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To Be or Not to Be Linked: Online Social Networks and Job Search by Unemployed Workforce

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Abstract. Prior research suggests that social connections, including acquaintances, friends, and family, are valuable in a job search process. In these studies, the size of an average job seeker's network was much smaller and limited by the available modes of communication and the costs associated with maintaining social connections. However, the recent growth of online social networks has enabled job seekers to stay connected with many connections, weak or strong. Thus, the number of online connections—especially weak—has increased significantly. In this paper, we first examine whether an individual's social network plays a role in driving job search behavior, taking into account online social networking sites (e.g., LinkedIn) and other job search modes. Second, we examine how ties in online social networks (both weak and strong) affect job search outcomes (modeled sequentially as job leads, interviews, and offers), and we compare the findings to job outcomes from traditional job search modes (e.g., career fairs, newspaper, Internet postings, and friends and family). To do so, we first construct an economic model of search behavior incorporating cost and benefit functions; we then estimate the model to recover structural parameters using the survey data of 424 users. Our findings show that users are spending more time searching for jobs on social networking sites. In addition, users' strong ties play a significant role in job search and are especially helpful in generating job leads, interviews, and offers; the weak ties, on average, are ineffective in generating positive outcomes and marginally negative in some cases.

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1. Introduction

Developments in Internet and communication technologies (ICT) have dramatically changed the job search process, introducing more modes of search and reallocation of search efforts across more diverse platforms (Stevenson 2008). First, online job boards (e.g., Monster.com and Careerbuilder.com) became the primary platform for job search, reducing the role of traditional channels, such as print media (newspapers, magazines, etc.), agencies (headhunters, libraries, etc.), and public career fairs and events. During the past decade, social networking sites (SNSs) have seen growth as a platform for job search. While Facebook has established itself as a personal SNS, sites like LinkedIn function as professional SNSs. Through such professional SNSs, recruiters can inform users of potential job opportunities, and job seekers can search for potential jobs through these platforms. According to a survey by Jobvite, 94% of recruiters turn to LinkedIn to find qualified candidates, 61% of candidates are hired through referral and company career pages, and only 14% are hired though job boards (Stadd 2013). LinkedIn users can search for a job in three ways: (1) searching for jobs posted and advertised on LinkedIn, (2) contacting friends or family in their network for leads and referrals, and (3) finding and contacting recruiters and hiring managers. In addition, users might be targeted and contacted by an employer/recruiter regarding a potential job opportunity.

An important element of these platforms is that much of job information is percolated via a user's social network. For example, when a user searches for jobs or recruiters, the results also show whether he or she has connections that are directly related to the job opening or the recruiter. Furthermore, if users do not have any connections to the recruiters, job seekers can contact them through a limited email service called "InMail," which requires a paid LinkedIn account. Still, the most commonly used approach is to get introduced by a common connection, and the number of introductions a job seeker can access is positively correlated with the job seeker's network size. Thus, more connections increase the likelihood of bridging any structural holes in the network (Burt 1995). More importantly, social connections have been recognized as potentially helpful because they provide direct access to hiring managers while improving trust and confidence in the quality of information shared through a common connection (Granovetter 2005), thus fueling the growth of these sites (Schwartz 2013). The link between job search and social structures reveals that "it's not what you know but who you know," suggesting that social connections influence labor market outcomes (Granovetter 1995, Montgomery 1991). Of the two widely used classifications of interpersonal ties (i.e., strong and weak), weak ties (which exhibit limited overlap in friendship circles) enable discovery of more novel information (Granovetter 1973, Yakubovich 2005), like job leads, and strong ties are more helpful in gaining job offers (Obukhova 2012, Yakubovich 2005).

SNSs allow users to build an online network, which is presumably useful. However, there is very little evidence on the use and benefits of these online networks on job search. For one, SNSs allow job seekers to build a much larger personal and professional social network than otherwise possible, because connecting to others is simply a click away. Naturally, much of this network predominantly comprises weak ties (de Meo et al. 2014). For example, 41% of LinkedIn users now report over 500 connections, and 15% of users report over 1,000 connections (Conner 2014). However, scholars suggest that the maximum number of meaningful connections an individual can have is much lower (Dunbar 2010) than what these online SNSs enable. Despite lots of media attention on the benefits of online social networks (OSNs),[1] little empirical work has been focused on the role of SNSs and OSNs in job search. Thus, it is natural to wonder how valuable these connections are. It is quite likely that many of these connections are not productive when a user is searching for a job. It is also possible that users may overestimate (underestimate) the value of these ties and search more (less) than is optimal on these networks. In this paper, we examine the following:

(1) *Allocation of search effort*. How do job seekers allocate their job search efforts on OSNs and across other modes (e.g., the Internet, print media, etc.)? How do a user's strong and weak ties on OSNs affect search effort allocation?

(2) *Job Outcomes*. How effective are OSNs in generating job outcomes (i.e., leads, interviews, and offers)? How do strong and weak ties influence these outcomes?

To answer these questions, we first build a model of users' search behavior that accounts for their demographics and their social network. Users decide how much time they want to allocate on a search mode by anticipating the benefits (job leads, interviews, and offers) associated with each mode. We derive optimal search intensity across different modes. Thus, our model provides a coherent framework combining users' job search and job outcomes in a consistent way and yields estimable regression equations. To estimate our model, we use detailed data on users' job search behavior, collected via a survey to unemployed users that included questions about their job search methods, their online and offline social networks, and job outcomes. In addition, since our data capture sequential job outcomes (job leads, interviews, and offers), we can examine the effects of online networks on each of these outcomes separately. Finally, our model allows us to recover the structural parameters of cost and benefit functions associated with job search.

Using survey responses of 424 users, we find that unemployed job seekers spend significant time searching for jobs on their OSN and receive more leads, interviews, and offers. We find that the size of the OSN positively influences not only search effort but also all outcomes. People with larger networks not only search more but also apply for jobs more intensely and get more interviews and offers. Looking into strong and weak ties individually, we find that strong ties play a positive role in all aspects of job search (search effort, job leads, job interviews, and job offers), confirming the strength of strong ties (Krackhardt 1992) hypothesis. However, the weak ties are mostly ineffective in generating job outcomes.[2] Users with more weak ties search less overall, though more on SNSs. They also get more job leads from SNSs. But many of these leads do not convert to successful interviews or eventually job offers. In general, we do not find any evidence that online weak ties make a meaningful difference in a user's job prospects.

Our paper makes three important contributions. First, to the best of our knowledge, we conduct one of the first studies that carefully examines the role of online connections in job search and outcomes. This study is not only interesting academically, but is also highly relevant for firms and policy makers who are figuring out how to use next-generation technologies effectively. Second, we provide a rich theoretical framework to model a more nuanced job search and outcome process. This model, in turn, guides our empirical specifications. Unlike past literature, we measure not only search effort, but also job leads, interviews, and job offers individually, for an improved understanding of outcomes. Finally, we assemble a unique data set, difficult to collect, that we bring to the model. Despite survey-related data limitations, our data are the first of their kind in this space and provide interesting insights into how users engage their network when searching for jobs.

2. Literature

We draw from three major strands in the literature. The first is the different search modes used by users. The second is the role of social networks on job outcomes. And finally, we draw from the work that has used economic theory to build job search models.

The modes of job search have been evolving with the adoption of new technologies. In 1973, 71% of job seekers reached out to employers directly, 40% reached out to agencies (public or private), and only 14% used their formal and informal social connections to search for jobs (Bradshaw 1973). By 1991, 22% of job seekers reached out to friends and family (Bortnick and Ports 1992). With increased adoption of ICT in the labor market, the Internet has been used increasingly as a mode for job search, by both unemployed and employed workers, and is seen as an effective platform because of low costs, which allows job seekers to collect more information about potential opportunities and to selectively submit their job applications (Autor 2001, Stevenson 2008). But the Internet is also shown to be ineffective in reducing the unemployment duration of job seekers (Kuhn and Skuterud 2004). Nevertheless, the Internet was found to be more effective than newspaper ads or direct applications but less effective than social networks (Feldman and Klaas 2002). Job seekers thus use multiple platforms for job search and select a combination of platforms to maximize the expected job outcomes (Burdett 1977, Mortensen 1986). With the growth of SNSs, users have another mode to search for jobs. In this paper, we examine in detail how users are allocating their time across different modes including SNSs.

The second strand of literature focuses on the role of social networks on job search. It is well established that social networks play an important role in the job search (Granovetter 1995, Lin 1999, Marsden and Gorman 2001) and wages (Montgomery 1992). The value of social networks in the labor market is derived from the trust and confidence in the quality of information shared by common connections (Granovetter 2005, Yakubovich 2005). Studies have found that the role of social networks (friends and family) on job outcomes is positive and larger than direct job applications (Holzer 1988), as well as headhunters (Petersen et al. 2000). Researchers have also looked at the role of weak ties (i.e., people who are acquaintances and neither close nor communicated with on a regular basis) and strong ties. There is ample work in literature that suggests that users' social networks help diffuse information (Angst et al. 2010, Aral et al. 2009, Bapna and Umyarov 2015, Dellarocas 2003, Garg et al. 2011, Ghose and Han 2011, Godes and Mayzlin 2004, Lee et al. 2015, de Matos et al. 2016, Tucker 2008),[3] but may have different effects based on the interaction between the ties and the network size. Weak ties contribute to a larger volume of novel information (Granovetter 1995) and are also expected to relay job offers more frequently that are drawn from a better wage-offer distribution (Montgomery 1992). Alternatively, strong ties are important in initiating actual changes and providing support (Krackhardt 1992), and in gaining job offers (Obukhova 2012). Strong ties are also shown to wield influence in job outcomes through trust and obligations (Bian 1997), and are more efficient in generating offers (Murray et al. 1981). However, the literature also provides somewhat conflicting assessments of the value of strong and weak ties on job outcomes (Korpi 2001).

Meanwhile, a tie's position in a network is shown to matter more than the tie strength (Burt 1995, Reagans and McEvily 2003). In addition, unemployed job seekers could see desocialization as a result of longer unemployment spells, which in turn is associated with a decrease in job offer probability (Calvó-Armengol and Jackson 2004). It has also been shown that a large number of connections tends to have a negative effect on job leads (information on vacancies) when it exceeds a threshold (Calvó-Armengol and Zenou 2005). Furthermore, individuals might be reluctant to share certain information broadly across their OSN, such as their unemployed status (Korpi 2001). Research also has raised the concern that if the size of social networks is correlated with job outcomes, then it should also be correlated with job search intensity (Mouw 2003). In addition, the job seeker's network does not necessarily influence the use of that network in a job search, but when it is used, the job seekers see improved job search outcomes (Obukhova and Lan 2013). Similarly, an increase in network diversity might increase the information novelty but at the cost of reducing information flow (Aral and Van Alstyne 2011). Because online social platforms enable much larger network formations, understanding whether online social connections are indeed helpful in contemporary job search becomes more important.

OSNs make it easy for users to make new connections, albeit mostly weak ties. Thus, we can expect that users might be able to get more information on job leads, but the quality of this information is unclear. Many of these leads might be ineffective. Hence, it is not clear if online weak ties would enhance a user's job prospects. Meanwhile, we expect that strong ties will continue to play a useful role, even on OSNs. After all, strong ties, almost by definition, are not an artifact limited to online networks. Strong ties are people with whom a user frequently interacts beyond the OSN.

Finally, the third strand of work that we borrow from is the economic models of job search. To investigate the role of various job search modes on an unemployed job seeker's search behavior and received job outcomes, we use the income–leisure utility model (Burdett 1977, Holzer 1988, Mortensen 1986). Income–leisure utility models have been extensively studied and applied in different settings and are used to estimate different structural parameters, such as the effect of benefits on unemployment, reservation wages, and employed versus unemployed users (Bloemen 2005). To further investigate the role of strong and weak ties on job search and job outcomes, we consider three sequential job outcomes: leads, interviews, and offers. Blau and Robins (1990) differentiate between different job outcomes, including offer probability, acceptance probability, and contact probability. They also differentiate unemployed versus employed individuals and reveal that offer probability is higher for the employed than the unemployed job seeker.

In this study, we estimate a structural model for the cost function for search that includes expected returns and benefit functions for three sequential job outcomes: applications, interviews, and offers. These estimated outcomes allow us to compare the online SNSs with traditional modes of job search. In addition, this research also presents the role of strong and weak ties on job search by unemployed workforce. Through this paper, we take a first step toward understanding the role of online SNSs and OSNs on job search and job outcomes for an unemployed workforce, using empirical (survey) data collected from these job seekers.

3. Data

Labor economists traditionally have relied on the National Longitudinal Survey (NLS) or Current Population Survey (CPS) to examine how users are searching for jobs and, in some cases, how their friends and family networks are helping them (Holzer 1988). Although these data sets are large, they lack details, such as network composition (strong or weak ties) and information about job leads, interviews, and job offers specific to a search mode. Therefore, we designed an institutional review board-approved survey to cover all gaps in the extant literature and surveys. This survey contained questions about the individual's current employment status, motivations for the job search, past and present job search strategies, job outcomes (i.e., leads, interviews, or offers), familiarity and use of online SNSs, and composition of OSNs for job search. The survey comprised the information shown in Figure 1.

Because the survey asked detailed questions and completion required more than 20 minutes of a subject's time, finding subjects and maintaining accuracy of data presented challenges. To test whether users would respond appropriately and commit to the survey, we created two pilot surveys: one was shared with LinkedIn job seekers and a second was administered by an outplacement firm. The first pilot was used to understand the time spent on each question to improve the attention of job seekers over the course of the questionnaire.

During the second pilot, an outplacement consulting firm facilitated the distribution of the survey to 288 individuals who had lost their jobs at a large (Fortune 500) organization in the United States during 2010. We sent the questionnaire to all 288; 163 individuals opened the email, and 109 took the survey. Eight surveys were either not fully completed 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 the help of professionals in the field. This phase of the data collection covered mostly educated, white collar workers, so the sample is neither representative of the general population nor perfectly random. However, given that educated and white collar workers are the people most likely to use SNSs like LinkedIn,[4] our survey targeted those users who could provide the most useful insight into the phenomenon of interest. Based on the first two pilots, we made adjustments to the questions. (The data from pilot surveys was ignored for the study.)

We conducted a second phase of the study in 2013–2014. The learning from the first phase allowed us to edit our survey to add more clarity, as well as to change some questions. The first phase also provided insights into the extent of LinkedIn use (which was significant). During this second phase, we partnered with a third-party organization to identify college graduates who were recently unemployed across the country and sent the survey to 10,000 people across the United States; 4,259 people opened the email; 3,427 opened the survey; and 876 agreed to continue the survey and met the

Figure 1. Survey Components

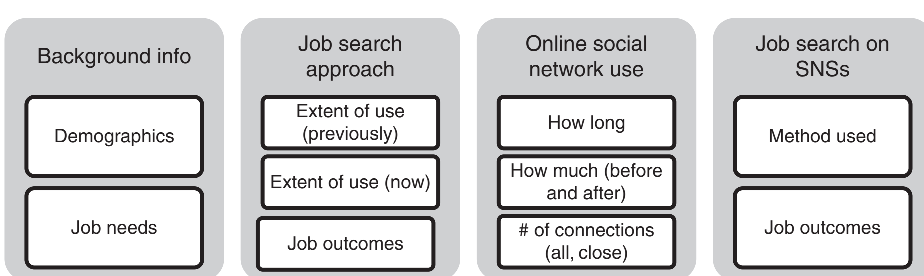

Table 1. Demographic Summary for Survey Takers

	Data set
Completed surveys	424
Currently unemployed	263
Married	201
Sex (female)	185
Age (average)	37.2 (12.1)
Total work experience (average)	13.1 (8.8)
Approximate salary (average)	$53.8 k ($26 k)
Education = college	300
Education = graduate	124
Race = white	299
Race = black	34
Race = Hispanic	35
Race = Asian and other	56

prerequisites (i.e., college graduate, recent unemployment status, recent job seeker, LinkedIn user). Of the 876 who agreed and were qualified, 450 completed the survey and passed the attention filters and data verification tests. Of these, 424 respondents were verified as providing accurate responses. Summary demographics are presented in Table 1.

The survey asked users about five major search modes they have used in their job search: (1) Internet sites (e.g., Monster.com), (2) online SNSs (e.g., LinkedIn), (3) offline close friends and family, (4) newspapers and other print media, and (5) recruiting agencies and career centers. Note that the selection of search modes is driven by the interaction and effort level needed to search for jobs using that specific mode. Table 2 shows the average search time allocated to each search mode, conditional on the search mode being actually used during the job search.

In addition, we asked users how many job leads, job interviews, and job offers resulted from each mode. Job leads are defined as relevant job opportunities for which the job seekers submitted an application. The summary of the number of individuals who used a specific search mode and the number of those for whom it resulted in one of the job outcomes (i.e., leads, interviews, and offers) is presented in Table 3.

Next, we asked users to specify how many connections they have and how many they consider "*close friends and family members that they communicate with at least once a month*." This definition of strong connections is derived from "*philos*" (Krackhardt 1992). We asked survey takers to pick a range for the number of close friends and family members with whom they communicate at least once a month. The phrase "close friends and family" was also used to classify individuals with whom a job seeker would interact offline (outside of the OSN) when searching for a job. Thus, these strong ties (or philos) would generate trust and serve as a valuable asset during job search. Because of the overlap of offline and online close friends and family, we expected that the strong ties on LinkedIn would serve as a proxy for professional strong ties in an offline network. Thus, this approach gave us an opportunity to explore how job seekers used their strong connections for their job search, both online and offline.

Table 2. Search Intensity for Each Job Search Mode, Conditional on Using the Search Mode

Job search mode	Count	Search intensity (hrs./week)
Internet posts (IN)	414	11.9 (9.9)
Online social networks (SN)	411	10.3 (10.4)
Friends and family (FF)	345	7.4 (9.2)
Print media (PM)	286	6.1 (7.5)
Agencies (AG)	200	7.7 (9.4)

Note. Mean values with standard deviations in parentheses.

Table 3. Number of Job Seekers Using Various Job Search Modes, Conditional on Search and Job Outcome

Job search mode	Searched	Job leads	Job interviews	Job offers
Internet posts (IN)	414	397	261	76
Online social networks (SN)	411	374	196	59
Friends and family (FF)	345	273	146	51
Print media (PM)	286	226	108	38
Agencies (AG)	200	162	85	31

Studies show that online platforms enable development of a much larger weak-tie network because of the low cost to create and maintain a tie (Pénard and Poussing 2010). In addition, online networks provide an opportunity to increase the search intensity across other modes (outside of SNSs). For example, if John is connected to Sarah, then he can potentially gain some job leads through Sarah or by looking for advertised jobs at her workplace using any of the other search modes. Thus, social ties open channels for discovery of new information.

From our data set, we observed that individuals have 263 connections, on average, on personal social platforms (e.g., Facebook) and 99 connections, on average, on professional social platforms like LinkedIn (see Table 4). As expected, individuals have a larger number of strong ties on Facebook compared to LinkedIn.

Individuals who did not use their OSN as a job search mode cited privacy concerns as the most

Table 4. Summary of Social Ties on LinkedIn and Facebook

	Mean	Std. dev.	Skewness	Kurtosis
Total ties (LinkedIn)	99	186	5.062	35.914
Strong ties (LinkedIn)	15	32	7.047	68.524
Weak ties (LinkedIn)	92	182	5.281	38.257
Total ties (Facebook)	263	309	3.204	19.985
Strong ties (Facebook)	43	70	4.724	35.211

important reason for not using their online personal SNS (Facebook) and lack of relevant job leads for not using their online professional SNS (LinkedIn).

3.1. Survey Data Validation and Reliability

We used three approaches to validate and build confidence in the response data: (1) we verified the accuracy of conditional responses, (2) we matched answers with actual publicly available data, and (3) we built redundancies into the survey. For example, we found that one job seeker reported that the number of interviews received from print media ads was higher than the number of job applications submitted. Although this discrepancy could simply be a typographical error, we dropped this individual's responses from the data.

We asked individuals about the number of connections they had on social networks, such as LinkedIn, Facebook, and Twitter, and encouraged users to visit their online SNSs so they could provide accurate information. To validate their responses, we used publicly available data from LinkedIn. We accessed the profiles of 450 job seekers, and the answers provided by 443 survey takers matched the observed data. (Connections above 500 were validated with the representation of 500+ on LinkedIn.) The seven responses that did not match the actual data were dropped from the data set to ensure accuracy.

We also asked users about "how" they searched for jobs within the OSN. We identified three modes of job search on LinkedIn, based on a separate set of responses from LinkedIn users. These three modes included the following: (1) searching for job posts and ads on LinkedIn, (2) contacting close friends and family (strong ties) on the online SNS for leads and/or references, and (3) contacting other connections (weak ties) on the online SNS for leads and/or references. In addition, job seekers may be contacted by recruiters for potential job opportunities. We asked users to identify how many leads, interviews, and offers they got from each of these modes. We added these numbers and compared them to the aggregate number of job outcomes (leads, interviews, or offers) from their OSN to verify whether the respondents provided consistent answers. Although a few respondents did not answer these questions and matching the answers perfectly was not always feasible, the answers were consistent in most cases.[5]

In summary, despite some limitations, we used several means of validation to confirm the overall robustness of our survey data.

4. Theory

The relationship between social connections, job outcomes, and search effort is complex. Answers to the questions we raise—how people allocate their time across different modes, how online connections affect these choices, and whether online connections affect job outcomes—require a formal treatment to carry out a convincing empirical analysis. In constructing such a treatment, we recognize that job outcomes are also affected by how diligently users search for jobs using a particular mode. Moreover, the job search decision itself is driven by users' beliefs about whether they can find a job.

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

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

4.1. Job Search Allocation

We turn to widely used income–leisure utility models (Burdett 1977, Holzer 1988, Mortensen 1986) to set up our empirical strategy. These models assume that being unemployed has a certain baseline utility. Searching for a job increases the probability of being employed, but it also has associated costs. Job seekers are rational and trade the costs of search with the benefits of being employed. We then modify the income–leisure utility models to include social connections that affect the job outcomes. More formally, we specify the utility of an unemployed individual who spends s_{ij} time searching for a job on mode j as follows:

$$\begin{aligned} &U_{ijt}(w_R, s_{ij}) \\ &\quad = v_{ij}(L_i - s_{ij}, Y_i - c_j(s_{ij})) + \pi_{ij}(s_{ij}, X_i, E_i) \\ &\qquad \cdot p_j(w \geq w_R) \cdot E(\psi_{ij}(w)) + (\pi_{ij}(s_{ij}, X_i, E_i)) \\ &\qquad \cdot (1 - p(w \geq w_R)) \cdot U_{t+1} + (1 - \pi_{ij}(s_{ij}, X_i, E_i)) \cdot U_{t+1}, \end{aligned} \tag{1}$$

where i indexes an individual, j indexes the search mode, and t indexes time. Here, $v_{i,j}$ is the current period utility from leisure and outside income. Searching is costly: it reduces leisure time and incurs monetary cost c_j; L_i is the leisure time for individual i, and Y_i is the nonwage income.

The second term in the utility function is the expected utility of being employed if the probability of an offer is π and the offered wage (w_t) is higher than the reservation wage ($w_{R,t}$). Here, X_i represents the user's demographic and other characteristics (e.g., education, age, experience, race, salary during last job), and E_i represents users' ties in the social structure.[6]

The third term in (1) is simply the probability that the user remains unemployed because the offered wage is not higher than his or her reservation wage.[7] The fourth term indicates that the user might not get any offer, despite the search effort, and hence remains unemployed in the next period.

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

$$\begin{aligned} &U_{i,j,t}(s_{ij}) - U_{i,j,t+1} \\ &\quad = v_{ij}(L_i - s_{ij}, Y_i - c_{ij}(s_{ij})) + \pi_{ijt}(s_{ij}, X_i, E_{ij}) \\ &\qquad \cdot \int_{w_R}^{\infty} [\psi_{ij}(w) - U_{i,j,t+1}(w_R, s_{ij})] \cdot f(w)\,\mathrm{d}w. \end{aligned} \tag{2}$$

The equation specifies the expected change in utility resulting from search effort s. The first part expresses the reduction in utility resulting from searching. The second part is the increase in utility resulting from 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.

For empirical tractability, we need to assume functional forms for both the cost and the job offer rate. Here, we rely on prior literature for these functions. Thus, v is assumed to be linear in its arguments (Holzer 1988). In addition, following previous work (Bloemen 2005), and given that these users are unemployed, we expect that the effect of search time on leisure time is minimal (and thus ignore v_1). The offer probability is a linear combination of the offer arrival rate (λ) and the search effort allocated to a job search mode (Bloemen 2005):

$$\begin{aligned} &\pi_{ij}(s_{ij}, X_i, E_{ij}) = \lambda_{ij}(X_i, E_{ij}) \cdot (\tau_0 + \tau_1 s_{ij}), \\ &\quad \text{where } \lambda_{ij}(X_i, E_{ij}) = \exp(\varphi_1 X_i + \varphi_{2j} E_{ij}). \end{aligned} \tag{3}$$

Here, λ is the offer arrival rate on a search mode during a given time period and depends on the user characteristics X and ties E of a job seeker. Coefficient of E suggests that job seekers who have more social connections on a particular search mode are more or less likely to receive job offers. Also evident from π, the higher the search, the more likely the job seeker is to receive an offer. A constant τ_0 allows for the fact that even zero search effort could lead to some positive job outcomes.

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

$$c_{ij}(s_{ij}) = \gamma_j \cdot \exp\left(-\frac{\delta_j \cdot X_i + \eta_j E_i}{\gamma_j}\right) \cdot \left[\exp\left(\frac{s_{ij}}{\gamma_j}\right) - 1\right]. \tag{4}$$

We allow cost to be affected not only by user characteristics, but also by their social embeddedness. So, users that have a bigger network might find searching on a particular model cheaper. Given that the benefit of search is linear, an interior solution is guaranteed. Taking first order of (2) yields the following:

$$-v_2 \alpha_1 \exp\left(\frac{s_{ij}}{\gamma_j}\right) + \tau_1 \lambda_{ij}(X_i, E_{ij}) \cdot R_{ij} = 0, \tag{5}$$

where

$$R_{ij} = \int_{w_R}^{\infty} [\psi_{ij}(w) - U_{i,j,t+1}(w_R, s_{ij})] \cdot f(w)\,\mathrm{d}w$$
$$\text{and} \quad \alpha_1 = \exp\left(-\frac{\delta_j \cdot X_i + \eta_j E_i}{\gamma_j}\right).$$

Because v is linear, v_2 (derivative of v with respect to its second argument) is simply a constant that we normalize to one. Solving for optimal s and simplifying (3) leads to the following:

$$\begin{aligned} s^*_{ij} = &(\gamma_j \cdot \log \tau_1) + (\delta_j + \gamma_j \cdot \varphi_1) \cdot X_i + (\eta_j + \varphi_{2j} \cdot \gamma_j) \\ &\cdot E_{ij} + \gamma_j \cdot \log(R_{ij}). \end{aligned} \tag{6}$$

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

$$s_{ij} = s^*_{ij} + \varepsilon^s_{ij}. \tag{7}$$

One missing component in estimating this equation is that we do not directly observe R, which is the expected benefit of employment, given the distribution of wages (w). We follow the approach suggested in prior literature (Bloemen 2005, Mortensen 1986) that assumes that the difference between the utility from employment and the utility from the unemployed search is equal to the difference in the expected employed wage and reservation wage. We assume that the reservation wage is equal to the last wage for a user. This assumption is often used in the literature (Feldstein and Poterba 1984) and is especially true when the duration of unemployment is small (as in our case, only up to three months). If the wage offer distribution is normal for a job search mode, then

$$R_{ij} = \int_{w_{i,\,last}}^{\infty} [w_j - w_{i,last}] \cdot N(w_j, \bar{w}_j, \sigma^2)\,\mathrm{d}w_j. \tag{8}$$

To get the model-specific mean and the variance of the job distribution, we aggregate various job offers users received from different modes during their past job search. To account for user-specific heterogeneity (users, even on the same mode, might see different jobs, depending on their characteristics), we allow the expected mean of the job distribution to vary with user characteristics:

$$\hat{w}_{ij} = \omega_j \cdot X_i. \tag{9}$$

Thus, from the past wage of a job seeker and the distribution of wages for each user on each search mode, we recover the value of the expected benefit of employment.

4.2. Effect of Social Ties on Job Outcome

As stated, our model of search allocation is derived from the expected benefits and costs calculations. If people perceive some modes to be more beneficial, they will search more using those modes. Thus, their search allocation is a sufficient statistic to underscore the value of a particular search mode to them, and we do not need to know the "actual" outcomes. However, our survey does provide data on actual outcomes: how many job leads, interviews, and offers an individual actually received. This information allows us to examine three additional models of interest: (1) it allows us to estimate the cost of each search mode in Equation (4), (2) it allows us to examine the productivity of each search mode in Equation (3), and (3) it allows us to estimate the marginal and total effect of connections on job outcomes.

Our job outcome model is as follows:

$$\pi_{ij}(s_{ij}, X_i, E_i) = (\tau_{0j} + \tau_{1j}s_{ij}) \cdot \exp(\varphi_{1j}X_i + \varphi_{2j}E_{ij}). \quad (10)$$

Ties E can affect job outcomes in two ways. First, as our model in Equation (6) shows, connections affect the search effort. Second, connections affect job outcomes, independent of the search effort, as in Equation (10). Formally, the effect of connections on job outcome could then be written using the chain rule, as follows:

$$\frac{\mathrm{d}\pi_{ij}}{\mathrm{d}E_i} = \frac{\partial \pi_{ij}}{\partial E_i} + \frac{\partial \pi_{ij}}{\partial s_j} \cdot \frac{ds_j}{dE_i}. \quad (11)$$

Many empirical research papers do not have details on search efforts. That is, the second term in Equation (11) is not estimable. We can clearly see that, if we do not measure "s," the effect of embeddedness on job outcomes will be either underestimated or overestimated. In this paper, by directly observing s and E, and writing down the structure of the search effort, we can estimate how social ties affect search outcomes by estimating all components of Equation (11).

An even more interesting aspect of our data is the granularity in job outcomes. Job search efforts usually generate relevant job leads, which convert to interviews and then to offers. Social connections affect these outcomes in different ways. For example, we would expect weak ties to have a strong effect on job leads. Weak ties might provide a user with potentially relevant job leads. The cost of diffusing information across weak links is low. However, weak ties might not influence interviews or offer probabilities. Meanwhile, strong ties potentially can play a bigger role. Interviews and offers depend on people's willingness to make phone calls, to write a recommendation letter on behalf of a user, or use social influence for a user's prospect for a job. This activity is costly, and only strong ties might be willing to make these investments.

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

$$\begin{aligned}\pi_{ij}^{JO}&(s_{ij}, X_i, E_{ij})\\ &= f(\pi_{ij}^{JI}(\pi_{ij}^{JL}(s_{ij}(X_i, E_{ij}), X_i, E_{ij}), X_i, E_{ij}), X_i, E_{ij}). \quad (12)\end{aligned}$$

Here, π^{JO} is the number of job offers received by user i from the search mode j, when a job seeker receives π^{JI} interviews and π^{JL} job leads from search effort s. Each of the sequential outcomes (leads, interviews, and offers) in Equation (12) follows the functional form presented in Equation (10) previously:

$$\begin{aligned}\pi_{ij}^{JL}&(s_{ij}, X_i, E_{ij})\\ &= (\tau_{0j}^3 + \tau_{1j}^3 s_{ij}) \cdot \exp(\varphi_1^3 X_i + \varphi_{2j}^3 E_{ij}) + \varepsilon_{ij}^L, \quad (13a)\\ \pi_{ij}^{JI}&(\pi_{ij}^{JL}, X_i, E_{ij})\\ &= (\tau_{0j}^2 + \tau_{1j}^2 \pi_{ij}^{JL}) \cdot \exp(\varphi_1^2 X_i + \varphi_{2j}^2 E_{ij}) + \varepsilon_{ij}^I, \quad (13b)\\ \pi_{ij}^{JO}&(\pi_{ij}^{JI}, X_i, E_{ij})\\ &= (\tau_{0j}^1 + \tau_{1j}^1 \pi_{ij}^{JI}) \cdot \exp(\varphi_1^1 X_i + \varphi_{2j}^1 E_{ij}) + \varepsilon_{ij}^O. \quad (13c)\end{aligned}$$

Using the chain rule, the effect of embeddedness on job outcomes could be readily calculated using Equation (11) above. In addition to estimating the effect of embeddedness on various job outcome classifications, the model also allows us to estimate the effectiveness of each job search mode in converting the search effort to job leads, the job leads to interviews, and the job interviews to offers.

5. Empirical Analysis and Results

5.1. Joint Models of Search Effort and Job Outcomes

Our models provide a clear empirical strategy. If we believe that social connections increase the value of a search mode, a rational user would also allocate more time on that mode. Similarly, allocation of more time would potentially lead to more job leads. In theory, we can separately estimate (6) and (13a–13c). However, our model indicates that search effort and job outcomes are correlated, and a shock is likely to affect both equations. Thus, a joint model better represents the data.

Technically, we would estimate all four equations jointly using a multivariate model. However, the nonlinear nature of the equations makes estimation of a four-way joint model very difficult. Therefore, we first estimate the search and lead ((6) and (13a)) together to demonstrate the utility of joint estimation. We then also jointly estimate Equations (13b) and (13c), taking the leads as given. Because we are assuming that ε^s_{ij} from (6) and ε^L_{ij} from (13a) are bivariate normal, we also estimate the correlation coefficient.

Before presenting our results, we discuss some details of the regression model and potential challenges with estimation. Our search effort regression, as in Equation (6), is as follows:

$$s_{ij} = (\gamma_j \cdot \log \tau_1) + (\delta_j + \gamma_j \cdot \varphi_{j1}) \cdot \mathbf{X}_i + (\eta_j + \varphi_{j2} \cdot \gamma_j) \cdot \mathbf{E}_i + \gamma_j \cdot \log(R_{ij}) + \varepsilon^s_{ij}. \tag{14}$$

First, note that E (or social connections) in our case is specific to OSNs (including both strong and weak ties). However, we test whether more OSN connections affect search across other modes as well. For example, OSN ties might be a reflection of a user's large social network and thus affect overall search efforts. In Equation (14), the first term is simply a constant, while the other terms are readily identified. As we show in Section 5.1.4, following from the fact that the other terms are readily identified, we can recover structural parameters for cost (γ_j, δ_j, and η_j).

Even though we do not observe users' choices over time, we do observe the same user over six job search modes. Thus, we have a data set that allows us to control for user-specific and search-mode–specific unobserved effects by including mode-specific dummies and user-specific random effects.

Some unobserved effect might also be correlated with embeddedness (social ties). For example, more social users might search more on OSNs and also have more connections. Thus, although we use user-specific random effects to control for unobserved effects, we also use Facebook connections as a potential control because social users are likely to have more connections on Facebook as well. More importantly, we specifically ask users about their social network *before* the job loss. We also control for duration of unemployment, which controls for effect on search intensity. Given the short unemployment spell in our sample, we believe that the effect of ties on job outcomes and search is cleanly identified.

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

$$s_{ij} = \omega_i + \theta_j + \alpha_1 \cdot \mathbf{X}_i + \alpha_2 \cdot \mathbf{E}_i + \alpha_3 \cdot \log(R_{ij}) + \alpha_4 \cdot E^f_i + \alpha_5 \cdot X^{dur}_i + \varepsilon^s_{ij}. \tag{15}$$

Here, ω_i is a user-specific random effect, and θ_j is a mode-specific, fixed-effect dummy. Note that by controlling for user- and mode-specific heterogeneity, we control for significant unobserved variations across modes and users. Thus, $\alpha_1 = \delta_j + \gamma_j \cdot \varphi_{j1}$ and $\alpha_2 = \eta_j + \varphi_{j2} \cdot \gamma_j$ are directly identified. The variable E^f_i is the number of Facebook connections for user i, and duration X^{dur}_i is the length of unemployment. We also split $\mathbf{E}_i$ into strong ties and weak ties 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 more online connections, on average, search more. For readability, we explain the variables used in our analysis in Table 5.

Table 5. Variable Codebook for Empirical Models

Variable	Description
i	User identifier
j	Job search mode identifier 1 = Internet (IN), 2 = online social networks (SN), 3 = close friends and family (FF), 4 = print media (PM), 5 = career centers and agencies (CF)
D_{SN}	Dummy variable indicating job search mode is online social networks (SN)
θ_j	Dummy variable for each search mode j (IN, SN, FF, PM, CF)
s_{ij}	Average weekly search intensity by user i on job search mode j
π^{JL}_{ij}	Total job leads received by user i from job search mode j
π^{JL}_{ij}	Total job interviews received by user i from job search mode j
π^{JL}_{ij}	Total job offers received by user i from job search mode j
R_{ij}	Employment value of a job search mode j for user i
E^{st}_i	Total strong-ties of a user i on LinkedIn
E^{wt}_i	Total weak-ties of a user i on LinkedIn
E^f_i	User demographic—Total ties of a user i on Facebook
X^{dur}_i	User demographic—Unemployment duration (in days) of user i
X^{wage}_i (or w_i)	User demographic—Past wage (in $1,000) of user i
X^{ex}_i	User demographic—Total work experience (years) of user i
X^{sex}_i	User demographic—Gender of user i (female = 1)
X^{mar}_i	User demographic—Marital status of user i (married = 1)
X^{edu}_i	User demographic—Education of user i (edu = college [BA], graduate [MA], other)
X^{race}_i	User demographic—Race of user i (race = white, black, Hispanic, Asian/other)
$\mathbf{X}_i$	Vector of all user demographic variables
$\mathbf{E}_i$	Vector of user's strong and weak ties on OSN

Equation (14) estimates the overall search efforts across all modes, but we also are interested in understanding how the OSN connections affect search efforts on online SNSs relative to other modes. If users have a larger number of weak and strong ties in their OSN, do they proportionally search more on online SNSs? If yes, we can suggest that people perceive OSN ties to be less portable and more relevant for outcomes received from online SNSs. Thus, the regression is as follows:

$$s_{ij} = \omega_i + \theta_j + \alpha_1 \cdot \mathbf{X}_i + \alpha_2 \cdot \mathbf{E}_i + \alpha_{2a} \cdot \mathbf{E}_i \cdot D_{SN} + \alpha_3 \cdot \log(R_{ij}) + \alpha_4 \cdot E^f_i + \alpha_5 \cdot X^{dur}_i + \varepsilon^s_{ij}. \tag{16}$$

Table 6. Estimates for Job Search Effort and Job Leads

	Search effort				Job leads			
	Coeff. (std. dev.) (1)		Coeff. (std. dev.) (2)		Coeff. (std. dev.) (3)		Coeff. (std. dev.) (4)	
Search intensity					0.245***	(0.061)	0.245***	(0.062)
Dummy (Internet)	8.124***	(0.502)	8.145***	(0.501)	3.813***	(0.975)	3.896***	(1.002)
Dummy (online social networks)	6.571***	(0.502)	4.048***	(0.967)	2.257***	(0.603)	2.095***	(0.6)
Dummy (offline friends and family)	2.446***	(0.499)	2.474***	(0.499)	1.111***	(0.357)	1.148***	(0.368)
Dummy (print media)	0.783	(0.505)	0.806	(0.504)	1.304***	(0.405)	1.338***	(0.416)
Dummy (career centers and agencies)	0.317	(0.507)	0.341	(0.506)	1.483***	(0.468)	1.524***	(0.481)
Log (LinkedIn strong ties)	0.878***	(0.141)	0.778***	(0.15)	0.056***	(0.016)	0.053***	(0.018)
Log (LinkedIn weak ties)	−0.374***	(0.105)	−0.423***	(0.11)	0.017	(0.014)	0.016	(0.015)
SN * Log (LinkedIn strong ties)			0.722*	(0.386)			0.013	(0.029)
SN * Log (LinkedIn weak ties)			0.414*	(0.231)			0.007*	(0.004)
Log (Facebook total ties)	−0.263***	(0.086)	−0.261***	(0.085)	−0.023**	(0.011)	−0.022**	(0.011)
Experience	−0.07***	(0.019)	−0.07***	(0.019)	−0.011***	(0.002)	−0.011***	(0.002)
Log (salary)	−3.45***	(0.994)	−3.377***	(0.982)	−0.045	(0.048)	−0.046	(0.048)
Log (unemployment spell)	0.27*	(0.139)	0.274**	(0.137)	0.108***	(0.024)	0.109***	(0.024)
Sex (female = 1)	−0.16	(0.311)	−0.151	(0.308)	0.093**	(0.036)	0.093**	(0.036)
Married (yes = 1)	0.071	(0.324)	0.094	(0.32)	0.002	(0.041)	0.003	(0.041)
Education (college degree)	−1.566***	(0.34)	−1.54***	(0.338)	−0.095**	(0.038)	−0.099**	(0.038)
Race (white)	−1.014***	(0.34)	−1.003***	(0.337)	0.069*	(0.041)	0.069*	(0.041)
Employment value (R)	2.885***	(0.583)	2.821***	(0.577)				
Constant	−3.62*	(2.106)	−3.176	(2.089)				

Notes. $N = 2{,}042$, bivariate joint likelihood estimates. User (424 groups) random effect. Standard deviations in parentheses. Omitted dummies: race (Asian and other), education (diploma and other), and search mode (career fair and other).
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Here, D_{SN} is a dummy variable for the online SNS search mode. Thus, we estimate whether online social ties affect search allocation differently for online SNS modes than for the other modes.

Notice from (13a) and (15) that many parameters appear in both regressions, indicating computational constraints. Thus, we jointly estimate (13a) and (15) (search effort and job leads) to recover structural parameters for cost. We then estimate interviews and offers as joint regressions.[8] We first report the estimates from joint estimation of (13a) and (14) and of (13a) and (15) in the two columns of Table 6. The omitted dummy (in θ_j) is the search mode, "career fairs and other."

5.1.1. Search Effort. First, note from column (1) that the coefficients for the dummies of Internet, OSNs, and friends and family are positive and significant. The estimates suggest that, relative to the career fairs and other modes, people devote more time to using these job search modes. Statistically, job seekers allocate most time searching for jobs on the Internet, followed by their OSN, which reflects the significance of job search on online SNSs (e.g., LinkedIn).

Regarding the role of ties, we find that people who have more strong ties spend more time on job search (across all modes, on average). In terms of economic significance, an estimate of 0.878 indicates that a 20% (or three-count) increase in the number of strong ties results in an increase of about 0.16 hours (or 10 minutes) in average search time (which is 6.1 hours per week per mode, on average). However, we observe that weak ties have a small negative effect, on average, across all search modes. Here, an estimate of −0.374 indicates that a 20% (or about 20-count) increase in the number of weak ties results in a decrease of about 0.07 hours (or four minutes) in average search time. Note that the economic magnitude of this effect is relatively small.

Broadly speaking, users with more strong ties are searching more overall. Potentially because strong tie's "multiplexed" nature (Verbrugge 1979) enables diffusion of job-related information across all modes—providing an incentive to search. In our model, the users search more when the marginal benefits are higher. Clearly, it seems that the strong ties enhance the value of a mode leading to more search. On the other hand, having more online weak ties (which is really what SNSs are very efficient at) does not make a big difference in users' search efforts, on average.

There is some evidence of substitution across modes. Users with more weak ties are searching more on SNSs (see subsequent discussion), but they seem to be reducing their efforts on other modes. It is also true that users who have more weak ties tend to have more strong ties as well, and since the effect of strong ties is large and positive, weak ties are not as useful relative to strong ties. Overall, we do not find a strong economic significance of the size of online weak tie network on a job seekers' search behavior.

Users that have more experience seem to search less; an additional year of experience reduces the time spent on job search by about five minutes per week. Job seekers with a college degree spend almost 1.5 hours per week less time on job search when compared to job seekers with graduate and advanced degrees. The estimate for unemployment duration is positive and suggests that a 1% increase in unemployment duration increases the search intensity by 0.27%. Literature also suggests that job seekers increase their job search effort when they are closer to the end of their unemployment insurance term (Krueger and Mueller 2010). In this study, all job seekers had lost their job involuntarily within the previous six months and as a result were more likely to be receiving unemployment insurance; thus, we expected that the search intensity would increase for individuals as they near the end of their benefit term. In addition, people with a 1% higher pre-unemployment wage spend 3.4% less time on job search. The negative relationship between the past wage and job search could be attributed to the smaller pool of job opportunities that offer a higher wage. Prior research has also demonstrated that employed individuals with a higher wage are less likely to engage in job search (Bloemen 2005). White job seekers also appear to spend an hour less (approximately) on job search when compared to all other races.

While column (1) of Table 6 examines the aggregate effect of online ties on job search, column (2) isolates the effect of these ties on search behavior on SNSs by interacting online ties with the OSN dummy. Here, we find that users with more weak and strong ties on SNSs are more likely to search on those SNSs (relative to other modes). Results suggest that online ties are more relevant for job search behavior on SNSs. This result also resonates with the strength-of-weak-ties theory (Granovetter 1973), which states that weak ties are considered valuable in generating leads and hence motivate greater effort on SNSs.

5.1.2. Job Leads. From job leads regression (13a), presented in columns (3) and (4) of Table 6, we report the effect of search efforts and OSNs on job leads. It is important to note that these are conditional regressions and that the results should be interpreted as such.

First, note that search effort increases job leads significantly: the more a user searches on a job search mode, the more leads are reported from the mode. This finding is important because, given the survey nature of our data, the possibility of users' mixing their search effort in one mode with outcomes from other modes is always a concern.[9]

We observe that the Internet generates the most leads, followed by SNSs. This finding is consistent with users' search effort allocation—where unemployed job seekers spend more time with digital platforms, such as the Internet and SNSs. We also find that both strong ties and weak ties, on average, generate more job leads; strong ties generate leads at a higher rate than weak ties, but the effect of weak ties is not significant at the 95% level. In column (4), we find evidence that weak ties on SNSs generate more leads from that SNS. This finding is somewhat intuitive because a larger number of weak ties is expected to provide additional leads from the platform that enables the connection to these ties, especially because weak ties are not truly portable and beneficial outside of that search mode.

Users with more experience receive fewer leads, possibly because they are more selective and target only relevant job opportunities. As expected, unemployment duration is positively correlated with the number of job leads. In addition, female job seekers are more successful in finding relevant job leads than males. Job seekers with college degree gain fewer job leads when compared to job seekers with graduate and advanced degrees. Consistent with previous research (McDonald et al. 2009), white job seekers report having more leads, on average, than other races.

To summarize, we find that users search more on the Internet, followed by SNSs. We also find that users with more strong ties search more, both in general and on SNSs. We find that strong ties generate more leads in general, and that weak ties provide marginally more job leads on SNSs.

5.1.3. Job Interviews and Offers. We now estimate Equations (13b) and (13c) to examine the role of SNSs and OSNs on job interviews and offers. As before, we control for any mode-specific unobserved effect by using a mode-specific dummy. We also cluster the errors at the user level. And, as before, we jointly estimate two models for each job outcome (interviews or offers). First, we estimate the effect of online ties (strong and weak) on job outcomes, and second, we separate the effects of ties on OSNs. Because we estimate using nonlinear regression, in Table 7, we report the actual coefficients (versus marginal effects).

In column (1), we estimate the probability of interviews, conditional on job leads (estimated jointly). First, note that users report the most number of job interviews as coming from the Internet. OSNs are not as effective as the Internet in converting leads to interviews. We expect that this result occurs because more job applications can be submitted through the Internet, and although the uncertainty around the quality of a candidate is high, it is intuitive that more job applications would result in more interviews.

In addition, we see that strong ties have a significant, and positive, effect on job interviews, which resonates with the strength-of-strong-ties argument (Krackhardt 1992). Weak ties, on the other hand, have a statistically insignificant estimate. One possible interpretation is that, for leads to convert into interviews, ties have to make phone calls or provide recommendations. These activities are costly, and perhaps only strong ties are

Table 7. Estimates for Job Interviews and Job Offers

	Job interviews		Job offers	
	Effect of ties on all modes (1)	Effect of ties on OSN vs. other modes (2)	Effect of ties on all modes (3)	Effect of ties on OSN vs. other modes (4)
Job leads	0.187*** (0.065)	0.19*** (0.066)		
Job interviews			0.037* (0.021)	0.035* (0.02)
Dummy (Internet)	1.482*** (0.533)	1.459*** (0.53)	0.007 (0.012)	0.004 (0.011)
Dummy (OSNs)	0.645** (0.28)	0.732** (0.347)	0.03 (0.023)	0.049 (0.035)
Dummy (offline friends and family)	0.59** (0.273)	0.579** (0.273)	0.009 (0.013)	0.007 (0.012)
Dummy (print media)	0.713** (0.318)	0.707** (0.319)	0.036 (0.026)	0.031 (0.023)
Dummy (career centers and agencies)	0.634** (0.312)	0.624** (0.313)	0.012 (0.015)	0.008 (0.013)
Log (LinkedIn strong ties)	0.077*** (0.027)	0.069** (0.03)	0.152*** (0.03)	0.175*** (0.032)
Log (LinkedIn weak ties)	−0.001 (0.02)	0.01 (0.022)	−0.315*** (0.025)	−0.313*** (0.027)
SN ∗ Log (LinkedIn strong ties)		0.041 (0.051)		−0.051* (0.03)
SN ∗ Log (LinkedIn weak ties)		−0.043 (0.037)		−0.003 (0.037)
Log (Facebook total ties)	−0.042** (0.018)	−0.045** (0.018)	0.006 (0.026)	0.006 (0.026)
Experience	0.003 (0.004)	0.002 (0.004)	−0.036*** (0.006)	−0.036*** (0.006)
Log (salary)	−0.017 (0.07)	−0.018 (0.07)	0.579*** (0.115)	0.579*** (0.115)
Log (unemployment spell)	−0.088*** (0.029)	−0.088*** (0.029)	0.049 (0.054)	0.05 (0.054)
Sex (female = 1)	0.15** (0.059)	0.15** (0.059)	0.176** (0.081)	0.179** (0.081)
Married (yes = 1)	0.349*** (0.071)	0.357*** (0.071)	0.625*** (0.118)	0.612*** (0.118)
Education (college degree)	0.107* (0.064)	0.105* (0.061)	−0.473*** (0.078)	−0.458*** (0.078)
Race (white)	−0.354*** (0.063)	−0.358*** (0.063)	−0.207** (0.087)	−0.204** (0.087)
N	969	969	320	320
Clusters	296	296	109	109
Conditional on	Job leads		Job interviews	

Notes. Nonlinear joint maximum likelihood regression; standard deviations in parentheses. Omitted dummies: race (Asian and other), education (diploma and other), and search mode (agencies).
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

willing to undertake them. The marginal interaction effect (column 2) of strong ties and weak ties is also statistically insignificant when pursuing leads through online SNSs.

In column (2), we examine the effect of ties on outcomes from OSNs versus other modes and find that ties have no significant effect on job interviews generated from OSNs. This could be due to the fact that the effect of strong ties extends on average to all modes and not just to OSNs. Users with more strong ties consistently get more interviews across all modes and not just from OSNs.

Analyzing job offers (columns 3 and 4), we see that strong ties play a significant and positive role in job offers, and that weak ties indicate a negative effect, on average. Statistically, estimated at average, a 10% increase (or about one tie increase) in strong ties suggests and increase in number of offers by 0.7%. On the other hand, a 10% increase (or about a 10-tie increase) in weak ties suggests a decrease in number of offers by 1.3%. The effects are small but consistent in various robustness checks. Notice that these are conditional effects. Unconditionally, strong ties have a larger effect since they have positive effects on every step, while weak ties have a lower negative effect since weak ties influence job leads somewhat positively (see the subsequent discussion in next section).

Clearly the estimate on weak ties results suggest weak ties do not help convert from interviews to offers (and even marginally hurt). One possible explanation is that weak ties provide relatively poor quality of job leads and interviews. In addition, we expect that weak ties are unable to invest the necessary effort in recommending an individual for a job offer because of limited information about the skills of the individual and potential concerns associated with their unemployment status. Another possible explanation for this outcome could be drawn from the "principle of reflected exclusivity" (Krackhardt 1998).[10] The principle suggests that the degree of influence a person wields among her connections is inversely proportional to the time she spends with all of her other connections. Thus, a large number of weak ties might reduce the strength of ties that is more valuable in converting job interviews to offers. This incongruity might result from the communication overhead associated with connections. Job seekers who allocate more time connecting with a large number of weaker connections have less time for their strong connections. As a result, they might not be able to receive the optimum level of benefits even from the strong ties.

More interestingly, online strong ties do not have a larger impact on offers received from OSNs. If anything, the effects is small and negative (though not significant at 95%). It seems that online strong ties are not additionally more helpful in converting interviews to offers on online SNSs. Effects of strong ties persist across all modes and are not necessarily limited to OSNs.

The control variables should also be interpreted carefully since we have conditional regression. So they should be interpreted as effects on offers conditional on having received an interview (or leads). A longer unemployment spell contributes to a lower number of interviews, which is somewhat intuitive and demonstrated in prior research (Kroft et al. 2013). In addition, longer unemployment duration is seen to have no significant effect on job offers (Eriksson and Rooth 2014). Female and married job seekers gain more job interviews (conditional on leads) and later offers. Furthermore, more experience results in fewer job offers because experience acts as a proxy for age, which is shown to be negatively associated with reemployment (Wanberg et al. 2016). Also, higher past wage may signal the re-employability of a job seeker and is associated with more offers. Job seekers with college degree see a larger number of interviews but fewer offers when compared to the job seekers with graduate and advanced degrees. It could be that more educated workers wait for a better offer and signal as such during interviews. It could also be a reflection of the market condition in the industry in which they working (inferior job prospected for white collars during survey period). White job seekers see fewer interviews and fewer offers. This could be attributed to a more diverse white population in our sample relative to Asians and Hispanics.

In summary, our results broadly suggest that strong ties largely have positive effect on users' job outcomes, and that the weak ties are mostly ineffective. Contrary to our expectation, we find no evidence that these online weak ties (that SNSs are very efficient at allowing us to connect with) provide any meaningful help in employment search. It also seems that users are aware of their potential (lack of) value, and their search behavior is consistent with the outcome we see.

5.1.4. Role of Social Connections on Job Outcomes. As we explained, more ties affect search intensity, but the effect of ties on job outcomes is complex. Our estimates from Table 6 confirm that users with more ties are more likely to search. To estimate the total (unconditional) effect of social connections on job outcomes, we use Equations (13a)–(13c), discussed in Section 4.2. The numbers can be readily substituted from our earlier regressions. We estimate these results for OSNs:

$$\frac{d\pi_{ij}^{JL}}{dE_{ij}} = \frac{\partial\pi_{ij}^{JL}}{\partial E_{ij}} + \frac{\partial\pi_{ij}^{JL}}{\partial s_{ij}} \cdot \frac{ds_{ij}}{dE_{ij}},$$

$$\frac{d\pi_{ij}^{JI}}{dE_{ij}} = \frac{\partial\pi_{ij}^{JI}}{\partial E_{ij}} + \frac{\partial\pi_{ij}^{JI}}{\partial\pi_{ij}^{JL}} \cdot \frac{d\pi_{ij}^{JL}}{dE_{ij}},$$

$$\frac{d\pi_{ij}^{JO}}{dE_{ij}} = \frac{\partial\pi_{ij}^{JO}}{\partial E_{ij}} + \frac{\partial\pi_{ij}^{JO}}{\partial\pi_{ij}^{JI}} \cdot \frac{d\pi_{ij}^{JI}}{dE_{ij}}.$$

Table 8. Effect of Ties on Job Outcomes

	Job leads	Job interviews	Job offers
Strong ties	0.736 (0.165)	0.237 (0.08)	0.096 (0.027)
Weak ties	0.148 (0.089)	−0.021 (0.045)	−0.154 (0.023)

The equations give the results shown in Table 8. Thus, an increase in weak ties essentially has a small positive effect on job leads but not on job interviews and offers (has a marginally negative effect on offers). On the other hand, strong ties have a significant effect on job leads, interviews, and offers received by an unemployed individual. In summary, the effect of a change in strong and weak ties on job outcomes from OSNs could be expressed as follows:

One limitation of these results is that they do not capture any spillover effect of ties; an individual that got a job lead through a weak tie might convert that lead to an interview or offer using a strong tie.

5.1.5. Estimating Structural Parameters of Cost Function. With these estimates in hand, we can recover the cost function. While δ_j is readily identified, we also need standard errors. We recover the standard errors by bootstrapping (using 70% of the sample at a time) and running a simulation.

Estimates for the parameters in the cost function are given in Table 9, and estimates of structural parameters for the benefit function were presented in Tables 6 and 7.

From the cost function (Equation (4)) estimates, we see that scale coefficient (γ) is smallest for agencies, followed by the Internet, which reflects the low overall search costs of the platform. In contrast, we believe that the cost of search is high for OSNs and offline friends and family because interacting with social connections about job loss and seeking help in finding a new job take significant effort and time. The coefficient for print media is somewhat intuitive in that magazines and newspapers provide only limited information that could be processed by a job seeker in a given time frame. Weak ties lower the cost, while strong ties increase the cost. The rest of the parameters are also intuitive. Users with more experience and more education have lower costs overall. In summary, the estimated structural parameter allows us to recover both cost and benefit functions for all five job search modes, which should help job seekers more effectively allocate their job search effort over the various modes and to improve the probability of outcomes.

6. Conclusion and Discussion

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

Table 9. Estimates of Structural Parameters in the Cost Function

Cost function parameter (δ_j/γ_j)	IN	SN	FF	PM	AG	OT
Search mode coefficient (γ_j)	4.066	5.565	4.405	4.491	3.762	5.363
	(1.347)	(1.45)	(1.369)	(1.28)	(1.274)	(1.56)
Log (LinkedIn strong ties)	0.27	0.158	0.23	0.266	0.285	0.195
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Log (LinkedIn weak ties)	−0.181	−0.125	−0.161	−0.179	−0.188	−0.143
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log (Facebook total ties)	−0.076	−0.042	−0.064	−0.075	−0.08	−0.053
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Experience	−0.018	−0.008	−0.015	−0.018	−0.02	−0.012
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log (salary)	−1.307	−0.843	−1.141	−1.293	−1.37	−0.995
	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
Log (unemployment spell)	−0.018	−0.05	−0.03	−0.019	−0.014	−0.04
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Sex (female = 1)	−0.184	−0.153	−0.173	−0.183	−0.188	−0.163
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Married (yes = 1)	−0.061	−0.042	−0.054	−0.06	−0.063	−0.048
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Education (college degree)	−0.574	−0.344	−0.492	−0.567	−0.605	−0.42
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Race (white)	−0.461	−0.326	−0.413	−0.457	−0.479	−0.37
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)

Note. Standard errors, presented in the parentheses, are estimated with 1,000 iterations of 70% of the randomly sampled data set.

across various search modes. Our key goal is to understand how users allocate their time on SNSs and how their online social capital influences job search behavior and subsequent job outcomes. This is one of the first papers to examine this important question rigorously. Using survey data of about 424 users, we estimate search allocation model and job outcome models jointly. Our data allow us to examine not only how users allocate their time across different modes, but also the effect of social ties on job leads, interviews, and offers. In short, we can study how leads convert to interviews and interviews to offers, and how ties affect these conversions.

We find the SNSs are becoming an important platform for job search, and that users are increasingly looking for jobs on these platforms. However, we also find that online weak ties seem to play no meaningful role in users' job outcomes. In some places (like job leads), weak ties show a positive effect but otherwise are mostly ineffective (even marginally negative for job offers). It seems that many online weak ties are simply a function of simplified connectivity—users do not have to invest any significant amount of time in maintaining or cultivating them. Given all of the hype surrounding these networks and the ease of connecting with other users, this is a possibly surprising but important result. On the other hand, strong ties continue to play an important and positive role, and are beneficial in enhancing job outcomes. Finally, our structural model allows us to estimate the cost of search for each mode and show how the job search costs are affected by various user characteristics.

An important implication of our model is that the users' weak connections are not as useful as users perceive them to be. Many users possibly spend considerable time establishing these connections in the hope of generating future benefits. What our research suggests is that while these connections might provide other useful information, they are not very useful for job outcomes.

Given the possibility of selection and endogeneity concerns, we take a variety of steps. First, we use user random effects to control for user heterogeneity. We also allow for a variety of controls, including their Facebook ties, as possible control for selection. To account for possible data errors in the survey, we build many redundancies into the survey to ensure that data are as error free as possible.

This study is not only academically interesting, but is also highly relevant for firms and policy makers who are figuring out how to use the next generation of technologies effectively. Firms increasingly rely on these networks to find the next employee. So, it is good to ask going forward: How effective are these networks in finding the right employee, and at what cost?

6.1. Limitations and Future Work

This study, like most survey-based studies, faces the limitation of not representing the entire population. The survey responses received from the unemployed job seekers represent individuals that have a college degree and use OSNs. Despite being careful, we cannot rule out the possibility of data error when users are responding to a survey.

Another limitation of our approach is that we use multiple nonlinear models for analysis, which creates the burden of having to jointly estimate the productivity model and the search model, along with the added challenge of simultaneous estimation across all job search modes. Although we were able to estimate the three nonlinear productivity models together and show the results from jointly estimating the search model with one nonlinear direct outcome model (job leads), joint and simultaneous estimations of search with all job outcomes require more sophisticated econometric modeling and are left for the future extension of this work.

Research has shown that individuals are impatient while unemployed and that potential employers assume they are willing to work at a lower wage (DellaVigna and Paserman 2004). For simplicity, in this paper, we assumed the reservation wage to be equal to the wage received during the previous employment term. This assumption might reduce the computed utility from employment for all individuals, and as a result our estimates for the cost function might be inflated. Still, we believe that the user random effect will limit the magnitude of this error because of differences in job seekers' preferences across different job search modes.

This area clearly is just starting to emerge as an important research discipline. There is considerable interest in how technology platforms and social capital can affect job outcomes. We believe that more research is needed to understand the interplay of social capital, user characteristics, and job outcomes. A variety of methods, including randomized experiments, could be used to further investigate these questions.

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Endnotes

[1] For example, a 2010 *Fortune Magazine* article suggested that connecting on LinkedIn is more useful than exchanging business cards or churning resumes (Hempel 2010). In addition, a 2014 survey by Jobvite found that 94% of recruiters turn to LinkedIn to find qualified candidates (Jobvite 2014).

[2] Note that our findings reflect the role of connections during the job search process by unemployed individuals; job search by employed individuals might result in different findings.

[3] For a discussion of features and a recent survey of SNSs, see Boyd and Ellison (2007).

[4] Based on a survey by Pew Research (Duggan and Smith 2013), "LinkedIn usage is especially high among people with a college degree or higher, and among those with an annual household income of $75,000 or more."

[5] We found two outliers when comparing the sum of the outcome from search on OSN versus the aggregate outcome from OSNs. We dropped these two outliers from the sample.

[6] According to Granovetter (1985), most behaviors are closely embedded in networks of interpersonal relations. We use the term "embeddedness" to classify the number of interpersonal ties (strong or weak).

[7] We use the past wage as the reservation wage for the unemployed workforce. For employed individuals, the reservation wage is their current wage.

[8] We can jointly estimate interviews and leads, and offers and interviews as well. They yield almost identical results.

[9] We thank a reviewer for pointing out this possibility.

[10] In articulating the principle of reflective exclusivity, Krackhardt paraphrased a line from Jean-Baptiste Poquelin's (Moliere's) *The Misanthrope* (1966): "L'ami du genre humain n'est point du tout mon fait" ["The friend of the whole human race is not to my liking"] (Act I, Scene I). In Krackhardt's words, "a friend of the world is no friend of mine."

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