

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

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ABSTRACT

Prior research has previously presented that social connections (like friends and family) - usually categorized as strong and weak ties - are valuable in a job search process. Still the size of job seeker's network was limited because of constraints posed by the 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 their job search behavior not only on social network but also on other modes. Secondly, we examine how the ties (weak and strong) and search intensity affect the job outcomes (which we model sequentially; job leads, interviews and offers) from online social networks vs. those from other job search modes like career fairs & agencies, newspapers & magazines, internet, and close friends and family (offline). We first build an economic model of search behavior with cost and benefit functions; then we estimate the model to recover some key estimates and structural parameters using a survey data of 109 users. We find that users with more weak ties search more on all modes. However, users with more strong ties search less on online social networks. We also find that weak ties are especially helpful in generating job leads but it is the strong ties which 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. 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 job seekers reached out to 22 percent of their friends and family. Growth 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. There is significant literature that suggests that “who you know” plays a very important role in someone finding a job. Granovetter (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 because online platforms have enabled a much larger competition amongst the job seekers as every job post is now available to every job seeker across the globe. According to a survey conducted by CareerBuilder.com¹ in 2009, each job post received over 75 resume. Social connections could potentially help job seekers in reaching directly to hiring managers and improve 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 which allows 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, Steinfield,

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

and Lampe 2007; Valenzuela, Park, and Kee 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 recent 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 each spending on average 4 minutes 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, advertizing 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 network is the ability of individuals to maintain and manage far more online connections - average number of friends on facebook.com² 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 may be helpful, but they may also make it harder for 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 consider online social networks a great tool for job search. After all, unemployment information is not something users may be willing to share with their network especially when the network consists of large number of weak ties. So users may be reluctant to conduct directed search on these networks.

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:

(i) How are people allocating their job search efforts across different modes, especially, online social networks? How does users' online social network (including weak ties) affect these search efforts?

(ii) Are online networks effective in generating job offers? Does users' online social network affect this effectiveness? How do strong and weak ties influence job leads vs. job interviews and offers?

Answers to these questions require having access to some detailed data on users' job search behavior. To do this, we administer a survey to unemployed users asking them detailed questions on their job search methods, their online and offline social capital, and job outcomes. We then provide a model of users' job search behavior and effectiveness of search modes, especially emphasizing the role of social capital.

Using completed survey of 109 users, we find that job seekers with larger number of 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" and "strength of strong-ties" arguments hold for online social networks but 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, a much larger network size might help job seeker find new leads but will 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, 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 question for labor economists, sociologists and technologists. The answer to our research questions are of importance to individuals who are searching for jobs and firms like LinkedIn whose business models depend on answers to these questions. More importantly, even 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 a particular focus on online networks has been possible due to lack of detailed data. Despite some limitations of our survey, 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 undoubtedly are needed to investigate this very important issue.

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

2 LITERATURE

We draw from two major literatures. First is job search literature in labor economics. Scholars have studied labor market and the role of social ties on the job outcomes (Granovetter 1983) (Holzer 1988), wages (Montgomery 1992), and job information diffusion (Granovetter 1995). It has been shown in the past 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).

Differentiating between the unemployed and employed workforce, researchers have found that the job search while being employed is more effective when compared to the job search when unemployed (Blau and Robins 1990). An analytical work using the diffusion of job lead information through network structure suggests duration dependence of unemployment (Calvó-Armengol and Jackson 2004).

As pointed in a recent review (Mouw 2006), estimating the role of social capital has been increasingly challenging due to homophily (McPherson, Smith-Lovin, and Cook 2001) and reflection (Manski 1993). He 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. 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).

Since the growth of Internet as a channel for job search, it has been increasingly used both by unemployed and employed workforce 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 Internet is also shown to have negative effect on the unemployment duration of job seekers (Kuhn and Skuterud 2004). Also, it is shown that internet maybe more effective when compared to newspaper ads or direct application, it is less effective compared to social networks (Feldman and Klaas 2002) thus creating a need for investigation of various job search modes including online social networks.

The second literature we explore is the economics and sociology literature examining the role of social capital. Seminal work in the area of sociology originated from 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) with a larger emphasis on product marketing or innovation diffusion. During the same time the origination of strength-of-weak-ties theory (Granovetter 1973) changed the perspective of social capital. Granovetter 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, Libai, and Muller 2001) but may have a different impacts based on the interaction between the ties and the size of the network. It was also shown that strong ties are important (Krackhardt 1992) 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 matter 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).

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

Online social networks allow users to maintain a large number of connections that are weak-ties; 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. Through this paper we try to take the first step at understanding the role of online social networks on job search by unemployed workforce using a survey data collected from that workforce.

3 THEORY

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? And, do online connections affect job outcomes? A key goal is to understand how online social 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 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 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 channels: 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].

3.1 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. In particular, individuals make decisions on how much to search based on their expected benefits and costs.

These models assume that there is certain baseline utility from being unemployed. Searching increases the probability of being employed but it also has associated costs. So users are essentially trading off these two costs. In particular if users perceive social connections to be useful, we should see them searching more on those modes. More formally, we can specify the utility of an unemployed individual as:

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

i indexes an individual, j indexes search model and t 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 $\pi(s_j, X_i, E_i)$ and wage offer (w_t) is higher than reservation wage ($w_{R,t}$). Here X_i represents the user's characteristics (like education, experience, age, salary during last job, race, etc). E_i represents the embeddedness or social capital of user i on online social network (especially the number of connections on LinkedIn). The third term in (1) is simply the probability that users will remain unemployed because the wage offer is not higher than reservation wage and the fourth term indicates that the user may not get any offer despite searching and hence remain unemployed in the next period.

Most job search models also have reservation wage as a decision variable. So in a dynamic model, individuals are also choosing their reservation wage over time. Given the cross section nature of our data over a period, and that our focus is on empirical identification of how users connections play a role, we assume the reservation wages are exogenous. We will revisit this shortly. Assuming that the wage offer distribution is given as $f(w)$, we can rewrite the above equation as:

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

The equation specifies expected change in utility over two time periods due to investing in 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. We will rely on prior literature for these functions. v is assumed to be linear in its arguments (Holzer 1988). Given that these are unemployed users who have more available time to search, the cost of search on leisure can 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 :

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

$$\text{where } \lambda_{ij}(X_i, E_i) = \exp(\varphi_{0j} + \varphi_1 X_i + \varphi_2 E_i)$$

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) as:

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

As expected cost is increasing in search efforts and it is convex. Typically embeddedness will be a part of the cost function if a job seeker uses the available time for job search in building her social network, but we assume that the individuals are unemployed are using their existing capital to find a new job. Thus the coefficient for embeddedness in cost function is assumed to be zero. Given that the benefit of search is linear, an interior solution is guaranteed. Taking first order of (2) will yield:

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

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:

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

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

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

While we have data to estimate this equation, there are many challenges.

First we do not directly observe R . Note that R is the expected benefit of employment given the distribution of wages distribution 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; we assume that reservation wage is proportional to the past wage³. If wage offer distribution is normal for a job search mode then:

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

If we know the past wage of a job seeker and distribution of wages received from a job search mode, we can recover the value of expected benefit of employment. As we will see later, we

³ One would expect that reservation wage will change with time. But we do not observe the users repeatedly, and hence use average of past wage and new wage (for those who found jobs) as a proxy for reservation wage.

collected wage information from job seekers and use that to compute the distribution for each of the job search modes, thus allowing us to estimate the value of R for each job seeker.

3.2 EFFECT OF EMBEDDEDNESS ON JOB OUTCOME

Once an unemployed job-seeker allocates time to each job search mode, the next step is to estimate the role of social embeddedness on the job outcomes. Our job offer model is straightforward.

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

Most models who estimate effect of social capital on job outcomes do not capture any details on search intensity “s” which is problematic as we show.

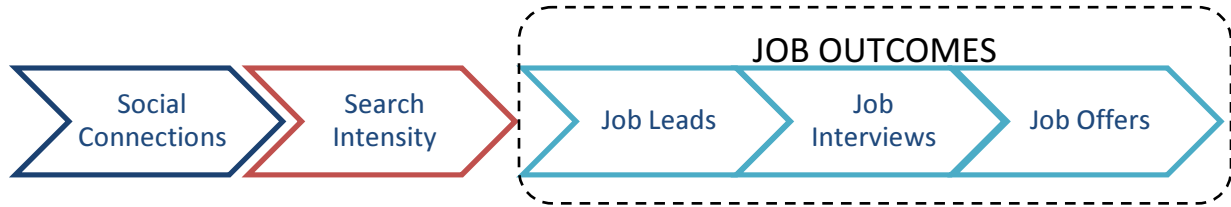
Embeddedness can affect job outcomes in two ways. First, as our model in (4) shows, more connections may lead to more search effort by users. Second, more connections would lead to more job outcomes independent of search effort. Formally, the effect of embeddedness on job outcome could then be written 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”, effect of embeddedness on job outcomes will be seriously 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 effects 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 offer as an outcome. However, the actual job offer process is more complex. Usually job search efforts generate relevant job leads. Job leads convert to interviews and finally 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 to potentially relevant job lead. 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 write recommendation letter on behalf of a user, or press 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 focus on three outcomes: job leads, job interviews and job offers. It is clear that these are linked sequentially. 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,

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

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.

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

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

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

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

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

$$\frac{dJI_{ij}}{dE_i} = \frac{\partial JI_{ij}}{\partial E_i} + \frac{\partial JI_{ij}}{\partial JL_{ij}} * \frac{dJL_{ij}}{dE_i}$$

$$\frac{dJL_{ij}}{dE_i} = \frac{\partial JL_{ij}}{\partial E_i} + \frac{\partial JL_{ij}}{\partial s_{ij}} * \frac{ds_{ij}}{dE_i}$$

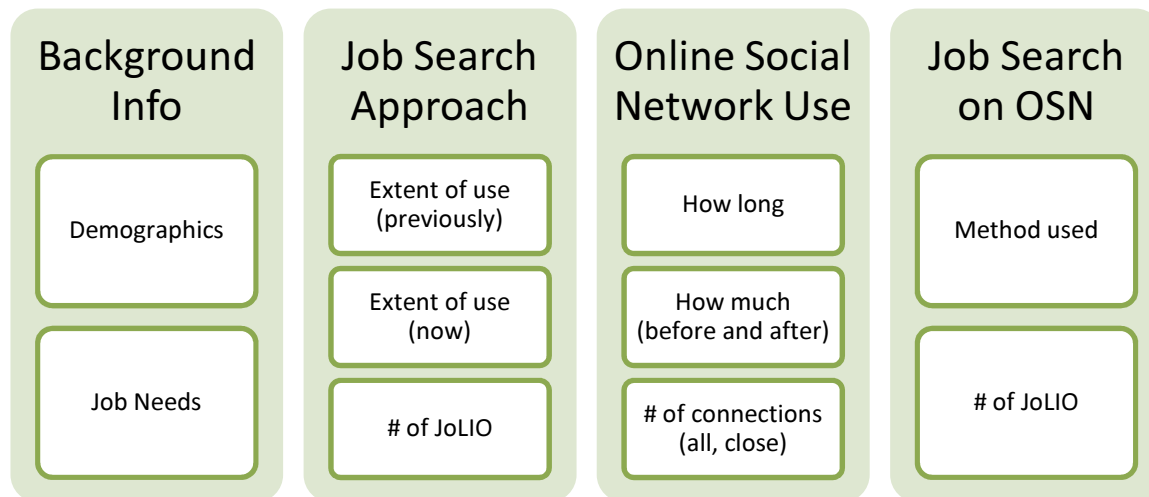
In addition to estimating the effect of embeddedness on various job outcome classifications, the above model also allows us to estimate the effectiveness of each job search mode in converting search effort to job leads, job leads to interviews, or job interviews to offers. Next we discuss the role of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

4 DATA

Traditionally labor economists have relied on National Longitudinal Survey (NLS) or Current Population Survey (CPS) to examine how users are searching for jobs and in some cases how do their social networks help them in job search (Holzer 1988). While these data have large observations, they do not contain many details that are needed to answers the question 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. Most of these surveys also do not have any details on users' online social capital and search behavior.

To better understand the role of online social networks on job outcomes, we designed an IRB approved survey and administered it to individuals that 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, their motivations for job search, their past and present job search strategies, their familiarity and use of online social networks, and their knowledge of using online social networks for job search. Thus the survey is much more detailed and required about 30 minutes of subject's time in answering all of the questions regarding their job search approach. The survey contains the following components:



To test if users would respond to the details asked in the survey and 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 to maintain the attention of job seekers during the entire time. We made some adjustments to the questions based on the feedback received and the actual data from this sample was ignored for the study.

The outplacement firm had access to 288 individuals whose emails were available to them. Of the 288 emails sent, 163 individuals opened the email and 109 individuals took our survey. 8 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 report created with help of professionals in the field. It should be clear that our survey was sent to mostly educated, white collar workers. So the sample is neither representative of general population nor is perfectly random. However, we also expect that educated and white collar workers are precisely the

people likely to use online social networks. So 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.

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 all survey takers

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 during last job search (sticky search) is given in Table 2. Table 2 shows how the job search behavior changed conditional on the search mode being selected during the current time period or the previous time period. Increase in the number of individuals using each job search mode suggests 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 see 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 internet (49% on average) with print media (29%) and agencies (25%) as the lowest two. We explicitly ask users how many job leads, job interviews and job offers they found via each model. The summary of search effort distribution across job search mode, their search intensity on that 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 (%).

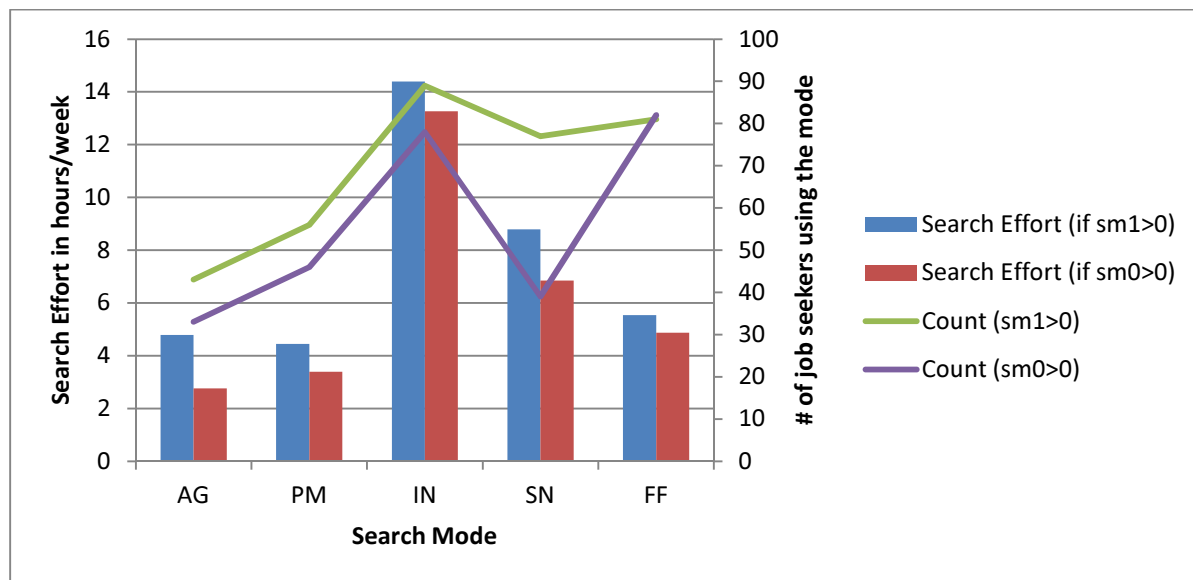


Figure 1: Job search mode selection and search effort allocation as a function of previous (sm0) or current (sm1) mode use

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

	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

Next we asked users to specify how many connections they have and how many they consider as weak and strong connections 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 who they frequently communicate with. The phrase “close friends and family” was also used to classify those group of individuals that a job seeker would talk to 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. Distribution of total, strong, and weak connections on both Facebook and LinkedIn is presented in Figure 2.

We observe that individuals have much larger share of strong-ties on Facebook yet a much larger share of weak-ties on LinkedIn. For individuals that did not use online social networks as a job search mode, we inquired about their distrust in that platform. All of the individuals (not using online social networks) selected privacy concern as the most important reason for not using online social networks (like Facebook) and lack of sufficient job leads 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.

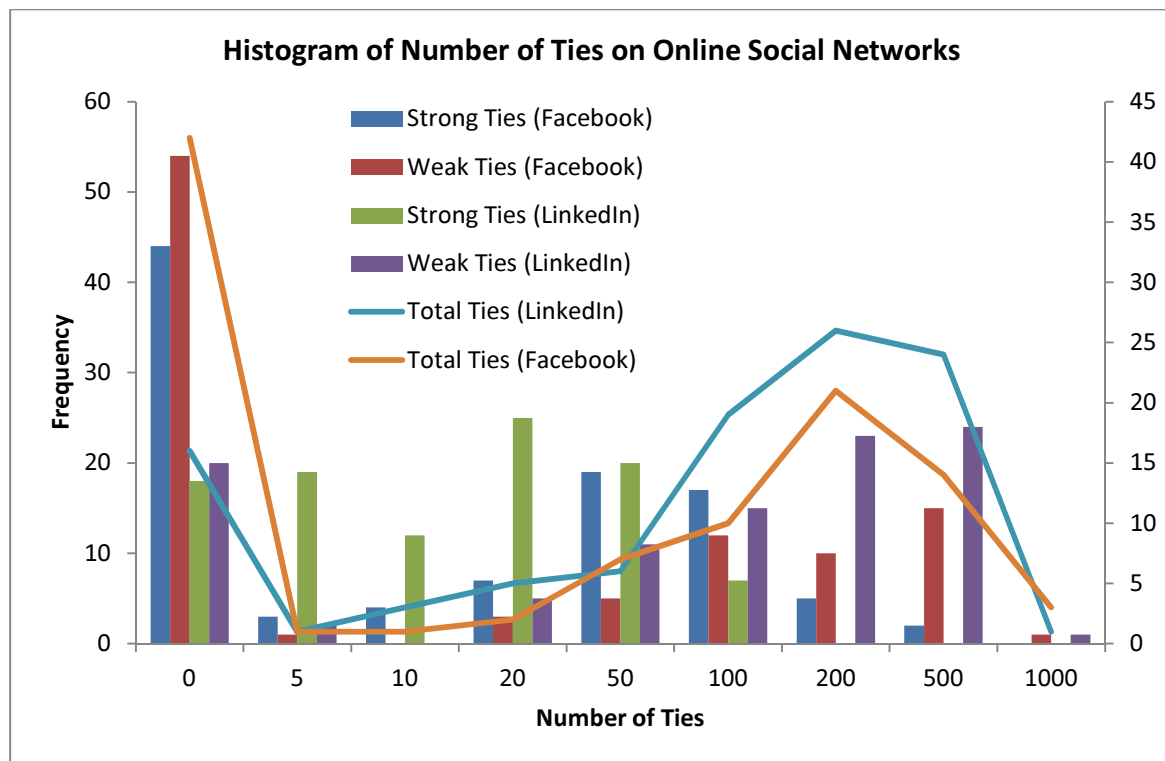


Figure 2: Distribution of number of online social ties on Facebook and LinkedIn

Since we know how much each job seeker received in the last job, we can create a distribution for each of the job search modes. Summary of the mean and standard deviation of wages is given 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

4.1 Survey Data Validation & Reliability

Typically a survey would ask multiple questions seeking a similar answer to estimate the reliability of the answers. Since this was a very detailed survey for unemployed individuals that were proctored by consultants, we tried to avoid redundancy. Thus we used three different approaches to build confidence in the response data: 1) inverted the flow so outcomes were

asked before probing question, 2) verified accuracy of conditional responses 3) matched answers with actual publicly available data.

With help from Denise Rousseau at Carnegie Mellon University, we designed a survey that conveyed the meaning of questions accurately without disclosing the reason for the question. This process followed throughout the survey where the demographic information was collected at the end. The flow of the survey sections is shown in appendix A.

By accuracy of conditional responses we mean validating if job seekers' responses to sequential questions like number of job leads, interviews, and offers followed a decreasing numerical value when the answer had no programmatic constraint/validation. From the responses of 109 individual, we found that one job seeker provided number of interviews received from newspaper to be higher than number of job applications submitted. Although this could be just a typographical error, we dropped that individual from the data.

We asked individuals about the number of connections they had on popular social networks like LinkedIn, Facebook, and Twitter and provided ranges as option to select their network size. We 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 to verify the responses. Of the 77 job seekers that used online social networks for job search we were able to access the profiles of 71 job seekers and the range 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 6 total connections. We dropped these individuals from the data for consistency.

Overall, we found that the error in responses for few survey questions was low and since the surveys were proctored, we assume the reliability for the entire data.

5 EMPIRICAL ANALYSIS & RESULTS

5.1 Search Effort Allocation

As discussed previously and in prior research (Mouw 2003) it is important to understand the role of social capital on the search effort to clearly identify any issues relating to endogeneity or homophily (McPherson, Smith-Lovin, and Cook 2001). Individuals with larger social capital could gain benefit from their network because they are connected to a few influential and highly social individuals and 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 capital on the search effort because a large social capital would require more effort and thus could eventually convert that effort into positive job outcomes. Thus, as a first step, we test if size of social capital indeed plays a role in the search effort allocated to online social network by the unemployed workforce.

Our regression equation is

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

The first two terms are simply a constant, while the other terms are readily identified. As we will show, we can recover structural parameters for cost (γ_j, δ_j) readily. 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 user specific and search mode specific unobserved. So we can rewrite this as:

$$s_{i,j} = \theta_j + \omega_i + \alpha_0 + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(R_{i,j}) + \varepsilon_{ij}$$

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 on 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 are unobserved.* Notice our optimal search model automatically incorporates the benefit function. From the benefit function it is clear that search efforts will be higher if $\varphi_{j,2}$ (effect of social connections on job outcomes) is positive and large. Thus in our model, a positive estimate on E is precisely 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 capital. So a mode may be more productive for reasons unknown. We control for these by using mode specific dummies.

(ii) Another worry 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. Though notice that we are testing the effect on online connections on search behavior on other modes as well.

(iii) 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. First we use 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:

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \quad (7)$$

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

We run two separate specifications. First is specification (7) where we split the online connections (E_i) into strong and weak connections and estimates their effect on search effort. Notice that (7) 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. In the second specification, 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.

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_{2a} * E_i * D_s + \alpha_{2b} * E_i * D_o + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \quad (7a)$$

D_s is dummy for online social network search mode while D_o is a dummy for any other mode. The estimates of these three separate regressions are given in the two columns of Table 6 below. The left out dummy (in θ_j) is the search mode "agencies".

From the table below, notice that the coefficients for all dummies are positive. This suggests people spend more time on online social network, Internet, print media and with friends and family for job search relative to agencies. Statistically speaking, job seekers allocate most time searching for jobs to the Internet followed by the online social networks. This is intuitive because online channels have been gaining popularity over the last few years in job search because of very low cost of search and ease of submitting a job application. Print media gets relatively lower search allocation possibly because of higher relative costs to search and apply for jobs. The coefficient for close friends and family (offline) is not significant possibly because of confounding effect of close friends and family.

We see that people with more strong ties search less on all modes. In terms of economic significance, an estimate of -0.43 indicates that a 100% increase in number of strong ties decreases the search effort by about 26 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 connections are either able to delegate their search to those connections or these users are more conservative (possibly because of a concern about their social reputation) in their search approach and thus do not disclose their unemployment status to those close friends and family.

Increase in weak-ties exhibit opposite behavior; a 100% increase in weak-ties increase the search intensity by 17 minutes per week and more so on LinkedIn. Unemployment spell has a positive and significant effect on search intensity, which is intuitive for the short duration of unemployment term observed in the data. Similarly past salary exhibits a positive and significant effect on the search intensity. Other demographic variables are not significant is expected given we control for user specific random effects and mode specific dummies.

Search Effort (hours/week)	Coeff (Std Dev)	Coeff (Std Dev)
Dummy (Online Social Networks)	6.306 (1.939)***	6.267 (1.947)***
Dummy (Offline Friends & Family)	1.709 (1.943)	1.71 (1.944)
Dummy (Internet)	10.695 (1.829)***	10.695 (1.83)***
Dummy (Print Media)	5.037 (2.104)**	5.033 (2.106)**
Log (LinkedIn Strong-Ties)	-0.431 (0.089)***	
Log (LinkedIn Weak-Ties)	0.295 (0.058)***	
SN * Log (LinkedIn Strong-Ties)		-0.155 (0.098)
SN * Log (LinkedIn Weak-Ties)		0.152 (0.057)***
OT * Log (LinkedIn Strong-Ties)		-0.486 (0.101)***
OT * Log (LinkedIn Weak-Ties)		0.317 (0.065)***
Log (Total Facebook Ties)	0.067 (0.032)**	0.063 (0.032)**
Log (Unemployment Spell)	0.829 (0.374)**	0.825 (0.374)**
Log (Salary)	7.085 (2.47)***	7.057 (2.472)***
Experience	-0.001 (0.066)	-0.001 (0.066)
Married (yes = 1)	-0.357 (0.747)	-0.37 (0.748)
Sex (male = 1)	-0.804 (0.681)	-0.799 (0.681)
Education (College Graduate)	-0.922 (0.979)	-0.908 (0.98)
Education (Graduate Degree)	-1.539 (1.136)	-1.52 (1.136)

Race (White)	1.144 (1.049)	1.148 (1.049)
Race (Black)	1.369 (1.51)	1.377 (1.511)
Race (Hispanic)	1.963 (1.517)	1.969 (1.519)
Employment Value (Online Social Networks)	1 (0.903)	0.957 (0.904)
Employment Value (Offline Friends & Family)	2.056 (0.945)**	2.054 (0.946)**
Employment Value (Internet)	2.111 (0.945)**	2.109 (0.946)**
Employment Value (Print Media)	0.879 (0.389)**	0.879 (0.389)**
Employment Value (Agencies & Career Fairs)	2.116 (0.883)**	2.114 (0.884)**
_cons	-35.886 (11.782)***	-35.706 (11.792)***

N = 450, bivariate joint likelihood 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(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- and weak-ties interacted with online social networks are not different and are of higher magnitude. Users with more weak online ties search more and with more strong ties search less on online networks. It is the weak ties that stimulate higher search intensity.

We see that the interaction of strong ties with other modes is not significant. However, online weak ties keep motivating the use of those connections for job search on other modes. Since SNS allow users to connect with a large number of weak-ties at a small or no cost, these ties could be perceived more valuable on the platform of connection.

5.1.1 Sequential Model (Search Intensity Affecting Job Leads)

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:

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

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

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

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.⁴ As before, we estimate two models. In the first one 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 as opposed to the absolute parameter estimates. They are presented in Table 7 below.

First we look at the job leads model. First notice that more search increases job leads significantly. Every additional hour of searching is associated with 0.33 additional leads. Notice that the effect of ties on job outcomes is not straightforward. More ties affects search which in turn affects leads. However ties have a direct effect on job outcomes. From the results in column (1), 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. The estimates are large and significant. Doubling the number of weak ties leads to about 0.7 more leads. The effect of strong ties is surprising. Higher 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

⁴ We cannot add a random effect readily given that we are estimating non-linear regressions.

tend to provide little or no new information to a job seeker. By definition most job leads are new piece of information that serves as potential job opportunities matching a user's skills for which a job seeker submits a customized 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					0.086 (0.018)***	0.077 (0.019)***
Dummy (OSN)	0.469 (1.294)	-3.405 (1.648)**	-0.557 (0.291)*	1.373 (1.276)	0.174 (0.135)	-0.077 (0.074)
Dummy (FF)	1.222 (1.427)	1.101 (1.411)	-0.324 (0.339)	-0.32 (0.346)	0.085 (0.118)	0.052 (0.092)
Dummy (Internet)	2.156 (1.471)	1.984 (1.475)	0.242 (0.39)	0.242 (0.394)	0.029 (0.09)	0.009 (0.073)
Dummy (Print Media)	0.821 (1.388)	0.62 (1.362)	-0.505 (0.277)*	-0.501 (0.278)*	-0.034 (0.105)	-0.05 (0.082)
Log (Strong-Ties)	-1.054 (0.405)***		0.386 (0.141)***		0.079 (0.023)***	
Log (Weak-Ties)	0.741 (0.251)***		-0.083 (0.09)		0.011 (0.011)	
SN * Log (Strong-Ties)		-0.303 (0.596)		0.096 (0.026)**		0.055 (0.027)**
SN * Log (Weak-Ties)		1.234 (0.453)***		-0.228 (0.118)*		-0.022 (0.014)
OT * Log (Strong-Ties)		-1.224 (0.4)***		0.425 (0.148)***		0.079 (0.019)***
OT * Log (Weak-Ties)		0.767 (0.246)***		-0.082 (0.097)		0.009 (0.011)
Log (Facebook Ties)	0.125 (0.16)	0.126 (0.155)	0.098 (0.066)	0.102 (0.065)	0.018 (0.008)**	0.013 (0.006)**
Log (Unemployment Spell)	0.103 (0.323)	0.078 (0.317)	0.003 (0.132)	-0.015 (0.125)	-0.01 (0.024)	-0.019 (0.016)
Log (Salary)	0.487 (1.041)	0.272 (1.081)	0.643 (0.369)*	0.627 (0.376)*	-0.109 (0.046)**	-0.103 (0.042)**
Experience	0.034 (0.059)	0.033 (0.059)	-0.021 (0.023)	-0.022 (0.024)	-0.019 (0.004)***	-0.017 (0.004)***
Married (yes = 1)	0.747 (0.773)	1.001 (0.742)	-0.392 (0.321)	-0.392 (0.323)	0.162 (0.057)***	0.139 (0.057)**
Sex (male = 1)	-1.835 (0.578)***	-1.72 (0.554)***	0.128 (0.214)	0.104 (0.218)	-0.022 (0.042)	-0.036 (0.034)
Education (College Graduate)	-3.213 (0.78)***	-3.258 (0.753)***	-0.068 (0.334)	-0.025 (0.35)	-0.032 (0.073)	-0.034 (0.06)
Education (Graduate Degree)	-2.377 (0.979)**	-2.464 (0.924)***	-0.489 (0.391)	-0.419 (0.407)	0.013 (0.072)	0.024 (0.058)
Race (White)	-1.485 (2.485)	-1.819 (2.377)	-0.254 (0.337)	-0.19 (0.336)	0 (0.04)	0.014 (0.034)
Race (Black)	-2.042 (1.594)	-2.195 (1.393)	-0.45 (0.275)	-0.47 (0.278)*	-0.065 (0.04)	-0.076 (0.03)**
Race (Hispanic)	-0.059 (2.156)	-0.521 (1.891)	-0.933 (0.174)***	-0.939 (0.166)***	0.226 (0.22)	0.098 (0.13)
R2	0.704	0.711	0.635	0.639	0.662	0.689
N	319	319	319	319	170	252
Clusters	89	89	88	88	76	88
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)						

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 the other modes. Now, the strong ties have no effect on job leads from social networks. However, weak ties are highly significant and quite large. Doubling the weak ties leads to 1.2 additional job leads. 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 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. When we interact ties with search modes, the effects persist (see column 4). Now the weak ties are negative and significant for 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 do this and not the weak ties. So while weak ties may help you get a lead, they do not necessarily help in converting these leads into interviews.

Coming to job offers (column 5 and 6), 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. 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 paraphrased⁵ statement "a friend of the world is no friend of mine" and more formally as 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

⁵ 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")

offers received. Although we see these negative coefficients to be marginal effects of social connections on job outcome the true impact still needs to be evaluated and follows.

5.1.2 Role of Social Connections on Job Outcomes

However, the effect of ties on job outcome is a complex. As we explained earlier, more ties affect search intensity as well. Our estimates from Table 6 confirm that users with more ties are also 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)

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = -0.303 - 0.332 * 0.155 \approx -0.354$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = 0.096 - 0.111 * 0.354 \approx 0.055$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = 0.055 + 0.077 * 0.055 \approx 0.059$$

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

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = 1.234 + 0.332 * 0.152 \approx 1.284$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = -0.228 + 0.111 * 1.284 \approx -0.085$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = -0.022 - 0.077 * 0.085 \approx -0.029$$

Thus for every 100% increase in number of weak-ties on LinkedIn, a job seeker can gain additional 1.3 job leads. But this 100% increase in weak-ties will decrease the number of job interviews by 0.085 and will decrease the number of offers by 0.029. Similarly, we can compute

the net effect of strong connections on the job outcomes. For 100% increase in strong-ties on LinkedIn, we expect to see a decrease in job leads by 0.35, increase in job interviews by 0.06, and an increase in job offers by 0.06.

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

$$\begin{aligned}\Delta J L_{i,j} &= 1.284 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} - 0.354 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}} \\ \Delta J I_{i,j} &= -0.085 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.055 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}} \\ \Delta J O_{i,j} &= -0.029 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.059 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}}\end{aligned}$$

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, thus this approach to estimate the effect of social connections on job outcomes should only be seen as a framework for future work. To better understand the net effect of search allocation and social capital on job outcome 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 the estimated parameters of equation 7a, because the 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 maximize the following bivariate likelihood model to recover the structural parameters in both the cost (equation 4) and benefit (equation 3) functions:

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

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

Cost Function	OSN	FF	IN	PM	AG
γ_j	0.56	1.33	1.39	0.58	1.44
δ_j / γ_j (Log(FB_Connections))	0.113	0.047	0.045	0.109	0.044
δ_j / γ_j (Log(Unemployment_Spell))	1.473	0.62	0.594	1.422	0.573
δ_j / γ_j (Log(Salary))	12.602	5.306	5.077	12.167	4.901
δ_j / γ_j (Experience)	-0.002	-0.001	-0.001	-0.002	-0.001
δ_j / γ_j (Married)	-0.661	-0.278	-0.266	-0.638	-0.257
δ_j / γ_j (Sex_Male)	-1.427	-0.601	-0.575	-1.378	-0.555

From the cost function (eq 4) estimates, we see that scale coefficient (γ) is smallest for online social networks suggesting the low overall search costs of the platform. We believe that it is intuitive that online social networks have 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 to find a new job. 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 pick the ones worth the time it takes for submitting 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 give time frame. The cost for agencies is highest because of interpersonal communication with an agency that may have additional costs to provide their services.

The estimates of structural parameters for benefit function (job leads) are presented below:

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

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

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

Structural Parameter	Benefit Function		Job Leads		Job Interviews		Job Offers	
	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)
τ_0	-0.007	-0.007	0.009	0.009	-0.012	-0.012		
τ_1	0.053	0.053	0.035	0.035	2.024	2.024		
ϕ_{0j}	2.326	3.473	3.574	2.752	-1.227	-0.521		
ϕ_{2j} (Log(LinkedIn Strong-Ties))	-0.036	-0.245	0.076	0.336	0.494	0.622		
ϕ_{2j} (Log(LinkedIn Weak-Ties))	0.234	0.155	-0.228	-0.129	-0.224	-0.051		
ϕ_1 (Log(FB_Connections))	0.022	0.022	0.078	0.078	0.109	0.109		
ϕ_1 (Log(Unemployment_Spell))	0.005	0.005	-0.046	-0.046	-0.172	-0.172		
ϕ_1 (Log(Salary))	0.049	0.049	0.502	0.502	-0.822	-0.822		
ϕ_1 (Experience)	0.004	0.004	-0.021	-0.021	-0.137	-0.137		
ϕ_1 (Married)	0.219	0.219	-0.346	-0.346	1.416	1.416		
ϕ_1 (Sex_Male)	-0.315	-0.315	0.043	0.043	-0.384	-0.384		

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 somewhat intuitive because the numbers of job posts, although steadily growing, are 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 other job search modes. We believe this is the case because a lot of recruiters are moving towards online social networks to screen candidates for interviews based on their interactions with their social community. The conversion to offer is lower for online social networks because we believe the strong-ties that play a strong role in conversion actually are portable and communication with them is achieved through faster modes like email or phone.

As discussed before, we see a negative effect of strong online connections and a positive effect of weak online connections on job leads suggesting that strong-ties are contributing less new information whereas weak-ties tend to provide more new information. The role of strong- and weak- ties flip when it comes to job interviews or offers.

The positive coefficient for strong-ties suggest the 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 might be lower thus impacting the conversion rate from job applications to interviews to offers. As discussed previously, online strong-ties tend to be multiplexed ties thus having a positive effect irrespective of the job search mode.

In summary, the estimated structural parameter allows us to build both cost and benefit functions for all of the five job search modes. This should help the job seekers to allocate their job search effort on various modes and improve the probability of outcomes (job leads, interviews, or offers) received from each search mode.

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 more educated and higher income individuals. 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 continuously expanding social capital plays an important role in the job search. But since the effect of weak- and strong- ties is 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 is intuitive because larger social capital will imply more opportunities to find new information through the network. Here we found that larger social capital will increase the search intensity allocated to both offline or online social job search modes and will cannibalize the time spent on Internet for job search.

This study also echoes the argument (Kuhn and Skuterud 2004) suggesting that the internet enabled 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 platform results 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 higher number of job interviews. This difference in outcome from job search modes has been used to suggest the value of information portability by many career transition experts. These industry experts suggest finding job leads from various job search modes and applying for positions like job seekers did a decade ago – mailing in a hardcopy cover letter with resume. This could then improve the chances receiving interview calls for every application.

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 internet and then tap into her social capital 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.

6.1 LIMITATIONS & FUTURE WORK

One limitation of our approach is that we use multiple non-linear models for analysis that caused burden of jointly estimating the productivity model and simultaneously estimating the models for all job search modes. Both joint and simultaneous estimation of job outcomes require more sophisticated econometric modeling and are 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 non linear 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. Although there are some limitations because of survey data, we have presented a framework for analyzing social capital for labor market and believe that future work should consider the approach presented here.

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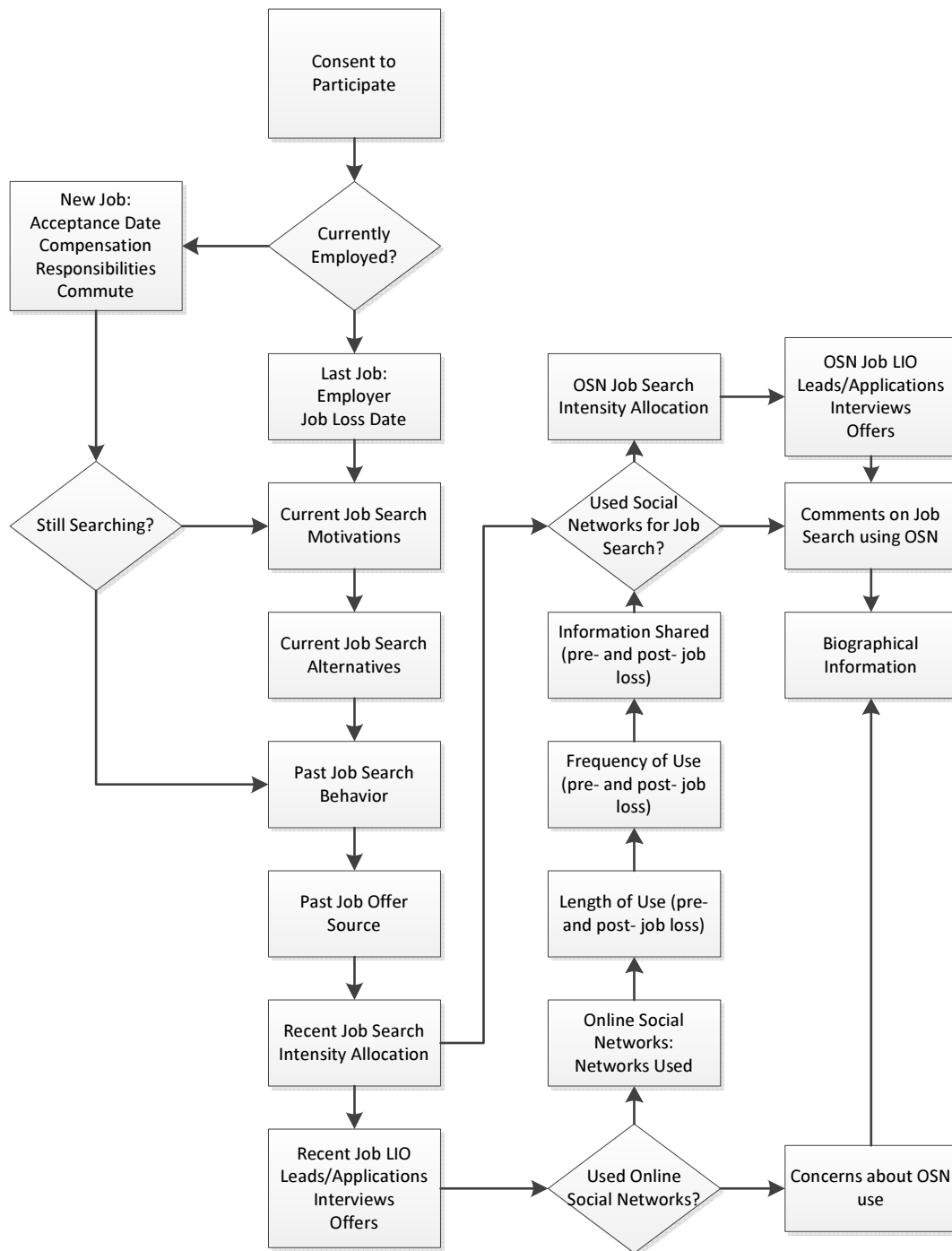
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9 APPNEDIX



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

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ABSTRACT

Prior research has previously presented that social connections (like friends and family) - usually categorized as strong and weak ties - are valuable in a job search process. Still the size of job seeker's network was limited because of constraints posed by the 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 their job search behavior not only on social network but also on other modes. Secondly, we examine how the ties (weak and strong) and search intensity affect the job outcomes (which we model sequentially; job leads, interviews and offers) from online social networks vs. those from other job search modes like career fairs & agencies, newspapers & magazines, internet, and close friends and family (offline). We first build an economic model of search behavior with cost and benefit functions; then we estimate the model to recover some key estimates and structural parameters using a survey data of 109 users. We find that users with more weak ties search more on all modes. However, users with more strong ties search less on online social networks. We also find that weak ties are especially helpful in generating job leads but it is the strong ties which 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. 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 job seekers reached out to 22 percent of their friends and family. Growth 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. There is significant literature that suggests that “who you know” plays a very important role in someone finding a job. Granovetter (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 because online platforms have enabled a much larger competition amongst the job seekers as every job post is now available to every job seeker across the globe. According to a survey conducted by CareerBuilder.com¹ in 2009, each job post received over 75 resume. Social connections could potentially help job seekers in reaching directly to hiring managers and improve 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 which allows 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, Steinfield,

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

and Lampe 2007; Valenzuela, Park, and Kee 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 recent 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 each spending on average 4 minutes 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, advertizing 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 network is the ability of individuals to maintain and manage far more online connections - average number of friends on facebook.com² 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 may be helpful, but they may also make it harder for 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 consider online social networks a great tool for job search. After all, unemployment information is not something users may be willing to share with their network especially when the network consists of large number of weak ties. So users may be reluctant to conduct directed search on these networks.

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:

(i) How are people allocating their job search efforts across different modes, especially, online social networks? How does users' online social network (including weak ties) affect these search efforts?

(ii) Are online networks effective in generating job offers? Does users' online social network affect this effectiveness? How do strong and weak ties influence job leads vs. job interviews and offers?

Answers to these questions require having access to some detailed data on users' job search behavior. To do this, we administer a survey to unemployed users asking them detailed questions on their job search methods, their online and offline social capital, and job outcomes. We then provide a model of users' job search behavior and effectiveness of search modes, especially emphasizing the role of social capital.

Using completed survey of 109 users, we find that job seekers with larger number of 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" and "strength of strong-ties" arguments hold for online social networks but 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, a much larger network size might help job seeker find new leads but will 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, 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 question for labor economists, sociologists and technologists. The answer to our research questions are of importance to individuals who are searching for jobs and firms like LinkedIn whose business models depend on answers to these questions. More importantly, even 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 a particular focus on online networks has been possible due to lack of detailed data. Despite some limitations of our survey, 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 undoubtedly are needed to investigate this very important issue.

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

2 LITERATURE

We draw from two major literatures. First is job search literature in labor economics. Scholars have studied labor market and the role of social ties on the job outcomes (Granovetter 1983) (Holzer 1988), wages (Montgomery 1992), and job information diffusion (Granovetter 1995). It has been shown in the past 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).

Differentiating between the unemployed and employed workforce, researchers have found that the job search while being employed is more effective when compared to the job search when unemployed (Blau and Robins 1990). An analytical work using the diffusion of job lead information through network structure suggests duration dependence of unemployment (Calvó-Armengol and Jackson 2004).

As pointed in a recent review (Mouw 2006), estimating the role of social capital has been increasingly challenging due to homophily (McPherson, Smith-Lovin, and Cook 2001) and reflection (Manski 1993). He 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. 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).

Since the growth of Internet as a channel for job search, it has been increasingly used both by unemployed and employed workforce 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 Internet is also shown to have negative effect on the unemployment duration of job seekers (Kuhn and Skuterud 2004). Also, it is shown that internet maybe more effective when compared to newspaper ads or direct application, it is less effective compared to social networks (Feldman and Klaas 2002) thus creating a need for investigation of various job search modes including online social networks.

The second literature we explore is the economics and sociology literature examining the role of social capital. Seminal work in the area of sociology originated from 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) with a larger emphasis on product marketing or innovation diffusion. During the same time the origination of strength-of-weak-ties theory (Granovetter 1973) changed the perspective of social capital. Granovetter 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, Libai, and Muller 2001) but may have a different impacts based on the interaction between the ties and the size of the network. It was also shown that strong ties are important (Krackhardt 1992) 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 matter 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).

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

Online social networks allow users to maintain a large number of connections that are weak-ties; 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. Through this paper we try to take the first step at understanding the role of online social networks on job search by unemployed workforce using a survey data collected from that workforce.

3 THEORY

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? And, do online connections affect job outcomes? A key goal is to understand how online social 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 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 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 channels: 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].

3.1 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. In particular, individuals make decisions on how much to search based on their expected benefits and costs.

These models assume that there is certain baseline utility from being unemployed. Searching increases the probability of being employed but it also has associated costs. So users are essentially trading off these two costs. In particular if users perceive social connections to be useful, we should see them searching more on those modes. More formally, we can specify the utility of an unemployed individual as:

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

i indexes an individual, j indexes search model and t 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 $\pi(s_j, X_i, E_i)$ and wage offer (w_t) is higher than reservation wage ($w_{R,t}$). Here X_i represents the user's characteristics (like education, experience, age, salary during last job, race, etc). E_i represents the embeddedness or social capital of user i on online social network (especially the number of connections on LinkedIn). The third term in (1) is simply the probability that users will remain unemployed because the wage offer is not higher than reservation wage and the fourth term indicates that the user may not get any offer despite searching and hence remain unemployed in the next period.

Most job search models also have reservation wage as a decision variable. So in a dynamic model, individuals are also choosing their reservation wage over time. Given the cross section nature of our data over a period, and that our focus is on empirical identification of how users connections play a role, we assume the reservation wages are exogenous. We will revisit this shortly. Assuming that the wage offer distribution is given as $f(w)$, we can rewrite the above equation as:

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

The equation specifies expected change in utility over two time periods due to investing in 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. We will rely on prior literature for these functions. v is assumed to be linear in its arguments (Holzer 1988). Given that these are unemployed users who have more available time to search, the cost of search on leisure can 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 :

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

$$\text{where } \lambda_{ij}(X_i, E_i) = \exp(\varphi_{0j} + \varphi_1 X_i + \varphi_2 E_i)$$

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) as:

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

As expected cost is increasing in search efforts and it is convex. Typically embeddedness will be a part of the cost function if a job seeker uses the available time for job search in building her social network, but we assume that the individuals are unemployed are using their existing capital to find a new job. Thus the coefficient for embeddedness in cost function is assumed to be zero. Given that the benefit of search is linear, an interior solution is guaranteed. Taking first order of (2) will yield:

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

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:

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

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

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

While we have data to estimate this equation, there are many challenges.

First we do not directly observe R . Note that R is the expected benefit of employment given the distribution of wages distribution 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; we assume that reservation wage is proportional to the past wage³. If wage offer distribution is normal for a job search mode then:

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

If we know the past wage of a job seeker and distribution of wages received from a job search mode, we can recover the value of expected benefit of employment. As we will see later, we

³ One would expect that reservation wage will change with time. But we do not observe the users repeatedly, and hence use average of past wage and new wage (for those who found jobs) as a proxy for reservation wage.

collected wage information from job seekers and use that to compute the distribution for each of the job search modes, thus allowing us to estimate the value of R for each job seeker.

3.2 EFFECT OF EMBEDDEDNESS ON JOB OUTCOME

Once an unemployed job-seeker allocates time to each job search mode, the next step is to estimate the role of social embeddedness on the job outcomes. Our job offer model is straightforward.

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

Most models who estimate effect of social capital on job outcomes do not capture any details on search intensity “s” which is problematic as we show.

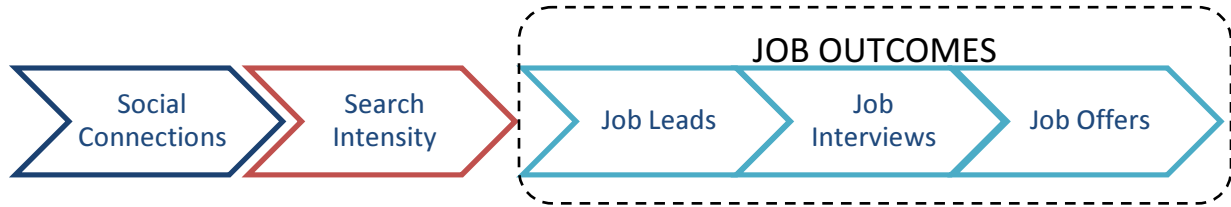
Embeddedness can affect job outcomes in two ways. First, as our model in (4) shows, more connections may lead to more search effort by users. Second, more connections would lead to more job outcomes independent of search effort. Formally, the effect of embeddedness on job outcome could then be written 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”, effect of embeddedness on job outcomes will be seriously 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 effects 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 offer as an outcome. However, the actual job offer process is more complex. Usually job search efforts generate relevant job leads. Job leads convert to interviews and finally 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 to potentially relevant job lead. 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 write recommendation letter on behalf of a user, or press 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 focus on three outcomes: job leads, job interviews and job offers. It is clear that these are linked sequentially. 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,

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

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.

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

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

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

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

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

$$\frac{dJI_{ij}}{dE_i} = \frac{\partial JI_{ij}}{\partial E_i} + \frac{\partial JI_{ij}}{\partial JL_{ij}} * \frac{dJL_{ij}}{dE_i}$$

$$\frac{dJL_{ij}}{dE_i} = \frac{\partial JL_{ij}}{\partial E_i} + \frac{\partial JL_{ij}}{\partial s_{ij}} * \frac{ds_{ij}}{dE_i}$$

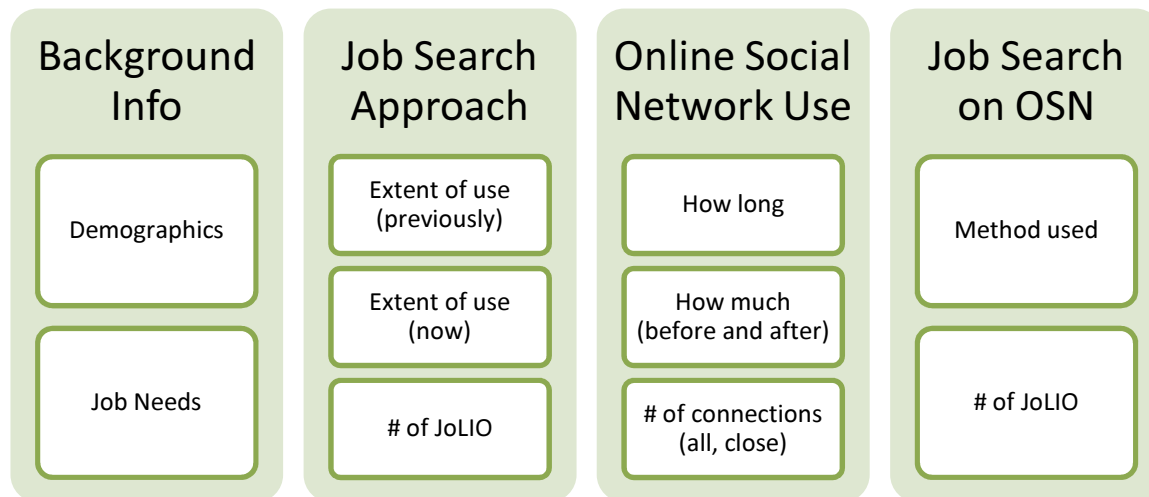
In addition to estimating the effect of embeddedness on various job outcome classifications, the above model also allows us to estimate the effectiveness of each job search mode in converting search effort to job leads, job leads to interviews, or job interviews to offers. Next we discuss the role of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

4 DATA

Traditionally labor economists have relied on National Longitudinal Survey (NLS) or Current Population Survey (CPS) to examine how users are searching for jobs and in some cases how do their social networks help them in job search (Holzer 1988). While these data have large observations, they do not contain many details that are needed to answers the question 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. Most of these surveys also do not have any details on users' online social capital and search behavior.

To better understand the role of online social networks on job outcomes, we designed an IRB approved survey and administered it to individuals that 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, their motivations for job search, their past and present job search strategies, their familiarity and use of online social networks, and their knowledge of using online social networks for job search. Thus the survey is much more detailed and required about 30 minutes of subject's time in answering all of the questions regarding their job search approach. The survey contains the following components:



To test if users would respond to the details asked in the survey and 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 to maintain the attention of job seekers during the entire time. We made some adjustments to the questions based on the feedback received and the actual data from this sample was ignored for the study.

The outplacement firm had access to 288 individuals whose emails were available to them. Of the 288 emails sent, 163 individuals opened the email and 109 individuals took our survey. 8 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 report created with help of professionals in the field. It should be clear that our survey was sent to mostly educated, white collar workers. So the sample is neither representative of general population nor is perfectly random. However, we also expect that educated and white collar workers are precisely the

people likely to use online social networks. So 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.

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 all survey takers

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 during last job search (sticky search) is given in Table 2. Table 2 shows how the job search behavior changed conditional on the search mode being selected during the current time period or the previous time period. Increase in the number of individuals using each job search mode suggests 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 see 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 internet (49% on average) with print media (29%) and agencies (25%) as the lowest two. We explicitly ask users how many job leads, job interviews and job offers they found via each model. The summary of search effort distribution across job search mode, their search intensity on that 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 (%).

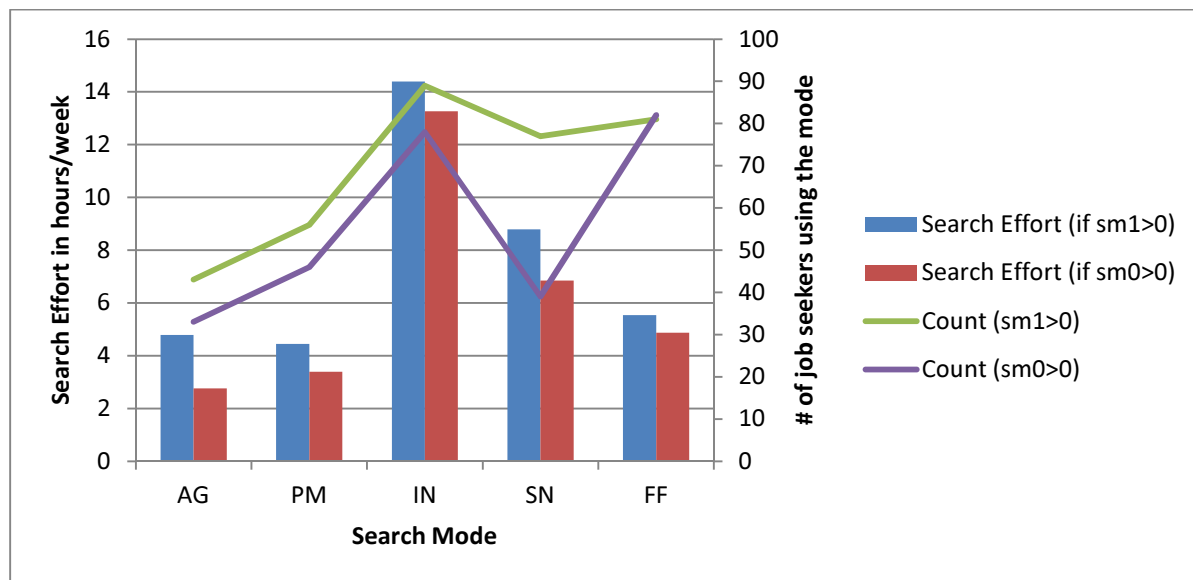


Figure 1: Job search mode selection and search effort allocation as a function of previous (sm0) or current (sm1) mode use

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

	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

Next we asked users to specify how many connections they have and how many they consider as weak and strong connections 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 who they frequently communicate with. The phrase “close friends and family” was also used to classify those group of individuals that a job seeker would talk to 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. Distribution of total, strong, and weak connections on both Facebook and LinkedIn is presented in Figure 2.

We observe that individuals have much larger share of strong-ties on Facebook yet a much larger share of weak-ties on LinkedIn. For individuals that did not use online social networks as a job search mode, we inquired about their distrust in that platform. All of the individuals (not using online social networks) selected privacy concern as the most important reason for not using online social networks (like Facebook) and lack of sufficient job leads 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.

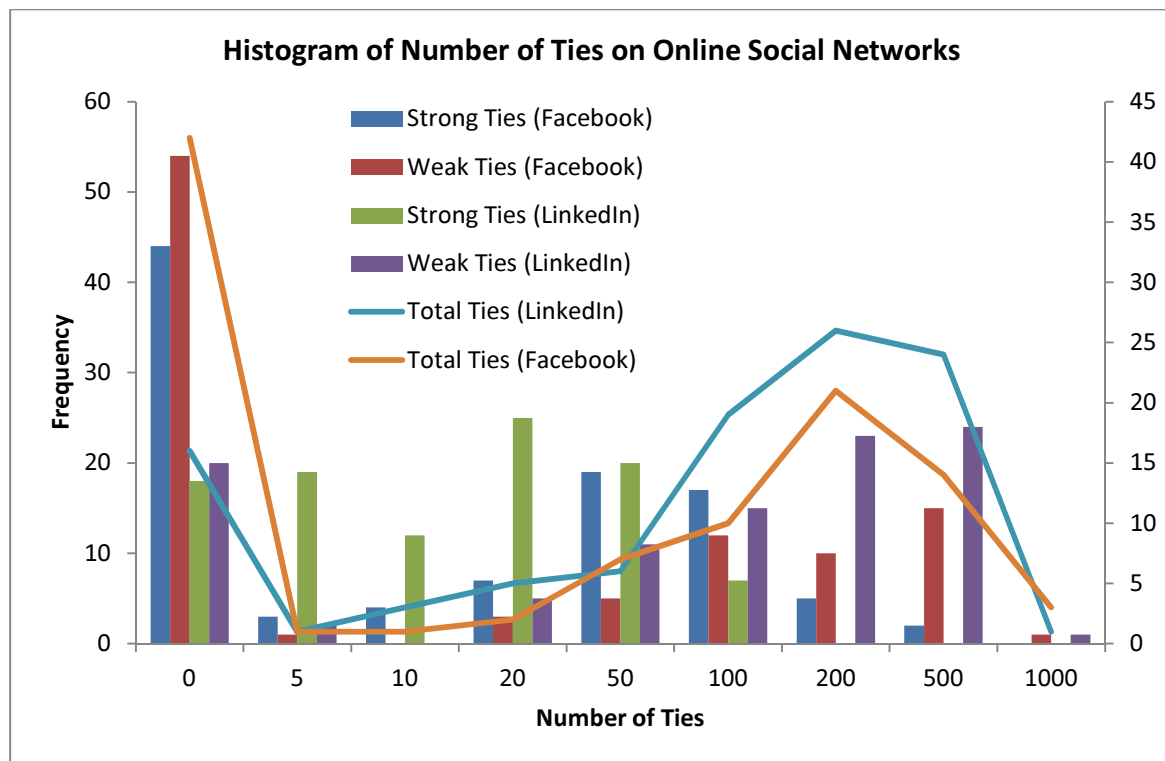


Figure 2: Distribution of number of online social ties on Facebook and LinkedIn

Since we know how much each job seeker received in the last job, we can create a distribution for each of the job search modes. Summary of the mean and standard deviation of wages is given 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

4.1 Survey Data Validation & Reliability

Typically a survey would ask multiple questions seeking a similar answer to estimate the reliability of the answers. Since this was a very detailed survey for unemployed individuals that were proctored by consultants, we tried to avoid redundancy. Thus we used three different approaches to build confidence in the response data: 1) inverted the flow so outcomes were

asked before probing question, 2) verified accuracy of conditional responses 3) matched answers with actual publicly available data.

With help from Denise Rousseau at Carnegie Mellon University, we designed a survey that conveyed the meaning of questions accurately without disclosing the reason for the question. This process followed throughout the survey where the demographic information was collected at the end. The flow of the survey sections is shown in appendix A.

By accuracy of conditional responses we mean validating if job seekers' responses to sequential questions like number of job leads, interviews, and offers followed a decreasing numerical value when the answer had no programmatic constraint/validation. From the responses of 109 individual, we found that one job seeker provided number of interviews received from newspaper to be higher than number of job applications submitted. Although this could be just a typographical error, we dropped that individual from the data.

We asked individuals about the number of connections they had on popular social networks like LinkedIn, Facebook, and Twitter and provided ranges as option to select their network size. We 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 to verify the responses. Of the 77 job seekers that used online social networks for job search we were able to access the profiles of 71 job seekers and the range 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 6 total connections. We dropped these individuals from the data for consistency.

Overall, we found that the error in responses for few survey questions was low and since the surveys were proctored, we assume the reliability for the entire data.

5 EMPIRICAL ANALYSIS & RESULTS

5.1 Search Effort Allocation

As discussed previously and in prior research (Mouw 2003) it is important to understand the role of social capital on the search effort to clearly identify any issues relating to endogeneity or homophily (McPherson, Smith-Lovin, and Cook 2001). Individuals with larger social capital could gain benefit from their network because they are connected to a few influential and highly social individuals and 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 capital on the search effort because a large social capital would require more effort and thus could eventually convert that effort into positive job outcomes. Thus, as a first step, we test if size of social capital indeed plays a role in the search effort allocated to online social network by the unemployed workforce.

Our regression equation is

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

The first two terms are simply a constant, while the other terms are readily identified. As we will show, we can recover structural parameters for cost (γ_j, δ_j) readily. 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 user specific and search mode specific unobserved. So we can rewrite this as:

$$s_{i,j} = \theta_j + \omega_i + \alpha_0 + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(R_{i,j}) + \varepsilon_{ij}$$

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 on 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 are unobserved.* Notice our optimal search model automatically incorporates the benefit function. From the benefit function it is clear that search efforts will be higher if $\varphi_{j,2}$ (effect of social connections on job outcomes) is positive and large. Thus in our model, a positive estimate on E is precisely 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 capital. So a mode may be more productive for reasons unknown. We control for these by using mode specific dummies.

(ii) Another worry 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. Though notice that we are testing the effect on online connections on search behavior on other modes as well.

(iii) 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. First we use 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:

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \quad (7)$$

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

We run two separate specifications. First is specification (7) where we split the online connections (E_i) into strong and weak connections and estimates their effect on search effort. Notice that (7) 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. In the second specification, 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.

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_{2a} * E_i * D_s + \alpha_{2b} * E_i * D_o + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \quad (7a)$$

D_s is dummy for online social network search mode while D_o is a dummy for any other mode. The estimates of these three separate regressions are given in the two columns of Table 6 below. The left out dummy (in θ_j) is the search mode "agencies".

From the table below, notice that the coefficients for all dummies are positive. This suggests people spend more time on online social network, Internet, print media and with friends and family for job search relative to agencies. Statistically speaking, job seekers allocate most time searching for jobs to the Internet followed by the online social networks. This is intuitive because online channels have been gaining popularity over the last few years in job search because of very low cost of search and ease of submitting a job application. Print media gets relatively lower search allocation possibly because of higher relative costs to search and apply for jobs. The coefficient for close friends and family (offline) is not significant possibly because of confounding effect of close friends and family.

We see that people with more strong ties search less on all modes. In terms of economic significance, an estimate of -0.43 indicates that a 100% increase in number of strong ties decreases the search effort by about 26 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 connections are either able to delegate their search to those connections or these users are more conservative (possibly because of a concern about their social reputation) in their search approach and thus do not disclose their unemployment status to those close friends and family.

Increase in weak-ties exhibit opposite behavior; a 100% increase in weak-ties increase the search intensity by 17 minutes per week and more so on LinkedIn. Unemployment spell has a positive and significant effect on search intensity, which is intuitive for the short duration of unemployment term observed in the data. Similarly past salary exhibits a positive and significant effect on the search intensity. Other demographic variables are not significant is expected given we control for user specific random effects and mode specific dummies.

Search Effort (hours/week)	Coeff (Std Dev)	Coeff (Std Dev)
Dummy (Online Social Networks)	6.306 (1.939)***	6.267 (1.947)***
Dummy (Offline Friends & Family)	1.709 (1.943)	1.71 (1.944)
Dummy (Internet)	10.695 (1.829)***	10.695 (1.83)***
Dummy (Print Media)	5.037 (2.104)**	5.033 (2.106)**
Log (LinkedIn Strong-Ties)	-0.431 (0.089)***	
Log (LinkedIn Weak-Ties)	0.295 (0.058)***	
SN * Log (LinkedIn Strong-Ties)		-0.155 (0.098)
SN * Log (LinkedIn Weak-Ties)		0.152 (0.057)***
OT * Log (LinkedIn Strong-Ties)		-0.486 (0.101)***
OT * Log (LinkedIn Weak-Ties)		0.317 (0.065)***
Log (Total Facebook Ties)	0.067 (0.032)**	0.063 (0.032)**
Log (Unemployment Spell)	0.829 (0.374)**	0.825 (0.374)**
Log (Salary)	7.085 (2.47)***	7.057 (2.472)***
Experience	-0.001 (0.066)	-0.001 (0.066)
Married (yes = 1)	-0.357 (0.747)	-0.37 (0.748)
Sex (male = 1)	-0.804 (0.681)	-0.799 (0.681)
Education (College Graduate)	-0.922 (0.979)	-0.908 (0.98)
Education (Graduate Degree)	-1.539 (1.136)	-1.52 (1.136)

Race (White)	1.144 (1.049)	1.148 (1.049)
Race (Black)	1.369 (1.51)	1.377 (1.511)
Race (Hispanic)	1.963 (1.517)	1.969 (1.519)
Employment Value (Online Social Networks)	1 (0.903)	0.957 (0.904)
Employment Value (Offline Friends & Family)	2.056 (0.945)**	2.054 (0.946)**
Employment Value (Internet)	2.111 (0.945)**	2.109 (0.946)**
Employment Value (Print Media)	0.879 (0.389)**	0.879 (0.389)**
Employment Value (Agencies & Career Fairs)	2.116 (0.883)**	2.114 (0.884)**
_cons	-35.886 (11.782)***	-35.706 (11.792)***

N = 450, bivariate joint likelihood 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(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- and weak-ties interacted with online social networks are not different and are of higher magnitude. Users with more weak online ties search more and with more strong ties search less on online networks. It is the weak ties that stimulate higher search intensity.

We see that the interaction of strong ties with other modes is not significant. However, online weak ties keep motivating the use of those connections for job search on other modes. Since SNS allow users to connect with a large number of weak-ties at a small or no cost, these ties could be perceived more valuable on the platform of connection.

5.1.1 Sequential Model (Search Intensity Affecting Job Leads)

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:

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

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

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

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.⁴ As before, we estimate two models. In the first one 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 as opposed to the absolute parameter estimates. They are presented in Table 7 below.

First we look at the job leads model. First notice that more search increases job leads significantly. Every additional hour of searching is associated with 0.33 additional leads. Notice that the effect of ties on job outcomes is not straightforward. More ties affects search which in turn affects leads. However ties have a direct effect on job outcomes. From the results in column (1), 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. The estimates are large and significant. Doubling the number of weak ties leads to about 0.7 more leads. The effect of strong ties is surprising. Higher 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

⁴ We cannot add a random effect readily given that we are estimating non-linear regressions.

tend to provide little or no new information to a job seeker. By definition most job leads are new piece of information that serves as potential job opportunities matching a user's skills for which a job seeker submits a customized 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					0.086 (0.018)***	0.077 (0.019)***
Dummy (OSN)	0.469 (1.294)	-3.405 (1.648)**	-0.557 (0.291)*	1.373 (1.276)	0.174 (0.135)	-0.077 (0.074)
Dummy (FF)	1.222 (1.427)	1.101 (1.411)	-0.324 (0.339)	-0.32 (0.346)	0.085 (0.118)	0.052 (0.092)
Dummy (Internet)	2.156 (1.471)	1.984 (1.475)	0.242 (0.39)	0.242 (0.394)	0.029 (0.09)	0.009 (0.073)
Dummy (Print Media)	0.821 (1.388)	0.62 (1.362)	-0.505 (0.277)*	-0.501 (0.278)*	-0.034 (0.105)	-0.05 (0.082)
Log (Strong-Ties)	-1.054 (0.405)***		0.386 (0.141)***		0.079 (0.023)***	
Log (Weak-Ties)	0.741 (0.251)***		-0.083 (0.09)		0.011 (0.011)	
SN * Log (Strong-Ties)		-0.303 (0.596)		0.096 (0.026)**		0.055 (0.027)**
SN * Log (Weak-Ties)		1.234 (0.453)***		-0.228 (0.118)*		-0.022 (0.014)
OT * Log (Strong-Ties)		-1.224 (0.4)***		0.425 (0.148)***		0.079 (0.019)***
OT * Log (Weak-Ties)		0.767 (0.246)***		-0.082 (0.097)		0.009 (0.011)
Log (Facebook Ties)	0.125 (0.16)	0.126 (0.155)	0.098 (0.066)	0.102 (0.065)	0.018 (0.008)**	0.013 (0.006)**
Log (Unemployment Spell)	0.103 (0.323)	0.078 (0.317)	0.003 (0.132)	-0.015 (0.125)	-0.01 (0.024)	-0.019 (0.016)
Log (Salary)	0.487 (1.041)	0.272 (1.081)	0.643 (0.369)*	0.627 (0.376)*	-0.109 (0.046)**	-0.103 (0.042)**
Experience	0.034 (0.059)	0.033 (0.059)	-0.021 (0.023)	-0.022 (0.024)	-0.019 (0.004)***	-0.017 (0.004)***
Married (yes = 1)	0.747 (0.773)	1.001 (0.742)	-0.392 (0.321)	-0.392 (0.323)	0.162 (0.057)***	0.139 (0.057)**
Sex (male = 1)	-1.835 (0.578)***	-1.72 (0.554)***	0.128 (0.214)	0.104 (0.218)	-0.022 (0.042)	-0.036 (0.034)
Education (College Graduate)	-3.213 (0.78)***	-3.258 (0.753)***	-0.068 (0.334)	-0.025 (0.35)	-0.032 (0.073)	-0.034 (0.06)
Education (Graduate Degree)	-2.377 (0.979)**	-2.464 (0.924)***	-0.489 (0.391)	-0.419 (0.407)	0.013 (0.072)	0.024 (0.058)
Race (White)	-1.485 (2.485)	-1.819 (2.377)	-0.254 (0.337)	-0.19 (0.336)	0 (0.04)	0.014 (0.034)
Race (Black)	-2.042 (1.594)	-2.195 (1.393)	-0.45 (0.275)	-0.47 (0.278)*	-0.065 (0.04)	-0.076 (0.03)**
Race (Hispanic)	-0.059 (2.156)	-0.521 (1.891)	-0.933 (0.174)***	-0.939 (0.166)***	0.226 (0.22)	0.098 (0.13)
R2	0.704	0.711	0.635	0.639	0.662	0.689
N	319	319	319	319	170	252
Clusters	89	89	88	88	76	88
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)						

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 the other modes. Now, the strong ties have no effect on job leads from social networks. However, weak ties are highly significant and quite large. Doubling the weak ties leads to 1.2 additional job leads. 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 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. When we interact ties with search modes, the effects persist (see column 4). Now the weak ties are negative and significant for 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 do this and not the weak ties. So while weak ties may help you get a lead, they do not necessarily help in converting these leads into interviews.

Coming to job offers (column 5 and 6), 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. 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 paraphrased⁵ statement "a friend of the world is no friend of mine" and more formally as 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

⁵ 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")

offers received. Although we see these negative coefficients to be marginal effects of social connections on job outcome the true impact still needs to be evaluated and follows.

5.1.2 Role of Social Connections on Job Outcomes

However, the effect of ties on job outcome is a complex. As we explained earlier, more ties affect search intensity as well. Our estimates from Table 6 confirm that users with more ties are also 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)

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = -0.303 - 0.332 * 0.155 \approx -0.354$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = 0.096 - 0.111 * 0.354 \approx 0.055$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = 0.055 + 0.077 * 0.055 \approx 0.059$$

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

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = 1.234 + 0.332 * 0.152 \approx 1.284$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = -0.228 + 0.111 * 1.284 \approx -0.085$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = -0.022 - 0.077 * 0.085 \approx -0.029$$

Thus for every 100% increase in number of weak-ties on LinkedIn, a job seeker can gain additional 1.3 job leads. But this 100% increase in weak-ties will decrease the number of job interviews by 0.085 and will decrease the number of offers by 0.029. Similarly, we can compute

the net effect of strong connections on the job outcomes. For 100% increase in strong-ties on LinkedIn, we expect to see a decrease in job leads by 0.35, increase in job interviews by 0.06, and an increase in job offers by 0.06.

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

$$\begin{aligned}\Delta J L_{i,j} &= 1.284 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} - 0.354 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}} \\ \Delta J I_{i,j} &= -0.085 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.055 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}} \\ \Delta J O_{i,j} &= -0.029 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.059 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}}\end{aligned}$$

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, thus this approach to estimate the effect of social connections on job outcomes should only be seen as a framework for future work. To better understand the net effect of search allocation and social capital on job outcome 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 the estimated parameters of equation 7a, because the 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 maximize the following bivariate likelihood model to recover the structural parameters in both the cost (equation 4) and benefit (equation 3) functions:

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

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

Cost Function	OSN	FF	IN	PM	AG
γ_j	0.56	1.33	1.39	0.58	1.44
δ_j / γ_j (Log(FB_Connections))	0.113	0.047	0.045	0.109	0.044
δ_j / γ_j (Log(Unemployment_Spell))	1.473	0.62	0.594	1.422	0.573
δ_j / γ_j (Log(Salary))	12.602	5.306	5.077	12.167	4.901
δ_j / γ_j (Experience)	-0.002	-0.001	-0.001	-0.002	-0.001
δ_j / γ_j (Married)	-0.661	-0.278	-0.266	-0.638	-0.257
δ_j / γ_j (Sex_Male)	-1.427	-0.601	-0.575	-1.378	-0.555

From the cost function (eq 4) estimates, we see that scale coefficient (γ) is smallest for online social networks suggesting the low overall search costs of the platform. We believe that it is intuitive that online social networks have 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 to find a new job. 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 pick the ones worth the time it takes for submitting 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 give time frame. The cost for agencies is highest because of interpersonal communication with an agency that may have additional costs to provide their services.

The estimates of structural parameters for benefit function (job leads) are presented below:

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

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

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

Structural Parameter	Benefit Function		Job Leads		Job Interviews		Job Offers	
	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)
τ_0	-0.007	-0.007	0.009	0.009	-0.012	-0.012		
τ_1	0.053	0.053	0.035	0.035	2.024	2.024		
ϕ_{0j}	2.326	3.473	3.574	2.752	-1.227	-0.521		
ϕ_{2j} (Log(LinkedIn Strong-Ties))	-0.036	-0.245	0.076	0.336	0.494	0.622		
ϕ_{2j} (Log(LinkedIn Weak-Ties))	0.234	0.155	-0.228	-0.129	-0.224	-0.051		
ϕ_1 (Log(FB_Connections))	0.022	0.022	0.078	0.078	0.109	0.109		
ϕ_1 (Log(Unemployment_Spell))	0.005	0.005	-0.046	-0.046	-0.172	-0.172		
ϕ_1 (Log(Salary))	0.049	0.049	0.502	0.502	-0.822	-0.822		
ϕ_1 (Experience)	0.004	0.004	-0.021	-0.021	-0.137	-0.137		
ϕ_1 (Married)	0.219	0.219	-0.346	-0.346	1.416	1.416		
ϕ_1 (Sex_Male)	-0.315	-0.315	0.043	0.043	-0.384	-0.384		

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 somewhat intuitive because the numbers of job posts, although steadily growing, are 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 other job search modes. We believe this is the case because a lot of recruiters are moving towards online social networks to screen candidates for interviews based on their interactions with their social community. The conversion to offer is lower for online social networks because we believe the strong-ties that play a strong role in conversion actually are portable and communication with them is achieved through faster modes like email or phone.

As discussed before, we see a negative effect of strong online connections and a positive effect of weak online connections on job leads suggesting that strong-ties are contributing less new information whereas weak-ties tend to provide more new information. The role of strong- and weak- ties flip when it comes to job interviews or offers.

The positive coefficient for strong-ties suggest the 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 might be lower thus impacting the conversion rate from job applications to interviews to offers. As discussed previously, online strong-ties tend to be multiplexed ties thus having a positive effect irrespective of the job search mode.

In summary, the estimated structural parameter allows us to build both cost and benefit functions for all of the five job search modes. This should help the job seekers to allocate their job search effort on various modes and improve the probability of outcomes (job leads, interviews, or offers) received from each search mode.

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 more educated and higher income individuals. 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 continuously expanding social capital plays an important role in the job search. But since the effect of weak- and strong- ties is 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 is intuitive because larger social capital will imply more opportunities to find new information through the network. Here we found that larger social capital will increase the search intensity allocated to both offline or online social job search modes and will cannibalize the time spent on Internet for job search.

This study also echoes the argument (Kuhn and Skuterud 2004) suggesting that the internet enabled 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 platform results 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 higher number of job interviews. This difference in outcome from job search modes has been used to suggest the value of information portability by many career transition experts. These industry experts suggest finding job leads from various job search modes and applying for positions like job seekers did a decade ago – mailing in a hardcopy cover letter with resume. This could then improve the chances receiving interview calls for every application.

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 internet and then tap into her social capital 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.

6.1 LIMITATIONS & FUTURE WORK

One limitation of our approach is that we use multiple non-linear models for analysis that caused burden of jointly estimating the productivity model and simultaneously estimating the models for all job search modes. Both joint and simultaneous estimation of job outcomes require more sophisticated econometric modeling and are 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 non linear 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. Although there are some limitations because of survey data, we have presented a framework for analyzing social capital for labor market and believe that future work should consider the approach presented here.

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

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ABSTRACT

Prior research has previously presented that social connections (like friends and family) - usually categorized as strong and weak ties - are valuable in a job search process. Still the size of job seeker's network was limited because of constraints posed by the 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 their job search behavior not only on social network but also on other modes. Secondly, we examine how the ties (weak and strong) and search intensity affect the job outcomes (which we model sequentially; job leads, interviews and offers) from online social networks vs. those from other job search modes like career fairs & agencies, newspapers & magazines, internet, and close friends and family (offline). We first build an economic model of search behavior with cost and benefit functions; then we estimate the model to recover some key estimates and structural parameters using a survey data of 109 users. We find that users with more weak ties search more on all modes. However, users with more strong ties search less on online social networks. We also find that weak ties are especially helpful in generating job leads but it is the strong ties which 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. 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 job seekers reached out to 22 percent of their friends and family. Growth 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. There is significant literature that suggests that “who you know” plays a very important role in someone finding a job. Granovetter (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 because online platforms have enabled a much larger competition amongst the job seekers as every job post is now available to every job seeker across the globe. According to a survey conducted by CareerBuilder.com¹ in 2009, each job post received over 75 resume. Social connections could potentially help job seekers in reaching directly to hiring managers and improve 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 which allows 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, Steinfield,

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

and Lampe 2007; Valenzuela, Park, and Kee 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 recent 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 each spending on average 4 minutes 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, advertizing 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 network is the ability of individuals to maintain and manage far more online connections - average number of friends on facebook.com² 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 may be helpful, but they may also make it harder for 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 consider online social networks a great tool for job search. After all, unemployment information is not something users may be willing to share with their network especially when the network consists of large number of weak ties. So users may be reluctant to conduct directed search on these networks.

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:

(i) How are people allocating their job search efforts across different modes, especially, online social networks? How does users' online social network (including weak ties) affect these search efforts?

(ii) Are online networks effective in generating job offers? Does users' online social network affect this effectiveness? How do strong and weak ties influence job leads vs. job interviews and offers?

Answers to these questions require having access to some detailed data on users' job search behavior. To do this, we administer a survey to unemployed users asking them detailed questions on their job search methods, their online and offline social capital, and job outcomes. We then provide a model of users' job search behavior and effectiveness of search modes, especially emphasizing the role of social capital.

Using completed survey of 109 users, we find that job seekers with larger number of 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" and "strength of strong-ties" arguments hold for online social networks but 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, a much larger network size might help job seeker find new leads but will 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, 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 question for labor economists, sociologists and technologists. The answer to our research questions are of importance to individuals who are searching for jobs and firms like LinkedIn whose business models depend on answers to these questions. More importantly, even 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 a particular focus on online networks has been possible due to lack of detailed data. Despite some limitations of our survey, 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 undoubtedly are needed to investigate this very important issue.

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

2 LITERATURE

We draw from two major literatures. First is job search literature in labor economics. Scholars have studied labor market and the role of social ties on the job outcomes (Granovetter 1983) (Holzer 1988), wages (Montgomery 1992), and job information diffusion (Granovetter 1995). It has been shown in the past 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).

Differentiating between the unemployed and employed workforce, researchers have found that the job search while being employed is more effective when compared to the job search when unemployed (Blau and Robins 1990). An analytical work using the diffusion of job lead information through network structure suggests duration dependence of unemployment (Calvó-Armengol and Jackson 2004).

As pointed in a recent review (Mouw 2006), estimating the role of social capital has been increasingly challenging due to homophily (McPherson, Smith-Lovin, and Cook 2001) and reflection (Manski 1993). He 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. 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).

Since the growth of Internet as a channel for job search, it has been increasingly used both by unemployed and employed workforce 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 Internet is also shown to have negative effect on the unemployment duration of job seekers (Kuhn and Skuterud 2004). Also, it is shown that internet maybe more effective when compared to newspaper ads or direct application, it is less effective compared to social networks (Feldman and Klaas 2002) thus creating a need for investigation of various job search modes including online social networks.

The second literature we explore is the economics and sociology literature examining the role of social capital. Seminal work in the area of sociology originated from 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) with a larger emphasis on product marketing or innovation diffusion. During the same time the origination of strength-of-weak-ties theory (Granovetter 1973) changed the perspective of social capital. Granovetter 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, Libai, and Muller 2001) but may have a different impacts based on the interaction between the ties and the size of the network. It was also shown that strong ties are important (Krackhardt 1992) 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 matter 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).

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

Online social networks allow users to maintain a large number of connections that are weak-ties; 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. Through this paper we try to take the first step at understanding the role of online social networks on job search by unemployed workforce using a survey data collected from that workforce.

3 THEORY

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? And, do online connections affect job outcomes? A key goal is to understand how online social 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 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 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 channels: 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].

3.1 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. In particular, individuals make decisions on how much to search based on their expected benefits and costs.

These models assume that there is certain baseline utility from being unemployed. Searching increases the probability of being employed but it also has associated costs. So users are essentially trading off these two costs. In particular if users perceive social connections to be useful, we should see them searching more on those modes. More formally, we can specify the utility of an unemployed individual as:

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

i indexes an individual, j indexes search model and t 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 $\pi(s_j, X_i, E_i)$ and wage offer (w_t) is higher than reservation wage ($w_{R,t}$). Here X_i represents the user's characteristics (like education, experience, age, salary during last job, race, etc). E_i represents the embeddedness or social capital of user i on online social network (especially the number of connections on LinkedIn). The third term in (1) is simply the probability that users will remain unemployed because the wage offer is not higher than reservation wage and the fourth term indicates that the user may not get any offer despite searching and hence remain unemployed in the next period.

Most job search models also have reservation wage as a decision variable. So in a dynamic model, individuals are also choosing their reservation wage over time. Given the cross section nature of our data over a period, and that our focus is on empirical identification of how users connections play a role, we assume the reservation wages are exogenous. We will revisit this shortly. Assuming that the wage offer distribution is given as $f(w)$, we can rewrite the above equation as:

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

The equation specifies expected change in utility over two time periods due to investing in 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. We will rely on prior literature for these functions. v is assumed to be linear in its arguments (Holzer 1988). Given that these are unemployed users who have more available time to search, the cost of search on leisure can 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 :

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

$$\text{where } \lambda_{ij}(X_i, E_i) = \exp(\varphi_{0j} + \varphi_1 X_i + \varphi_2 E_i)$$

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) as:

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

As expected cost is increasing in search efforts and it is convex. Typically embeddedness will be a part of the cost function if a job seeker uses the available time for job search in building her social network, but we assume that the individuals are unemployed are using their existing capital to find a new job. Thus the coefficient for embeddedness in cost function is assumed to be zero. Given that the benefit of search is linear, an interior solution is guaranteed. Taking first order of (2) will yield:

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

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:

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

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

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

While we have data to estimate this equation, there are many challenges.

First we do not directly observe R . Note that R is the expected benefit of employment given the distribution of wages distribution 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; we assume that reservation wage is proportional to the past wage³. If wage offer distribution is normal for a job search mode then:

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

If we know the past wage of a job seeker and distribution of wages received from a job search mode, we can recover the value of expected benefit of employment. As we will see later, we

³ One would expect that reservation wage will change with time. But we do not observe the users repeatedly, and hence use past wage as a proxy for reservation wage.

collected wage information from job seekers and use that to compute the distribution for each of the job search modes, thus allowing us to estimate the value of R for each job seeker.

3.2 EFFECT OF EMBEDDEDNESS ON JOB OUTCOME

Once an unemployed job-seeker allocates time to each job search mode, the next step is to estimate the role of social embeddedness on the job outcomes. Our job offer model is straightforward.

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

Most models who estimate effect of social capital on job outcomes do not capture any details on search intensity “s” which is problematic as we show.

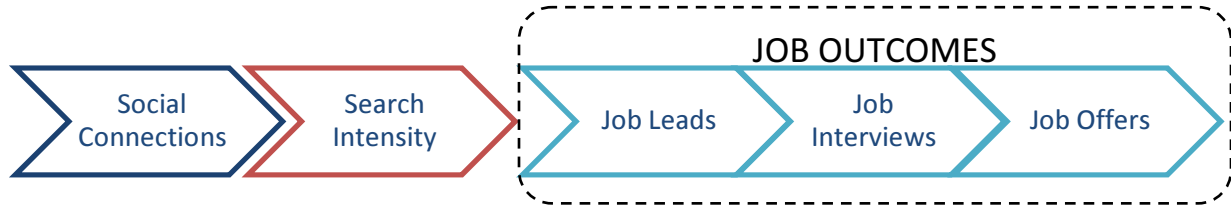
Embeddedness can affect job outcomes in two ways. First, as our model in (4) shows, more connections may lead to more search effort by users. Second, more connections would lead to more job outcomes independent of search effort. Formally, the effect of embeddedness on job outcome could then be written 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”, effect of embeddedness on job outcomes will be seriously 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 effects 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 offer as an outcome. However, the actual job offer process is more complex. Usually job search efforts generate relevant job leads. Job leads convert to interviews and finally 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 to potentially relevant job lead. 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 write recommendation letter on behalf of a user, or press 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 focus on three outcomes: job leads, job interviews and job offers. It is clear that these are linked sequentially. 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,

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

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.

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

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

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

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

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

$$\frac{dJI_{ij}}{dE_i} = \frac{\partial JI_{ij}}{\partial E_i} + \frac{\partial JI_{ij}}{\partial JL_{ij}} * \frac{dJL_{ij}}{dE_i}$$

$$\frac{dJL_{ij}}{dE_i} = \frac{\partial JL_{ij}}{\partial E_i} + \frac{\partial JL_{ij}}{\partial s_{ij}} * \frac{ds_{ij}}{dE_i}$$

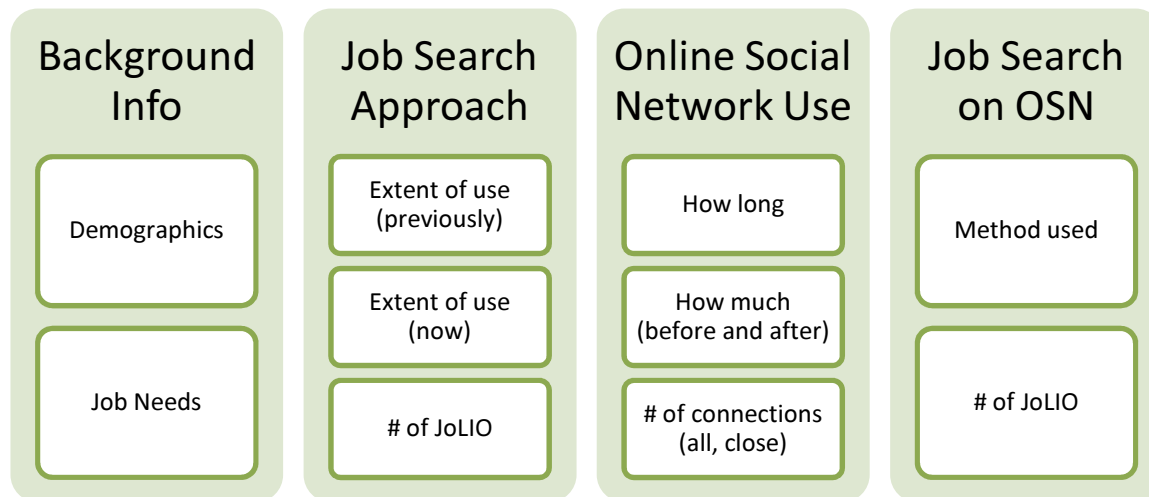
In addition to estimating the effect of embeddedness on various job outcome classifications, the above model also allows us to estimate the effectiveness of each job search mode in converting search effort to job leads, job leads to interviews, or job interviews to offers. Next we discuss the role of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

4 DATA

Traditionally labor economists have relied on National Longitudinal Survey (NLS) or Current Population Survey (CPS) to examine how users are searching for jobs and in some cases how do their social networks help them in job search (Holzer 1988). While these data have large observations, they do not contain many details that are needed to answers the question 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. Most of these surveys also do not have any details on users' online social capital and search behavior.

To better understand the role of online social networks on job outcomes, we designed an IRB approved survey and administered it to individuals that 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, their motivations for job search, their past and present job search strategies, their familiarity and use of online social networks, and their knowledge of using online social networks for job search. Thus the survey is much more detailed and required about 30 minutes of subject's time in answering all of the questions regarding their job search approach. The survey contains the following components:



To test if users would respond to the details asked in the survey and 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 to maintain the attention of job seekers during the entire time. We made some adjustments to the questions based on the feedback received and the actual data from this sample was ignored for the study.

The outplacement firm had access to 288 individuals whose emails were available to them. Of the 288 emails sent, 163 individuals opened the email and 109 individuals took our survey. 8 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 report created with help of professionals in the field. It should be clear that our survey was sent to mostly educated, white collar workers. So the sample is neither representative of general population nor is perfectly random. However, we also expect that educated and white collar workers are precisely the

people likely to use online social networks. So 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.

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 all survey takers

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 during last job search (sticky search) is given in Table 2. Table 2 shows how the job search behavior changed conditional on the search mode being selected during the current time period or the previous time period. Increase in the number of individuals using each job search mode suggests 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 see 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 internet (49% on average) with print media (29%) and agencies (25%) as the lowest two. We explicitly ask users how many job leads, job interviews and job offers they found via each model. The summary of search effort distribution across job search mode, their search intensity on that 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 (%).

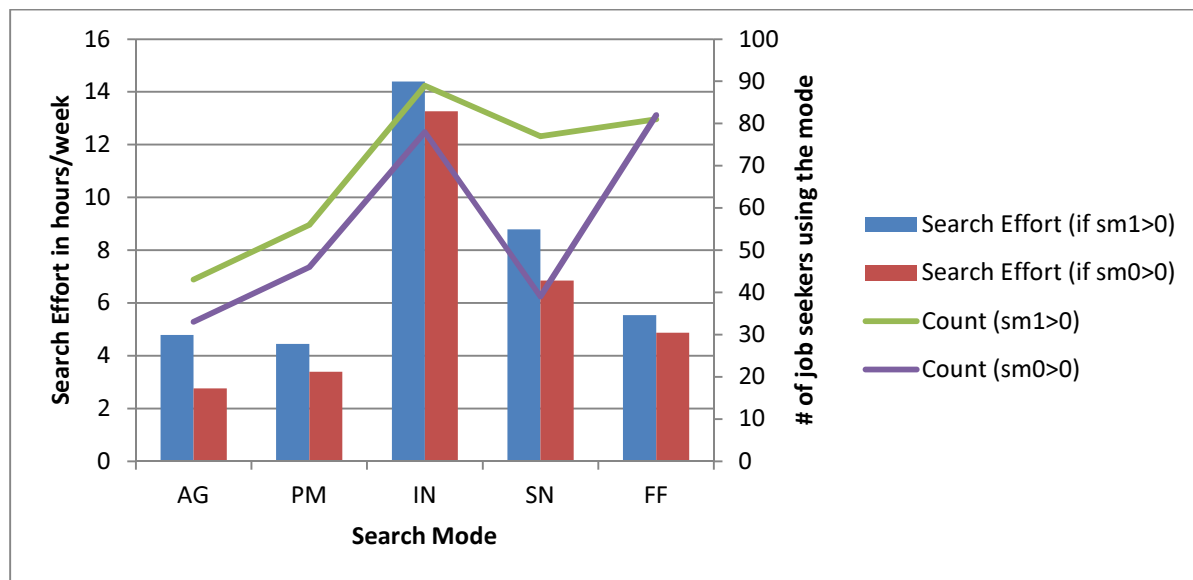


Figure 1: Job search mode selection and search effort allocation as a function of previous (sm0) or current (sm1) mode use

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

	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

Next we asked users to specify how many connections they have and how many they consider as weak and strong connections 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 who they frequently communicate with. The phrase “close friends and family” was also used to classify those group of individuals that a job seeker would talk to 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. Distribution of total, strong, and weak connections on both Facebook and LinkedIn is presented in Figure 2.

We observe that individuals have much larger share of strong-ties on Facebook yet a much larger share of weak-ties on LinkedIn. For individuals that did not use online social networks as a job search mode, we inquired about their distrust in that platform. All of the individuals (not using online social networks) selected privacy concern as the most important reason for not using online social networks (like Facebook) and lack of sufficient job leads 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.

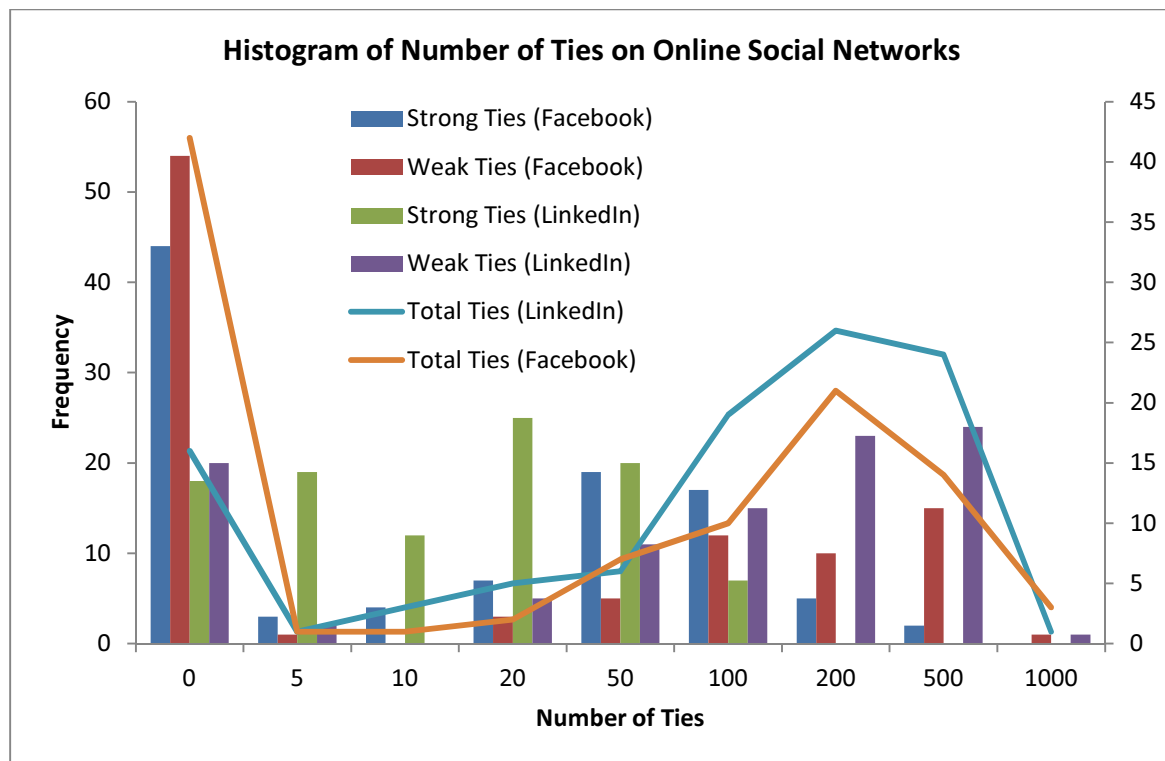


Figure 2: Distribution of number of online social ties on Facebook and LinkedIn

Since we know how much each job seeker received in the last job, we can create a distribution for each of the job search modes. Summary of the mean and standard deviation of wages is given 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

4.1 Survey Data Validation & Reliability

Typically a survey would ask multiple questions seeking a similar answer to estimate the reliability of the answers. Since this was a very detailed survey for unemployed individuals that were proctored by consultants, we tried to avoid redundancy. Thus we used three different approaches to build confidence in the response data: 1) inverted the flow so outcomes were

asked before probing question, 2) verified accuracy of conditional responses 3) matched answers with actual publicly available data.

With help from Denise Rousseau at Carnegie Mellon University, we designed a survey that conveyed the meaning of questions accurately without disclosing the reason for the question. This process followed throughout the survey where the demographic information was collected at the end. The flow of the survey sections is shown in appendix A.

By accuracy of conditional responses we mean validating if job seekers' responses to sequential questions like number of job leads, interviews, and offers followed a decreasing numerical value when the answer had no programmatic constraint/validation. From the responses of 109 individual, we found that one job seeker provided number of interviews received from newspaper to be higher than number of job applications submitted. Although this could be just a typographical error, we dropped that individual from the data.

We asked individuals about the number of connections they had on popular social networks like LinkedIn, Facebook, and Twitter and provided ranges as option to select their network size. We 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 to verify the responses. Of the 77 job seekers that used online social networks for job search we were able to access the profiles of 71 job seekers and the range 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 6 total connections. We dropped these individuals from the data for consistency.

Overall, we found that the error in responses for few survey questions was low and since the surveys were proctored, we assume the reliability for the entire data.

5 EMPIRICAL ANALYSIS & RESULTS

5.1 Search Effort Allocation

As discussed previously and in prior research (Mouw 2003) it is important to understand the role of social capital on the search effort to clearly identify any issues relating to endogeneity or homophily (McPherson, Smith-Lovin, and Cook 2001). Individuals with larger social capital could gain benefit from their network because they are connected to a few influential and highly social individuals and 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 capital on the search effort because a large social capital would require more effort and thus could eventually convert that effort into positive job outcomes. Thus, as a first step, we test if size of social capital indeed plays a role in the search effort allocated to online social network by the unemployed workforce.

Our regression equation is

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

The first two terms are simply a constant, while the other terms are readily identified. As we will show, we can recover structural parameters for cost (γ_j, δ_j) readily. 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 user specific and search mode specific unobserved. So we can rewrite this as:

$$s_{i,j} = \theta_j + \omega_i + \alpha_0 + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(R_{i,j}) + \varepsilon_{ij}$$

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 on 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 are unobserved.* Notice our optimal search model automatically incorporates the benefit function. From the benefit function it is clear that search efforts will be higher if $\varphi_{j,2}$ (effect of social connections on job outcomes) is positive and large. Thus in our model, a positive estimate on E is precisely 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 capital. So a mode may be more productive for reasons unknown. We control for these by using mode specific dummies.

(ii) Another worry 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. Though notice that we are testing the effect on online connections on search behavior on other modes as well.

(iii) 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. First we use 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:

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \quad (7)$$

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

We run two separate specifications. First is specification (7) where we split the online connections (E_i) into strong and weak connections and estimates their effect on search effort. Notice that (7) 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. In the second specification, 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.

$$s_{i,j} = \omega_i + \theta_j + \alpha_1 * X_i + \alpha_2 * E_i + \alpha_{2a} * E_i * D_s + \alpha_{2b} * E_i * D_o + \alpha_3 * \log(R_{i,j}) + \alpha_4 * E_i^F + \alpha_5 * Dur_i + \varepsilon_{ij} \quad (7a)$$

D_s is dummy for online social network search mode while D_o is a dummy for any other mode. The estimates of these three separate regressions are given in the two columns of Table 6 below. The left out dummy (in θ_j) is the search mode "agencies".

From the table below, notice that the coefficients for all dummies are positive. This suggests people spend more time on online social network, Internet, print media and with friends and family for job search relative to agencies. Statistically speaking, job seekers allocate most time searching for jobs to the Internet followed by the online social networks. This is intuitive because online channels have been gaining popularity over the last few years in job search because of very low cost of search and ease of submitting a job application. Print media gets relatively lower search allocation possibly because of higher relative costs to search and apply for jobs. The coefficient for close friends and family (offline) is not significant possibly because of confounding effect of close friends and family.

We see that people with more strong ties search less on all modes. In terms of economic significance, an estimate of -0.43 indicates that a 100% increase in number of strong ties decreases the search effort by about 26 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 connections are either able to delegate their search to those connections or these users are more conservative (possibly because of a concern about their social reputation) in their search approach and thus do not disclose their unemployment status to those close friends and family.

Increase in weak-ties exhibit opposite behavior; a 100% increase in weak-ties increase the search intensity by 17 minutes per week and more so on LinkedIn. Unemployment spell has a positive and significant effect on search intensity, which is intuitive for the short duration of unemployment term observed in the data. Similarly past salary exhibits a positive and significant effect on the search intensity. Other demographic variables are not significant is expected given we control for user specific random effects and mode specific dummies.

Search Effort (hours/week)	Coeff (Std Dev)	Coeff (Std Dev)
Dummy (Online Social Networks)	6.306 (1.939)***	6.267 (1.947)***
Dummy (Offline Friends & Family)	1.709 (1.943)	1.71 (1.944)
Dummy (Internet)	10.695 (1.829)***	10.695 (1.83)***
Dummy (Print Media)	5.037 (2.104)**	5.033 (2.106)**
Log (LinkedIn Strong-Ties)	-0.431 (0.089)***	
Log (LinkedIn Weak-Ties)	0.295 (0.058)***	
SN * Log (LinkedIn Strong-Ties)		-0.155 (0.098)
SN * Log (LinkedIn Weak-Ties)		0.152 (0.057)***
OT * Log (LinkedIn Strong-Ties)		-0.486 (0.101)***
OT * Log (LinkedIn Weak-Ties)		0.317 (0.065)***
Log (Total Facebook Ties)	0.067 (0.032)**	0.063 (0.032)**
Log (Unemployment Spell)	0.829 (0.374)**	0.825 (0.374)**
Log (Salary)	7.085 (2.47)***	7.057 (2.472)***
Experience	-0.001 (0.066)	-0.001 (0.066)
Married (yes = 1)	-0.357 (0.747)	-0.37 (0.748)
Sex (male = 1)	-0.804 (0.681)	-0.799 (0.681)
Education (College Graduate)	-0.922 (0.979)	-0.908 (0.98)
Education (Graduate Degree)	-1.539 (1.136)	-1.52 (1.136)

Race (White)	1.144 (1.049)	1.148 (1.049)
Race (Black)	1.369 (1.51)	1.377 (1.511)
Race (Hispanic)	1.963 (1.517)	1.969 (1.519)
Employment Value (Online Social Networks)	1 (0.903)	0.957 (0.904)
Employment Value (Offline Friends & Family)	2.056 (0.945)**	2.054 (0.946)**
Employment Value (Internet)	2.111 (0.945)**	2.109 (0.946)**
Employment Value (Print Media)	0.879 (0.389)**	0.879 (0.389)**
Employment Value (Agencies & Career Fairs)	2.116 (0.883)**	2.114 (0.884)**
_cons	-35.886 (11.782)***	-35.706 (11.792)***

N = 450, bivariate joint likelihood 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(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- and weak-ties interacted with online social networks are not different and are of higher magnitude. Users with more weak online ties search more and with more strong ties search less on online networks. It is the weak ties that stimulate higher search intensity.

We see that the interaction of strong ties with other modes is not significant. However, online weak ties keep motivating the use of those connections for job search on other modes. Since SNS allow users to connect with a large number of weak-ties at a small or no cost, these ties could be perceived more valuable on the platform of connection.

5.1.1 Sequential Model (Search Intensity Affecting Job Leads)

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:

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

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

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

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.⁴ As before, we estimate two models. In the first one 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 as opposed to the absolute parameter estimates. They are presented in Table 7 below.

First we look at the job leads model. First notice that more search increases job leads significantly. Every additional hour of searching is associated with 0.33 additional leads. Notice that the effect of ties on job outcomes is not straightforward. More ties affects search which in turn affects leads. However ties have a direct effect on job outcomes. From the results in column (1), 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. The estimates are large and significant. Doubling the number of weak ties leads to about 0.7 more leads. The effect of strong ties is surprising. Higher 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

⁴ We cannot add a random effect readily given that we are estimating non-linear regressions.

tend to provide little or no new information to a job seeker. By definition most job leads are new piece of information that serves as potential job opportunities matching a user's skills for which a job seeker submits a customized 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					0.086 (0.018)***	0.077 (0.019)***
Dummy (OSN)	0.469 (1.294)	-3.405 (1.648)**	-0.557 (0.291)*	1.373 (1.276)	0.174 (0.135)	-0.077 (0.074)
Dummy (FF)	1.222 (1.427)	1.101 (1.411)	-0.324 (0.339)	-0.32 (0.346)	0.085 (0.118)	0.052 (0.092)
Dummy (Internet)	2.156 (1.471)	1.984 (1.475)	0.242 (0.39)	0.242 (0.394)	0.029 (0.09)	0.009 (0.073)
Dummy (Print Media)	0.821 (1.388)	0.62 (1.362)	-0.505 (0.277)*	-0.501 (0.278)*	-0.034 (0.105)	-0.05 (0.082)
Log (Strong-Ties)	-1.054 (0.405)***		0.386 (0.141)***		0.079 (0.023)***	
Log (Weak-Ties)	0.741 (0.251)***		-0.083 (0.09)		0.011 (0.011)	
SN * Log (Strong-Ties)		-0.303 (0.596)		0.096 (0.026)**		0.055 (0.027)**
SN * Log (Weak-Ties)		1.234 (0.453)***		-0.228 (0.118)*		-0.022 (0.014)
OT * Log (Strong-Ties)		-1.224 (0.4)***		0.425 (0.148)***		0.079 (0.019)***
OT * Log (Weak-Ties)		0.767 (0.246)***		-0.082 (0.097)		0.009 (0.011)
Log (Facebook Ties)	0.125 (0.16)	0.126 (0.155)	0.098 (0.066)	0.102 (0.065)	0.018 (0.008)**	0.013 (0.006)**
Log (Unemployment Spell)	0.103 (0.323)	0.078 (0.317)	0.003 (0.132)	-0.015 (0.125)	-0.01 (0.024)	-0.019 (0.016)
Log (Salary)	0.487 (1.041)	0.272 (1.081)	0.643 (0.369)*	0.627 (0.376)*	-0.109 (0.046)**	-0.103 (0.042)**
Experience	0.034 (0.059)	0.033 (0.059)	-0.021 (0.023)	-0.022 (0.024)	-0.019 (0.004)***	-0.017 (0.004)***
Married (yes = 1)	0.747 (0.773)	1.001 (0.742)	-0.392 (0.321)	-0.392 (0.323)	0.162 (0.057)***	0.139 (0.057)**
Sex (male = 1)	-1.835 (0.578)***	-1.72 (0.554)***	0.128 (0.214)	0.104 (0.218)	-0.022 (0.042)	-0.036 (0.034)
Education (College Graduate)	-3.213 (0.78)***	-3.258 (0.753)***	-0.068 (0.334)	-0.025 (0.35)	-0.032 (0.073)	-0.034 (0.06)
Education (Graduate Degree)	-2.377 (0.979)**	-2.464 (0.924)***	-0.489 (0.391)	-0.419 (0.407)	0.013 (0.072)	0.024 (0.058)
Race (White)	-1.485 (2.485)	-1.819 (2.377)	-0.254 (0.337)	-0.19 (0.336)	0 (0.04)	0.014 (0.034)
Race (Black)	-2.042 (1.594)	-2.195 (1.393)	-0.45 (0.275)	-0.47 (0.278)*	-0.065 (0.04)	-0.076 (0.03)**
Race (Hispanic)	-0.059 (2.156)	-0.521 (1.891)	-0.933 (0.174)***	-0.939 (0.166)***	0.226 (0.22)	0.098 (0.13)
R2	0.704	0.711	0.635	0.639	0.662	0.689
N	319	319	319	319	170	252
Clusters	89	89	88	88	76	88
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)						

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 the other modes. Now, the strong ties have no effect on job leads from social networks. However, weak ties are highly significant and quite large. Doubling the weak ties leads to 1.2 additional job leads. 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 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. When we interact ties with search modes, the effects persist (see column 4). Now the weak ties are negative and significant for 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 do this and not the weak ties. So while weak ties may help you get a lead, they do not necessarily help in converting these leads into interviews.

Coming to job offers (column 5 and 6), 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. 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 paraphrased⁵ statement "a friend of the world is no friend of mine" and more formally as 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

⁵ 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")

offers received. Although we see these negative coefficients to be marginal effects of social connections on job outcome the true impact still needs to be evaluated and follows.

5.1.2 Role of Social Connections on Job Outcomes

However, the effect of ties on job outcome is a complex. As we explained earlier, more ties affect search intensity as well. Our estimates from Table 6 confirm that users with more ties are also 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)

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = -0.303 - 0.332 * 0.155 \approx -0.354$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = 0.096 - 0.111 * 0.354 \approx 0.055$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = 0.055 + 0.077 * 0.055 \approx 0.059$$

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

$$\frac{dJL_{i,j}}{dE_{i,j}} = \frac{\partial JL_{i,j}}{\partial E_{i,j}} + \frac{\partial JL_{i,j}}{\partial s_j} * \frac{ds_j}{dE_{i,j}} = 1.234 + 0.332 * 0.152 \approx 1.284$$

$$\frac{dJI_{i,j}}{dE_{i,j}} = \frac{\partial JI_{i,j}}{\partial E_{i,j}} + \frac{\partial JI_{i,j}}{\partial JL_j} * \frac{dJL_j}{dE_{i,j}} = -0.228 + 0.111 * 1.284 \approx -0.085$$

$$\frac{dJO_{i,j}}{dE_{i,j}} = \frac{\partial JO_{i,j}}{\partial E_{i,j}} + \frac{\partial JO_{i,j}}{\partial JI_j} * \frac{\partial JI_j}{\partial E_{i,j}} = -0.022 - 0.077 * 0.085 \approx -0.029$$

Thus for every 100% increase in number of weak-ties on LinkedIn, a job seeker can gain additional 1.3 job leads. But this 100% increase in weak-ties will decrease the number of job interviews by 0.085 and will decrease the number of offers by 0.029. Similarly, we can compute

the net effect of strong connections on the job outcomes. For 100% increase in strong-ties on LinkedIn, we expect to see a decrease in job leads by 0.35, increase in job interviews by 0.06, and an increase in job offers by 0.06.

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

$$\begin{aligned}\Delta J L_{i,j} &= 1.284 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} - 0.354 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}} \\ \Delta J I_{i,j} &= -0.085 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.055 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}} \\ \Delta J O_{i,j} &= -0.029 * \frac{\Delta E(WT)_{i,j}}{E(WT)_{i,j}} + 0.059 * \frac{\Delta E(ST)_{i,j}}{E(ST)_{i,j}}\end{aligned}$$

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, thus this approach to estimate the effect of social connections on job outcomes should only be seen as a framework for future work. To better understand the net effect of search allocation and social capital on job outcome 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 the estimated parameters of equation 7a, because the 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 maximize the following bivariate likelihood model to recover the structural parameters in both the cost (equation 4) and benefit (equation 3) functions:

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

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

Cost Function	OSN	FF	IN	PM	AG
γ_j	0.56	1.33	1.39	0.58	1.44
δ_j / γ_j (Log(FB_Connections))	0.113	0.047	0.045	0.109	0.044
δ_j / γ_j (Log(Unemployment_Spell))	1.473	0.62	0.594	1.422	0.573
δ_j / γ_j (Log(Salary))	12.602	5.306	5.077	12.167	4.901
δ_j / γ_j (Experience)	-0.002	-0.001	-0.001	-0.002	-0.001
δ_j / γ_j (Married)	-0.661	-0.278	-0.266	-0.638	-0.257
δ_j / γ_j (Sex_Male)	-1.427	-0.601	-0.575	-1.378	-0.555

From the cost function (eq 4) estimates, we see that scale coefficient (γ) is smallest for online social networks suggesting the low overall search costs of the platform. We believe that it is intuitive that online social networks have 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 to find a new job. 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 pick the ones worth the time it takes for submitting 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 give time frame. The cost for agencies is highest because of interpersonal communication with an agency that may have additional costs to provide their services.

The estimates of structural parameters for benefit function (job leads) are presented below:

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

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

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

Structural Parameter	Benefit Function		Job Leads		Job Interviews		Job Offers	
	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)	OSN	Others (FF, IN, PM, AG)
τ_0	-0.007	-0.007	0.009	0.009	-0.012	-0.012		
τ_1	0.053	0.053	0.035	0.035	2.024	2.024		
ϕ_{0j}	2.326	3.473	3.574	2.752	-1.227	-0.521		
ϕ_{2j} (Log(LinkedIn Strong-Ties))	-0.036	-0.245	0.076	0.336	0.494	0.622		
ϕ_{2j} (Log(LinkedIn Weak-Ties))	0.234	0.155	-0.228	-0.129	-0.224	-0.051		
ϕ_1 (Log(FB_Connections))	0.022	0.022	0.078	0.078	0.109	0.109		
ϕ_1 (Log(Unemployment_Spell))	0.005	0.005	-0.046	-0.046	-0.172	-0.172		
ϕ_1 (Log(Salary))	0.049	0.049	0.502	0.502	-0.822	-0.822		
ϕ_1 (Experience)	0.004	0.004	-0.021	-0.021	-0.137	-0.137		
ϕ_1 (Married)	0.219	0.219	-0.346	-0.346	1.416	1.416		
ϕ_1 (Sex_Male)	-0.315	-0.315	0.043	0.043	-0.384	-0.384		

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 somewhat intuitive because the numbers of job posts, although steadily growing, are 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 other job search modes. We believe this is the case because a lot of recruiters are moving towards online social networks to screen candidates for interviews based on their interactions with their social community. The conversion to offer is lower for online social networks because we believe the strong-ties that play a strong role in conversion actually are portable and communication with them is achieved through faster modes like email or phone.

As discussed before, we see a negative effect of strong online connections and a positive effect of weak online connections on job leads suggesting that strong-ties are contributing less new information whereas weak-ties tend to provide more new information. The role of strong- and weak- ties flip when it comes to job interviews or offers.

The positive coefficient for strong-ties suggest the 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 might be lower thus impacting the conversion rate from job applications to interviews to offers. As discussed previously, online strong-ties tend to be multiplexed ties thus having a positive effect irrespective of the job search mode.

In summary, the estimated structural parameter allows us to build both cost and benefit functions for all of the five job search modes. This should help the job seekers to allocate their job search effort on various modes and improve the probability of outcomes (job leads, interviews, or offers) received from each search mode.

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 more educated and higher income individuals. 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 continuously expanding social capital plays an important role in the job search. But since the effect of weak- and strong- ties is 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 is intuitive because larger social capital will imply more opportunities to find new information through the network. Here we found that larger social capital will increase the search intensity allocated to both offline or online social job search modes and will cannibalize the time spent on Internet for job search.

This study also echoes the argument (Kuhn and Skuterud 2004) suggesting that the internet enabled 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 platform results 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 higher number of job interviews. This difference in outcome from job search modes has been used to suggest the value of information portability by many career transition experts. These industry experts suggest finding job leads from various job search modes and applying for positions like job seekers did a decade ago – mailing in a hardcopy cover letter with resume. This could then improve the chances receiving interview calls for every application.

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 internet and then tap into her social capital 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.

6.1 LIMITATIONS & FUTURE WORK

One limitation of our approach is that we use multiple non-linear models for analysis that caused burden of jointly estimating the productivity model and simultaneously estimating the models for all job search modes. Both joint and simultaneous estimation of job outcomes require more sophisticated econometric modeling and are 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 non linear 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. Although there are some limitations because of survey data, we have presented a framework for analyzing social capital for labor market and believe that future work should consider the approach presented here.

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