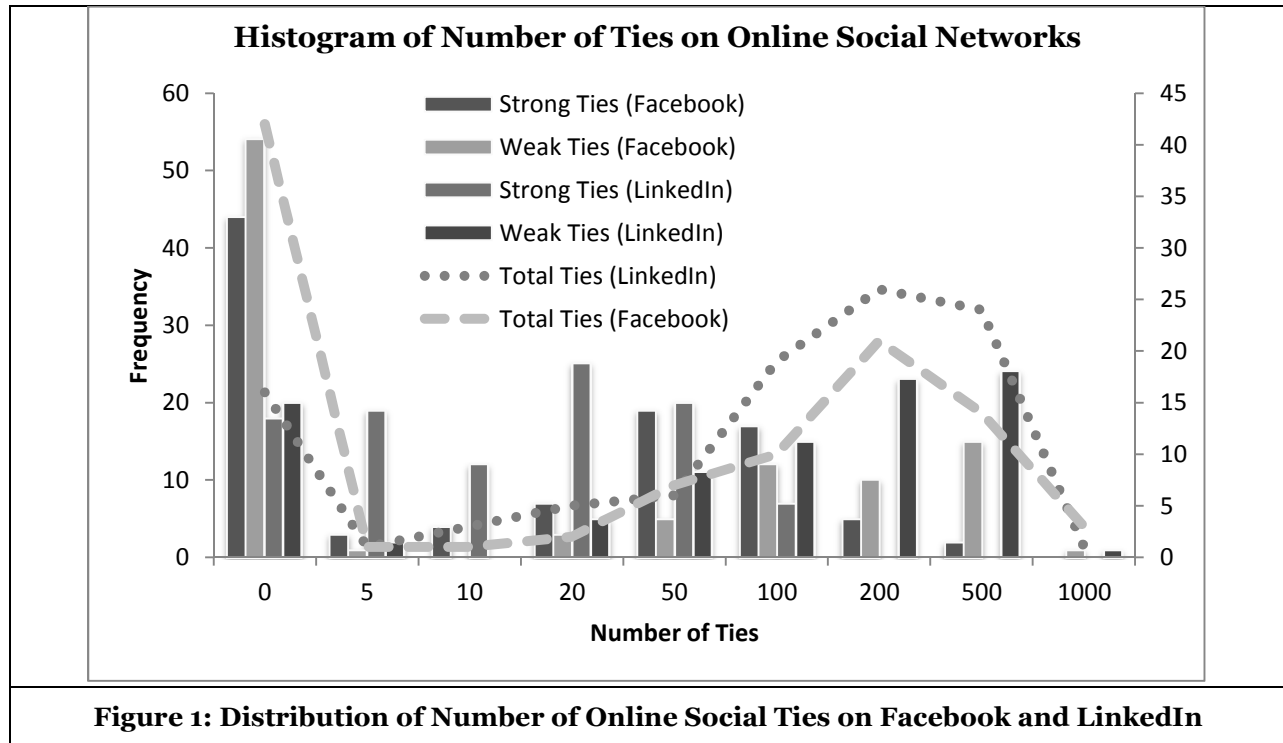
Figure 1: Distribution of Number of Online Social Ties on Facebook and LinkedIn

Empirical Analysis & Results

We are interested in exploring two main questions that we outline in the introduction. How do people allocate their times across different modes and how online connections affect those choices? Do online connections affect job outcomes? Unfortunately, job outcomes are also affected by how hard users are searching for jobs on a particular mode. Moreover, job search decision itself will be driven by how likely users think they will find a job. In short, the relationship between social connections, 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 users' expected benefits and cost calculation. In the following, 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 modes: 1) agencies [AG] - like libraries, career fairs, etc., 2) print media [PM] - newspapers, magazines, etc.), 3) internet job boards [IN] - like monster.com, hotjobs.com, etc., 4) online social networks [SN], and 5) close friends and family [FF].

Search Effort Allocation

As discussed previously and in prior research (Mouw 2003), it is important to understand the role of social network on the search effort to clearly identify any issues relating to endogeneity or homophily (McPherson et al. 2001). Individuals with larger social network could get benefit from their network because they are connected to a few influential and highly social individuals while there might be no significant value provided by the entire network. Thus it was suggested (Mouw 2003) that a clean identification should include the effect of social network on the search effort because a large social network would require more effort and more effort could translate into more positive job outcomes. Thus, as a first step, we test if size of social networks indeed plays a role in the search effort allocation by the unemployed workforce.

For simplicity, let's begin by assuming that job seekers allocate time on various job search modes as a linear function of their characteristics. Thus, our regression equation for search effort allocation could be written as:

$$s_{i,j} = \alpha_0 + \alpha_1 * X_i + \alpha_2 * E_i + \varepsilon_{ij} \tag{1}$$

Where i indexes an individual, j indexes search mode, X_i represents the user's characteristics (like education, experience, age, salary during last job, race, etc.), and E_i represents the embeddedness or social network of user i on online platform (like LinkedIn). Even though we do not observe users choices repeatedly, we do observe the same user over five modes. Thus we have a panel data set which allows us to control for unobserved user specifics and unobserved search mode specifics. So we can rewrite this as

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \varepsilon_{ij} \tag{2}$$

ω_i is user specific dummy and θ_j is mode specific dummy. If we include user specific fixed effects, we cannot estimate α_1 and α_2 directly. So we will control for user heterogeneity in the form of user random effects. Notice that by controlling for user and mode specific heterogeneity, we control for significant unobserved variations across modes and users. We will 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 of social embeddedness, α_2. A positive estimate suggests that users with higher online connections search more. However, there are many potential issues

(i) *Users are searching more because they expect more job offers which is unobserved.* Notice our optimal search model automatically incorporates the benefit function. From the benefit function it is clear that search effort will be higher if $\varphi_{j,2}$ (effect of social connections on job outcomes) is positive and large. Thus in our model, the estimate on E is positive because users expect E to influence job outcomes. We also use expected wages R as a way to control for expected wage distribution on a search mode.

One may still worry that some unobserved mode specific characteristics would not only drive search time but will also drive social network. So a mode may be more productive for reasons unknown. We control for these by using mode specific dummies.

(ii) Another concern is reverse causality. If users spend more time on LinkedIn looking for jobs, they are more likely to make more social connections. In our data, we ask users explicitly how many connections they had before they lost their jobs. Moreover, we also include unemployment duration as a possible control. Notice that we are testing the effect on online connections, which serve as proxy for social network outside of OSN, on search behavior on other modes as well.

(iii) One may still worry that some unobserved may be correlated with embeddedness. For example, some social users may search more on online social networks and also have more connections. First we utilize user specific random effects to control for unobserved. We also use Facebook connections as a control. So if users are more social, they are also more likely to have larger connections on Facebook.

After adding all controls, we have an estimable form for job search efforts as:

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \tag{3}$$

We include additional control in the form of E_i^F which is users' Facebook connections. Dur_i is the users' unemployment duration.

Notice that equation 4 estimates the effect of E on search effort across all modes. Thus we examine if higher number of strong (and weak) ties affect search effort on other modes. However, as we outlined

earlier, the effect may be dependent on the search model itself. Thus, we treat online social networks as one potential search mode and the remaining four modes as "other modes". We then interact E_i with these two modes. The goal is to estimate the marginal effect of an online tie (weak and strong) on search effort when the search mode is LinkedIn vs. other modes. Thus in this specification we examine if strong (and weak) ties affect search time on online social network search model vs. the other modes.

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * E_i * D_s + \alpha_2 * E_i * D_o + \alpha_3 * X_i + \alpha_5 * E_i^F + \alpha_6 * Dur_i + \varepsilon_{ij} \qquad (4)$$

Ds is dummy for online social network search mode while Do is a dummy for any other mode. The estimates of these three separate regressions are given in the two columns of Table 4 below. The left out dummy (in θ_j) is the search mode "agencies".

Table 4: Time Spent on Job Search Using Various Job Search Modes	
Search Effort (hours/week)	**Coeff (Std Dev)**
Dummy (Online Social Networks)	1.01 (1.275)
Dummy (Offline Friends & Family)	2.5 (0.516)***
Dummy (Internet)	11.144 (1.281)***
Dummy (Print Media)	0.378 (0.436)
SN * Log (LinkedIn Strong-Ties)	0.81 (0.637)
SN * Log (LinkedIn Weak-Ties)	0.902 (0.369)**
OT * Log (LinkedIn Strong-Ties)	0.972 (0.411)**
OT * Log (LinkedIn Weak-Ties)	-0.139 (0.236)
Log (Total Facebook Ties)	0.084 (0.169)
Log (Unemployment Spell)	0.305 (0.438)
Log (Salary)	1.055 (0.935)
Experience	0.087 (0.089)
Married (yes = 1)	-1.408 (0.992)
Sex (female = 1)	-0.256 (0.873)
Education (College)	-0.752 (1.051)
Education (Graduate School)	-0.733 (1.333)
Race (White)	1.944 (1.134)*
Race (Black)	2.148 (1.199)*
Race (Hispanic)	2.29 (1.452)
_cons	-7.228 (4.348)
R2	0.318
N = 450, ordinary least square regression estimates User (90 groups) random effect Standard deviation in parenthesis Significance: *(p<0.1), **(p<0.05), ***(p<0.01) Omitted dummies: Race(Asian & Other), Education(Other), Search Mode (Agencies)	

In Table 4, notice that the coefficients for all dummies except online social networks are significant. This suggests that people spend more time on Internet, print media and with friends and family for job search relative to agencies. The number of strong ties (which serves as a proxy for social capital) affects job search intensity on all other modes (except online social networks). In terms of economic significance, an estimate of 0.97 indicates that a 10% increase in number of strong ties increases the search effort by about 0.097 hour per week. This follows from the traditional argument about multiplexed ties (Verbrugge 1979), which suggests that some social connections could have overlapping social relationships. We believe these strong-ties exhibit multiplexed relationships that span across various modes of communication (like online or offline) and thus affect the search behavior across various job search modes.

Estimate of 1.01 on online social network simply suggests that users spend, on average, 1.01 hours more on social network relative to agency (if the number of connections is zero). Now, the estimate on weak ties interaction with online social network is positive and significant. This suggests users with more weak online ties are more likely to search on online social networks. A 10% increase in weak ties increases the time by about 0.09 hours per week. However, the estimate on strong ties is not significant for online network. Users with more strong online ties do not search more on online networks. It is the weak ties that stimulate higher search intensity.

In summary, larger number of strong ties stimulates more search on other modes but more number of weak ties stimulate more search on social networks. An implication of this result is that strong ties, in general, suggest a social network that is not specific to a mode and may suggest the multiplexed nature of those relationships. However, online weak ties probably cannot be readily leveraged on other modes. Since social network sites (SNS) allow users to connect with a large number of weak-ties at a small or no cost, these ties could be perceived valuable only on the platform of connection. Taking an example, if John Doe is connected with a close buddy Sam Smith on LinkedIn, he can utilize his help with job search irrespective of a job search mode being discussed. On the other hand if John worked with Sarah Jones as an intern during college and got connected with her on LinkedIn, he probably won't call her to ask for job leads and most likely will send her a message updating her about his employment status first. Thus strong-ties that add to social network define the job search behavior of an unemployed individual in general but the weak-ties on a SNS contribute to the changed behavior on that specific social networking site.

Job Outcomes

For empirical tractability and our interest in understanding the job outcomes, we need to assume functional forms for job offer rate. We will rely on prior literature for this function. 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:

$$\pi_{ij}\left(s_{ij},\ X_i,\ E_{i,}\right) = \lambda_{ij}\left(X_i, E_j\right) * \left(\tau_0 + \tau_1 s_{ij}\right) \tag{5}$$

$$where\ \lambda_{ij}(X_i, E_i) = \exp\left(\varphi_{0j} + \varphi_1 X_i + \varphi_{2j} E_i\right)$$

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 number of 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.

As discussed earlier, job search delivers outcomes that are sequential in nature; search effort will typically allow users to apply for relevant job opportunities, which will allow employers to call the job seeker for interviews and eventually make an offer. 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 if one search mode is more effective in converting search to leads, leads to interviews or interviews to offers. We believe that this information is useful for job seekers because of the portability of information enabling them to maximize the returns by using a blend of various job search modes.

Here we consider the following three non-linear models:

$$JO_{i,j}\big(JI_{i,j},\ X_i,\ E_i\big) = \big(\tau_{0,j}^1 + \tau_{1,j}^1\ JI_{i,j}\big) * \exp\big(\varphi_{0,j}^1 + \varphi_1^1 X_i +\ \varphi_{2,j}^1 E_i\big) +\ \varepsilon_j^1 \qquad (6)$$

$$JI_{i,j}\big(JL_{i,j},\ X_i,\ E_i\big) = \big(\tau_{0,j}^2 + \tau_{1,j}^2\ JL_{i,j}\big) * \exp\big(\varphi_{0,j}^2 + \varphi_1^2 X_i +\ \varphi_{2,j}^2 E_i\big) +\ \varepsilon_j^2 \qquad (7)$$

$$JL_{i,j}\big(s_{i,j},\ X_i,\ E_i\big) = \big(\tau_{0,j}^3 + \tau_{1,j}^3\ s_{i,j}\big) * \exp\big(\varphi_{0,j}^3\ + \varphi_1^3 X_i +\ \varphi_{2,j}^3 E_i\big) +\ \varepsilon_j^3 \qquad (8)$$

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.[3] As before, we estimate two models. In the first one we estimate the effect of online ties E (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 as opposed to the absolute parameter estimates. They are presented in Table 5 below.

Table 5: Job Outcomes (Leads, Interviews, and Offers) Received as Dependent Variable for Non-Linear Estimation			
	Job Leads	**Job Interviews**	**Job Offers**
Search Intensity	0.356 (0.07)***		
Job Leads		0.111 (0.027)***	
Job Interviews			0.09 (0.022)***
Dummy (OSN)	-2.096 (1.887)	1.373 (1.276)	-0.107 (0.119)
Dummy (FF)	1.199 (1.358)	-0.32 (0.346)	0.056 (0.129)
Dummy (Internet)	2.42 (1.401)*	0.242 (0.394)	-0.002 (0.089)
Dummy (Print Media)	0.801 (1.326)	-0.501 (0.278)*	-0.086 (0.114)
SN * Log (Strong-Ties)	-0.552 (0.555)	0.096 (0.056)*	0.093 (0.041)**
SN * Log (Weak-Ties)	0.942 (0.449)**	-0.228 (0.118)*	-0.043 (0.023)*
OT * Log (Strong-Ties)	-1.434 (0.363)***	0.425 (0.148)***	0.117 (0.026)***
OT * Log (Weak-Ties)	0.777 (0.23)***	-0.082 (0.097)	0.011 (0.018)
Log (Facebook Ties)	0.227 (0.167)	0.102 (0.065)	0.022 (0.01)**
Log (Unemployment Spell)	-0.217 (0.328)	-0.015 (0.125)	-0.027 (0.024)
Log (Salary)	-0.18 (1.164)	0.627 (0.376)*	-0.163 (0.058)***
Experience	0.111 (0.08)	-0.022 (0.024)	-0.028 (0.006)***
Married (yes = 1)	0.391 (0.862)	-0.392 (0.323)	0.312 (0.095)***

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[3] We cannot add a random effect readily given that we are estimating non-linear regressions.

Sex (female = 1)	-2.152 (0.654)***	0.104 (0.218)	-0.073 (0.048)
Education (College)	0.043 (1.212)	-0.025 (0.35)	-0.023 (0.1)
Education (Graduate School)	-0.541 (1.232)	-0.419 (0.407)	0.095 (0.099)
Race (White)	-2.529 (1.435)*	-0.19 (0.336)	0.089 (0.044)**
Race (Black)	-2.707 (0.841)***	-0.47 (0.278)*	-0.06 (0.056)
Race (Hispanic)	-0.26 (1.116)	-0.939 (0.166)***	0.155 (0.224)
R2	0.682	0.650	0.683
N	319	252	170
Clusters	89	88	76
Non-linear least square regression marginal effects Standard deviation in parenthesis Significance: *(p<0.1), **(p<0.05), ***(p<0.01) Omitted dummies: Race(Other), Education(Other), Search Mode (Agencies)			

Looking at the job leads model we notice that increased time spent on search increases job leads significantly. Every additional hour of searching is associated with 0.36 additional leads. Notice that the effect of ties on job outcomes is not as straightforward. More number of ties affects search which in turn affects leads. However ties have a direct effect on job outcomes. From the estimates for job leads, we see that the effect of strong ties is to decrease the number of leads across all modes but the effect of weak ties is to increase the job leads. This follows from the strength of weak-ties argument (Granovetter 1973). The estimates are significant and suggest that a 10% increase in weak-ties results in a 0.1 increase in number of new job leads received. 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 on job leads is surprising; larger number of strong online ties seems to reduce the number of leads. It may be that users with 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 novel information that serve as potential job opportunities matching a user's skills for which a job seeker submits a customized job application.

Next we look at job interviews model where we estimate the probability of interviews conditional on job leads. Notice that the effect of OSN 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. The effect of weak ties on OSN is negative and significant. One might believe this to be true because providing references (written or oral) might be perceived as a costly activity and only strong ties may be willing to incur these costs. So while weak ties may help you get a lead, they do not necessarily help in converting these leads into interviews. Looking at job offers, we see the results consistent with those seen from the job interview regression – strong-ties play a significant positive role in job offers and weak-ties suggest a negative or no effect on the job offers. Doubling of strong ties leads to 0.1 more offer on average. The effect is persistent across modes.

An interesting and counter-intuitive finding here is the negative marginal effect of weak-ties on job interviews and job offers. We believe this supports Krackhardt's paraphrased[4] statement "a friend of the world is no friend of mine" and more formally the principle of reflected exclusivity (Krackhardt 1998), suggesting that a large number of weak-ties may reduce the strength of strong-ties, which in turn suggests a negative effect of weak-ties on the job interviews and offers received.

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[4] 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")

Conclusion & Discussion

This study, not unlike most survey based studies, faces the limitation of not representing the entire population accurately. The survey responses received from the unemployed job seekers represent highly educated earning much more than the average population wage. Still, this is the first study - to the best of our knowledge – that investigates the role of online social networks in labor market. We have found that the expanding social networks play an important role in the job search. But since the effects of weak- and strong- ties are different in the job outcomes, the results presented here could be used to strategically build a social network to maximize the job offer probability.

In this study, we have empirically investigated the behavior of job seekers allocating search effort across different job search modes. This approach was useful to address the rising concern about homophily when estimating the role of social network in the labor market. While this study does not conduct a controlled random experiment that could minimize the effect of homophily, it does a reasonable job of suggesting that online social network has a positive effect on time spent by job seekers on job search. This is intuitive because larger social networks will provide more opportunities to find new information though one's network. We found that a larger social network will increase the search intensity allocated to both offline and online social job search modes.

Furthermore, we used a non-linear model for understanding the role of social network 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 internet and then tap into her social network to convert those leads to interviews and offers. This porting of information might cause confounding effect in a research study, especially in the case of close friends & family and friends & family on online social networks. We found positive effect of weak-ties on job leads (new information) and positive effect of strong-ties on the job offers (trust driven information) both in harmony with the extant research. In summary, this study shows that the online social networks play a significant role in the job search by unemployed professionals.

To extend and strengthen the current findings we need to collect more data preferably 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.

Acknowledgements

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