The Online Professional Social Network: Further Understanding the Relationship between Contacts and Labor Market Outcomes

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Abstract: Empirical findings on the impact of social networks on wages and job search outcomes are contradictory. One reason for these inconsistent findings is that researchers must rely on pre-existing data sets with limited information on networking. Each study differs in how they define and measure the networking variables as well as the population targeted by the surveys they employ. By using a dataset specifically created to unambiguously measure the relationship between the size and the composition of an individual's online professional social network and labor market outcomes, this paper seeks to overcome the inherent shortcomings encountered when using existing data to examine these relationships. The findings reveal that networking matters. There is strength in weak ties when it comes to salaries and wages; however, the composition of the network impacts hourly workers differently than salaried workers. Furthermore, the analysis reveals that reservation salaries increase when a contact is used to find employment, but reservation wages for hourly workers are not impacted by the use of a contact or the size of one's network. Finally, the use of a contact reduces search time for salaried workers, but not for wageworkers.

Keywords: Social Networks, Wage Determination, Job Search, LinkedIn, Contacts

JEL Classification: J31, J64, Z13

1. Introduction

Social networks can play a vital role during a job search, and utilizing one's network has the potential to impact labor market outcomes including earnings, job match, and tenure. Informal search methods such as leveraging one's contacts may provide an individual with information that allows them to screen available job opportunities, reduce the duration of unemployment spells, improve job match, and better negotiate wages. Further, employers may prefer to hire individuals that are recommended through a network since productivity and job match cannot be observed during the interview process. The additional information that a contact can provide to an employer about a candidate leads to increased compensation for the job-seeker, since they are expected to exhibit higher levels of productivity (Delattre and Sabatier, 2007). The benefits associated with improved information transmitted through networking are well documented in the literature (for a review see the seminal work by Granovetter, 1973, 1995, 2004; Ionnides and Loury, 2004; Lin, 1999, 2001; Mouw, 2003). Researchers have offered theoretical frameworks to model the relationship between the utilization of networks and labor market outcomes such as wages and job search (Cahuc and Fontaine, 2009; Calvo-Armengol and Jackson, 2004, 2007; Fainmesser, 2013; Fontaine, 2008; Montgomery, 1991). The theoretical findings suggest that for those who transition from unemployment to employment the use of a contact leads to improved wage and employment outcomes. These same improvements in wage and employment outcomes are observed for those with larger social networks even when a contact is not used when compared to those with smaller social networks. However, the use of the network is not necessarily the most efficient in terms of job match depending on the employment status of the contacts and whether they are considered weak ties. Social networks have also been shown to induce wage and employment inequalities if there are differences in the dropout rates of the network by racial group (Calvo-Armengol and Jackson, 2004). Finally, depending on the market structure, social networks can lead to unraveling of the market towards early hiring, which benefits connected workers, but lower benefits to the firms who hire them (Fainmesser, 2013).

To test these theoretical predictions, economists have presented empirical methodologies to determine whether social ties do in fact influence job search behavior and affect labor market outcomes (Caliendo et al., 2011; Dawid and Gemkow, 2013; Delattre and Sabatier, 2007; Urwin et al., 2008; Weber and Mahringer, 2008; and Franzen and Hangartner, 2006 to list a few); however, the empirical findings regarding the link between social networks, wages, and other job search behavior is inconclusive. For example, some empirical studies suggest a positive wage benefit from the use of the network, whereas others find that search productivity increases with the use of a contact, but leads individuals to accept lower wage offers. Another finding is that networks may only be advantageous for those who are currently employed and seek other employment opportunities. Finally, the use and density of one's social network leads to increased wage inequalities if firms who hire through referrals pay on average higher wages.

The contradictory findings in the literature are not surprising. Ionnides and Loury (2004) point out that the value of the network depends on the characteristics of the job seeker and the characteristics of the contacts they use. This is consistent with Pelizzari (2010), who find that the wage effect of social networks depends on the type of referral used. Furthermore, the use of a personal contact can have either a positive or negative wage effect depending on the efficiency of the formal search method used, which differs by labor market. Most of these studies rely on pre-existing data sets with limited information specific to networking. The contradictory empirical findings across these papers may be attributed to differences in how the networking variable of interest is measured, differences in the segment of the population targeted by the surveys employed, and differences in the sample restrictions imposed. Moreover, most studies are only able to observe the gender of the contact and determine whether the contact is a strong tie. Very few if any have been able to measure the exact contribution of specific network attributes by quantifying the number of contacts in the network and categorizing the type of contacts in the network.[1] Without knowing the characteristics of an individual's social network it is hard to identify the relationship between professional social ties and labor market outcomes. The size and composition of the network itself can impact the degree to which it provides benefits to a job seeker.

This paper adds to the discussion regarding professional social networking and labor market outcomes through the use of a unique data set designed to overcome some of the limitations imposed by using existing data. The contribution comes in the creation and use of this data set, which provides a way for researchers to unambiguously measure the size and composition of an individual's online professional social network by leveraging an existing online platform, LinkedIn. This allows one to easily observe specific characteristics of their individual network. The objective of this paper is to use this unique dataset to provide additional insight on the relationship between professional social networks and labor market outcomes such as earnings, reservation wages, and search time by specifically controlling for the size and composition of an individual's professional network across salaried and hourly workers. No other study compares hourly workers and salaried workers in the same analysis, which could potentially be important if one believes that there is correlation between the worker type and the value that contacts from those networks provide. By highlighting the differences between how these different groups of workers are impacted by the composition of their network, I demonstrate that failing to control for such differences when researching the impact of networking on labor market outcomes could lead to findings that contradict the existing literature.

LinkedIn users were chosen as the target subjects for this survey because LinkedIn is the leading online professional networking platform, which provides a relatively easy way to observe the size and composition of one's network. Furthermore, LinkedIn allows users to interact with others in a way that mimics one's interpersonal professional network and is designed to limit access to other members unless the users know each other or are introduced by an acquaintance (Papacharissi, 2009).

2. Literature Review

2.1 Contradictory Findings in the Literature

There has been extensive research on whether whom you know matters and what effect this has on labor market outcomes; however, as mentioned earlier, the empirical findings are contradictory. Studies by Rosenbaum et al. (1999), Marmaros and Sacerdote (2002), and Koreman and Turner (1996) all find evidence that using a contact provides a wage benefit. However, Kugler (2003) shows that the wage premium associated with using an informal contact becomes statistically insignificant once she controls for job sector. Mouw (2003) attempts to replicate previous studies by using NLSY data from 1982 to determine the direct effect contacts have on wages and job satisfaction. His results suggest that while 54% of respondents used a contact to obtain a job and 69% stated that the contact was "very important" in obtaining the job, there is no evidence that the use of a contact affects labor market outcomes. Job seekers did not find work more quickly or obtain jobs with better pay. Corcoran et al. (1980) and Simon and Warner (1992) find that if there is a wage premium associated with using informal search methods, this premium decreases over time, whereas Holzer (1988), Mardsen and Gorman (2001), Franzen and Hangartner (2006), and Urwin et al. (2008) all observe no wage effect. Finally, some researchers suggest that using contacts results in negative returns (Green et al., 1999; Bentolia et al., 2010; Delattre and Sabatier, 2007).

One possible explanation for why the empirical results are inconclusive is because each study defines and measures its network variable differently. Delattre and Sabatier (2007) conclude that their results may differ from previous studies due to how networks are defined. They only observe the use of strong ties, whereas other studies may have only observed the use of weak ties. Lin (1999) argues that knowing the structure and composition of the network may explain differences in outcomes among individuals. For example, contacts that are more experienced, further along in their career, and considered to be in high status positions are able to exert more influence and provide better information about higher paying jobs or employment opportunities. Kramaraz and

Skans (2014) examine the use of strong ties in finding a job for recent graduates in Sweden. They find that strong ties are beneficial to finding an individual's first job out of school and that the effect is stronger for those with lower education. Furthermore, the effect of the contact on the probability of finding a job is also strong if the referrer has higher wages or tenure at the place of work. Loury (2006) argues that some of this difference can be explained by the fact that those who find positive correlation between contact use and earnings are likely to be estimating the effects of high offer contacts and those who find negative results are estimating the effects of low offer contacts. This is confirmed by Antoninis (2006) who uses a unique data set on a manufacturing firm, which includes information on the type of job vacancy available and the type of relationship the referrer has with the employee. The study finds that new hires recommended by an individual who previously had a working relationship received a higher starting salary, whereas those who received a referral from friends or relatives had either no effect or a negative effect on wages depending on the skill level of the new hire.

Only a few of the empirical studies mentioned above say anything about the size of the individual's network or attempt to control for the characteristics of the contact. Surveys such as the NLSY only ask whether a friend or colleague assisted in the job search (Mouw, 2003; Loury, 2006; Kugler, 2003) but do not elaborate on what it means to be assisted. Other studies attempt to measure quality of the network by measuring the degree of socialization they engage in through community service, socialization with friends at home, or other activities. Urwin et al. (2008) base their research on the UK Time Use Survey and the British Household Panel Survey, where networking is proxied using measures of social ability and is quantified based on the number of hours of socialization with household and non-household members, as well as the number of hours of volunteer work. While the authors' objective is to measure network quality, there is no way to identify whether the time spent socializing actually measures professional socialization that directly benefits labor market outcomes. Delattre and Sabatier (2007) use a French longitudinal survey, where network is defined as the use of strong ties (relatives, friends, or non-professional associations) to find a job and is a dichotomous variable. Because I create a dataset specifically for the purpose of measuring network characteristics, at the very least I hope to reconcile the contradictory findings from previous papers in the literature.

2.2 Conceptual Framework and Hypotheses

The seminal works published by Granovetter (1973, 1974) regarding the impact that social networks have on job seekers provide several simple and intuitive hypotheses: (i) job seekers benefit more from utilizing a social contact rather than using formal job search methods because contacts reduce job search time, (ii) there is strength in weak ties, which implies that better information is generated through people who are less similar to the job seeker, and (iii) jobs obtained through informal contacts generate higher satisfaction due to better job match and higher wages.

Since Granovetter there have been many extensions of the hypothesis proposed by other researchers. For example, Delattre and Sabatier (2007) hypothesize that individuals who utilize their network are more likely to have higher wages through the information effect and productivity effect. That is, networks provide information about job opportunities and employers expect that job seekers hired through a contact will be more productive. Hence, both of these effects should result in higher predicted equilibrium wages. However, if the network helps job seekers find a job more quickly, workers may accept lower wage offers. This is highlighted in Bentolia et al., 2010. They hypothesize that jobs found through social contacts will pay on average a lower wage since workers will sacrifice their productive advantage if they accept the first job offer. This implies that jobs found through a contact may not be the optimal match for one's skill and abilities, but the job seeker may take this job anyways to reduce search time.

While the opportunity cost of finding a job more quickly through a contact is potentially a lower wage offer or a mismatched job opportunity, this is under the assumption that people in the network are not in the same industry or are not weak ties. Montgomery (1991) shows that the use of a weak tie is consistent with lower expected wages and predicts that, "individuals with large networks and/or a large proportion of weak ties in their networks will set relatively high reservation wages…such individuals also receive relatively high expected wages." This is consistent with Caliendo et al. (2011) who hypothesize that as the size of the network grows, search productivity will intensify and increase the value of the search in the form of a higher reservation wage. However, as the reservation wage increases, search time is hypothesized to increase. Nonetheless, there is still a net positive predicted effect on reservation wages if the network size increases.

Below is a summary of the hypotheses discussed in the literature that relate to this study:

1. Jobs found through the use of a contact are correlated with higher expected wages.
2. Jobs found through the use of a contact are negatively correlated with search time.
3. The direction of the correlation between network size and reservation wages depends on the network composition. In particular, increases in the number of weak ties (industry contacts) are positively correlated with reservation wages, whereas increases in the number of strong ties (friends and family) are negatively correlated with reservation wages. The degree to which these ties affect reservation wages depends on the worker type.
4. The direction of the correlation between network size and expected wages depends on the network composition. In particular, increases in the number of weak ties (industry contacts) are positively correlated with wages, whereas increases in the number of strong ties (friends and family) are negatively correlated with wages. The degree to which these ties affect wages depends on the worker type. For example, one would expect that former colleagues provide first-hand information about the worker's productivity to the employer and therefore an individual would expect to experience higher wages from old colleagues than friends and family if the worker is of high ability (Antoninis, 2006).

3. Data

The data used to analyze the relationship between professional social networks and labor market outcomes comes from a survey developed specifically for users of the professional networking site LinkedIn. LinkedIn is the leading professional social networking site, with 100+ million users as of 2013. Unlike online social networking sites such as Facebook, Twitter, and Instagram, LinkedIn is solely for professional networking. Professional networking is a specific type of social networking that focuses on maintaining contacts of a business nature, rather than including personal/non-professional social interactions. LinkedIn's architecture facilitates this by limiting interactions between users only to users who know one another from previous professional interactions or have been introduced by an acquaintance (Papacharissi, 2009). LinkedIn is primarily designed to provide a platform to organize and replicate one's pre-existing connections. As such, according to Papacharissi (2009) "professional etiquette offline transfers online and a network that emulates the protocol, routines and formalities of a professional interaction [is created]." Secondarily, LinkedIn users can then leverage their trusted connections to expand their professional network through a vetting and approval process controlled by one's peers. The goal is not to merely add connections in order to expand the perceived size of the network, but to reinforce and maintain business relations without having to deal with offline constraints (Boyd and Ellison, 2007; Haythornthwaite, 2002).

The LinkedIn platform makes it easy for users to answer questions regarding the gender composition of their networks and the number of people they know within their profession and industry in a way that offline professional networking cannot. A trade group or alumni association may have demographic details about its members, but it is doubtful that any individual member could quantify their network in a meaningful way beyond merely providing an estimate of network size and composition. The value LinkedIn provides to its members is the ability to easily find others that may have shared an employer, professional skill, or alma mater. It is thus logical to leverage their data collection and organization for the purposes of describing one's professional social network and determining how their network may have impacted their ability to find employment or advance in their career. Beyond an Internet connection and email address, LinkedIn has essentially no entrance fees to join the service.

LinkedIn user data is not publicly or commercially available. Even if LinkedIn provided access to their vast database of user information, I would only be able to observe basic demographic information, network size, network composition, and job type. I would not be able to observe labor market outcomes such as earnings, reservation wages, search time, or whether a contact was used to obtain a job.[2] Therefore, a survey was designed to collect the necessary data to supplement the basic demographic and network composition data on LinkedIn. Harris Interactive was chosen to administer the survey because, as a large market research firm, they are better able to reach out to participants who fall under the selected screening criteria. Potential participants were targeted from Harris' online panels by age, gender and employment status. The subjects were sent an online invitation from Harris Interactive to determine if they qualified for the survey, and those who did were asked to take our online survey. Respondents were compensated for their time by receiving HIpoints^{sm} through Harris' loyalty program (HIpoints^{SM} work much like airline reward points and can be redeemed for gifts such as Amazon gift cards). Respondents were also entered into a monthly sweepstakes as a thank you for their participation through Harris Interactive.

The data consists of a sample of 2000 LinkedIn users from the United States surveyed between January and March of 2013 who are full time workers between the ages of 18 and 65 with no mental or physical disabilities and that have an active LinkedIn account. Because LinkedIn has gained widespread use over the last five years among professionals who are seeking new opportunities or who simply want to maintain or expand their professional network and stay connected with peers and colleagues, it is important that the survey focus on individuals that have obtained a job in the last five years to capture any potential benefit from the use of LinkedIn. Additionally, I focus on individuals who gained employment or had changed jobs within the last five years because previous research suggests that there is a relationship between the composition of the network, utilization of the network, and economic cycles (see Franzen and Hangartner, 2006;

and Green et al., 1999). Focusing on those who found a job within the past five years ensures that everyone was subject to similar economic characteristics/landscape.[3]

Because a market research firm administered this survey, it is not possible to report a standard response rate. The budget allowed for a target sample of approximately 2,000 observations. Initially, 133,660 individuals were chosen to take part in a pre-screening questionnaire. Of those, 4,823 passed the pre-screening for our survey; those who did not pass the pre-screening moved on to other surveys. Of the 4,823 that passed the pre-screening, 2,264 qualified for the survey, and a total of 2,003 individuals completed the survey.

3.1 Survey Instrument

Participants responded to a twenty-minute questionnaire regarding current employment status, job search, professional network characteristics, and demographic information. Employment data includes current industry, occupation, job title, annual salary or hourly wage, type of role/position (non-management, lower, middle, or upper management), number of employees at current company, state respondent is employed in, and whether the current job is in a field that matches the individual's educational degree. Job search variables include hourly reservation wage or annual reservation salary, length of job search, and whether the individual was actively searching for a job or the opportunity arose unsolicited. The survey also captured information on professional network characteristics such as total number of LinkedIn contacts, composition of network,[4] whether someone within an individual's LinkedIn network or outside of their LinkedIn network assisted them in getting their most recent job, and if so how the contact assisted the individual in obtaining their most recent job. Finally, the demographic variables include gender, race, education in years, degree, major, experience, marital status, number of children, and highest educational degree attained by parents.[5]

3.2 Descriptive Statistics

After excluding individuals who were missing responses or provided unreliable data on network questions and outcome variables such as salary/wages, the sample of 2,000 LinkedIn users is further reduced to 1,921 observations. Furthermore, we exclude individuals who are in the military and those that earn less than $10,000 (for salaried employees) or the federal minimum wage of $7.25 (for hourly employees). The final sample includes 1,006 males and 915 females.

Since the variable of interest in most studies is whether the use of a contact results in higher earnings, higher reservation wages, and shorter search time, Table 1 reports the number of individuals who used a contact during their job search. The variable, *contact assisted* is binary and takes on the value of 1 if the respondent answered yes to either "have your LinkedIn contacts ever assisted you in getting a job?" or if someone outside of their LinkedIn network assisted the individual with obtaining employment, excluding headhunters or recruiters. Consistent with most other studies (such as Mouw, 2003; Loury, 2006; Bentolila et al., 2010), more than half of the sample (60 percent) used a contact to obtain a job. More specifically, 151 participants reported that they used a contact from their LinkedIn network only, whereas 290 participants were assisted by contacts from both their LinkedIn network and offline sources. Table 2 describes the sample statistics separately for those who did and did not find their job through a contact. Those who found a job through contacts appear to be slightly younger; have slightly less labor market experience; are more likely to be male; and have shorter search durations, higher salaries, higher hourly wages, higher reservation salaries, and a larger LinkedIn network on average.[6] There is no statistical difference in years of education or reservation wages for hourly workers between the two groups.

4. Empirical Model

To empirically determine how the size and composition of one's professional social network impacts labor market outcomes, the following model is specified:

$$Y = \alpha' X + \delta C + \beta' Z + \varepsilon \tag{1}$$

Let Y be the labor market outcome of interest, such as salary, reservation salary, or search duration. The matrix X includes individual level and market-valued characteristics such as years of education, experience, gender, race, marital status, children, region, industry, firm size, and job position. The variable C represents a dummy variable indicating whether or not the individual used a contact to find a job, and Z includes other network variables that measure the composition such as total number of contacts, number of male and female contacts, etc. This empirical model is similar to those estimated by Loury (2006), Bentolila et al. (2010), and Mouw (2003). According to Bentolila et al. (2010) the theoretical implications can be empirically tested with standard regression analysis. While I follow the standard regression model and employ variables that are typically used in the literature, I recognize that there are limitations to the analysis, in particular the issue of causality. It is not clear whether those who are higher earners tend to network more or whether larger networks lead to higher earnings; however, this study still provides insight and a new avenue to explore the relationship between networks and labor market outcomes.

5. Results

Research suggests that there are differences in network utilization and benefits based on the type of worker. Marmaros and Sacerdote (2002) find there is a correlation between job type and the type of people individuals typically network with. For example, Holzer (1987) finds that low-wage jobs are more likely to be filled by employee referrals, which is similar to Antoninis (2006), who uncovers that the frequency of referrals is negatively correlated with the skill content of the job. In particular, Mouw (2003) finds that blue-collar workers are more inclined to use contacts relative to white-collar workers. This may be dependent on the nature of the networking platform used. As a result, it is important to control for industry and differentiate between salaried and hourly workers in the analysis. If one assumes that salaried positions are more desirable than hourly work then it is important to distinguish between these two groups and determine if networks benefit one group over another.

5.1 Salary and Wage Regressions

5.1.1 Salaried Respondents

To examine whether jobs found through social contacts pay higher salaries on average, I estimate equation 1 using log annual salaries as the dependent variable. Column 1 of Table 3 presents the common network regressor used in the literature, where the variable of interest is a dummy indicating whether a contact was used to land their present job (see Bentolila et al. (2010), which suggests that standard regression analysis is sufficient to test conditional differences in outcomes for those who use a contact). After controlling for the baseline specification, which includes gender and the typical Mincer variables, the results suggest that annual salaries of workers who found their job through contacts are approximately 9.5 percent higher on average than those who did not use a contact, and this is statistically significant.[7] After controlling for industry, job role, and search type (actively searching for job = 0, opportunity arose unsolicited = 1) this gets reduced to 5.9 percent, and after controlling for region, marital status, presence of children, and parental education this premium is further reduced to approximately 5 percent. While the coefficient on the contact variable is predicted to be positive, one may argue that there is a self-selection issue if more able individuals tend to have better networks. The estimated coefficient could be biased if there are any omitted variables that are correlated with the use of a contact or the number of contacts in one's network. For example, it is easy to imagine that family background or socio-economic characteristics could impact the use of a contact. Highly educated parents tend to have highly educated children and therefore may be connected to other high-ability individuals. It also may be easier to increase the size of one's network if the individual is employed by a large company. For these reasons, the survey asks questions regarding parental education, company size, and other socioeconomic characteristics. The variables included in the analysis are standard regressors used in this line of literature.

Table 4, Column 1 presents the full specification with the addition of a new variable that measures the total number of contacts in one's online social network. The results reveal that individuals with larger networks tend to earn higher salaries on average. This supports the theoretical predictions introduced by Montgomery (1991), where increases in network size are positively correlated with earnings. Column 2 of Table 4 suggests that having a greater number of males in your professional online network is positively correlated with salary, whereas having a greater number of females in the network is negatively correlated with salary.[8] This is consistent with Loury's (2006) finding that the estimated coefficients vary by type of contact and in particular female friends and relatives are found to be negatively correlated with wages, likely because women in the sample earn lower salaries on average compared to their male counterparts. If women in the sample earn lower salaries and women have more female contacts, more female contacts could thus be associated with lower salaries.

To test the impact of weak ties, contact type is broken down further in Column 3 of Table 4. Unlike other studies, which focus on the type of tie actually used to find a job, we apply Montgomery's (1992) notion of "networks as resources" and include the size of different kinds of network structure as independent variables such as number of former colleagues, number of friends, and number of family members. In this specification, the variable *contact assisted* is also statistically insignificant. This is not surprising given that the use of a contact will be highly correlated with the size of the network. The table also indicates that increases in the number of family members included in one's online professional network are associated with lower salary, whereas having more former colleagues is associated with higher salaries on average. This is consistent with Granovetter's (1973) concept that there is strength in weak ties.

5.1.2 Hourly Wage Respondents

The next set of regressions focuses on hourly workers in the sample. For the sake of space, I only examine the fully specified regressions. The results in Table 5, Column 1 suggest that jobs found with the help of a contact tend to be associated with higher levels of compensation than jobs found another way; however, the estimated coefficient on *contact assisted,* in Column 2, becomes statistically insignificant once the total number of LinkedIn contacts is controlled for in the regression. This is not surprising as there is a strong correlation between network use and number of contacts. Column 3 of Table 5 separates the total number of contacts variable into the total number of male contacts and total number of female contacts. The coefficients on the network variables suggest that there is a statistically significant positive correlation between number of male contacts in one's network and hourly wages, whereas having more female contacts is associated with lower wages, but the coefficient is statistically insignificant. The last set of regressions in Column 4 of Table 5 breaks contact type down further. The variable *contact assisted* is still statistically insignificant; however, having more friends in one's network is positively correlated with hourly wages and coefficient is statistically significant.[9] This differs from the results for salaried workers discussed in section 5.1.1, where an increase in the number of close friends in one's online professional network is statistically insignificant. Furthermore, hourly workers benefit from having more former and current colleagues in their network, whereas having more contacts that are family members is negatively correlated with wages. Together this may suggest that hourly workers benefit more from friends in their network since they are more job-oriented and tend to associate with others like themselves, whereas salaried employees have more colleagues in their network because they are more career oriented and benefit more from weaker ties.

5.2 Reservation Salary and Reservation Wage Regressions

A common outcome of interest when analyzing job search behavior is the annual reservation salary or the hourly reservation wage. Larger networks should facilitate increased transfer of job-related information between individuals, such that workers with large networks should be better informed about the job market and be able to use this information to set higher reservation wages (Caliendo et al., 2011). The survey respondents were asked to report the lowest hourly wage (if hourly employee) or annual salary (if salaried employee) they were willing to accept before accepting their last job offer. To test whether individuals with larger networks set higher reservation wages/salaries on average, I separately estimate equation 1 using log annual reservation salaries as the dependent variable as well as log hourly reservation wages. The variables included in X and Z are similar to those used in the previous set of regressions except search duration is included as an independent variable. It is important to note that the size and composition of one's current network is not necessarily reflective of the size and composition of one's network at the time of their job hunt. However, at the very least I can provide some insight into whether contacts matter when it comes to setting reservation wages and salaries. Since I only have the individual's most current network data, I control for number of current colleagues to best account for this problem.

5.2.1 Reservation Salary

The regression results for reservation salary are presented in Table 6. The sample is restricted to those who reported a reservation salary that was below or equal to the actual salary received. The first column does not control for any of the network variables except for whether a contact assisted the individual in getting their last job. The coefficient is positive and statistically significant at the 5 percent level. Individuals who found jobs through the help of a contact set higher reservation salaries on average than those who did not. Once the total number of contacts is introduced in the regression, the *contact assisted* variable remains statistically significant, but only at the 10 percent level. The results show that there is a positive correlation between individuals with larger networks and setting higher reservation salaries. This may suggest that individuals are gaining information from their network even if their contacts are not directly assisting them with obtaining the job and thus are more confident in valuing their true productivity.[10] This is consistent with Caliendo et al. (2011), who find a positive relationship between network size and reservation wages. As shown in Column 3 of Table 6, when the total number of contacts is broken down into total number of male and female contacts, individuals with more male LinkedIn contacts had higher reservation salaries on average, whereas having more women in one's contact list does not have a statistically significant effect on setting reservation salary. The last column presents the estimated effects that certain types of contacts have on reservation salary. In this specification, the only coefficient that is statistically significant is number of former colleagues. This supports Montgomery's (1992) theoretical prediction that "worker's reservation wage rises as the proportion of weak ties in the worker's network increases. But although network composition is an important determinant of labor market success, the use of a weak tie does not imply higher expected wages." Finally, one would expect that job seekers may settle for a lower-paying job as their unemployment spell increases and therefore set lower reservation salaries. The table reveals that the number of months an individual spends searching for a job does not have a statistically significant effect on reservation salaries.

5.2.2 Reservation Wage

The variable *contact assisted* is not statistically significant in any of the regression specifications. Column 2 of Table 7 shows that there is a positive correlation between individuals who have larger networks and setting higher reservation wages, and this is statistically significant at the 1 percent level. According to Column 3 of Table 7, the gender composition of the contact does not matter when setting reservation wages and, finally, the last column breaks down contact type further and shows having more friends in the network, more former colleagues, and more current colleagues are positively correlated with higher reservation wages.

5.3 Search Duration

Finally, this paper examines how social contacts impact search costs. It is hypothesized that individuals who network should experience a shorter unemployment spell than those who do not network (Granovetter, 1973); there is empirical evidence in the literature to support this theory.

Mouw (2003), Bentolila et al. (2010), and Franzen and Hangartner (2006) all find that workers who used contacts to find work on average had a shorter job search relative to other workers. The raw data in this analysis indicates that 278 individuals reported that their job search took less than a month, and 75% of those individuals reported that they found their job with the help of a contact. To examine the relationship between the use of one's network to find a job and search time, I estimate equation 1 using the number of months it took for the respondent to search for their most current job as the dependent variable. I also include two additional independent variables to the matrix, X, reservation wage and whether the job was in the same field as the worker's degree.[11] Reservation wage/salary is included in the analysis because it is possible that individuals are willing to undergo a longer search time in order to land a higher paying job.[12] According to Franzen and Hangartner (2006), the benefits of networking can be non-pecuniary; thus, educational match is included in the regression. In particular, the use of informal search channels increases the chance that an individual will find a job that matches their educational qualifications. It may be possible that individuals who are searching for a job that is within the same educational field could take longer without the assistance of a contact if job seekers are searching for the best job match.

5.3.1 Salaried Workers

Similar to previous findings, the results shown in Table 8 suggest that the use of a contact reduces job search time for salaried workers as well. The use of a contact to help land the job is associated with a statistically significant reduction of about 1.8 months in search time on average compared to those who were not assisted by a contact. This is very close to the findings of Bentolila et al. (2010), who find that contacts shorten the unemployment spell by 1.5 months. The estimated parameter on *contact assisted* is robust given that the coefficient does not change in magnitude or statistical significance across alternate specifications.

5.3.2 Wage Workers

The same analysis on search duration was conducted for hourly wageworkers, and the results in Table 9 suggest that none of the network variables have a statistically significant impact on the length of time it takes to find a job. One explanation for this result is that the number of individuals who responded to the question on degree match was very low, thus imprecisely estimating the effects. I therefore run another set of regressions where the degree match variable is eliminated and the network variables remain statistically insignificant, though the coefficient has the correct theoretical sign on *contact assisted*. Perhaps the rise of the information economy has a different impact on outcomes for this generation of workers compared to the findings of other studies in the literature. One explanation could be that wageworkers in the past used their network differently than they do now.

5.4 Alternate Specifications

Next I explore if there is a wage premium or search premium for how the contact assisted the individual in their job search. For example, does a referral have more value than a contact submitting a resume to the HR office? The results in Table 10 suggest that there is no observed wage premium associated with how the contact assisted the individual. This is not surprising given that the coefficient on *contact assisted* in most specifications in Tables 4 and 5 were statistically insignificant. An alternate explanation is that it may not matter how the contact assists a job candidate as long as the network is providing relevant information. Simply the act of referring someone may signal to an employer that the candidate is a better fit or that the risk of a bad hire will be reduced. The employer may also be able to gain additional information about the individual from the contact that could not be determined during an interview. For example, questions about marriage and children cannot be legally asked during a job interview, but could be asked to a referrer. There is, however, empirical evidence suggesting there are benefits in terms of reducing the length of the job search among salaried employees. Table 11 shows that individuals whose contact assisted them by providing a referral, notifying them of the job opening, or assisting in some other way significantly reduced the length of the job search relative to having the contact submit a resume to the HR office.

Finally, in an attempt to reconcile previous findings in the literature with the results from this study, I replicate the sample restrictions that other authors impose. Prior research examining the effects that contacts have on earnings has focused on different populations of interest. For example, Franzen and Hangartner (2006) restricted their sample to recent college graduates, while Bentolila et al. (2010) restricted their sample to individuals under the age of 35 and found that contacts have no effect on earnings in the former and negative effects in the latter. According to Granovetter (1995), social networks for young workers can be ineffective. The inclusion of recent graduates may underestimate the effects of using a contact to gain employment. Recent graduates have less-developed networks, less experience in the process of searching for a job, and less information about the job market overall, and may thus have lower reservation wages. Similarly, by restricting the sample to those under 35, the authors are not able to observe individuals across various stages of their career. One would expect older individuals to have well-formed networks consisting of colleagues in and out of their field.[13] For example, Simon and Warner (1992) find a positive association between the use of a contact and earnings using data that reflects career-focused individuals from the 1972 survey of Natural and Social Scientists. Based on the different sampling criteria, it is no surprise that estimated effects across studies are contradictory. The wage regression from Bentolila et al. (2010) is reproduced using the LinkedIn data, where the sample is restricted to individuals who are under the age of 35. Table 12 shows that the variable of interest, *contact assisted*, is negative, but statistically insignificant. This suggests that the conflicting results may be explained by the age of the sample.

6. Conclusion

This paper is one of the first studies to design a survey that utilizes data on users of the online social networking site LinkedIn to examine the relationship between the size of one's network and labor market outcomes. Collecting data on LinkedIn members provided a population of users that could leverage the LinkedIn platform to answer questions regarding the number of family, friends, and colleagues that they professionally network with, gender composition of their networks and the number of people they know within their profession and industry in a way that offline professional networking could not. This comprehensive data set provides another avenue to explore how individuals network and whom they network with to resolve some of the contradictory findings that exist in the current literature.

The main findings of this study can be summarized as follows. Networks do in fact matter. There is evidence to suggest that there is strength in weak ties when it comes to salaries and wages; however, the composition of the network impacts hourly workers differently than salaried employees. For example, the use of a contact does not necessarily yield higher earnings for salaried and hourly workers after controlling for the size of the network; however, the size of certain groups in the network does matter. This suggests that individuals may benefit more from indirectly absorbing information through their contact list than using the help of a contact directly to land the job.[14] An alternative explanation is that that the returns to social networking are derived from the positive signal that large networks convey to employers (Urwin et al., 2008). Furthermore, the analysis reveals that reservation salaries increase with the use of a contact; however, the use of a contact or size of the network does not impact reservation wages. Finally, the use of a contact reduces search time for salaried workers.

While I recognize that there are limitations to this study, in particular the issue of causality, this paper provides a unique way to explore the relationship between networks and labor market outcomes. While it is not clear whether those who are higher earners tend to network more or whether larger networks lead to higher earnings, it is apparent that there is a definitive link between networks and labor market outcomes. A larger-scale survey on networks is necessary to further enhance this line of research with questions that would provide a way to isolate the causal relationship between contacts and the outcome variable of choice.

Mouw (2003) says, "I believe the weight of anecdotal evidence and intuition suggests that being 'well connected' is an advantage in the labor market. The question I have posed is whether we have any idea how much contacts matter…it is certainly plausible that future surveys with more extensive network information will prove that." I hope that this survey has shed some light on the relationship between social networks and labor market outcomes. Utilizing a professional online tool can prove to be beneficial to those who are trying to build their network and further their career. The low cost of developing networks of this nature may potentially help minority groups who historically have had fewer advantages in the labor market.

Endnotes

[*]Assistant professor. Graduate School of Business and Public Policy, Naval Postgraduate School. 555 Dyer Road, Monterey, CA, 93943. Tel: 831-656-2755. E-mail: dshatnaw@nps.edu. I wish to acknowledge that financial support was provided through the Naval Postgraduate School's Research Initiation Program, sponsored by the United States Navy, which provides research funds for new assistant tenure track faculty members. The Navy was not involved in any aspect of the research including the study design, collection, analysis, interpretation and the decision to submit this study for publication. I would also like to thank Kathryn Aten for her assistance on the survey.

1. Allen (2000) and Franzen and Hangartner (2006) are among the few that quantify the number of friends in the individual's network. Allen (2000) uses data from the Wisconsin Entrepreneurial Climate Study to examine how the size and composition of the network impact self-employment decisions, whereas Franzen and Hangartner (2006) use the ISSP 2001 survey, which asks respondents about the number of close friends at the work place and in their neighborhood and how they found their present job. While this provides a decent proxy for an

individual's social network, it is not clear whether the number of close friends from the workplace or neighborhood is an accurate measure of one's professional network or reflects contacts that can directly help with the job search. A more recent study by Dawid and Gemkow (2013) uses simulation data and finds the ratio of referral wages and non-referral wages is positively correlated with the density of the network for all skill groups but declines with the general skill level.

2. No other data set contains information on both earnings and reservation wages/salaries or can differentiate between hourly/salaried employees in the same file.

3. There may be some concern over whether the characteristics of an individual's current network are representative of their job search outcomes in the past. The assumption that participants had an account at the time of their last job search is not necessary as the literature suggests that users of LinkedIn transferred their offline network to their online network. I controlled for years on LinkedIn in the regressions and it does not impact the results. I also do not assume that the respondent's online network has not changed as a result of their current employment. I have the individual's most current salary and wage information and therefore any salary increases since the time of employment might be due to changes in the network. This should also not be an issue as I control for number of current colleagues.

4. This includes number of male and female contacts, number of LinkedIn contacts who are close friends, family, former colleagues, current colleagues, current employer, past employer, within same industry, and profession.

5. Appendix 1 provides a detailed description of the survey along with a complete list of the variables used in this paper and their definitions.

6. Potential experience is used in the analysis, measured as age – years of education – 5.

7. The estimated partial effects on the dummy variables are an approximation. See Halvorsen and Palmquist (1980) on how to interpret the estimated coefficients on dummy variables in semi-log regressions. The differences between the two approaches are nearly identical using this data.

8. This is also true even after running separate regressions for males and females. Individuals benefit less from having more women in their network.

9. Franzen and Hangartner (2006) find that the more friends the respondents have at work and the more friends they report to have outside of work, the higher their hourly wages. This is somewhat consistent with my results, which suggest that having more friends is associated with higher hourly wages; however, having more current colleagues has no effect. This highlights the importance of differentiating between current co-workers, past-co-workers, and friends.

10. Historically, sharing salary information among peers has been considered in poor taste; however, new generations of workers share this information more freely (Weber and Silverman, 2014). Thus, it is not unreasonable to assume that users of LinkedIn are gaining information regarding salary among other things. Furthermore, it is much easier to figure out compensation using other online resources such as monster.com and glassdoor.com.

11. I also run these regressions using a Weibull model and find qualitatively similar results to the least squares regressions and to the findings of Mouw (2003) and Franzen and Hangartner (2006). The tables are available upon request.

12. I run the regressions including the reservation wage and excluding reservation wage, and it does not affect coefficient estimates of the variables of interest.

13. Fontaine (2005) derives a theoretical framework that predicts that younger workers are less likely to see benefits from their social network early in their career because they are looking for their first job and probably connected to other young workers who are also searching for a job. Granovetter (1995) finds that social networks are ineffective in a young worker's job search.

14. This paradox is observed by Lin (1999) and Franzen and Hangartner (2006) where a correlation exists between large networks and high income jobs; however, using the network does not necessarily yield higher wages. It is important to note that, unlike Franzen and Hangartner (2006), I control for industry and job position and still observe this difference.

Appendix 1. Survey design, data classifications and definitions

The survey was administered with the assistance of the market research firm. Harris Interactive was chosen because of their prior research relationship with LinkedIn and due to their large nationally representative recruitment pool to survey. Subjects received a recruitment email inviting volunteers to complete an online survey regarding their use of LinkedIn and responded to a preliminary questionnaire for screening purposes. The survey was open on Harris Interactive's secure website until quota was reached between January and March of 2013. As incentives, respondents received "HIpoints" through Harris' loyalty program for completing the survey. Funding allowed for 2,000 subjects who met the sample restrictions.

Dependent Variables

Annual Salary. Participants were asked if they are salaried or paid by the hour. If the subjects indicated that they are paid as salaried employees, they were asked to report their current annual pretax salary in dollars. I exclude observations flagged as possible errors. For example, individuals who earned less than $10,000 were dropped because the salary amount was unusual for the education, experience, job title, and industry they reported.

Hourly Wage. If the subject indicated that they are paid by the hour, the respondents were asked about their current pretax hourly wage in dollars, not including tips and bonuses. Observations were dropped if the individual earned less than $7.25, which is the federal minimum wage for hourly employees.

Reservation Salary/Reservation Wage. Subjects were asked, "When you were searching for your current job, what was your annual reservation salary (i.e., the lowest wage you were willing to accept)? If you were searching for a job that pays by the hour, what was the lowest hourly wage you were willing to accept?"

Search Time. Subjects were asked, "How long did the search for your current job take? That is, how much time it took from when you started looking until you secured your new job." Data were reported in number of years and months, which I convert into total number of months.

Control Variables

Contact Assisted. Binary variable defined to take on the value of 1 if the respondent either answered yes to "have your LinkedIn contacts ever assisted you in getting a job?" or indicated that they were assisted by an interpersonal contact. Interpersonal contact was determined if the participant indicated that someone outside of their LinkedIn network assisted the individual with obtaining employment that was not a headhunter or a recruiter.

 # Contacts. Subjects were asked, "How many LinkedIn contacts do you have?" The survey was designed so that an error message would appear if the #Males+#Females did not add up. Range: 0–9999.

#Males. Subjects were asked, *"*How many of your LinkedIn contacts are male?" Range: 0–9999.

#Females. Subjects were asked, *"*How many of your LinkedIn contacts are female?" Range: 0–9999.

#Friends. Subjects were asked, *"*How many of your LinkedIn contacts are close friends?" Range: 0–9999.

#Family. Subjects were asked, *"*How many of your LinkedIn contacts are family?" Range: 0–9999.

#Former Colleagues. Subjects were asked, *"*How many of your LinkedIn contacts are former colleagues?" Range: 0–9999.

#Current Colleagues. Subjects were asked, *"*How many of your LinkedIn contacts are current colleagues?" Range: 0–9999.

Female. Indicator if the subject's gender is female.

Education. Number of years in school including Kindergarten.

Experience. Computed as *Age – Education – 5.*

Search Type. Subjects were asked, "Prior to securing your current job, were you actively searching or did the opportunity come up?" The variable, *Search Type*, is binary and defined to take the value 1 if the respondent selected the latter option. Actively searching is the left-out reference group.

Company Size. Subjects were asked to report, "How many employees are at your current company? Please provide information based on all locations ad include, full-time, part-time and temporary employees." Range: 1–999999. *Company Size* is included in all regressions as a continuous variable.

Degree Field Match. A binary variable defined to take on the value 1 if the subject responded, "yes" to the question, "Is your current job in the same field in which you received your highest academic degree?"

Industry. Subjects were asked to select the industry that best matches their primary job. The survey included 35 categories, which were aggregated to eleven industries that best match the two-digit industry codes from the 2007 Census Industrial Classification. Aggregation was necessary given that there were not enough observations in each of the 35 categories. The eleven broader categories and their composition are as follows: 1) Financial Activities (includes banking and finance, finance, insurance, real estate). 2) Professional and Business Services (includes business services, engineering services, legal services, research services, technology services, advertising/marketing, communications, mining). 3) Leisure and Hospitality (includes accommodation and food services, arts, entertainment and recreation, travel). 4) Other Services (includes administration support services, automotive services, waste management/remediation services, other services, religious/non-profit organizations). 5) Public Administration (includes public administration/government). 6) Health Care and Social Assistance (includes medicine/healthcare/social assistance). 7) Manufacturing (includes manufacturing, pharmaceutical). 8) Wholesale and Retail Trade (includes printing trade, retail trade, wholesale). 9) Transportation and Utilities (includes telecommunications, transportation and warehousing, utilities). 10) Educational Services (includes education). 11) Other (includes construction, mining, agriculture forestry, fishing, hunting, other (open-ended answers)).

State. Subjects were asked to report the state they reside in. While there was a representative sample of individuals from each state, some states had too few observations. As a result, the regressions were run using regions rather than individual states. The states were aggregated into nine regions as defined by the U.S. Census Bureau: New England (ME, NH, VT, MA, RI, CT), Mid Atlantic (NY, NJ, PA), East North Central (OH, IN, IL, MI, WI), West North Central (MN, IA, MO, ND, SD, NE, KS), South Atlantic (DE, MD, DC, VA, NC, SC, GA, FL), East South Central (KY, TN, AL, MS), West South Central (AR, LA, OK, TX), Mountain (MT, ID, WY, CO, NM, AZ, UT, NV), and Pacific (WA, OR, CA, AK, HI).

Position (Job Role). Subjects were asked to select which category best describes their current role or position: 1) Non-management. 2) Lower Management (i.e., supervisory personnel or first-level manager). 3) Middle Management (i.e., department or business unit head). 4) Upper Management (i.e., high level, senior executive that sets policy for the company). 5) other (open-ended answers).

Race. Categories include Hispanic, white, black, Asian, other. The sample was comprised of 85% white/Caucasian individuals.

Marital Status. Respondents indicated whether they were never married, married or civil union, divorced, separated, widower/widow, or living with partner. These categories were aggregated into 1) married/together (includes married, living with partner), 2) single (includes never been married), and 3) divorced (separated, widow, divorced).

Children. Subjects reported how many children they have. A binary variable was created for the regression indicating that the subject has at least one child.

Parental Education. Subjects were asked to report the highest level of education or degree received for each of their parents. Categories included less than high school, completed high school, completed some college or associate degree, completed college, completed some graduate school, completed graduate school, or not sure.

How contact assisted. The below categories were created based on the answers to the following questions: The first questions was, “You mentioned that your LinkedIn contacts have assisted you in getting a job. Please select all that apply." The options were 1) LinkedIn contact employed by place I was seeking work and provided referral to hiring manager. 2) LinkedIn contact employed by place I was seeking work and provided referral to someone other than hiring manager. 3) LinkedIn contact employed by place I was seeking work and provided my resume to human resources. 4) LinkedIn contact referred me to an employee at place I was seeking work. 5) Found out about job opportunity through LinkedIn contact. 6) Other. The other question was, "In what way has a contact outside of your LinkedIn network assisted you with obtaining employment? Please select all that apply. 7) Provided recommendation/reference. 8) Gave resume to HR or hiring manager. 9) Notified me of opening. 10) Ended up hiring me. 11) Some other way."

Contact provided a referral. Dummy variable = 1 if subject indicated categories 1, 2, 4, 7, or 9.

Contact notified hiring manager. Dummy variable = 1 if subject indicated category 1.

Contact assisted in other way. Dummy variable = 1 if subject indicated categories 5, 6, 9, 10, or 11.

Contact assisted in multiple ways. Selected more than one category.

Contact sent resume to HR (left out reference group). Dummy variable = 1 if subject indicated categories 3, 8.

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Table 1. Used Contact (Online and/or Offline) to Obtain Job

Contact Assisted	Frequency	Percent
0	764	39.77
1	1157	60.23
Total	1921	100

Table 2. Sample Characteristics of the Data by Contact Assist

	Contact Assisted			Other Channels		
Variable	Mean	S.D	n	Mean	S.D	n
age	43.41227	12.21564	1157	44.73953	12.35469	764
female	0.4563526	0.4983067	1157	0.5065445	0.5002847	764
educ_yr	17.09248	3.511117	1157	17.15969	3.69203	764
exper	21.31979	12.50722	1157	22.57984	12.77644	764
contacts	129.7087	377.7425	1157	69.66623	144.6402	764
search time	7.565255	11.13383	1157	8.98822	11.71253	764
res_wage	17.49211	16.74473	237	16.4199	22.24863	198
salary	75405.75	39572.63	802	67347.15	35039.81	470
hourlywage	22.02724	19.78464	355	18.78486	13.01587	294
reservation salary	66119.35	35237.17	675	58613.95	28173.92	400

Table 3. Log Annual Salary Regressions

	Variable	(1)	(2)	(3)
Network	Contact Assisted	0.0946***	0.0589**	0.0497**
		[0.027]	[0.025]	[0.025]
Mincer	Female	-0.2373***	-0.1540***	-0.1450***
		[0.026]	[0.025]	[0.025]
	Education	0.0220***	0.0232***	0.0202***
		[0.004]	[0.003]	[0.004]
	Experience	0.0269***	0.0234***	0.0241***
		[0.004]	[0.004]	[0.004]
	Experience Squared	-0.0005***	-0.0004***	-0.0004***
		[0.000]	[0.000]	[0.000]
	Constant	10.4274***	10.4191***	10.3394***
		[0.081]	[0.084]	[0.138]
Job Characteristics	Search Type - non-active search	-	0.0580**	0.0635**
			[0.027]	[0.026]
	Company Size	-	0.0000***	0.0000***
			[0.000]	[0.000]
	Industry, Position	-	✓	✓
Other Demographics	Race, Marital Status, Children, Parental Education	-		✓
	Region			✓
	Observations	1,272	1,272	1,272
	R-squared	0.151	0.303	0.364

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 4. Log Annual Salary Regressions

	Variable	(1)	(2)	(3)
Network	Contact Assisted	0.0390	0.0397	0.0394
		[0.025]	[0.025]	[0.025]
	# Contacts	0.0002***	-	-
		[0.000]		
	# Males	-	0.0007***	-
			[0.000]	
	# Females	-	-0.0005**	-
			[0.000]	
	# Friends	-	-	0.0001
				[0.000]
	# Family	-	-	-0.0042***
				[0.001]
	# Former Colleagues	-	-	0.0009***
				[0.000]
	# Current Colleagues	-	-	0.0000
				[0.000]
Mincer	Female	-0.1459***	-0.1368***	-0.1426***
		[0.025]	[0.025]	[0.024]
	Education	0.0192***	0.0189***	0.0191***
		[0.003]	[0.003]	[0.003]
	Experience	0.0243***	0.0242***	0.0212***
		[0.004]	[0.004]	[0.004]
	Experience Squared	-0.0004***	-0.0004***	-0.0003***
		[0.000]	[0.000]	[0.000]
	Constant	10.3523***	10.3606***	10.3410***
		[0.137]	[0.137]	[0.136]
Job Characteristics	Search Type - non-active search	0.0666**	0.0626**	0.0668***
		[0.026]	[0.026]	[0.026]
	Company Size	0.0000***	0.0000***	0.0000***
		[0.000]	[0.000]	[0.000]
	Industry, Position	✓	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓	✓
	Observations	1,272	1,267	1,198
	R-squared	0.378	0.384	0.393

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 5. Log Hourly Wage Regressions

	Variable	(1)	(2)	(3)	(4)
	Contact Assisted	0.0616*	0.0492	0.0437	0.0368
		[0.036]	[0.036]	[0.037]	[0.037]
	# Contacts	-	0.0005***	-	-
			[0.000]	0.0012**	
	# Males	-	-	[0.001]	-
				-0.0004	
	# Females	-	-	[0.001]	-
Network	# Friends	-	-	-	0.0037***
					[0.001]
	# Family	-	-	-	-0.0120**
					[0.005]
	# Former Colleagues	-	-	-	0.0013***
					[0.000]
	# Current Colleagues	-	-	-	0.0027**
					[0.001]
	Female	-0.0855**	-0.0908**	-0.0861**	-0.0883**
		[0.038]	[0.037]	[0.039]	[0.038]
	Education	0.0157***	0.0148***	0.0144**	0.0132**
		[0.006]	[0.006]	[0.006]	[0.006]
Mincer	Experience	0.0145***	0.0149***	0.0143***	0.0144***
		[0.005]	[0.005]	[0.006]	[0.005]
	Experience Squared	-0.0002*	-0.0002**	-0.0002*	-0.0002**
		[0.000]	[0.000]	[0.000]	[0.000]
	Constant	2.1808***	2.1958***	2.4220***	2.4122***
		[0.192]	[0.191]	[0.189]	[0.187]
	Search Type - non-active search	-0.0212	-0.0125	-0.0127	-0.032
		[0.042]	[0.042]	[0.043]	[0.044]
Job Characteristics	Company Size	0.0000	0.0000	0.0000	0.0000
		[0.000]	[0.000]	[0.000]	[0.000]
	Industry, Position	✓	✓	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓	✓	✓
	Observations	649	649	626	626
	R-squared	0.323	0.335	0.341	0.359

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 6. Log Annual Reservation Salary Regressions

	Variable	(1)	(2)	(3)	(4)
Network	Contact Assisted	0.0677**	0.0537*	0.0538*	0.0525
		[0.033]	[0.032]	[0.032]	[0.033]
	# Contacts	-	0.0004***	-	-
			[0.000]		
	# Males	-	-	0.0006***	-
				[0.000]	
	# Females	-	-	0.0001	-
				[0.000]	
	# Friends	-	-	-	0.0005
					[0.001]
	# Family	-	-	-	-0.0036
					[0.002]
	# Former Colleagues	-	-	-	0.0009***
					[0.000]
	# Current Colleagues	-	-	-	0.0004
					[0.000]
Mincer	Female	-0.1344***	-0.1249***	-0.1211***	-0.1334***
		[0.033]	[0.033]	[0.033]	[0.033]
	Education	0.0196***	0.0183***	0.0182***	0.0192***
		[0.005]	[0.005]	[0.005]	[0.005]
	Experience	0.0275***	0.0274***	0.0274***	0.0253***
		[0.005]	[0.005]	[0.005]	[0.005]
	Experience Squared	-0.0004***	-0.0004***	-0.0004***	-0.0004***
		[0.000]	[0.000]	[0.000]	[0.000]
	Constant	10.1028***	10.1272***	10.1301***	10.1755***
		[0.171]	[0.168]	[0.169]	[0.170]
Job Characteristics	Search Type - non-active search	0.0747**	0.0724**	0.0678*	0.0800**
		[0.035]	[0.034]	[0.035]	[0.035]
	Search Time	-0.0018	-0.0021	-0.0019	-0.0016
		[0.001]	[0.001]	[0.001]	[0.001]
	Company Size	0.0000***	0.0000***	0.0000***	0.0000***
		[0.000]	[0.000]	[0.000]	[0.000]
	Industry, Position	✓	✓	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓	✓	✓
	Observations	1,075	1,075	1,070	1,010
	R-squared	0.280	0.306	0.307	0.294

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 7. Log Hourly Reservation Wage Regressions

	Variable	(1)	(2)	(3)	(4)
Network	Contact Assisted	0.0542	0.0374	0.0423	0.0222
		[0.048]	[0.047]	[0.049]	[0.048]
	# Contacts	-	0.0007***	-	-
			[0.000]		
	# Males	-	-	0.0009	-
				[0.001]	
	# Females	-	-	0.0004	-
				[0.001]	
	# Friends	-	-	-	0.0051***
					[0.001]
	# Family	-	-	-	-0.0092
					[0.007]
	# Former Colleagues	-	-	-	0.0018***
					[0.001]
	# Current Colleagues	-	-	-	0.0051**
					[0.002]
Mincer	Female	-0.0924*	-0.1000**	-0.1100**	-0.1151**
		[0.049]	[0.048]	[0.050]	[0.048]
	Education	0.0401***	0.0387***	0.0387***	0.0368***
		[0.007]	[0.007]	[0.008]	[0.007]
	Experience	0.0156**	0.0161**	0.0152**	0.0160**
		[0.007]	[0.007]	[0.008]	[0.007]
	Experience Squared	-0.0002	-0.0003	-0.0003	-0.0003
		[0.000]	[0.000]	[0.000]	[0.000]
	Constant	1.8454***	1.8556***	2.1432***	2.1030***
		[0.257]	[0.254]	[0.247]	[0.242]
Job Characteristics	Search Type - non-active search	-0.0752	-0.0711	-0.0702	-0.0575
		[0.055]	[0.055]	[0.056]	[0.054]
	Search Time	0.0008	0.0005	0.0002	0.0004
		[0.002]	[0.002]	[0.002]	[0.002]
	Company Size	0.0000	0.0000	0.0000	0.0000
		[0.000]	[0.000]	[0.000]	[0.000]
	Industry, Position	✓	✓	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓	✓	✓
	Observations	435	435	415	415
	R-squared	0.34	0.358	0.370	0.402

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 8. Search Time (Months) Regressions for Salaried Workers

	Variable	(1)	(2)	(3)	(4)
Network	Contact Assisted	-1.7772**	-1.8324**	-1.8394**	-1.8463**
		[0.737]	[0.739]	[0.742]	[0.745]
	# Contacts	-	0.0018	-	-
			[0.001]		
	# Males	-	-	0.0007	-
				[0.005]	
	# Females	-	-	0.0033	-
				[0.006]	
	# Friends	-	-	-	-0.0170
					[0.015]
	# Family	-	-	-	0.0811
					[0.054]
	# Former Colleagues	-	-	-	-0.0002
					[0.004]
	# Current Colleagues	-	-	-	-0.0030
					[0.007]
Mincer	Female	-2.0710***	-2.0463***	-2.0743***	-2.0713***
		[0.751]	[0.751]	[0.759]	[0.757]
	Education	0.0318	-0.0252	-0.0255	-0.0255
		[0.116]	[0.107]	[0.107]	[0.107]
	Experience	0.0010	0.0358	0.0318	0.0268
		[0.003]	[0.116]	[0.117]	[0.118]
	Experience Squared	0.001	0.0009	0.0010	0.0011
		[0.003]	[0.003]	[0.003]	[0.003]
	Constant	18.6589**	20.4135**	20.7425**	17.8512**
		[8.008]	[8.123]	[8.277]	[8.281]
Job Characteristics	Search Type - non-active search	-3.2089***	-3.2040***	-3.2042***	-3.1682***
		[0.796]	[0.796]	[0.798]	[0.800]
	Reservation Salary	-0.8701	-1.0338	-1.0218	-0.7607
		[0.698]	[0.710]	[0.712]	[0.712]
	Degree Field Match	0.5394	0.5245	0.5747	0.5042
		[0.759]	[0.759]	[0.763]	[0.765]
	Company Size	0.0000	0.0000	0.0000	0.0000
		[0.000]	[0.000]	[0.000]	[0.000]
	Industry, Position	✓	✓	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓	✓	✓
	Observations	982	982	978	978
	R-squared	0.099	0.101	0.100	0.101

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definition are in Appendix 1.

Table 9. Search Time (Months) Regressions for Hourly Workers

	Variable	(1)	(2)	(3)	(4)
Network	Contact Assisted	0.3029	0.1844	0.4581	0.4738
		[1.236]	[1.245]	[1.251]	[1.271]
	# Contacts	-	0.0041	-	-
			[0.005]		
	# Males	-	-	0.0212	-
				[0.024]	
	# Females	-	-	-0.0215	-
				[0.034]	
	# Friends	-	-	-	-0.0347
					[0.035]
	# Family	-	-	-	0.0571
					[0.161]
	# Former Colleagues	-	-	-	0.0083
					[0.018]
	# Current Colleagues	-	-	-	0.0102
					[0.048]
Mincer	Female	0.1982	0.1337	-0.1575	-0.1112
		[1.327]	[1.330]	[1.347]	[1.347]
	Education	0.2222	0.2191	0.2212	0.2383
		[0.207]	[0.207]	[0.210]	[0.212]
	Experience	-0.2584	-0.2503	-0.2378	-0.2656
		[0.193]	[0.193]	[0.193]	[0.194]
	Experience Squared	0.0080*	0.0077*	0.0072	0.0078*
		[0.004]	[0.004]	[0.004]	[0.004]
	Constant	6.5343	7.2405	9.3794	7.5558
		[7.199]	[7.252]	[7.530]	[7.665]
Job Characteristics	Search Type - non-active search	-4.4440***	-4.4179***	-4.8330***	-4.6806***
		[1.457]	[1.458]	[1.462]	[1.474]
	Reservation Wage	-1.4244	-1.628	-1.8426	-1.5464
		[1.325]	[1.347]	[1.363]	[1.407]
	Degree Field Match	1.1857	1.2794	0.6497	0.6609
		[1.342]	[1.347]	[1.351]	[1.346]
	Company Size	0.0000	0.0000	0.0000	0.0000
		[0.000]	[0.000]	[0.000]	[0.000]
	Industry, Position	✓	✓	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓	✓	✓
	Observations	289	289	280	280
	R-squared	0.226	0.229	0.236	0.237

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 10. Returns to How the Contact Assisted, (1) Log Annual Salary, (2) Log Hourly Wages

	Variable	(1)	(2)
Network	Contact provided a referral	-0.0391	0.0297
		[0.092]	[0.147]
	Contact notified hiring manager	0.0231	0.1455
		[0.093]	[0.145]
	Contact assisted in other way	0.0423	-0.0550
		[0.143]	[0.256]
	Contact assisted in multiple ways (at least one of the above)	0.0739	0.0877
		[0.084]	[0.134]
	Contact sent resume to HR (left out reference group)	-	-
Mincer	Female	-0.1025***	-0.0553
		[0.032]	[0.054]
	Education	0.0259***	0.0224***
		[0.005]	[0.008]
	Experience	0.0302***	0.0221***
		[0.005]	[0.008]
	Experience Squared	-0.0005***	-0.0004**
		[0.000]	[0.000]
	Constant	10.0358***	1.9695***
		[0.199]	[0.304]
Job Characteristics	Search Type - non-active search	0.0287	-0.0743
		[0.032]	[0.056]
	Company Size	0.0000***	0.0000
		[0.000]	[0.000]
	Industry, Position	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓
	Observations	802	355
	R-squared	0.385	0.386

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 11. How the Contact Assisted and Search Time (Months), (1) Salaried Workers, (2) Hourly Workers

	Variable	(1)	(2)
Network	Contact provided a referral	-4.7410*	2.3002
		[2.587]	[4.393]
	Contact notified hiring manager	-5.0400*	2.4593
		[2.598]	[4.340]
	Contact assisted in other way	-6.9310*	3.9396
		[3.745]	[8.202]
	Contact assisted in multiple ways (at least one of the above)	-3.6947	-0.1492
		[2.361]	[4.035]
	Contact sent resume to HR (left out reference group)	-	-
	# contacts	0.0025	0.0031
		[0.002]	[0.006]
Mincer	Female	-1.0199	2.3192
		[0.914]	[1.833]
	Education	0.0708	0.0096
		[0.131]	[0.293]
	Experience	0.0172	-0.1667
		[0.141]	[0.280]
	Experience Squared	0.0026	0.0054
		[0.003]	[0.006]
	Constant	34.8843***	9.4132
		[10.391]	[10.491]
Job Characteristics	Search Type – non-active search	-3.1126***	-6.0530***
		[0.899]	[1.846]
	Reservation Wage	-2.2190**	-1.2620
		[0.912]	[2.104]
	Degree Field Match	1.3809	0.4801
		[0.937]	[1.835]
	Company Size	0	0
		[0.000]	[0.000]
	Industry, Position	✓	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓	✓
	Observations	613	165
	R-squared	0.129	0.429

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.

Table 12. Log Hourly Wage Regression for Those under 35 Years Old

	Variable	(1)
Network	Contact Assisted	0.0215
		[0.065]
	# Contacts	-
	# Males	-
	# Females	-
	# Friends	-
	# Family	-
	# Former Colleagues	-
	# Current Colleagues	-
Mincer	Female	-0.0616
		[0.067]
	Education	0.0395***
		[0.014]
	Experience	0.0223
		[0.016]
	Experience Squared	0.0001
		[0.001]
	Constant	1.4146***
		[0.489]
Job Characteristics	Search Type - non-active search	-0.0504
		[0.080]
	Company Size	0.0000
		[0.000]
	Industry, Position	✓
Other Demographics	Region, Race, Marital Status, Children, Parental Education	✓
	Observations	208
	R-squared	0.412

Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Dashes signify an intentionally left-out variable. Dummy variables for region, industry, job role, race, marital status, child indicator, and categories for mother and father's highest education level were included in specified regressions. Variable definitions are in Appendix 1.