Social Capital and Finding a Job: Do Contacts Matter?

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Does social capital affect labor market outcomes? The prevalent use of job contacts to find work suggests that "who you know" is an important means of getting a good job. Network theories of social capital argue that well-connected workers benefit because of the job information and influence they receive through their social ties. Although a number of studies have found a positive relationship between measures of social capital and wages and/or occupational prestige, little is known about the causal effect of social networks on labor market outcomes. Four data sets are used to reassess findings on the role of social capital in the labor market. A test of causality is proposed based on the argument that if social capital variables do have a causal effect on job outcomes, then workers with high levels of social capital should be more likely to use contacts to find work, all else being equal. Results suggest that much of the effect of social capital in the existing literature reflects the tendency for similar people to become friends rather than a causal effect of friends' characteristics on labor market outcomes.

The old cliche about finding work—"it's not what you know but who you know that matters"—suggests that having good connections is important in the labor market. The prevalent use of job contacts to find work—approximately 40 to 50 percent of all jobs in the United States are found through help or information from friends or relatives (Granovetter 1995)—seems to confirm this intuition. A large literature in sociology argues that using job contacts (Granovetter 1974) or having good contact networks (Lin 2001b) increases wages and/or occupational prestige (for a review, see Granovetter 1995; Lin 1999).

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Despite the theoretical appeal of the role of job contacts in the labor market, there is conflicting evidence on whether job contacts actually affect labor market outcomes. On one hand, several recent studies using data from individual firms on the hiring process have found that applicants who were referrals from current employees had higher rates of receiving job offers than other applicants (Fernandez, Castilla, and Moore 2000; Fernandez and Weinberg 1997; Petersen, Saporta, and Seidel 2000). On the other hand, however, the purported benefits of using contacts fail to show up in surveys of workers: There is little evidence that using contacts to find work results in higher wages or increased occupational prestige (Bridges and Villemez 1986; Corcoran, Datcher, and Duncan 1980; Korenman and Turner 1996; Staiger 1990). This is not a trivial issue. If using contacts seems to have little overall impact on labor market outcomes, then perhaps economic models of the labor market can safely ignore "embeddedness"—the connections and ties among individuals—without sacrificing explanatory power.

Nonetheless, despite the null results in studies that look at the blanket effect of *using* job contacts, studies that use social network data seem to indicate that "who you know" is important for labor market success (for a review, see Lin 1999). These "social capital" models of the labor market are based on the notion that the benefit of using contacts to find work depends on how well connected the contact network is; it is not the use of contacts per se but the quality and quantity of the social resources that are accessed through using contacts that matters. The empirical literature seems to confirm this intuition, as numerous authors have found that the status of the contact person or the overall quality of the worker's social networks seems to increase the occupational prestige and/or wages of their current job (Lin 1999).

Research on social capital in the labor market seems to indicate that the social embeddedness of the labor market is important. Here, however, I reassess the empirical evidence on the role of job contacts and social capital. In particular, I argue that the nonrandom acquisition of friendship ties means that we must be careful about inferring causality from the results of studies of labor market social capital. Substantial evidence indicates that individuals tend to choose as friends people who are similar to them (McPherson, Smith-Lovin, and Cook 2001). If successful people prefer to socialize with other successful people, then this preference would result in a correlation between friends' income and occupational status, even in the absence of a causal effect of social capital on labor market outcomes. Hence, research that links individual outcomes to the average characteristics of friends may overstate the true effect of social capital on job outcomes.

I attempt to determine whether the positive correlation between social capital variables and labor market outcomes is causal or, instead, represents a spurious effect attributable to nonrandom friendship data. I argue that, all else equal, workers who have better-connected social networks should be more likely to use contacts to find work. As a result, a test of whether particular social capital variables have a causal effect on job opportunities has to do with whether these variables increase the probability of using contacts to find work.

LITERATURE REVIEW

Informal contacts with friends or relatives can affect the matching of workers to jobs by providing information and/or influence (Granovetter 1974; Lin 1999; Marsden and Hurlbert 1988). Information supplied via contacts to workers or employers can increase the number of job openings a worker hears about as well as provide information that is otherwise difficult to obtain (such as an accurate description of working conditions at a firm). This may increase the number of job offers a worker receives or improve the fit between the worker and the job. In addition to offering information, the contact person may also directly influence the job-matching process by providing entree into desirable occupations (Lin 1999). In this review of the literature, I use several recent review articles (Bartus 2001; Granovetter 1995; Lin 1999; Marsden and Gorman 2001) to divide the research into three main categories: the direct effect of using contacts, single-firm studies, and social capital models.

STUDIES OF INDIVIDUAL WORKERS

Many studies have investigated the direct relationship between the use of contacts and labor market outcomes. There is no evidence that using contacts affects occupational prestige (Bartus 2001:15; De Graaf and Flap 1988; Lin 1999:481; Lin, Ensel, and Vaugh 1981; Volker and Flap 1999). As for wages, the majority of the studies reviewed by Granovetter (1995), Marsden and Gorman (2001), and Bartus (2001) find no effect of using contacts on wages (Bridges and Villemez 1986; Campbell and Rosenfeld 1985; Corcoran, Datcher, and Duncan 1980; De Graf and Flap 1988; Elliot 1999; Marsden and Hurlbert 1988; Ornstein 1976; Volker and Flap 1999).

Of all the empirical studies reviewed by Granovetter (1995) or Marsden and Gorman (2001), only Korenman and Turner (1996), Green, Tigges, and Browne (1995), Simon and Warner (1992), and Rosenbaum et al. (1999) find evidence of positive effects of contacts on wages. Further inspection reveals that in each of these studies the evidence is suspect. For example, although Korenman and Turner (1996) find a positive effect among whites with a small sample of inner city Boston youth (N = 264), they find no effect of contacts on wages in a larger sample from the 1982 National Longitudinal Study of Youth. Green et al. (1995) find evidence of a positive effect, but the result is not statistically significant at the $p < .05$ level. Simon and Warner (1992) find that scientists and engineers who were told of a position by an acquaintance in the organization had higher salaries than those who answered a want ad or who went through a public agency, but not more than those who were recruited by a personnel officer or who found out about the job via college placement, a private agency, or a professional meeting. Finally, Rosenbaum et al. (1999) find that while contacts have no effect on earnings right out of high school, contacts with relatives seem to lead to higher wages down the road (about 7 percent higher after nine years).

In sum, there is little consistent evidence that using contacts affects wages or occupational prestige. In his review of the literature, Lin (1999) argues, "it is clear by now that the use of informal channels by itself offers no advantage over other channels, especially formal channels . . ." (p. 481), a conclusion echoed by Granovetter (1995:147), Marsden and Gorman (2001:36), Bartus (2000:15–16), and Davern (1999:844).

SINGLE-FIRM STUDIES

In recent papers using data on the employer side of the labor market, Fernandez and Weinberg (1997), Fernandez et al. (2000), and Petersen et al. (2000) study, respectively, the hiring process for a bank, a phone center, and a high-technology firm. All three papers find that applicants who were referrals from current employees had a higher probability of being hired than did nonreferrals. Fernandez and Weinberg (1997), for example, analyze the hiring process for 326 jobs at a single retail bank and find that while nonreferred applicants had only a 6-percent chance of getting a job, applicants who were employee referrals had a 32-percent chance.[1] Although these studies present data just from single firms, their results suggest that having a contact inside the firm is an important advantage in the hiring process.

Nonetheless, if personal referrals are as important in the rest of the labor market as they were in these three single-firm studies, then the implications for the supply side of the labor market are clear: Individuals with good contacts should get more job offers per application than otherwise identical individuals without contacts. This should either result in higher wages, because well-connected workers can choose the best offer from a larger number of choices, or in shorter periods of unemployment between jobs, because they receive offers more quickly. Consequently, I argue that Fernandez and Weinberg's (1997) results make the inconclusive results in the empirical literature on the supply side of the labor market even more puzzling. One explanation is that all workers are equally well connected. In this case, employee referrals might increase hiring probabilities, but no overall effect would be observed across individuals. Contacts would be important, but would not affect the overall distribution of good jobs and income inequality.

A SEQUENTIAL SEARCH MODEL

One way to reconcile the divergent findings between the firm studies and worker studies of contacts is to consider Montgomery's (1992) multiple-method sequential search model. Montgomery shows that comparing the wages of accepted job offers is a misleading way to determine the effectiveness of job search methods if workers use multiple methods of job search.[2] Imagine, for example, that workers use two search methods, formal search (answering advertisements, sending out resumes, and looking for help-wanted signs) and informal search (job

[1] Author's calculation from Fernandez and Weinberg's (1997) results.

[2] Although his argument is directed at research on the effect of strong ties versus weak ties, Montgomery's (1992) logic holds if we want to consider the effect of using contacts versus not using contacts to find work.

contacts through friends and relatives). In addition, assume that workers have a "reservation wage," which is the lowest wage that they would find acceptable in a new job. Any wage that is higher than the reservation wage is accepted. In general, increasing the probability of receiving job offers or increasing the wages of the offers will increase the reservation wage (Devine and Kiefer 1991; also see Appendix A). A worker who is "well-connected" may indeed receive better job offers through contacts than through a formal search (or, as suggested by the single-firm studies, he or she may have a higher probability of being hired). As a result, however, a well-connected worker will have a higher reservation wage (reflecting his or her expectation of good opportunities through an informal search) and hence will be more selective about which offers to accept than would an equally skilled but less well-connected worker. The consequence of having a high reservation wage is that the wages of accepted offers from both formal and informal methods of search will be high. Therefore, the difference between accepted job offers would not indicate the true difference between the overall quality of job offers from contacts and formal search. The basic conclusion of Montgomery's model is that in order to assess the effect of having good connections on labor market outcomes we cannot look at the direct relationship between using contacts and wages but must look at the relationship between the structure and composition of social networks and labor market outcomes. This points to social capital models.

The Social Capital Perspective

According to the social capital perspective, job contacts affect labor market outcomes, but the effect depends on the resources that can be accessed through those contacts. For example, Burt's (1992, 2000) theory of "structural holes" hypothesizes that low-density networks (i.e., networks where few of the members are mutual friends) result in better sources of valuable information. The result is simple: Better-connected people do better (Burt 2000:3).

Lin (1999) defines social capital as "resources that are accessible through one's direct and indirect ties" (p. 468) and stresses the role of information and influence. By reaching up the status hierarchy one obtains help from well-placed contacts "who are better able to exert influence on positions whose actions may benefit ego's interest" (Lin 1999:470). Workers who have successful friends benefit because of the information and influence that their friends can provide for them.

The focus of the social capital perspective is on the characteristics of the job searcher's social networks. As reviewed in Lin (1999), numerous studies confirm that among those who use contacts to find work, the status of the job contact person seems to affect the respondent's occupational status (Bian 1997; De Graaf and Flap 1988; Ensel 1979; Lin et al. 1981; Marsden and Hurlbert 1988; Volker and Flap 1999; Wegener 1991). In addition, with social network data on the demographic and human capital characteristics of respondent's friends, it is possible to test for the relationship between network social capital and labor market outcomes. As reviewed by Lin (1999), there has been consistent evidence that social network resources are positively correlated with labor market outcomes such as job prestige, income, and wages (Boxman, De Graaf, and Flap 1991; Burt 1992; Campbell, Marsden, and Hurlbert 1986; Flap and Boxman 2001; Green et al. 1999; Lai, Lin, and Leung 1998; Lin and Dumin 1986; Volker and Flap 1999). Finally, in a study of the effect of social capital on unemployment, Korpi (2001) finds that the number of social ties contacted about jobs has the same effect as the number of employers contacted directly on the length of the respondent's period of unemployment.

SOCIAL HOMOPHILY AND CAUSALITY

Overall, the results of social capital models suggest that individuals with well-connected social networks do better in the labor market. However, does this result reflect causality or merely the fact that similar people tend to associate with each other? The cliche about like attracting like—"birds of a feather flock together"—suggests that friendship does not occur at random. Evidence on social homophily—the tendency for similar people to become friends—is reviewed in McPherson et al. (2001). These authors cite many studies that document the degree of homophily on the basis of social demographic characteristics, such as race, gender, social class, and religion, as well as behaviors and values. The consequence of this evidence is simple: Our friends are a selective sample of the population because friendship is based on social processes that defy random assignment. This fact could result in a positive correlation between one's wages and the wages of one's friends, even if they provide no help or assistance in the labor market.

The problem of bias arising from correlated unobserved variables is a familiar one in the literature on neighborhood and peer effects (for a general treatment of this issue, see Manski 1995; Moffit 2001:22). Because measures of ability on surveys are crude, it is reasonable to expect that a significant component of each individual's ability and talents will go unrecorded. If this "unobserved ability" is correlated with observed levels of human and social capital, it will bias estimates of the effect of both human and social capital on wages. Concern over such sources of bias on estimates of the effect of education on earnings has resulted in a large literature in economics that uses creative quasi-experimental data in an attempt to isolate the "true" effect of education on wages and income (see the extensive review in Card 1999). Without some inferences about the process of friendship formation and the degree of selectivity in social networks—or some instrumental variable that is correlated with social capital but not with unobserved ability—it is difficult to estimate the true effect of social capital on labor market outcomes.

The problem posed by homophily in distinguishing between the selection of friends and the influence of friends has long been recognized in the literature on peer effects (Arcidiacono and Nicholson 2001; Bauman and Fisher 1986; Coggans and McKellar 1994; Cohen 1977; Ennett and Bauman 1994; Hanushek et al. 2001; Kandel 1978, 1996; Rowe, Woulbraun, and Gulley 1994; Sacerdote 2001; Zimmerman 2003). In a recent critique, Durlauf (2002) argues that much of the recent empirical research on social capital fails to adequately consider the possibility of bias due to endogeneity problems. Kandel (1978) uses longitudinal data on adolescent social networks and finds that a substantial proportion of the similarity between friends in behavior and attitudes is attributable to similar individuals becoming friends rather than friends becoming more alike. In a different approach to avoid the potential bias of homophily, Sacerdote (2001) and Zimmerman (2003) use random assignment of college freshmen's roommates to estimate peer effects on achievement. They find that freshman grade-point average is related to the achievement levels of randomly assigned roommates. The quasi-experimental nature of this data makes it possible to argue that the problem of selection bias on the estimated peer effects has been mitigated.

A Test of Causality: The Use of Contacts to Find Work

In the absence of quasi-experimental data (e.g., randomly assigned roommates), the problem of selection bias due to social homophily should make us cautious about interpreting the results of social capital models. In this section I develop an indirect test of the causal effect of social capital on labor market outcomes. This test is based on whether individuals with purportedly high levels of network social capital are more likely to use contacts to find work. By "network social capital" I mean social capital that exists in the connections and ties to other people. In the context of the labor market, network social capital refers to the information and influence that job contacts can provide. Because it is a characteristic of social ties with other people, job-seekers access their network social capital by asking friends and relatives for help or information in finding work. In contrast, other forms of social capital, such as manners, culture, language, group membership, and so on, may affect outcomes regardless of whether or not a worker uses social networks to search for work. The following test assesses only whether network social capital—help and information from job contacts—has a causal effect on labor market outcomes.

The basic logic of this test of causality is straightforward: If having good contacts really is beneficial, then well-connected individuals should be more likely to obtain their job through contacts than otherwise identical individuals who are not well-connected.[3] If, on the other hand, frequently used measures of network social capital such as the education and occupational prestige of network members reflect homophily rather than a causal effect of social capital, then "better-connected" individuals will not have better opportunities through job contacts vis-à-vis other workers, and as a result we would not expect them to be more likely to obtain work via contacts. The proposed test of causality is:

Proposition 1: A necessary but not sufficient condition for network social capital to have a causal effect on wages is that the social capital variable (a) has a positive effect on wages and (b) has a positive effect on the probability of obtaining work through contacts.

This proposition has been suggested in general terms before. Lin (2001b), who has perhaps the most fully developed theory of labor market social capital, contends that actually utilizing one's contacts is critical for reaping the benefits of network resources, defining social capital as "resources embedded in a social structure that are accessed and/or mobilized in purposive action" (p. 29). In attempting to establish the causal role of social capital, Lin stresses the importance of individual action, arguing that "the general expectation is that the better the accessible embedded resources, the more embedded resources can and will be mobilized in purposive actions by an individual" (Lin 2001a:21). Similarly, Lai et al. (1998:162) argue that well-connected individuals are more likely to use a resource-rich tie to find a job.

SEQUENTIAL AND EXTENSIVE SEARCH MODELS

Although the logic behind Proposition 1—that better-connected individuals should be more likely to use contacts to find work, all else equal—has intuitive appeal, it is useful to formalize the relationship between network social capital and the use of contacts. Both the sequential and extensive search models described below depict logical models of the process of looking for work. I view these as models that can guide our intuition about the role of social capital in the job search process rather than as models reflecting exact blueprints for the behavior of job seekers.

The *sequential search model* assumes that workers receive job offers one at a time and must decide to accept or reject one job offer before receiving another. Based upon the arrival rate of job offers, the distribution of wage offers, and the degree to which workers discount future earnings, it is possible to calculate a "reservation wage," which indicates the minimally acceptable wage offer. If the wage offer is greater than or equal to the reservation wage, then the worker maximizes income by accepting. If the wage is less than the reservation wage, then the worker is better off rejecting the job offer and continuing to search. For a book-length treatment of the sequential search model and a review of the literature, see Devine and Kiefer (1991).

The *extensive search model* assumes that workers apply to jobs and then wait for the job offers to come in. When all the job offers have been received, the worker selects the offer with the highest wage. For a discussion of the sequential search model, see Stigler (1961).

In both the extensive and sequential search models, I assume that individuals use two methods of job search: formal search (i.e., sending out resumes, contacting employers directly) and informal search (asking friends and relatives for job information). In addition, in both the sequential and extensive

[3] There is a distinction between the methods used to search for work and the specific method that results in securing the job. Most workers use multiple methods to search for work. In the Multi-City Study of Urban Inequality data used here (see Appendix C), 40 percent of respondents obtained their last job through contacts with a friend or relative, 75 percent used contacts to search for work, and 90 percent of those who used contacts to search for work also used at least one other method to look for work. In the remainder of the paper, "using contacts" indicates that the job was obtained via contacts.

search models, two factors are central: the probability of receiving an offer, and the wage distribution of job offers. Let the probability of receiving an offer through formal methods be represented by P_F and the probability of receiving an offer through informal methods be represented by P_C. For sequential search, P_F and P_C represent the probability of receiving an offer by formal and informal means during each time period of a job search, while for extensive search they represent the probability that each job application sent out or each friend contacted, respectively, will result in a job offer. Similarly, let μ_F represent the mean of the wage offer distribution for formal search, and μ_C represent the mean of the average wage offer distribution for informal search.

The search models allow us to formalize the relationship between social capital and job-search behavior. It is important to differentiate between three different factors: observed human capital, network social capital, and "spurious" social capital. For the purpose of these models, observed human capital represents individual characteristics and skills that improve productivity and hence attractiveness to employers. As a result, human capital increases the probability of receiving offers and increases the wages of those offers for both formal and informal searches. In contrast, network social capital is assumed to represent the effectiveness of a worker's social networks at providing job information and/or influence. Consequently, network social capital affects the wages and the probability of receiving an offer via informal search but not via formal search. Spurious social capital, in contrast, represents a measure of some aspect of individuals' social networks that is correlated with an unobserved component of human capital but doesn't have an independent causal effect on the effectiveness of social networks in finding work. As discussed in the previous section, spurious social capital effects may arise from the nonrandom acquisition of social ties and the presence of unobserved ability in survey data.

To depict the role of human capital, network social capital, and spurious social capital in the sequential and extensive search models, I represent P_C, P_F, μ_C, and μ_F as a function of these variables:

$$P_F = aP_{HC} + bP_{SC}^{Spurious} + \eta_1 \quad (1)$$

$$P_C = aP_{HC} + bP_{SC}^{Spurious} + cP_{SC} + \eta_2 \quad (2)$$

$$\mu_F = d\mu_{HC} + e_{SC}^{Spurious} + \eta_3 \quad (3)$$

$$\mu_C = d\mu_{HC} + e\mu_{SC}^{Spurious} + f\mu_C + \eta_4 \quad (4)$$

where a through f are coefficients, η_1 through η_4 are constants, and P_{HC}, $P_{SC}^{Spurious}$, P_{SC}, μ_{HC}, $\mu_{SC}^{Spurious}$, and μ_{SC} depict the effects of human capital, spurious social capital, and social capital on the probability of receiving a job offer and on the average wage of job offers, respectively. Thus, based on these equations, network social capital affects only P_C and μ_C, while human capital and spurious social capital affect P_C, P_F, μ_C, and μ_F.

Based upon these basic parameters, Proposition 1 can be restated with respect to the sequential and extensive models of job search. Proposition 1a states the first part of Proposition 1 in terms of the parameters of the search model:

Proposition 1a: Increasing P_{SC}, μ_{SC}, $P_{SC}^{Spurious}$, *or* $\mu_{SC}^{Spurious}$ increases expected wages.

Proposition 1a states that increasing network social capital or spurious social capital—as represented by Equations 1 through 4 above—increases expected wages. The logic behind this is simple. First, increasing the probability of receiving offers—for either the sequential or extensive search model—means that the job-seeker will receive more job offers and consequently can be more selective in choosing the job offer that will be accepted. This results in a higher reservation wage for the sequential search model and (on average) more offers to choose from for the extensive search model. Second, increasing the mean wage of wage offers for all jobs (i.e., $\mu_{SC}^{Spurious}$) or jobs found through contacts (μ_{SC}) results in higher expected wages because the job-seeker is choosing from a better selection of jobs. For a detailed proof of Proposition 1a see Appendix A for the sequential search model and Appendix B for the extensive search model.

Next, Proposition 1b rephrases the second part of Proposition 1—the relationship between social capital and the propensity to use contacts to find work—in the language of the search model.

Proposition 1b: Increasing P_{SC} or μ_{SC} increases the probability of using contacts to find work. In contrast, increasing $P_{SC}^{Spurious}$ or $\mu_{SC}^{Spurious}$ has an ambiguous (and generally small) effect on the probability of using contacts to obtain work.

For a proof of Proposition 1b with respect to the two heuristic search models used here again refer to Appendices A and B. In general, however, the logic behind Proposition 1b should be fairly intuitive. First, think about the effects of increasing network social capital. Increasing P_{SC} means that you are increasing the probability of receiving a job offer via informal methods while holding constant the probability of receiving an offer via formal methods (see Equations 1 and 2). This increases the proportion of job offers that arrive through informal means (i.e., contacts) and, consequently, increases the likelihood that the accepted job offer would be found via contacts. Likewise, increasing μ_{SC} increases the average wage of informal wage offers (see Equation 4), making jobs found through contacts relatively more attractive than jobs found through formal methods. As a result, this also increases the probability of using contacts to find work. In contrast, increasing $P_{SC}^{Spurious}$ increases the probability of receiving job offers for both informal and formal methods, and increasing $\mu_{SC}^{Spurious}$ increases the average wages of both formal and informal job offers. Intuitively, we might predict that increasing $P_{SC}^{Spurious}$ *or* $\mu_{SC}^{Spurious}$ would have little (if any) effect on the probability of using contacts because the effects of increasing the attractiveness of both formal and informal job offers would tend to cancel each other out. Appendices A and B show that the magnitude of the effect of increasing spurious social capital is indeed likely to be small compared with the effect of increasing P_{SC} or μ_{SC}, but may be positive or negative. Overall, Proposition 1b indicates that, under the assumptions of the sequential and extensive search models, if a proposed social capital variable has no effect, or a negative effect, on the probability of using contacts, then it is not exerting a causal effect on wages via the information and influence of contact networks.

As Appendices A and B show, both the extensive and sequential search models predict that the use of contacts is endogenous to the level of network social capital, despite different assumptions about how workers search for work. The sequential search model, which is popular in the economics literature, relies on assumptions such as the existence of "reservation wages" and information about wage distributions, which have been criticized by sociologists (Granovetter 1974). The extensive search model, although it is not as elegant as the sequential search model, makes fewer assumptions about how workers search for work, and Appendix B shows that it arrives at the same conclusions as the sequential search model with respect to Proposition 1: Better-connected workers should be more likely to use contacts to find work.

It is possible, however, to reject both the sequential and extensive search models and argue that the use of contacts to obtain work is exogenous to the level of social capital. Theoretically, the exogeneity of the use of contacts can be maintained if, for example, it is assumed that workers accept the first job offer they receive (or a randomly chosen job offer) and that the probability of receiving a job offer through informal means does not depend on social capital ($c = 0$ in Equation 2 above). In this case, social capital may affect wages ($f > 0$ in Equation 4), but "better-connected" workers would not be more likely to use contacts to find work. I refer to this model of job search as the "take the first offer" model. Assuming that the use of contacts is exogenous to the level of social capital allows one to reject the causal test of social capital stated in Proposition 1. However, as I discuss in the next section, there are empirical implications of assuming that the use of contacts does not depend on the level of network social capital, and these implications are also tested in the subsequent empirical analysis.

THEORIES AND EMPIRICAL TESTS

Here I present multiple tests of the effect of contacts and social capital on labor market outcomes. Figure 1 presents a flow chart of

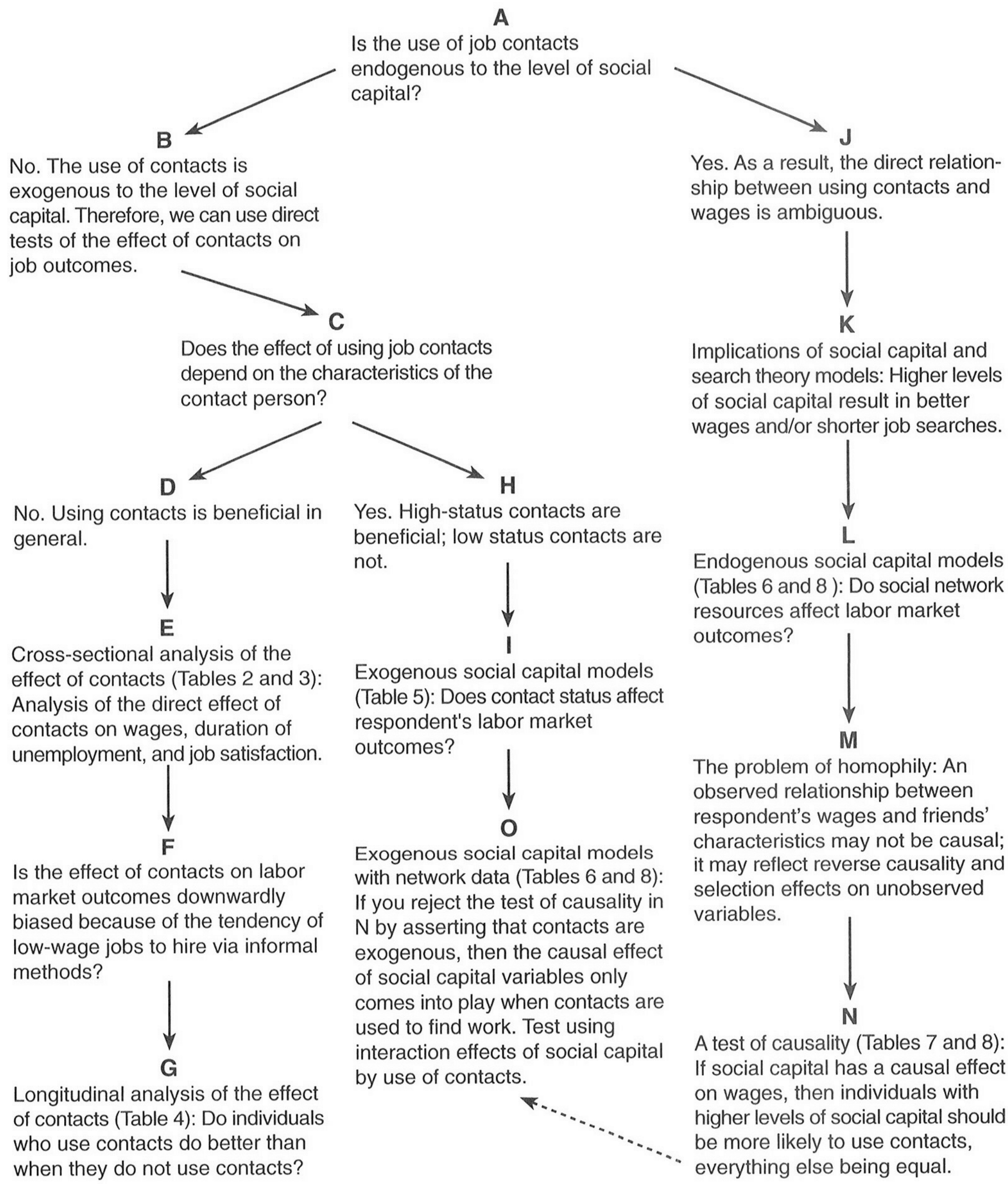

Figure 1. Flow Chart of Alternative Theories and Empirical Tests

the competing theories, the proposed tests, and the data used to test them. Letters (i.e., N) refer to discussion points in this flow chart. Appendix C provides detailed information on each of these data sets and on the selection of the samples used in this paper. The complete computer files and data used in the paper, as well as selected responses to questions raised by reviewers, are available on the author's web page (www.tedmouw.org).

A. As depicted in Figure 1, the central question affecting empirical research on the importance of job contacts is whether the basic intuition of the job-search models described above is accepted. If workers try to maximize wages or income by setting "reservation wages" (the sequential search model) or choosing the best offer among several offers (the extensive search model), then Proposition 1 shows that the probability of obtaining work via contacts will depend on the worker's level of labor market social capital. As a result, the use of contacts is endogenous to the level of social capital (see the discussion of J through N below for implications).

B. On the other hand, it is possible to reject the assumptions of the sequential and extensive search models and their theoretical implications. Empirical research that estimates the direct "effect" of contacts on wages implicitly assumes that the use of contacts is an exogenous variable unaffected by the level of social capital (i.e., poorly connected workers are just as likely to use contacts as are well-connected workers; see the "take the first offer" model above). Rejecting the job-search models described above also allows one to reject the test of causality described in Proposition 1 (point N). However, I argue here that there are equally significant empirical consequences of assuming that the use of contacts is an exogenous variable.

C. The literature on the direct effect of contacts splits over the question of whether the effect of using contacts depends on the characteristics of the contact person. Is using contacts always beneficial, or does it depend on who is contacted? Lin (1999, 2001a) has argued that high-status contacts are more likely to be able to provide influence in obtaining good jobs; hence the benefit of the contact is contingent upon the social status of the contact person (see H below).

D. Alternatively, one might argue that the primary benefit of contacts is information about job openings rather than influence, and that information will be useful regardless of the social characteristics of the person who provided it. As a result, one might stress the general benefit of using contacts versus other methods to find work.

DIRECT EFFECTS MODELS

E. Using data from the National Longitudinal Study of Youth (NLSY), Tables 1 through 3 test the direct effect of contacts on labor market outcomes. As indicated by the literature review, previous research has found little evidence of a direct effect of contacts on wages and job prestige (Bartus 2001; Granovetter 1995; Lin 1999; Marsden and Gorman 2001). While replicating the

Table 1. Summary Statistics: National Longitudinal Study of Youth, 1982 Sample

Variable	Mean	Standard Deviation
Contact	.539	—
Hourly Wage (log)		
1982	1.553	.486
1985	1.769	.495
1990	2.144	.676
Weak tie (friend or acquaintance)	.327	—
Strong tie (relative)	.212	—
Working when offered job	.350	—
Looking for work when offered job	.776	—
Sex (female)	.449	—
Race		
Hispanic	.169	—
Black	.212	—
Education in 1982	11.982	1.930
Union Job		
1982	.200	—
1985	.193	—
1990	.208	—
Total Labor Market Experience (in Weeks)		
1982	131.4	58.8
1985	257.2	81.0
1990	479.0	112.5
Job Tenure (in Weeks)		
1982	72.3	67.8
1985	126.1	115.3
1990	207.6	199.7
Use of Contacts		
Was there anyone specifically who helped you get your job with (employer name)?		
Yes = 53.8%		
No = 46.2%		
Importance of Contact [a]		
How important was the help that this person gave you?		
Very important		N = 1,261
Somewhat important		N = 490
Not very important		N = 69

Note: Individuals not enrolled in school in 1982 and with labor market information for 1982, 1985, and 1990. Number of cases = 3,383.

[a] Importance for those who used a contact.

Table 2. Coefficients from Models Testing the Direct Effect of Contacts on Wages and Job Satisfaction: National Longitudinal Study of Youth, 1982, 1985, 1990, and 1994

	1982		Wages (log)					
	Wages (log)	Job Satisfaction	1985	1990	1982	1982	1982	1994
Independent Variable	Model 1	Model 2[a]	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8[b]
Used contact in 1982	–.009 (.015)	–.001 (.039)	–.007 (.015)	–.014 (.023)	—	–.009 (.017)	—	—
Used contact in 1994	—	—	—	—	—	—	—	–.041 (.049)
Contact × union	—	—	—	—	—	.0004 (.038)	—	—
Weak contact	—	—	—	—	–.013 (.017)	—	—	—
Strong contact	—	—	—	—	–.004 (.021)	—	—	—
Importance of Contact								
Very important	—	—	—	—	—	—	–.011 (.017)	—
Somewhat important	—	—	—	—	—	—	–.004 (.023)	—
Not very important	—	—	—	—	—	—	–.049 (.055)	—
Number of cases	3,383	3,383	3,383	3,383	3,383	3,383	3,383	1,108
R^2	.233	–3,649[a]	.279	.142	.233	.233	.233	.209

Notes: Numbers in parentheses are standard errors. No coefficients were significant at the $p < .05$ level (two-tailed tests). All models also include education, race, gender, experience, experience squared, job tenure, union job, working when offered job, and looking for work when offered job. A model of "job duration" was also tested using a probit model of whether the job lasted at least one year. Results indicate no effect of using contacts on job duration.

[a] Job satisfaction analysis is an ordered probit; the log-likelihood equals –3,649.

[b] The sample uses only professional, managerial, and technical (PMT) workers employed in the 1994 NLSY survey. Seventeen percent of the employed sample of 6,687 respondents were in these occupations.

findings on wages, I also assess the direct effect of using contacts on future wages, unemployment duration, job satisfaction, and job tenure.

Table 1 presents the basic summary statistics for the 1982 NLSY data. About 54 percent of respondents used a contact to obtain their job. In addition, the survey asked them how important the help from the contact person was in obtaining the job, and 69 percent claimed that the contact was "very important" in obtaining the job.

Table 2 presents results for a number of models of the direct effect of contacts on labor market outcomes. All models also include controls for education, race, gender, experience, job tenure, union jobs, whether the respondent was employed when searching, and whether the respondent was looking for work. The results in Table 2 are easy to summarize: There is no evidence that using contacts affects labor market outcomes. Using a contact in 1982 has no effect on 1982 wages (Model 1) or on job satisfaction (Model 2). Granovetter (1995:153) argues that using contacts may result in a "snowball" process of advantage where contacts in one job lead to better contacts in another job, but Models 3 and 4 show that there is no relationship between using contacts early in one's career (1982) and subsequent wages in 1985 or 1990. Model 5 shows that the type of contact—weak or strong—does not matter, and Model 6 shows that contacts that

Table 3. Coefficients from Weibull Models of log Unemployment Duration: National Longitudinal Study of Youth, 1994 to 1998

Independent Variable	Model 1 All Unemployed	Model 2 Unemployed because of Plant Closing or Layoff: Coefficient (S.E.)	Model 2 Unemployed because of Plant Closing or Layoff: Mean (S.D.)[a]
Used contact	.245** (.057)	.208* (.098)	.197
Proportion in 3-digit occupation using contacts	.002 (.001)	–.003 (.002)	.221 (.091)
Missing proportion in 3-digit occupation using contacts	.269** (.044)	.200** (.079)	.104
Female	–.102** (.043)	.060 (.077)	.387
Race			
Black	.213** (.091)	.155 (.160)	.181
White	–.154* (.082)	–.059 (.141)	.740
Education	–.028** (.010)	–.047** (.018)	12.7 (2.05)
Constant	3.004** (.146)	3.564** (.262)	—
$1/\ln(p)$	–.168** (.013)	–.024 (.028)	—
Number of observations	3,162	733	733

Note: Unless otherwise noted, numbers in parentheses are standard errors.

[a] Standard deviations are not reported for dummy variables. Mean unemployment duration equals 21.5 weeks (S.D. = 24.2).

$^{*}p < .05$ $^{**}p < .01$ (two-tailed tests)

provide entree into unionized jobs do not provide a wage advantage (the interaction term between using contacts and a union job is not significant). Model 7 shows that if we test for an effect of contacts based on the respondent's own evaluation of the importance of the contact, even contacts deemed "very important" are not associated with higher wages. Finally, Model 8 shows that if we restrict our attention to professional, managerial, and technical workers, there is still no effect of contacts on wages.

Table 3 presents models of unemployment duration from 1994–1998 NLSY data. As discussed above, demand-side studies of the hiring process in single firms find that applicants who had a contact at the firm had a higher probability of being hired. If this result generalizes beyond the individual firms used in those studies, then we might expect that workers who used contacts to find work had a shorter period of unemployment than did other workers. Table 3 tests the effect of using contacts on unemployment duration using two samples. First, Model 1 considers all workers in the survey who were unemployed sometime between 1994 and 1998. However, it is possible that the workers with the best contacts are less likely to experience unemployment because they can use their contacts to find new jobs while still employed at their previous job. To attempt to mitigate this potential problem, Model 2 restricts the sample to workers who were unemployed because of a plant closing or layoff. If plant closings and layoffs can be considered an exogenous factor pushing workers into unemployment, then the sample of unemployed workers will include workers with both good and bad contact networks. Table 3 shows the means and standard deviations of the variables for the plant closings/layoff sample. Both Models 1 and 2 of Table 3 indicate that the effect of using contacts on log unemployment duration is positive. If anything, then, workers who used contacts to find work had longer rather than shorter periods of unemployment duration than workers who did not use contacts.

The results in Tables 2 and 3 suggest that using contacts does not help a job-seeker find work more quickly or help obtain jobs that pay better. This is puzzling if you believe the results of the demand-side literature, which argues that workers with inside contacts have higher rates of getting hired. If contacts really are important, why don't the results show up when we look at the effect of using contacts on worker's labor market outcomes?

F. One explanation for the null results in Table 2 is that estimates of the effect of contacts on wages are biased because of the tendency of low-wage jobs to be filled by informal methods. Researchers have found that low-wage jobs (Holzer 1987) and nonprofessional jobs (Marsden 2001) are more likely to be filled via employee referrals, and that blue-collar workers are more likely than white collar workers to use contact (Corcoran et al 1980; Marsden 2001). If this is true and there is some aspect of blue-collar or low-wage jobs that is not adequately controlled for by observed human capital variables, then it is possible that the true effect of using job contacts is biased downward.

G. One way to try to get around this problem of bias due to unobserved characteristics would be to estimate longitudinal models of multiple job searches for the same individual. If the use of contacts is exogenous (i.e., see B), then we can observe the true effect of contacts by comparing how a worker does when he uses contacts with how he does when he does not use contacts. As mentioned above, a significant advantage of using the NLSY data is that questions about the use of contacts to find work were asked for all jobs found in the 1994, 1996, and 1998 waves of the survey. This allows us to estimate a longitudinal analysis of the effect of contacts on wages.

Using the NLSY panel data on multiple job searches for the same worker from 1994 to 1998, Table 4 estimates fixed-effects models that difference out the constant effect of each worker's unobserved characteristics.[4] Table 4 shows the means and standard deviations for the independent variables used in the analysis (standard deviations are not shown for dichotomous variables).[5] In addition to the usual demographic and human capital variables, the analysis includes measures indicating whether the worker was unemployed and/or actively searching for work when he or she obtained the new job. Because the fixed-effects models estimate longitudinal models of multiple job searches for the same person, Models 3 and 4 only use workers who changed jobs at least once between 1994 and 1998. Models 3 and 4 indicate no significant effect of using contacts.[6] Nonetheless, there is an appreciable increase in the size of the coefficient in Model 4 (.024) when compared with the negative coefficient for contacts in the cross-sectional estimate in Model 2 (–.026).

The models in Table 4 indicate that workers who found their jobs while currently employed and not actively searching for work ("employed nonsearch") had higher wages than other workers. Granovetter (1974) argues that workers who find jobs without an active search are likely to have found them through incidental social interaction with friends and acquaintances. If this is true, then the results in Model 4 of Table 4 suggest one way that contacts may be important. However, an alternative explanation is that employed workers who are not actively searching for work are satisfied with their current job and simply set a high

[4] See Mouw (2002) for a depiction of the use of fixed-effects models to analyze the effect of contacts on wages.

[5] Models 1 and 2 of Table 4 show cross-sectional models for the 1994 NLSY data. Model 1 uses all workers who have wage data for 1994. Model 2 uses all workers with wage data in 1994 who subsequently changed jobs between 1994 and 1996. The fact that the coefficients in Models 1 and 2 are similar suggests that there is nothing unusual about the workers who switched jobs during this period.

[6] If you believe Montgomery's (1992) multiple method search model (see J), then the null result here is not surprising, as one of the things we are "differencing out" as a fixed effect is heterogeneity in the reservation wage across workers.

Table 4. Coefficients from Fixed-Effects Models of log Wages: Individuals Who Changed Jobs between 1994 and 1998, NLSY

	Cross-Section, 1994		Fixed-Effects Models		
Independent Variable	Model 1[a] All Cases	Model 2 Job-Changers	Model 3	Model 4	Mean (S.D.)[b]
Race					
Hispanic	.025 (.024)	.043 (.036)	—	—	.065
Black	−.097** (.018)	−.097** (.026)	—	—	.150
Sex (female)	−.211** (.012)	−.225** (.018)	—	—	.481
Years of education	.080** (.002)	.074** (.004)	—	—	13.18 (2.43)
Used contact	−.031 (.017)	−.026 (.025)	.016 (.015)	.024 (.016)	.139
Search[c]					
Unemployed search	−.099** (.014)	−.108** (.021)	—	−.075** (.013)	.399
Employed non-search	.026 (.018)	.076** (.028)	—	.042* (.017)	.182
Unemployed non-search	−.062** (.021)	−.088** (.033)	—	−.032 (.022)	.086
Tenure	.058** (.004)	.046** (.007)	—	.031** (.006)	1.85 (2.68)
$(\text{Tenure})^2$	−.003** (.000)	−.002** (.001)	—	−.001** (.000)	10.63 (33.49)
Experience	.003 (.009)	−.018 (.013)	—	.039 (.035)	12.54 (3.84)
$(\text{Experience})^2$	.001** (.000)	.002** (.001)	—	.000 (.001)	172.0 (87.4)
Year					
1996	—	—	.093** (.010)	.101** (.015)	.307
1998	—	—	.171** (.011)	.178** (.015)	.275
Constant	1.060** (.061)	1.225** (.086)	2.190** (.007)	1.729** (.248)	—
Number of observations	6,693	3,064	7,409	7,409	7,409
Number of cases	—	—	3,281	3,281	—
R-squared	.31	.30	.06	.09	—

Note: Unless otherwise noted, numbers in parentheses are standard errors.

[a] Model 1 includes all cases in the 1994 survey who have wage data. Models 2 through 4 use only those workers who changed jobs between 1994 and 1998 (see text).

[b] Mean of log hourly wage equals 2.32 (S.D. = .581). Standard deviations are not shown for dichotomous variables.

[c] Excluded category is "employed search."

$^{*}p < .05$ $^{**}p < .01$ (two-tailed tests) reservation wage for competing job offers. The real question, in my opinion, is whether better-connected workers are more likely to obtain job offers through nonsearch, thereby leading to higher wages. In future research, this question could be assessed using the social capital models tested below combined with information on whether a job was found without an active search (none of the current data sets have information on both nonsearch and social networks).

H. The results from Table 4 indicate that when we use fixed-effects models to difference out fixed unobserved individual characteristics there is little evidence that using contacts increases wages, apart from the evidence on "nonsearch." Nevertheless, it is possible to argue that it is not the use of contacts per se that is beneficial, but the use of "high-status" contacts in particular that provides entree into desirable jobs.

Exogenous Social Capital Models

I. Does the status of the contact person affect the respondent's status? As noted above, the exogenous social capital models find positive results: The occupational prestige of the contact person is positively associated with the occupational prestige of the respondent. This is interpreted as evidence that having a well-placed and influential contact helps a job-seeker gain entree to desirable positions (Lin 1999).

Nonetheless, it is possible that these findings are misleading because in many cases, the contact person is in the same job as the respondent. If a significant percentage of job contacts are in the same job, a positive correlation will occur between occupational statuses even if there is no causal effect of the contact person's position on the type of job the respondent winds up in. I propose to replicate the exogenous social capital models omitting same-occupation social ties. Lin's (1999:470) social resources theory argues that reaching up in the social hierarchy for an influential contact should improve one's labor market outcomes, while contacts with lower social status individuals should have a negative effect. This should be true whether or not we include the cases with same-occupation ties.

I use the 1970 Detroit Area Study to test the hypothesis that contact's status increases respondent's status even when same-occupation ties are excluded. This study has information on the occupation of job contacts. These data allow me to replicate the findings of Marsden and Hurlbert (1988), who found a strong positive relationship between contact's prestige and respondent's prestige using these data. The 1970 Detroit Area Study was a study of the career histories of 638 male respondents between the ages of 16 and 60. My analysis focuses on only those respondents who used a contact to find work.[7] Like Marsden and Hurlbert (1988), I exclude from the analysis all persons entering the labor market for the first time, those moving out of periods of education, unemployment, or military service, and those whose prior employment state was not recorded because it occurred before 1945.[8] The first column of Table 5 shows the summary statistics for this data set. The dependent variable is the Hodge-Siegel-Rossi occupational prestige of the respondent's current job. The independent variables are coded to replicate the results of Marsden and Hurlbert (1988) and Lin et al. (1981:402).[9] In addition, the first column of Table 5 also includes a variable indicating whether the respondent is in the exact 3-digit occupation as his or her contact person. Twenty-eight percent of job contacts were in the same occupation as the respondent. The simple correlation between contact and respondent prestige scores drops from .498 (the coefficient on contact's prestige in Model 1) to .22 if I exclude the same-occupation cases (results not shown here), but this figure is still statistically significant. What happens when other explanatory variables are included?

Model 2 in Table 5 replicates the results of Marsden and Hurlbert (1988:1044, table

[7] The Detroit Area Study data distinguish between individuals who used a specific personal contact (332 cases) and a vague personal contact (i.e., the guys at work, the grapevine, etc.). I use only those who could name a specific contact.

[8] Including these respondents does not change the results (results available from the author).

[9] As in Marsden and Hurlbert (1988), missing values are recoded to the mean. Adding dummy variables for the missing variables makes no difference in the results.

Table 5. Coefficients from Exogenous Social Capital Models of Respondent's Occupational Prestige, Detroit Area Study, 1970

Independent Variable	Mean (S.D.)[a]	Model 1	Model 2	Model 3[b]	Model 4
Father's job prestige	37.05 (11.57)	—	.060 (.061)	.024 (.074)	—
Education	11.76 (2.72)	—	1.136** (.278)	1.364** (.346)	—
Prior job prestige	37.20 (13.26)	—	.266** (.060)	.300** (.074)	.556** (.059)
Tie strength (1 = strong, 0 = weak)	.94	—	3.135 (2.714)	3.405 (3.589)	—
Contact's job prestige	43.91 (12.57)	.498** (.059)	.254** (.063)	.035 (.077)	—
Contact connected to firm	.73	—	–.217 (1.504)	–.797 (1.849)	—
Difference in Prestige[c]					
Contact higher prestige	.648	—	—	—	–.297 (2.084)
Contact lower prestige	.192	—	—	—	–7.910** (2.367)
Constant	—	18.846** (2.676)	1.304 (4.350)	7.712 (5.934)	21.734** (3.187)
Contact is in same occupation as respondent	.28	—	—	Excluded[b]	—
Observations	219	219	219	154	219
R^2	—	.25	.41	.29	.33

Note: Unless otherwise noted, numbers in parentheses are standard errors.

[a] Standard deviations are not reported for dummy variables. Mean of respondent's occupational prestige is 40.7 (S.D. = 12.5).

[b] Excludes same-occupation ties.

[c] These are dummy variables indicating whether the contact person had higher or lower occupational prestige than the respondent's previous job; the excluded category is "equal prestige."

$^{*}p < .05$ $^{**}p < .01$ (two-tailed tests)

1, model 1), except for the fact that they attempt a correction for selectivity bias. This model also closely resembles the analysis of Lin et al. (1981:402, table 3) with different data. In this model, the coefficient indicates that increasing the occupational prestige of the contact by one point would result in a .254-point increase in the prestige of the respondent's new job. As in Marsden and Hurlbert, the coefficient for this variable is significant at the $p < .001$ level. In contrast, however, Model 3 estimates the same model excluding the 65 cases in which the respondent and contact were in the same 3-digit occupation. In this case, the coefficient on contact's prestige drops to .035 and is not statistically significant. I argue that this indicates that the evidence in favor of the social resources perspective is largely an artifact of the incidence of same-occupation information flows between contacts and job-seekers. Aside from same-occupation ties, there is no evidence that having contacts with high prestige is better than having contacts with low prestige in models that also control for the respondent's education and the prestige of his or her prior job.

An alternative way to test Lin's hypothesis is to compare the status of the contact person with the status of the respondent's previous job. Model 4 looks at the effect of relative status on the respondent's current prestige by grouping the cases into three categories depending on whether the contact had a higher prestige, a lower prestige, or the same prestige as the respondent's previous occupation. Model 4 shows that respondents who used a higher-status contact did not wind up in more prestigious jobs than respondents who used a same-occupation contact (coefficient = –.297, S.E. = 2.084).[10] The results in Models 3 and 4 indicate that Lin's hypothesis about the benefits of reaching up the status hierarchy for job contacts is not substantiated.

Finally, note that even if there were a positive effect of contact's status in Model 3, we would still have to consider whether the effect was causal or the result of selection effects due to social homophily (see M below). Nonetheless, I do not interpret these results as indicating that contacts are not important in job matching and mobility. Indeed, the finding in Table 5, that 28 percent of job contacts were in the same occupation as the respondent, suggests that same-occupation contacts, in contrast to contacts from higher-status occupations, may be an important source of job information. I consider this possibility in detail below with a data set that has information on the occupation of social network members.

Overall, the discussion of points B through I in Figure 1 suggests that if you reject the basic intuition of the job-search model and argue that contacts are an exogenous variable, then the results in Tables 2 through 5 yield little evidence that contacts affect labor market outcomes.

Endogenous Social Capital Models

In contrast to the direct effect and exogenous social capital models discussed in points B through I of Figure 1 and tested in Tables 2 through 5, points J through N depict endogenous social capital models. The basic theory behind endogenous social capital models is described above in the discussion of job search, social homophily, and Propositions 1a and b. Here I briefly review the discussion in light of Figure 1.

[10] If prior job prestige is excluded from Model 4, the coefficient for "contact higher prestige" is –7.20 (S.E. = 2.31, p = .002). If the other variables from Model 3 (except contact's prestige) are added to Model 4, the coefficient is –1.16 (S.E. = 1.99).

J. If the argument that the use of contacts to obtain work is endogenous to the level of social capital is accepted, then the direct relationship between using contacts and wage levels is misleading. Search theory models can be used to explain the relationship between social capital and labor market outcomes.

K. The logic of the search theory models supports the basic assertion of social capital models. As argued above, looking only at the relationship between using contacts and wages obscures the true benefit of job contacts if individuals attempt to maximize their earnings by rejecting "bad" job offers; instead we must look at the effect of the characteristics of social networks on labor market outcomes.

L. The predictions of both social capital theory and the sequential and extensive search models are that workers who have better-connected social networks will do better in the labor market. I test for the effect of network measures of social capital on wages using the Urban Poverty and Family Life Study (UPFLS) and the Multi-City Study of Urban Inequality (MCSUI) data sets. Both data sets have information on the demographic characteristics of up to three friends for each respondent. I use these data to calculate the average education of respondent's friends, the proportion of their friends who are unemployed (in the UPFLS data) or who have steady employment (in the MCSUI data), and the proportion who are on welfare. The UPFLS data are particularly interesting because the survey also collected information on the occupation of friends and relatives using a 20-category variable. I use this to calculate the proportion of friends and relatives who work in the same occupation group as the respondent. If same-occupation social ties are an important source of job information, then this may be a better measure of network social capital than the average education of network members. In addition, the UPFLS also asked whether the respondent used contacts to find work for up to six previous jobs. I use this to construct a variable of the proportion of previous jobs that were found using contacts. Finally, the proportion of jobs in the same 3-digit occupation that were found using contacts in the 1994 through 1998 NLSY data (see Appen-

Table 6. Coefficients from OLS Models Predicting log Wages: Urban Poverty and Family Life Study, 1987

Independent Variable	Model 1	Model 2	Model 3	Model 4[a]
Used contacts	–.153** (.027)	—	—	–.106 (.055)
Proportion of previous jobs that used contacts	—	–.093** (.036)	–.080* (.035)	—
Race [b]				
Non-Hispanic white	.329** (.053)	.324** (.053)	.296** (.052)	.300** (.052)
Mexican	.228** (.044)	.217** (.045)	.224** (.046)	.224** (.045)
Puerto Rican	.076 (.058)	.062** (.059)	.078 (.058)	.089 (.057)
Female	–.186** (.026)	–.189** (.027)	–.191** (.027)	–.205** (.027)
Education	.054** (.005)	.052** (.005)	.039** (.006)	.039** (.006)
Social Network Measures				
Proportion of friends with the same job	—	—	.183** (.044)	.111* (.055)
Proportion of friends with the same job × used contact	—	—	—	.138 (.088)
Proportion of relatives with the same job	—	—	–.010 (.068)	–.056 (.089)
Proportion of relatives with the same job × used contact	—	—	—	.109 (.135)
Proportion of friends unemployed	—	—	–.068 (.059)	.002 (.073)
Proportion of friends unemployed × used contact	—	—	—	–.173 (.115)
Average education of friends	—	—	.032** (.007)	.034** (.007)
Average education of friends x used contact	—	—	—	–.006 (.005)
Proportion of friends on welfare	—	—	–.102 (.074)	–.180 (.098)
Proportion of friends on welfare × used contact	—	—	—	.196 (.142)
Proportion in 3-digit occupation using contacts	—	–.484** (.177)	–.429* (.173)	–.386* (.172)
Dummy variables for missing social network data (see text)	No	Yes	Yes	Yes
Constant	1.396** (.071)	1.516** (.091)	1.261** (.110)	1.276** (.109)
R^2	.16	.15	.20	.22

Notes: Numbers in parentheses are standard errors; number of observations = 1,266.

[a] Model 4 tests the exogenous social capital model, with interaction effects. See point O in Figure 1.

[b] "Black" is the omitted category.

*$p < .05$ **$p < .01$ (two-tailed tests)

dix C) is included as a control variable for the tendency of particular occupations to use contacts.

Table 6 presents the coefficients from OLS models of log wages for the UPLFS data. Model 1 estimates a direct-effect model of contacts on wages. The result indicates a negative relationship between using contacts and wages in these data (–.153, $p < .01$). Nonetheless, this does not mean that using contacts has a negative causal effect on wages in these data, if the use of contacts is endogenous to the opportunities available through formal and informal job search, then the coefficient on contacts has no direct causal interpretation (for a detailed explanation, see Mouw 2002). Model 2 shows that the proportion of previous jobs found using contacts has a negative relationship with wages, as does the proportion of jobs in the respondent's occupation that are found via contacts. This last variable is used to control for the possibility that occupations that are most likely to hire through informal methods are low-skilled jobs that pay lower wages. (For a discussion of the effects of such bias in direct-effects models, see the discussion of points F and G above.)

Model 3 adds the social capital variables. The proportion of friends in the same occupation has a substantial effect on wages (.183, $p < .01$), as does their average education (.032, $p < .01$). The proportion of relatives in the same job as well as the unemployment and welfare status of network members has no effect on log wages. The results for same-occupation ties and average education indicate that some social capital variables are correlated with labor market outcomes. This result for the UPFLS data is corroborated by the MCSUI data in Model 3 of Table 8 (see page 22). In the MCSUI data, the average education of network members has a positive effect on log wages (.016, $p < .05$), as does the proportion of friends who have "steady jobs" (.227, $p < .01$).

M. The problem of homophily (i.e., the tendency of similar individuals to associate with each other) makes it difficult to directly infer causality from the result of the UPFLS and MCSUI social capital models. It seems clear, for instance, that the average education of network members is positively associated with the respondent's wages. Does this reflect the causal effect of having well-educated friends, or the fact that individuals of similar education levels tend to associate with each other? The evidence in Model 3 of Table 6 and in Model 3 of Table 8 may reflect reverse causality and selection effects rather than the causal effect of network social capital.

N. If the use of contacts is endogenous to the level of network social capital, as argued above, a test of the causal effect of network social capital variables can be constructed. Propositions 1a and 1b suggest that if a particular network social capital variable has a causal effect—either by increasing the rate at which the worker receives job offers or by providing entree into high-paying jobs—then it should increase both wages and the probability of using contacts to find work. Again, the intuition here is simple: All else equal, someone with good connections should be more likely than someone with poor connections to find work via contacts.

A key consideration in conducting this test is that certain types of jobs may, for various reasons, be more likely to be filled via informal means such as employee referrals. The literature on contacts finds, for example, that low-skilled jobs are more likely to be filled via informal methods (Corcoran et al. 1980; Holzer 1987). Therefore, any empirical test of the effect of social capital on the probability of using job contacts must take this possibility into account. The data used here are able to take the occupation-specific prevalence of contacts into account by using data on the use of contacts for a large sample of 11,610 jobs from the 1994–1998 waves of the NLSY79 (see Appendix C). With these data, I can control for the baseline probability of using contacts for detailed (3-digit) census occupations, allowing me to estimate the effect of social capital net of demand-side, occupation-specific effects that might otherwise distort the results.

Table 7 presents logit models of the probability of using contacts for the UPFLS data. Model 1 shows that the proportion of previous jobs found using contacts has a large effect on the probability of using contacts to find work (.942, $p < .01$). This indicates that there is something individual-specific about the use of contacts to find work (i.e., the use

Table 7. Coefficients from Logit Models Predicting the Probability of Using Contacts: Urban Poverty and Family Life Study, 1987

Independent Variable	Mean (S.D.)	Model 1	Model 2	Model 3
Proportion of previous jobs that used contacts	.388 [a] (.420)	.942** (.158)	—	.692** (.167)
Race [b]				
Non-Hispanic white	.063	—	–.100 (.258)	–.081 (.259)
Mexican	.182	—	.255 (.214)	.228 (.216)
Puerto Rican	.053	—	.373 (.269)	.341 (.272)
Female	.488	—	–.419** (.128)	–.387** (.129)
Education	11.62	—	–.100** (.028)	–.087** (.029)
Social Network Measures				
Proportion of friends unemployed	.146 [a] (.271)	—	–.055 (.284)	–.059 (.285)
Average education of friends	12.07 [a] (2.63)	—	–.049 (.032)	–.040 (.033)
Proportion of friends on welfare	.083 [a] (.222)	—	.514 (.348)	.513 (.352)
Proportion of friends with the same job	.193 [a] (.326)	—	–.379* (.216)	–.442* (.219)
Proportion of relatives with the same job	.116 [a] (.190)	—	.249 (.326)	.266 (.330)
Proportion in 3-digit occupation using contacts [c]	.212 (.078)	4.032** (.777)	2.287** (.835)	2.182** (.838)
Dummy variables for missing data	—	Yes	Yes	Yes
Constant	—	–1.637** (.186)	1.062* (.513)	.526 (.530)

Notes: Unless otherwise noted, numbers in parentheses are standard errors; number of observations = 1,266.

[a] Number of missing cases: proportion of previous jobs using contacts = 234, proportion of friends unemployed = 147, average education of friends = 286, proportion of friends on welfare = 234, Proportion of friends with same job = 213, proportion of relatives with same job = 32.

[b] "Black" is the omitted category.

[c] Variable constructed from NLSY data (see text).

$^{*}p < .05$ $^{**}p < .01$ (two-tailed tests)

of contacts is not random). Model 1 also indicates that the use of contacts is affected by the proportion of jobs in the respondent's 3-digit occupation (in the 1994–1998 NLSY data) that were found using contacts (4.032, $p < .01$). By including the occupation-specific proportion of jobs found through contacts, we are estimating individual models of the probability of using contacts net of occupation-level differences in the degree of informal hiring.

Models 2 and 3 of Table 7 add the social capital measures. In Model 3, we see that the unemployment, education, and welfare levels of one's friends do not significantly affect the use of contacts. Moreover, the proportion of relatives in the same job category has no effect on the probability of using contacts, and the proportion of friends in the same job has a negative effect. None of the proposed social capital variables seem to influence the probability of using contacts. In contrast, the variable measuring the proportion of previous jobs the respondent found using contacts is still large and statistically significant. So there is individual heterogeneity in the use of contacts, but it is not captured by the proposed social capital variables.

Taken together, Tables 6 and 7 demonstrate that the UPFLS social capital variables that are associated with higher earnings (the proportion of friends with the same job and the average education of friends) do not also increase the probability of using contacts to find work. Using Proposition 1 as a guide, I argue that these variables represent a spurious effect of social capital, the result of selection effects due to social homophily rather than a causal effect of network social capital. It is possible, as discussed above, that these social capital variables are picking up positive effects of non-network social capital (i.e., beneficial aspects of group membership, cultural style, language, dress, etc.) that do not directly translate into information and influence obtained through job networks.

These results for the UPFLS data are again corroborated by the MCSUI data in Model 1 of Table 8. The MCSUI social capital variables that were associated with higher earnings (mean education and steady job) in Model 3 have no effect on the probability of using contacts to find work.[11]

In addition to the results in Tables 7 and 8, several other studies have estimated the relationship between social capital and the propensity to use contacts. In a study of job mobility among Dutch managers, Boxman et al. (1991) find, in a bivariate analysis, that respondents who said they had "many" work contacts with managers in other organizations were more likely to use contacts to find work than were mangers who had "very few" or "none." Although they do not test this relationship controlling for other variables (such as occupation), their results do suggest that ties with fellow managers may be a source of network social capital under the framework proposed here. Reingold (1999) tests the effect of a wide range of social capital variables on the probability of using contacts also using the UPFLS data. For whites (N = 198) and Puerto Ricans (N = 320) he finds a negative effect of friends' education and a positive effect of the proportion-employed contacts—but both of these variables have no effect on the probability of using contacts for blacks (N = 698) and Mexicans (N = 319).[12] Finally, Lai et al. (1998) test for the effect of social capital variables on the probability of using contacts and find that social capital measures, such as the range of occupational statuses, highest status, and number of occupations among respondent's friends, have no effect on the probability of using contacts.[13] In the context of the predictions for causal effects of social capital depicted in Proposition 1, the results from Tables 6 through 8 in this paper, combined with the results in Boxman et al. (1991), Reingold (1999), and Lai et al. (1998), suggest that social capital measures, such as average education, employment levels, or the occupational status of social network members, do not have a causal effect on labor market outcomes—or, if they do, it is not via the information and influence of contact networks. Instead, more concrete measures of

[11] The MCSUI data have no information on the use of contacts to find work in previous jobs or on the occupation of network members, so these variables are not included in Table 8.

[12] Reingold's (1999) finding of a positive effect of percent-employed friends for whites and Puerto Ricans can be reconciled with my findings in Tables 7 and 8 by noting that the effect of proportion-unemployed friends has no effect on log wages in Table 6; hence, by Proposition 1, proportion-employed cannot have a causal effect on wages. I do not find these results when I repeat Table 6 by race, but Reingold's and my models are slightly different.

[13] Flap and Boxman (2001) find a positive effect of social capital on informal search and on income. However, their measure of informal search is not the use of contacts, but the frequency and time spent talking to contacts about jobs (p. 167), while their measure of social capital is partly a function of the frequency of contact with network members (p. 168). Hence, the measures of informal search and social capital are mathematically related.

Table 8. Coefficients from Models Predicting the Use of Contacts and Log Wages, Multi-City Study of Urban Inequality, 1994

		Logit Model/ Used Contact	OLS Models Predicting log Wages		
Independent Variable	Mean (S.D.)	Model 1	Model 2	Model 3	Model 4 [a]
Used contacts	.396	—	–.069** (.025)	—	.059 (.139)
Female	.528	–.347** (.114)	–.193** (.024)	–.174** (.024)	–.183** (.024)
Race[b]					
Black	.132	–.574** (.171)	–.107** (.037)	–.092* (.036)	–.100** (.036)
Hispanic	.212	.478** (.176)	–.191** (.036)	–.169** (.037)	–.177** (.037)
Asian	.027	–.401 (.368)	.234** (.074)	.284** (.074)	.280** (.074)
Other	.0003	1.012 (3.440)	–.094 (.741)	–.068 (.731)	.016 (.727)
Education	13.77 (2.89)	–.044 (.028)	.061** (.005)	.050** (.006)	.049** (.006)
City [c]					
Los Angeles	.54	–.154 (.168)	.108** (.037)	.130** (.036)	.128** (.036)
Boston	.31	–1.112** (.177)	.136** (.038)	.173** (.037)	.147** (.038)
Social Network Measures					
Average education of friends	13.41 (2.59)	.010 (.032)	—	.016* (.007)	.020* (.008)
Average education of friends × used contact	—	—	—	—	–.006 (.010)
Proportion of friends with a "steady job"	.788 (.310)	.090 (.200)	—	.227** (.041)	.265** (.057)
Proportion of friends with a "steady job" × used contact	—	—	—	—	–.081 (.082)
Proportion of friends on welfare	.049 .171	.751* (.365)	—	–.006 (.074)	–.241* (.116)
Proportion of friends on welfare × used contact	—	—	—	—	.392** (.151)
Proportion in 3-digit occupation using contacts	.189 (.082)	.390 (.719)	—	–.092 (.150)	–.122 (.150)
Constant	—	.907* (.521)	1.590** (.078)	1.280** (.108)	1.283** (.131)
R-squared	—	—	.26	.28	.29

Notes: Unless otherwise noted, numbers in parentheses are standard errors; number of observations = 1,434.

[a] Model 4 tests exogenous social capital model with interaction effects. See point O in Figure 1.

[b] "White" is the omitted category.

[c] "Atlanta" is the omitted category.

* $p < .05$ ** $p < .01$ (two-tailed tests)

social capital that stress information flows, such as Boxman et. al.'s (1991) measure of same-occupation ties, might matter.

One might argue that the information used to construct the network social capital variables for the UPFLS and MCSUI data is limited because these data only have information on the demographic characteristics of up to three friends per person. It is undoubtedly true that there is considerable measurement error in the social capital variables. However, it is important to note that even these poorly measured social capital variables have a significant effect on wages in both surveys. What is striking, then, is that there is no corresponding effect on the probability of using contacts. As a result, I conclude that the effect of these social capital variables on wages is spurious, not causal.

O. One final theoretical possibility depicted in the flow chart in Figure 1 involves using the social capital models in Table 6 but rejecting the argument that the use of contacts is endogenous to the level of social capital. In this case, one would be arguing that the use of contacts is exogenous (thereby rejecting the test of causality in Proposition 1), but that the benefit of contacts depends on the social capital embedded in those contacts (thereby skirting the fixed-effects results in Table 4 showing no average effect of using contacts among the same worker over time). If this were true, well-connected workers would not be more likely to use contacts than would poorly connected workers, but when they did use contacts they would benefit more than other workers. The empirical implication of this theoretical wriggle-room is that the interaction term between social capital variables and the use of contacts should be significant because the causal effect of beneficial network social capital would only come into play when the worker actually used contacts (in contrast to the search theory model, for which beneficial contacts raise the reservation wage thereby increasing the expected wage of all accepted job offers). In this sense, the interaction term indicates the increase in the effect of the social capital variable when contacts are used to obtain work. This model was tested in Model 4 of Table 6 using the UPFLS data by interacting the use of contacts with the social capital variables, and all the interaction terms were not significant. A similar result is obtained in Model 4 of Table 8 using the MCSUI data (also see a similar result in Flap and Boxman 2001:176, table 2).

DISCUSSION AND CONCLUSION

My central argument is that if the use of contacts is seen as endogenous to the level of social capital—as suggested by the sequential and extensive search models—then a test of the causal effect of measures of network social capital is whether purported social capital variables increase both wages and the probability of using contacts. It is possible to reject the two job-search models and the test of causality I have proposed here, but we can't have our theoretical cake and eat it too. Rejecting the sequential and extensive search models means accepting an alternative theory, with empirical implications that are just as disconfirming to the notion that contacts and network social capital affect labor market outcomes.

If the notion that a job-seeker's use of job contacts depends on the level of social capital is rejected, then "direct effects" models (E and G) and "exogenous social capital" models (point I) can be estimated. However, the results from Tables 2 through 5 show that these models provide no evidence that the use of contacts, or the use of higher-status contacts (i.e., contacts who are in a higher status job than the respondent), have any effect on labor market outcomes such as wages, occupational prestige, or unemployment duration. If the use of contacts is seen as exogenous to the level of social capital, I would argue that the most damaging evidence to the argument that contacts matter are shown by the fixed-effects results in Table 4. Using longitudinal data, Table 4 shows that workers who use contacts do not do better than when they do not use contacts.

As discussed above, recent research using data on the hiring process in single firms suggests that applicants with a contact inside the firm have a higher probability of being hired than do other applicants (Fernandez et al. 2000; Fernandez and Weinberg 1997; Petersen et al. 2000). However, the evidence in Tables 2 through 5 shows that the supposed benefits do not seem to show up in surveys of individual workers. I contend that while the results from these recent studies using single-firm data are provocative, we should observe the effects of using contacts on representative samples of individual workers before we believe that the results from single firms can be generalized to the labor market as a whole.

I have argued that the best way to make sense of the findings in Tables 2 through 5—and the apparent discrepancy between single-firm studies and studies of workers—is to consider Montgomery's (1992) sequential search model (or, alternatively, a model of extensive search). According to these search models, the benefit of contacts cannot be measured by analyzing the difference in wages for jobs found with and without contacts, because well-connected workers raise their reservation wages so that the wages of *all* accepted job offers are higher, regardless of whether they were found via contacts.

A key insight of the search models is that better-connected workers should be more likely to use contacts to find work, all else equal. Because network social capital refers to the information and influence that contacts can provide during job search, better-connected workers should be more likely to obtain acceptable job offers through contacts than would poorly connected workers. Because the empirical models in Tables 7 and 8 control for the overall proportion of jobs in the respondent's 3-digit occupation that use contacts, I control for occupation-specific variation in the use of informal methods to find work that might otherwise distort the results. The results of the UPFLS and MCSUI analyses indicate that although the social capital measures have an "effect" on wages, they do not have a concurrent effect on the probability of using contacts. This suggests that the relationship with wages, at least for these variables, is spurious or involves aspects of social capital not transmitted through networks. In addition, it should be pointed out that, according to the model developed here, Proposition 1 is a necessary but not sufficient indicator of causality; satisfying the conditions of Proposition 1 does not guarantee that all of the observed effect is causal. The exact relationship between the probability of using contacts and the causal effect on wages depends on the parameters of the job search model—such as the offer arrival rates and the distributions of job offers for all methods of job search. Estimation of such a model is beyond the scope of this paper and is a subject for future research. The benefit of the current paper is that it provides both a theoretical framework for thinking about the causal effect of social capital on labor market outcomes and an easily implemented check on the causality of proposed indicators of network social capital.

Although I have critiqued social capital models of labor market outcomes, I also think it would be naive to argue that contacts do not matter. 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, given that the nonrandom acquisition of friendship ties means we are likely to overestimate the effect of social capital on labor market outcomes. My results suggest that conventional social capital variables, such as the education or employment status of network members, do not have a causal effect on wages. It is certainly plausible that future surveys with more extensive network information will prove that the results using data from the Detroit Area Study, UPFLS, and MCSUI were premature. At the moment, however, intuition and anecdote aside, we have little empirical evidence showing that contacts matter.

Research on social capital must take seriously the problem of differentiating between the nonrandom way in which friends are acquired and the subsequent effect of those friends on individuals' social and economic outcomes. Indeed, my goal here has been to propose a framework for thinking about the role of network social capital in the labor market that can help adjudicate between two opposing perspectives—the view that the effect of social capital is causal, and the view that it reflects the correlation between friends' characteristics and unobserved individual productivity. Although the underlying theories about the role of contacts and social capital in the labor market make sense, the results here indicate that we must focus on more concrete mechanisms by which information and influence are transmitted by social networks. Only by doing this can we correctly identify the relevant indicators of network social capital and estimate their effect on labor market outcomes.

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APPENDIX A

A Model of Sequential Job Search

The following shows a derivation of the sequential search theory model and proofs of Propositions 1a and 1b. Start with an unemployed worker. During each period, the worker may receive job offers. The probability density of the wage distribution is $h(w)$. For the sake of simplicity, assume that jobs last for as long as the worker remains in the labor force. The worker retires and leaves the labor force permanently with a probability $1 - b$ each period (alternatively, b can be though of as the rate at which the worker discounts future earnings). Therefore, the expected total wages for a given job is the lifetime expected value of the wage, which equals $w + bw + b^2w + \ldots = w/(1 - b)$. If an offer is received, the worker must then decide whether to accept or reject the offer. The "reservation wage," w^R, is the wage that makes the worker indifferent between accepting and rejecting the job offer. The reservation wage can be defined as follows (see Devine and Kiefer 1991; Montgomery 1992:587):

$$w^R = \frac{b}{1-b}\int_{w^R}^{\infty}(w - w^R)h(w)dw. \qquad \text{(A-1)}$$

The worker will accept any offer with a wage greater than w^R.

While the worker is actively searching for work, offers can arrive from either formal or informal job searches. The probability density of the wage-offer distribution can be represented as

$$h(w) = P_C f_C(w) + P_F f_F(w), \qquad \text{(A-2)}$$

where P_F and P_C are the probabilities of receiving an offer through formal and informal means, respectively, and $f_F(w)$ and $f_C(w)$ are the probability densities of the formal and informal offer distributions. This specification of $h(w)$ assumes that only one job offer is received per period. This is a reasonable assumption if the length of each period is small (Mortensen 1986:858). Hence,

$$w^R = \frac{b}{1-b}P_C\int_{W^R}^{\infty}(w - w^R)f_C(w)dw + \frac{b}{1-b}P_F\int_{W^R}^{\infty}(w - w^R)f_F(w)dw. \qquad \text{(A-3)}$$

After some rearranging, we can find the derivative of the reservation wage with respect to an increase in μ_{SC} by taking the total differential using Leibniz's rule (note that the relationship between μ_{SC} and μ_C is given in Equation 4 of the text):

$$\frac{dw^R}{d\mu_{SC}} = \frac{1}{f}\cdot\frac{dw^R}{d\mu_C} = \frac{1}{f}\cdot\frac{\frac{b}{1-b}P_C[1 - F_C(w^R)]}{1 + \frac{b}{1-b}\{P_C[1 - F_C(w^R)] + P_F[1 - F_F(w^R)]\}} \in (0,1), \qquad \text{(A-4)}$$

(which is greater than zero, except in the limiting case where $F_C(w^R) = 1$).

To find the derivative of the reservation wage with respect to an increase in increase in P_{SC}, take the total derivative of A-3 with respect to w^R and P_C (and note that the relationship between P_{SC} and P_C is given in Equation 2 of the text). We find that

$$\frac{dw^R}{dP_{SC}} = \frac{1}{c}\cdot\frac{dw^R}{dP_C} = \frac{1}{c}\cdot\frac{\frac{b}{1-b}[E_C(w)|(w > w^R) - w^R][1 - F_C(w^R)]}{1 + \frac{b}{1-b}\{P_C[1 - F_C(w^R)] + P_F[1 - F_F(w^R)]\}} > 0, \qquad \text{(A-5)}$$

where $E_C(w)|w > w^R$ is the expected value of the informal wage distribution given that the wage is greater than the reservation wage. The reader can compare these results to Devine and Kiefer's (1991, eqs. 2.7d and 2.7c) results for the standard search model.

Proposition 1a: Increasing P_{SC}, μ_{SC}, $P_{SC}^{Spurious}$, or $\mu_{SC}^{Spurious}$ increases expected wages.

Proof: Because the expected wage is the mean of the wage distribution truncated from below at the reservation wage, it is straightforward to show that increasing the reservation wage implies an increase in the expected wage (see Devine and Kiefer 1991:18). From Equation 4 of the text, $\mu_C = d\mu_{HC} + e\mu_{SC}^{spurious} + f\mu_{SC} + \eta_4$, hence from A-4 we have $\frac{dw^R}{d\mu_{SC}} = \frac{1}{f}\cdot\frac{dw^R}{d\mu_C} \geq 0$, (assuming that $f > 0$), which means that increasing μ_{SC} raises the expected wage. Similarly, it is easy to show that $\frac{dw^R}{d\mu_{SC}^{Spurious}} \geq 0$, and that increasing $\mu_{SC}^{Spurious}$ increases expected wages (from Equations 3 and 4, $\mu_{SC}^{Spurious}$ increases both μ_S and μ_C). From Equation A-5 we know that increasing P_{SC} increases the reservation wage and hence expected wages. Following Equations 1 and 2 of the text and the derivation of Equation A-5, it is easy to show that increasing $P_{SC}^{Spurious}$ increases expected wages.

Proposition 1b: Increasing P_{SC} or μ_{SC} increases the probability of using contacts to find work. In contrast, increasing $P_{SC}^{Spurious}$ or $\mu_{SC}^{Spurious}$ has an ambiguous (and generally small) effect on the probability of using contacts to find work.

Proof: The probability of using contacts equals the probability of receiving an informal job offer that is higher than the reservation wage divided by the probability of receiving any offer higher than the reservation wage. Therefore,

$$\Pr(C) = \frac{P_C \int_{w^R}^{\infty} f_C(w)dw}{P_C \int_{w^R}^{\infty} f_C(w)dw + P_F \int_{w^R}^{\infty} f_F(w)dw}. \qquad \text{(A-6)}$$

Let $A = P_C \int_{w^R}^{\infty} f_C(w)dw = P_C[1 - F_C(w^R)]$ be the per-period probability of receiving an acceptable job offer via contacts, and $B = P_F \int_{w^R}^{\infty} f_F(w)dw = P_F[1 - F_F(w^R)]$ be the per-period probability of receiving an acceptable job offer via formal search. Increasing P_C has both a positive direct effect on A due to the increased probability of receiving an offer via contacts, and a negative effect because increasing P_C raises the reservation wage ($\frac{dw^R}{dP_C} > 0$ in A-5) and makes the worker more selective about accepting a job offer. Differentiating A with respect to P_C we find:

$$\frac{dA}{dP_C} = [1 - F_C(w^R)] - P_C f_C(w^R)\frac{dw^R}{dP_C}. \qquad \text{(A-7)}$$

The first right-hand side term is the direct effect of increasing P_C, and the second term is the indirect effect due to the increase in the reservation wage. In contrast, the effect of increasing P_C on B only contains the indirect effect of the reservation wage,

$$\frac{dB}{dP_C} = -P_F f_F(w^R)\frac{dw^R}{dP_C} < 0. \qquad \text{(A-8)}$$

To find the net effect of increasing P_C, on $\Pr(C)$, differentiate A-6 with respect to P_C. We find that the net effect is positive, provided we make certain general assumptions about the wage offer distribution (sufficient conditions given below):

$$\frac{d\Pr(C)}{dP_C} = \frac{B\frac{dA}{dP_C} - A\frac{dB}{dP_c}}{(A+B)^2} > 0. \qquad \text{(A-9)}$$

Because $\frac{dB}{dP_C} < 0$, and all the other terms in Equation A-9 except $\frac{dA}{dP_C}$ are positive, a sufficient condition for $\frac{d\Pr(C)}{dP_C} > 0$ is that $\frac{dA}{dP_C} > 0$. In the context of the standard search model, Burdett (1981) shows that $\frac{dA}{dP_C} > 0$ if the probability density function of the wage distribution is log-concave (also see Mortensen 1986:865). A distribution is log-concave if the ratio of the probability density function to the cumulative density function is monotone decreasing (Bagnoli and Bergstrom 1989:3). Bagnoli and Bergstrom (1989) show that many statistical distributions are log-concave, including the uniform, normal, logistic, extreme value, chi-square, chi, exponential, and Laplace distributions. In addition, van den Berg (1994) shows that $\frac{dA}{dP_C} > 0$ is also satisfied by many other distributions which are not log-concave but are often used by economists to model wage distributions, including the lognormal, log-uniform, and Pareto distributions. Finally, even if $\frac{dA}{dP_C} < 0$, it can still be shown that $\frac{d\Pr(C)}{dP_C} > 0$ provided that the informal and formal wage distributions are the same (in which case the indirect effects in $\frac{dA}{dP_C}$ and $\frac{dB}{dP_C}$ will cancel out in A-9), or the informal wage distribution is superior to the formal wage distribution (i.e., $F_C(w) < F_F(w)$ for all w, contact the author for details). Hence, sufficient conditions for $\frac{d\Pr(C)}{dP_C} > 0$ are that $f_C(w)$ is either log-concave, satisfies the weaker conditions given by Van den Berg (1994), or is identical to or superior to $f_F(w)$.

An increase in $P_{SC}^{Spurious}$ increases both P_C and P_F, and inspection of A-6 suggests that the effect of increasing both P_C and P_F by equal amounts should roughly cancel out. However, the effect also depends on the change in A and B due to a change in the reservation wage, which may not be equal. Hence $\frac{d\Pr(C)}{dP_{SC}^{Spurious}}$ may be greater than or less than zero.

To find $\frac{d\Pr(C)}{d\mu_C}$, let $D = P_C \int_{w^R(\mu_C)}^{\infty} f_c(w - \mu_C)dw$, and note that $\frac{dD}{d\mu_C} = P_C f_C(w^R) - \frac{dw^R}{d\mu_C}P_C f_C(w^R)$ and $\frac{dB}{d\mu_C} = -\frac{dw^R}{d\mu_C}P_F f_F(w^R)$. Hence,

$$\frac{d\Pr(C)}{d\mu_C} = \frac{d}{d\mu_C}\frac{D}{D+B} = \frac{\frac{dD}{d\mu_C}B - \frac{dB}{d\mu_C}D}{(D+B)^2},$$

which simplifies to

$$\frac{d\Pr(C)}{d\mu_C} = \frac{P_C f_C(w^R)(1 - \frac{dw^R}{d\mu_C})B + P_F f_F(w^R)\frac{dw^R}{d\mu_C}D}{(D+B)^2} > 0, \qquad \text{(A-10)}$$

as $\frac{dw^R}{d\mu_C} \in (0,1)$ from A-4 and all of the other terms in A-10 are greater than 0. For an increase in $\mu_{SC}^{Spurious}$, both μ_F and μ_C increase by the same amount. Similar to equation A-10 it can be shown that

$$\frac{d\,\Pr(C)}{d\mu_{SC}^{Spurious}} = \frac{\left[P_C f_C(w^R)B - P_F f_F(w^R)D\right](1-\frac{dw^R}{d\mu_{SC}^{Spurious}})}{(D+B)^2} \in (-\infty,+\infty). \quad \text{(A-11)}$$

Thus, increasing $\mu_{SC}^{Spurious}$ has an ambiguous effect on the probability of using contacts. Inspection of the term inside the brackets on the right-hand side of A-11 indicates that if the formal and informal wage distributions are similar, then $\frac{d\,\Pr(C)}{d\mu_{SC}^{Spurious}}$ will be close to zero.

As shown in Equations A-9 and A-10, the effect of increasing either P_C or μ_C on the probability of using contacts is positive (keeping in mind the sufficient conditions needed for A-9). Hence, increasing P_{SC} or μ_{SC} increases the probability of using contacts. In contrast, the effect of increasing $\mu_{SC}^{Spurious}$ (see Equation A-11) or $P_{SC}^{Spurious}$ is ambiguous.

Finally, the reader will note that a more realistic model could be developed to include search intensity, where the worker could choose how much effort is put forth in the search (i.e., amount of time, number of applications) using each method. If workers behave rationally, those with better contact networks would increase their search intensity using contacts compared with other workers, which would result in a more pronounced relationship between social capital and the probability of using contacts.

APPENDIX B

Extensive Search Model

We can prove the equivalent of Proposition 1 for a model of extensive search. Because the proof of Proposition 1 is fairly straightforward, Appendix B outlines the proof.

Suppose a worker sends off M applications to firms (formal search) and also asks N friends about job openings (informal search). The probability that each application from formal search results in a job offer is P_F, and the probability that each friend results in a job offer is P_C. The worker waits until all the job offers are in and then chooses the one with the highest wage. In contrast to the case of sequential search, the formal and informal offer distributions do not have to be known by the worker. Let the cumulative density function (CDF) of the formal-offer distribution be $F_F(w)$, and the CDF of the informal offer distribution be $F_C(w)$. This tells us that the probability that a random draw from the informal wage distribution will be less than or equal to w. As a result, if we select the best offer among $P_C N$ offers, then the CDF of the distribution of best offer from informal search will equal $\sum_{x=0}^{N} B(P_C,x,N)F_C(w)^x$, where $B(P_C,x,N)$ is the probability of receiving x offers from N applications from the binomial distribution. Similarly, the CDF of the best offer from formal search will be $\sum_{x=0}^{M} B(P_F,x,M)F_F(w)^x$.

Proposition 1a: Increasing P_{SC}, μ_{SC}, $P_{SC}^{Spurious}$, or $\mu_{SC}^{Spurious}$ increases expected wages.

Increasing P_{SC} (see Equation 2 in the text) increases the expected number of offers from informal search. Similarly, increasing $P_{SC}^{Spurious}$ increases the expected number of offers from both informal and formal search. Because we choose the best offer out of a larger pool, it is easy to show that increasing P_{SC} or $P_{SC}^{Spurious}$ results in an increase in the expected wage. Increasing μ_{SC} (see Equation 4) increases the average wage of informal offers, which increases expected wages and the average wage of the highest offer. Likewise, increasing $\mu_{SC}^{Spurious}$ increases average wages from both formal and informal search, which increases the expected wage of the highest job offer.

Proposition 1b: Increasing P_{SC} or μ_{SC} increases the probability of using contacts to find work. In contrast, increasing $P_{SC}^{Spurious}$ or $\mu_{SC}^{Spurious}$ has an ambiguous (and generally small) effect on the probability of using contacts to find work.

Increasing P_{SC} or μ_{SC}: Given the assumption that the worker selects the highest offer among all the job offers he/she receives, the probability that the job is found through contacts is just the probability that the highest offer was a job found through contacts. Let Z represent the highest wage offer found through formal methods. Then, for any Z, the probability of using contacts is:

$$\Pr(C) = 1 - \sum_{x=0}^{N} B(P_C,x,N)F_C(Z)^x. \quad \text{(B-1)}$$

Using Equation B-1, it can be shown that $\frac{d\,\Pr(C)}{dP_C} \geq 0$. Intuitively, this means that increasing the probability of receiving informal offers increases the expected number of informal offers and hence increases the probability that the highest offer will have arrived from informal means of job search. Therefore, increasing P_{SC} increases $\Pr(C)$.

Similarly, increasing the mean of the informal offer distribution also increases $\Pr(C)$: If $G_C(w)$ is the new CDF resulting from an increase in the mean of the informal offer distribution, then $G_C(w)$ stochastically dominates $F_C(w)$. Hence, $G_C(w) < F_C(w)$ for all w. Therefore,

$$\Pr(C)\,|\,G_C(Z) = 1 - \sum_{x=0}^{N} B(P_C, x, N) G_C(Z)^x$$
$$> \Pr(C)\,|\,F_C(Z)$$
$$= 1 - \sum_{x=0}^{N} B(P_C, x, N) F_C(Z)^x. \qquad \text{(B-2)}$$

Because increasing μ_{SC} increases the mean of the informal offer distribution and holds everything else constant, increasing μ_{SC} increases Pr(C). Holding everything else constant, increasing the wages of informal offers increases the chance that the highest wage offer will come from informal means.

Increasing $P_{SC}^{Spurious}$ ***or*** $\mu_{SC}^{Spurious}$: Increasing $P_{SC}^{Spurious}$ results in an increase in the probability of receiving formal and informal offers (Equations 1 and 2 in the text). This improves the expected wage of the highest offer found through both formal and informal search. Increasing the expected wage of the highest informal offer increases the probability of using contacts while increasing the expected wage of the highest formal offer decreases the probability of using contacts. These two effects tend to cancel each other out, but the precise effect may be positive or negative depending upon the shape of the formal and informal offer distributions as well as N and M. By rewriting Equation B-1 in terms of the probability that the highest wage offer is Z and differentiating with respect to $P_{SC}^{Spurious}$ it can be shown that $\frac{d\Pr(C)}{dP_{SC}^{Spurious}}$ can be positive or negative.

Similarly, increasing $\mu_{SC}^{Spurious}$ increases the average wage of both formal and informal offers. Intuitively, one might expect these effects to cancel each other out, but it can be shown that $\frac{d\Pr(C)}{dP_{SC}^{Spurious}}$ may be greater than or less than zero.

APPENDIX C

Description of Data Sets Used

This appendix describes each of the data sets used in the analysis. Complete data management and analysis files used in this paper as well as links to the data can be found on the author's web site (http:www.tedmouw.org).

1982 National Longitudinal Study of Youth (NLSY)

The NLSY data (used in Tables 1 and 2) is a nationally representative sample of 12,686 young men and women who were 14 to 22 years of age when first surveyed in 1979. The NLSY has reinterviewed respondents annually from 1980 through 1992, and biannually since 1992. In 1982, the NLSY asked a number of detailed questions about the use of contacts to find work, such as the relationship to the respondent, whether or not the contact was helpful, and how the contact helped. The analysis in Table 1 is limited to respondents who were out of school and working in 1982 (at which time the age range was between 17 and 25 years of age) and who had wage information for 1982, 1985, and 1990.

1994–1998 NLSY

In the 1994, 1996, and 1998 interviews (used in Tables 3 and 4) the NLSY asked questions on the use of contacts to find work and whether the respondent had actively searched for work for all jobs between 1993 and 1998. The question about the use of contacts to find work was asked only of those workers who actively searched for work. As a result, a dummy variable for nonsearch is included in all the models estimated here. See the discussion of point G for an interpretation of the significance of the nonsearch variable.

(a) Combining the 1994 through 1998 waves of the NLSY with the NLSY work history data (which provides a week by week history of labor force status), I construct a data set of unemployment duration. The data used in Table 3 are restricted to jobs that were preceded by an unemployment spell of at least one week. The data used in Model 2 of Table 3 are further restricted only to cases where the previous job was lost due to a plant closing (151 cases) or a layoff (581 cases).

(b) The data for Models 3 and 4 of Table 3 are restricted to individuals from the 1994 through 1998 waves of the NLSY who changed jobs at least once between the 1994 and 1998 interviews.[C-1] Only current job in 1994 is used, and only new current jobs in 1996 and 1998 are used, resulting in a maximum of three observations for a person who changed jobs twice between 1994 and 1998. Fifty-one cases are deleted because of missing information on labor market experience or tenure. This results in a data set composed of 3,281 individuals and 7,409 total jobs. Seventy-four (73.8) percent of respondents reported that they had actively searched for work, and 15.1 percent of the jobs were found via contacts with a friend or relative. The question about contacts was not asked of workers who did not actively search for work. Among active searchers, 20.5 percent used contacts, which makes it similar to the frequencies reported in other studies.[C-2]

[C-1] Of 7,409 individuals who were employed in 1994 and in 1996 or 1998, 3,064 changed jobs and employers during that period. In addition, 86 cases with missing variables or hourly wages of less than \$2 or greater than \$100 an hour were excluded.

[C-2] The question in 1994 and 1996 asked: "Which method led to your being offered your job with (employer)?" and "contacted friends or relatives" was the response for contacts. In contrast, the 1982 question, "Was there anyone who specifically helped you get your job with (employer)" is more inclusive and resulted in 53.9 percent using contacts (see Table 1). The more restrictive form of this question was also asked in 1982, and 27 percent reported that asking friends or relatives resulted in their current job.

(c) The measure of the proportion of workers in 3-digit occupations who used contacts was created from the 1994–1998 NLSY data. This measure uses all jobs where the respondent was actively searching for work (if the respondent reported that he or she was not actively searching for work, then the question about using contacts was not asked)—a total of 11,610 jobs from 1994 to 1998. The proportion of workers using contacts in 3-digit 1970 occupations is calculated and used as a control variable in Table 2 (where it is calculated excluding the respondent's current job), and in Tables 6 through 8 (where 1970 census 3-digit codes are converted to 1980 and 1990 census 3-digit codes using a crosswalk data set of NLSY data that has both 1970 and 1980 codes and a "crosswalk" between 1980 and 1990 occupational codes).

1970 Detroit Area Study

The 1970 Detroit Area Study (used in Table 5) is a study of the career histories of 638 male respondents between the ages of 16 and 60. The analysis here focuses on only those respondents who used a contact to find work.[C-3] See point I in the text for more details on the sample used in the analysis.

1987 Urban Poverty and Family Life Study (UPFLS)

The 1987 UPFLS (used in Tables 6 and 7) is a stratified random sample collected by the National Opinion Research Center of 2,490 respondents aged 18 through 47 years old living in poverty areas in Chicago. There are several advantages of these data. First, demographic information was collected on up to three friends for each respondent. These data were used to construct the social network measures. Second, information on the occupations of social network members and of relatives was used to construct indicators of same-occupation ties. Third, information on the respondent's use of contacts to find up to eight previous jobs was used to construct a variable measuring the previous use of contacts. The analysis in Tables 6 and 7 includes all currently employed respondents, excluding 64 cases who refused to answer the salary question and 1 case with a self-reported salary of $500,000 (who did not use contacts), 8 cases missing information about the use of contacts for the current job, and 32 cases missing years of education.

1994 Multi-City Study of Urban Inequality

Data from the 1994 Multi-City Study of Urban Inequality (used in Table 8) are used to test the relationship between social networks and wages. These data come from a sample of households in four cities: Atlanta, Detroit, Boston, and Los Angeles. Similar to the UPFLS, there is information on the demographic composition of workers' social networks, which can be used as a measure of social resources.[C-4] The survey asked for the demographic characteristics of up to three people that the respondent regularly interacted with. I use the average education and employment status of the respondent's network members as indicators of social resources.[C-5] The data in Table 7 include all respondents from Atlanta, Boston, and Los Angeles who had searched for work in the past five years. Out of 2,523 possible cases, 457 cases were dropped because of missing wage information, 39 cases were dropped because wages were calculated to be less than $3 per hour, 3 cases were dropped because of missing data on education, and 590 cases were dropped because of missing social network information.

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[C-3] The Detroit Area Study data distinguish between individuals who used a specific personal contact (332 cases) and a vague personal contact (i.e., the guys at work, the grapevine, etc.). I use only those who could name a specific contact.

[C-4] The social network data was not collected in the Detroit subsample.

[C-5] In contrast to a study with the same data (Green et al. 1995), I do not use the number of ties as a measure of social resources because the survey only probed for three network members, and it is not clear whether respondents who have only one or two network members really have only one or two friends or merely did not complete the question.

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