Network-Based Job Search

An Analysis of Monetary and Non-Monetary Labor Market Outcomes for the Low-Status Unemployed

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Summary: Using a search-theoretical model proposed by Montgomery (1992), we analyze the effects of information flow via social networks (friends, relatives, and other personal contacts) on monetary and non-monetary labor market outcomes. Propensity score matching on survey data from low-status unemployed respondents is used to identify causal effects. The analysis takes into account unobserved heterogeneity by applying Rosenbaum bounds. We show that the standard approach to investigating labor market outcomes in terms of how jobs are found is misleading. As an alternative, we propose focusing comparative analyses of labor market outcomes on how individuals search for jobs and, more particularly, on whether they search for jobs via social networks. Using this approach we find no evidence for causal effects on monetary outcomes such as wages and wage satisfaction. We also find no effects for non-monetary outcomes like job satisfaction.

Keywords: Social Networks; Unemployment; Job Search; Labor Market Outcomes.

Zusammenfassung: Der Aufsatz analysiert den Einfluss der Informationsübertragung über soziale Netzwerke (Freunde, Verwandte und andere persönliche Kontakte) auf monetäre und nicht-monetäre Arbeitsmarkterträge. Die theoretische Basis der Analyse ist ein von Montgomery (1992) vorgeschlagenes suchtheoretisches Modell. Um kausale Effekte zu identifizieren, verwenden wir Propensity-Score-Matching. Unbeobachtete Heterogenität wird mit Hilfe von Rosenbaum-Bounds in der Analyse berücksichtigt. Als Datenbasis dient uns eine Befragung von geringqualifizierten und/oder Langzeitarbeitslosen. Im Zuge der Analyse stellt sich die weit verbreitete Vorgehensweise als irreführend heraus, den Einfluss sozialer Netzwerke auf der Basis eines Vergleichs verschiedener Wege zu identifizieren, auf denen Arbeitsplätze gefunden werde. Stattdessen schlagen wir vor, Personengruppen miteinander zu vergleichen, die mit bzw. ohne Einbindung sozialer Kontakte nach Arbeit gesucht haben. Aus einer solchen Analyse ergeben sich keinerlei Hinweise darauf, dass die Suche über soziale Netzwerke kausale Effekte auf monetäre Erträge wie den Lohn oder die Lohnzufriedenheit oder nichtmonetäre Aspekte wie die Jobzufriedenheit hat.

Schlagworte: Soziale Netzwerke; Arbeitslosigkeit; Arbeitsplatzsuche; Arbeitsmarkterträge.

1 Introduction

In this paper, we aim to contribute to the discussion on the effect of social capital or social networks on labor market outcomes. According to Pierre Bourdieu (1997: 51), social capital is "the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintances and recognition […] which provides each of its members with the backing of collectively-owned capital". From a slightly different perspective and with a focus on instrumental rationality, James

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Coleman (1988: 98) defines social capital as "a particular kind of resource available to an actor […] Like other forms of capital, social capital is productive, making possible the achievement of certain ends that in its absence would not be possible." A field of research often associated with – but not identical to – social capital research is social network analysis. The key assumptions of social network analysis are "that actors and actions are to be viewed as interdependent rather than dependent, and that the relational ties between actors are channels for the transfer or flow of material and nonmaterial resources" (Schuller et al. 2010: 19).

These social resources can take different forms. Sandefur & Laumann (1998) build upon Coleman (1988) and propose to differentiate social capital in terms of the benefits provided to actors. These authors argue that a given form of social capital can have various benefits, most importantly information, influence/control, and social solidarity. The various benefits are "the mechanisms through which a form of social capital acts to increase an actor's capacity for action" (Sandefur & Laumann 1998: 493).

In this paper, we focus on information flow via social networks and its role in the job search process. Obtaining information is an important aspect of searching for a job. Rees (1966) distinguishes two different dimensions of the search for information: the extensive and the intensive dimension. The extent of an individual's job search efforts refers to his/her attempt to acquire information about the existence of suitable vacancies. In contrast, the intensity of job search in this context refers to the amount of effort expended in order to acquire more information about a specific vacancy that he/she has already identified. Because the search for information is costly, both in terms of time and effort as well as financial resources, Rees (1966) argues that, in addition to "formal" search strategies such as replying to employment ads or using public or private employment services, individuals also rely on personal contacts as an informal, and therefore cheaper, job search strategy.

In his seminal works, Granovetter (1973, 1974) explicitly employs a social networks perspective to address information flow via personal contacts as one of the most important informal search strategies. One of the key aspects of Granovetter's research design is the comparison of labor market outcomes of employed individuals according to how they found their job, whether via personal contacts or formal search methods. The term "'personal contacts' […] implies that there is some individual known personally in some context *unrelated* to a search for job information, from whom he has found out about his new job" (Granovetter 1995: 11). In his survey of 282 workers in a firm near Boston, Massachusetts, USA, Granovetter found that more than half of the respondents had found their jobs via personal contacts. Granovetter argues that, in addition to cost/benefit considerations and a higher degree of trust in information received via personal contacts, one major reason for the widespread use of social networks in job searches is that they also lead to better jobs. According to Granovetter, those who find their jobs via personal contacts fare better in their jobs with regard to both monetary and non-monetary labor market outcomes; most notably, they experience higher job satisfaction, they have a higher income and a lower intention to quit compared to those who used other, predominantly formal means (Granovetter 1995: 13ff.).

Ever since Granovetter (1974) introduced this comparative design focusing on job-finding methods, it has become a widely used approach for researching the effect of social networks on labor market outcomes. However, Mouw (2003: 869f.), and Granovetter (1995: 147ff.) himself, have noted that the literature shows rather mixed results. Some researchers find support for a positive effect of using networks in job searches, whereas others find negative effects, and still others find no effect at all. Montgomery (1992) provides an explanation for these varying results: focusing on how the accepted job offer was received ignores the effect that alternative, rejected job offers might have had on the individual's reservation wage. These alternative job offers will influence labor market outcomes, irrespective of the method by which the accepted job was identified. Focusing on job-finding methods therefore presents researchers with a spurious correlation rather than a causal effect. Taking up Montgomery's line of reasoning, Mouw (2003: 870) argues that focusing on how the job was found "is a misleading way to determine the effectiveness of job search methods if workers use multiple methods of job search". Mouw shows that, given this problem, there is no empirical evidence for a significant effect of networks on job search outcomes, either positive or negative.

Our paper will proceed as follows. In a review of the literature, we will show that, despite the strong empirical and theoretical evidence presented by Mouw (2003) and Montgomery (1992), most empirical research has not recognized Montgomery's critique (2.). As a consequence, the literature is still characterized by a puzzling range of diverging results. We present the theoretical reasoning of Montgomery's critique in more detail and illustrate this reasoning with a stylized example (3.). Subsequently, we summarize two potential solutions (4.), one based on Franzen & Hangartner (2006) and one based on Mouw (2003). Because neither solution is applicable in our context, we introduce a solution of our own as an alternative. We turn to a population of interest and present hypotheses (5.); we discuss our survey data and the methodology of propensity score matching used in analyzing them (6.). Finally, we report our findings (7.) and offer several conclusions (8.).

2 Recent Studies of Labor Market Outcomes

In this brief review of recent studies, we focus on studies of the effect of social networks on labor market outcomes. We also restrict the review to research that follows or is similar to Granovetter's original analytical approach of comparing labor market outcomes based on how an individual found his/her current job.[1] Huang & Western (2011) conducted an analysis of social networks and occupational attainment in Australia, asking "which one method was most important for getting your current/last job" (Huang & Western 2011: 274). Looking at wages, occupational status, and whether the respondent held a professional or managerial position, these authors find negative effects of social networks on all three labor market outcomes. Most notably, individuals who found their job via social networks had wages that were, on average, 9 percent lower than those who found their job via other methods. Similarly, Chua (2011) found that using personal contacts had a negative effect on wages in Singapore. His indicator for network usage combines the following items: "I asked (a) friend/person who told me about the job," "A friend/person who knew I was looking for a job contacted me" or "A friend/person who did not know I was looking for a job contacted me" (Chua 2011: 4). Yogo (2011) analyzed the relationship of networks and wages in Cameroon. In contrast to Chua, Yogo found a positive effect of social networks ("How did you get your job?") on wages. This wage premium for network users held in regression models with and without controlling for unobserved confounders, and it ranged from about 0.06 to 1.5 percent. Investigating the outcomes of networking intensity, Wanberg et al. (2000) asked formerly unemployed job seekers to report how they learned about the job that they held at the time of the interview (Wanberg et al. 2000: 496). The analysis of these authors indicates no significant effect of using networks on job satisfaction. Similarly, there was no effect on self-reported intentions to quit. Focusing on Colombian urban workers and how they found their current jobs, Diaz (2012) found negative wage differentials for individuals who used personal contacts when compared to those who used other methods. This finding remains robust across regression models that do or do not control for unobserved confounders. Focusing on personal contacts as a job-finding method, Pellizzari (2010) presents results for several European countries and the United States. A regression without controlling for potentially unobserved confounders finds negative effects in approximately half the countries, including Germany and the Netherlands. For the other half of the countries, including the US, the analysis presents null effects. However, the more credible fixed-effect estimation in the same paper reports a null effect for Germany, a positive effect for the Netherlands, and a null effect for the US. Finally, Franzen and Hangartner (2006) find a negative and significant effect of finding jobs via social networks on wages, with an effect magnitude of 5 percent. Similarly, the effect on perceived adequacy of payment is also negative, whereas effects on educational adequacy and similar indicators of job quality were significantly positive. Focusing on job finding via strong ties only, Delattre and Sabatier (2007) initially find no significant impact of networks on wages. After controlling for unobserved heterogeneity, they conclude that the real effect is negative.

It seems an appropriate conclusion that, decades after Granovetter's original work, there is still no consensus about whether network-based job-search indeed leads to better jobs. What those recent studies have in common is that they consider *finding a job* via personal contacts to unambiguously reflect the effect of using networks in *searching for a job*. As has been noted, for example, by Elliott (1999: 213), "researchers have been vague about whether 'job networks' refer to search behavior or recruitment and acquisition methods." Given that this vagueness was criticized by Montgomery as early

[1] See Mouw (2003: 869ff.) and Granovetter (1995: 147ff.) for reviews of earlier work. Broader reviews of the literature are provided by Voss (2007) and Ioannides & Datcher Loury (2004)

as 1992, the widespread focus on job-finding methods in the literature is surprising. Montgomery argued that the accepted job and the way in which a job seeker has heard of it are not reliable indicators of the ability of the network as a whole to transmit useful information. To better understand why this is the case, it is useful to take a closer look on Montgomery's critique (1992).

3 Montgomery's Critique

Montgomery's criticism of focusing on job-finding methods is based on a formal model of sequential job search. Sequential job search theory (see Rogerson et al. 2005 for an overview) considers searching for a job as a sequence of job search periods. In every period, a job seeker must decide whether to accept or refuse a job offer (if an offer is received).[2] A job seeker will make this decision based on his/her reservation wage, i. e. he/she will only accept a job in which the wage exceeds a certain threshold. If a job offer is not accepted, the job seeker will continue searching. There is a specific probability of receiving job offers[3] in a given search period. This probability, or the job offer arrival rate, depends on various characteristics of the job seeker, e. g. the level of human capital, or the labor market context. In this type of theoretical model, the job offer arrival rate has two important effects: First, the higher the job offer arrival rate, the shorter an unemployed individual's search duration will be. Intuitively, additional job offers in each search period raise the probability that one of these offers is above the job seeker's reservation wage. Second, and more importantly in the context of this paper, the higher the job offer arrival rate, the higher the (reservation) wage. Intuitively, the more job offers one receives, the more selective an individual can be about the corresponding wages.

Montgomery extends this search-theoretical model by introducing social networks as a job search method in addition to formal methods. In this model, networks can have an impact on a job seeker's wages via two distinct mechanisms: First, the effect of searching for a job via one's social network depends on whether it influences the job offer arrival rate; in less technical terms, this means that searching for a job via social networks influences the probability that an individual's job application will be accepted by the potential employer, irrespective of whether the job seeker takes the job or not. We can call this the *indirect mechanism* because its influence on wages is via extending the range of jobs to choose from. Second, the social network can also directly influence the level of wage offers received, also known, in more technical terms, as the wage offer distribution[4] (*direct mechanism*). This is the case if wages in jobs identified through social networks are higher than in jobs found through formal means (Franzen & Hangartner 2006: 355).

Because it focuses only on wages, this search-theoretical model seems rather restrictive at first glance. However, as Franzen and Hangartner (2006) have shown, the model can be extended to non-monetary job search outcomes as well. In addition to the wage distribution, these authors assume the existence of what they call "job adequacy distribution" and analyze non-monetary outcomes such as the educational adequacy of the newfound job.

An important aspect of Montgomery's theoretical model is that the direct and indirect mechanisms can, but need not, coincide. Researchers, however, usually will have no valid a priori knowledge of whether the mechanisms coincide: There might, for example, be an indirect effect if employers prefer to employ individuals referred to them via networks because the use of networks is a screening device to lower search costs (Fernández et al. 2000; Holzer 1987: 30f.). In addition, employers may or may not pay higher wages to those individuals recruited via networks. One reason to pay higher wages would be that employers might anticipate higher productivity from individuals with preexisting personal contacts within the firm due to peer pressure mechanisms (Delattre & Sabatier 2007: 212).

The key insight of Montgomery's model is that the standard approach of comparing wages (or other labor market outcomes) between job-finding methods can be misleading, depending on which of the above-mentioned search-theoretical mechanisms is empirically effective: the direct effect, the indirect effect, or both (Montgomery 1992: 590ff.).

In order to understand this relationship, we need to carefully distinguish between job-finding methods

[2] Mouw (2003: Appendices A and B) also shows that similar predictions can be derived from an extensive job search model in which a job seeker waits until he/she receives all job offers and then accepts the best offer.

[3] Please note that job offer means that the job seeker's application has been accepted by the potential employer, who, in turn, awaits the job seekers positive reply.

[4] In a search-theoretic model, each individual wage offer is conceptualized – from the perspective of the job seeker – as a random draw from a known wage distribution, e. g. from the normal or the log normal distribution.

Table 1 A stylized example illustrating Montgomery's critique

	Scenario 1		Scenario 2	
Source of wage offer	**Network**	**Formal**	**Network**	**Formal**
Job offer arrival rate	1	0.5	1	0.5
Individual				
A	**10.5**	–	**10**	–
B	10.5	**11**	10	**11**
C	**11.5**	–	**11**	–
D	**11.5**	10	**11**	10
E	**9.5**	–	**9**	–
F	**9.5**	8	**9**	8
G	8.5	**9**	8	**9**
H	**8.5**	–	**8**	–
Average wage offered	80/8 = 10	38/4 = 9.5	76/8 = 9.5	38/4 = 9.5
Average wage accepted (by source)	**61/6 = 10.167**	**20/2= 10**	**58/6 = 9.67**	**20/2= 10**
Average wage accepted	**81/8 = 10.125**		**78/8 = 9.75**	

Scenario 1: positive indirect effect, positive direct effect; scenario 2: positive indirect effect, no direct effect.

and job-searching methods. It is intuitively clear that a person might use any number of different search methods, but, in the end, a specific job is mostly found through a single search method. This is sometimes called the problem of "multiple methods of job search" (Mouw 2003: 870). For example, a job seeker might have searched for a new job via both his/her social network and formal search methods, but the job he/she finally accepts is one that a neighbor mentioned. Therefore, focusing on how a job was found may not be representative of the overall job search process.

Let us consider a stylized example to better understand the consequences of this distinction for interpreting results from empirical research.[5] In this example, we have job seekers A to H using multiple job search methods in the sense that everybody utilizes both social network and formal methods. We distinguish two different scenarios.[6] In both scenarios individuals profit from using their social networks in their job search. Let us assume that in scenario 1 the job search via personal contacts is effective under both the direct and the indirect mechanism. In the stylized example below, the job offer arrival rate is 1 for networks and 0.5 for formal methods (indirect mechanism). Therefore, every individual receives an offer from his/her network, but only one of every two individuals receives an additional offer based on formal search methods. In addition, the corresponding wage offers are, on average, 10 monetary units for jobs identified via networks compared to 9.5 monetary units for jobs identified via formal search methods (positive effect via direct mechanism). Individuals faced with two offers will choose the highest wage offer, irrespective of its origin.[7]

The accepted wage offer is indicated in Table 1 by bold typeface. Note that the example was construed to yield a positive causal effect based on the value added by using social networks as an (additional) search strategy: had individuals not used networks, their average wages would be 9.5 monetary units. These individuals would have accepted all job offers received via formal searching. However, because they had additional job offers available to them from the network, they received wages of, on average, 10.125. The causal effect, therefore, is positive and amounts to 0.615 monetary units. Let us now consider what researchers would con-

[5] A more formal treatment is provided by Krug (forthcoming).

[6] What we call scenario 1 here is similar to what Montgomery attributes to Lin (1982), and scenario 2 resembles what Montgomery attributes to Granovetter (1974). Originally, Montgomery's model, however, focused on comparing searches via weak vs. strong ties. Montgomery (1992:593) hints at the generalizability of this model, but Mouw (2003: Appendices A and B) extends the model to compare searches via networks vs. formal search methods. Mouw (2003) also shows that similar predictions can be derived from an extensive job search model.

[7] For the sake of simplicity, we assume that all wage offers surpass the job seeker's reservation wage.

clude by applying the standard approach of comparing accepted wages by job-finding method. Comparing the average wage of 10.167 in jobs identified via networks to 10 monetary units in other jobs, the standard approach yields a positive difference (or regression coefficient) of 0.167 monetary units. This is not the exact size of the causal effect, but it has the same sign, correctly suggesting that using networks is beneficial for job seekers.

Multiple search strategies become a problem only in what we call scenario 2. In this scenario, networks are also beneficial, albeit only via the indirect mechanism (again with an arrival rate of 1 for networks vs. 0.5 for formal search methods). However, the wage offer distribution is the same for both search methods. The causal effect is, again per construction, 9.75–9.5 = 0.25 monetary units. In this scenario, however, the standard approach yields the wrong answer. Whenever an individual receives a formal offer, he/she also receives an offer from the network (individuals B, D, F, G):

"In the period in which an offer is accepted, an individual accepting a job through a [formal method] is […] likely to have received two offers. An individual accepting a job through a [personal contact], on the other hand, is likely to have received only one offer. Because the expected highest offer increases as the number of offers rises, the use of a [personal contact] implies a lower expected wage." (Montgomery 1992: 590)

Rational job seekers will choose the job from formal sources only if the corresponding wage is higher than the alternative from the network (individuals B and G). Rational choice will result in the problem that data observed by the researcher are actually distorted (Mouw 2002: 513), potentially obscuring the beneficial effects of social networks in searching for a job (or vice versa, making networks seem more beneficial even if they are not). In the stylized example, the observed difference is 9.67–10 = –0.33 monetary units. In contrast to scenario 1, this result is misleading, not merely with regard to the size of the effect: More importantly, it suggests that using networks actually diminishes wage prospects even though individuals actually profited from using networks as a job search strategy.

To the best of our knowledge, available survey data do not contain information on wage offer and only report accepted wages (though some surveys do contain information on the number of rejected job offers). Therefore, in empirical research using the standard approach, one cannot empirically distinguish between scenarios 1 and 2. For the sake of argument, let us assume that we find a positive effect of networks. This effect could either reflect an actual positive effect, if networks are effective via the direct and the indirect mechanism or it could reflect a spurious effect that conceals a negative effect of networks. The latter would be the case if the formal channel provided more job offers, e. g. because having to rely on networks is a negative signal, as Elliott (1999) argues,[8] without improving wages. It is this problem of interpretation that sometimes makes results obtained by the standard approach counterintuitive (Montgomery 1992: 593) and often makes them ambiguous (Mouw 2003: 875).

4 Potential Solutions

If not by using the standard Granovetter-like approach, how can researchers attempt to avoid the problem of ambiguity? The first strategy might be to be as explicit as possible about one's assumptions regarding job offer arrival rates and wage offer distributions. This strategy can be found in Franzen & Hangartner's (2006) analysis of social networks and monetary as well as non-monetary labor market outcomes. Specifically acknowledging Montgomery's critique, these authors assume that most individuals use both networks and formal search methods and that job offer arrival rates are higher for network-based searches. For monetary outcomes, they assume that wage offer distributions are identical for both search methods (Franzen & Hangartner 2006: 355). In contrast, for non-monetary outcomes, it is assumed that the job adequacy distribution differs between the two search methods: compared to jobs from formal channels, on average, jobs from social networks have a higher job adequacy, and the respective distribution is skewed to the right (Franzen & Hangartner 2006: 356). This difference occurs because network contacts provide information on specific job characteristics that would be inaccessible through a formal search (e. g. about workload and colleagues) as well as better information on the preferences of the job seeker. Network contacts can filter potential vacancies with regard to the job seeker's preferences and

[8] Please note that others consider searching for a job via social networks to constitute a positive signal (Montgomery 1991). This further emphasizes our point that, a priori, we usually do not know what to expect.

the working conditions associated with the employer.[9]

Even if researchers plausibly justify their assumptions, one disadvantage of this strategy is that, because neither wage/job adequacy distribution nor the job offer arrival rate can be observed directly, the ambiguity noted by Montgomery (1992) and Mouw (2003) can be reduced but not removed entirely. One way to further reduce ambiguity would be to obtain reliable information about the presence of the direct effect (different wage distribution) and the indirect effect (higher job offer arrival rate) of networks. However, empirical evidence is scarce. For example, Holzer (1988) finds that network-based job search increases the number of job offers for unemployed youth in the US, and Van Hoye et al. (2009) find a similar result for the unemployed in Flanders, Belgium. Koning et al. (1997) present empirical evidence that wage offer distributions do not differ between formal and informal job searches in Holland. Drawing on Montgomery's (1992) model, Obukhova (2012) finds that, in urban China, searching via strong ties increases the number of job offers but not the quality of those job offers. However, these few studies do not give us sufficient grounds to make assumptions about whether the direct and/or the indirect mechanism is at work in our research context; consequently, relying on an assessment of job-finding methods to evaluate the benefits of network-based job search would be problematic.

In contrast, Mouw (2003) proposes an indirect assessment of the existence of positive network effects on wages, relying on weaker assumptions. The test follows Montgomery's reasoning to focus on the effect of network structure. In contrast to approaches focusing on the job-finding method, analyzing the effect of certain features of a person's social network yields unambiguous predictions (Montgomery 1992: 593). Mouw (2003) therefore argues that for social networks to have a causal effect on wages two conditions must hold: a specific indicator of network structure (e. g., network size) should be positively correlated with the probability that the job was found via personal contacts and, at the same time, be positively correlated with wages in this job. Although focusing on network structure is a theoretically valid strategy, there may be some practical limitations. As Mouw notes, passing this test will only be a necessary (but not sufficient) condition for inferring a causal effect from cross-sectional data (Mouw 2003: 891). In addition, there is the question of whether a specific survey item is a valid indicator of network structure. For example, Sattler & Diewald (2009) show that research results might differ depending on the number of name generators used in a survey.

For Mouw's strategy to be applicable, data obviously must contain valid information on network structure. If this is not the case, we suggest replacing the indicator for job-finding method with an indicator for the use of networks as a job *search* strategy.[10] The indicator equals 1 for all job seekers who actively used personal contacts as one of their search methods, irrespective of how the current job was ultimately found. The indicator equals 0 if, during the preceding job search, the job seeker never actively used personal contacts to collect information about vacancies, again, irrespective of how the current job was ultimately found.

With this indicator of network use, any positive effect of social capital on reservation wages (via the indirect mechanism) or on the wage offer distribution (via the direct mechanism) should be confined to the group of network users. The reason for this is that we are comparing individuals who only have wage offers from formal sources (in Table 1, on average, 9.5 monetary units under both scenarios) to individuals who combine both search strategies (10.125 in scenario 1 and 9.75 in scenario 2). In other words, we are analyzing the subgroup for which the problem of multiple job search methods does not exist. The major advantage of this strategy

[9] In their empirical analysis, Franzen & Hangartner (2006) focus on university graduates. Regarding effects on non-monetary outcomes, these authors find positive effects on several indicators of job adequacy, which they see as an indication of a positive effect of networks on non-monetary outcomes. For monetary outcomes, their results indicate that jobs found through social networks pay, on average, approximately 5 % less than jobs found by other means. According to our interpretation of Montgomery's model, this model, the negative difference – in combination with Franzen & Hangartner's assumptions – can be seen as an indication of a positive effect of searching via social networks. In contrast, even if these authors do interpret the negative difference to be in line with Montgomery's model (Franzen & Hangartner 2006: 363), they also state that "searching via social contacts has no monetary advantage" (Franzen & Hangartner 2006: 361).

[10] Even if this idea seems straightforward it has, to the best of our knowledge, not been systematically employed as a solution to the problem of ambiguity of job-finding methods. In addition, one might consider this indicator to be a more valid operationalization of network usage than the narrow focus on how jobs are found, irrespective of our search-theoretical reasoning.

is that the result is unambiguous under both scenario 1 and scenario 2 in the sense that a positive difference always corresponds to a positive effect of social networks.

Of course, our test also has limitations. A first and obvious limitation is that to conduct such an analysis, the number of persons who do not use personal contacts in job searches must be sufficiently large. Second, those who do not use networks to collect job information might be a selective group. Assuming instrumental rationality, we would expect individuals with somewhat less helpful social networks to refrain from using their personal contacts. In this case, the difference in labor market outcomes could be positively biased because the comparison is not as intended (using vs. not using networks) but a comparison of using helpful networks vs. using none at all. Third, a downward bias is possible if individuals resort to social networks as a job search strategy only after other search strategies have proven unsuccessful. However, on one hand, given that networks are among the cheaper search methods, it is unlikely that job seekers use costly means first and only then resort to the cheaper alternative.[11] On the other hand, controlling for job search duration should reduce the problem – if it indeed exists.

What makes our approach a useful complement to Mouw's (2003) solution is that it does not depend on the researcher finding the right indicator for those aspects of network structure that are relevant for job seekers. Our approach will capture the effect of social networks on labor market outcomes even in the absence of any network information. That is not to say that such information is unnecessary; it only means that the validity of our analysis does not depend on it. What we can conclude from our analysis, however, does. Therefore, we try to at least survey the literature to get an idea of what the social networks among individuals in our own empirical sample might look like.

5 Population of Interest and Hypotheses

In this paper, we focus on the low-status unemployed. To be specific, we focus on those who have either been unemployed over the long term before finding a new job or those who lack formal qualifications (the so-called low-skilled unemployed). One reason for our interest in this population is that most research on social networks and job quality focuses on high-status individuals (e. g., Franzen & Hangartner 2006), the unemployed in general (Delattre & Sabatier 2007) or currently employed individuals (Chua 2011). However, the low-status unemployed face more difficulties in finding a job and generally have lower earning prospects than the average job seeker. As is argued by Vishwanath (1989), employers tend to interpret long-term unemployment as a signal of low productivity. Similarly, Oberholzer-Gee (2008) argues that due to this stigma the long-term unemployed (and, in a similar way, the low-skilled unemployed) have to lower their reservation wage in order to get a job. Given such difficulties, using networks as a means of searching for a job might be helpful to overcome such stigmatization. For example, being recommended by somebody within the firm might send a positive signal that counterbalances the negative stigma of long-term unemployment (Montgomery 1991).

However, in contrast to the potential usefulness of networks, unemployed job seekers might suffer from less effective networks. The literature often reports that the long-term unemployed experience a change in the composition of their networks as ties to former colleagues fade (Calvó-Armengol & Jackson 2004). Lindsay (2009) reports that job seekers in long-term unemployment are indeed less likely than other unemployed job seekers to use work-related social contacts. However, searching for a job via friends and family remains virtually constant. Therefore, the long-term unemployed experience a shift from weak to strong ties, i. e. to family ties (Sattler & Diewald 2010; Diewald 2007). The literature demonstrates that employed contacts (Cingano & Rosolia 2012) and weak ties (Granovetter 1974) are much more effective in providing information about vacancies; thus, this change in network composition is clearly a disadvantage. As for the low-skilled unemployed, they might not experience this shift toward less effective networks (assuming that they are not also long-term unemployed), but their networks tend to be less effective to begin with. Due to homophily, their networks will mainly consist of individuals who are also low skilled, whereas the literature indicates that it is high-status contacts that are most useful in a job search (Lin 1999).

Despite the disadvantages that the low-status unemployed might face with regard to their network composition, we have no reason a priori to regard those networks as useless. Even if they are not as effective as the networks of other labor market par-

[11] According to Lindsay (2009: 29), the propensity to use social networks as a search strategy is rather stable over time with regard to family and friends, and it decreases with regard to work-related contacts.

ticipants, the networks of disadvantaged job seekers might still outperform the job search via formal methods. For example, Brandt (2006) shows that for unemployed members of low-income households the number of strong ties influences the likelihood of ending unemployment. In addition, from a firm's perspective, Holzer (1996) reports that firms tend to prefer networks as recruiting methods for jobs that require no or only low formal qualifications (cf. Klinger & Rebien 2009). However, the question is not only whether the low-status unemployed find jobs with the help of their network. We consider it of equal importance to analyze the effect of network-based job search on the quality of obtained jobs. Empirical evidence in this regard is scarce, as we have seen above (2.). None of the recent studies focused on unemployed subjects with potentially low employment prospects.[12] In light of our assumption that even weak networks can be stronger than formal job-searching methods, we present the following two hypotheses.

Hypothesis 1: ***Network-based job search has positive effects on job seekers' monetary labor market outcomes***

Hypothesis 2: ***Network-based job search has positive effects on job seekers' non-monetary labor market outcomes***

The next section will discuss the empirical data and methodology used to test these hypotheses.

6 Data and Methods

6.1 Data

In many population surveys, the number of low-status unemployed job seekers is small. This is particularly true for the subset of low-status unemployed who successfully re-enter employment. In the following analysis, we use survey data that were originally collected to evaluate the success of a pilot project investigating in-work benefits in Germany (Krug 2009a, 2009b). This survey focuses specifically on low-skilled or long-term unemployed workers who re-entered employment. Interviews were conducted with formerly unemployed persons who started work with or without in-work benefits between January 2001 and August 2002 (regional pilot project phase) and between September 2002 and March 2003 (nationwide implementation). For our analysis, we focus on the subsample of approximately 1,100 low-skilled and/or long-term unemployed individuals.

Another advantage of this survey is that it contains a variety of information on the persons re-entering employment, ranging from objective data on socio-demographic characteristics, employment history, household context, and individual and household income, to subjective information on attitudes about life and employment as well as job satisfaction. The survey includes extensive information on job search behavior during unemployment and information on how the accepted job was found; it includes the question "How did you find your job?" which can be used to construct an indicator for job finding via social networks. The indicator equals 1 for those who responded "Via acquaintances, neighbors, friends, relatives" and 0 for other search methods. However, as we have argued above, this indicator will not be sufficient to identify the causal effect of networks unambiguously. Therefore, we also construct an indicator for job search via social networks based on the survey question "What did you do during your time of unemployment to get a job?". The value is 1 for those who reported having, among other methods, "asked acquaintances and relatives".[13]

As for labor market outcomes, because of the wide range of information, we can address several aspects of the monetary and non-monetary outcomes of searching for a job and distinguish between objective and subjective indicators. As objective indicators for monetary outcomes, we used the respondents' monthly and hourly wages in Euros. Because the interviews were conducted early after leaving unemployment, the wages can be regarded as starting wages. Monthly wages will reflect

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[12] The only study that we know of that focuses on the labor market outcomes of the low-status unemployed was conducted by Elliot (1999). He argues that the low-status unemployed are not so much isolated from using social contacts in searching for a job but, rather, are excluded from using formal means. He also finds that, in contrast to formal means, finding a job via strong ties leads to lower wages. However, because this result is also subject to Montgomery's critique, it should be considered with caution.

[13] Approximately 25 % of the survey participants reported having found their jobs via social contacts, and 83 % reported having, at one time or another, asked someone in their social network about a job. These findings are similar to the findings of Noll and Weick (2002), who report 31 % for job-finding and 74 for job-searching via social networks in a representative sample of all employed individuals in Germany in 1996. Brandt (2006) reports 29 % job-finding via social contacts among low-income respondents in 2002.

whether a job is only part-time, whereas hourly wages will indicate productivity in the new job. As a subjective indicator, we used the question "How satisfied have you been with your earnings?" and measured the responses on a four-point scale that we dichotomized to "not satisfied" and "satisfied." To analyze the effect of the networks on non-monetary outcomes, we used questions on general job satisfaction and task satisfaction as subjective indicators (again dichotomized to "not satisfied" and "satisfied"). For a more objective indicator, we used information on whether the employment contract was fixed-term or permanent.

6.2 The Matching Estimator for Causal Effects

We use propensity score matching (PSM) to estimate the effects of a job search through social networks. For the following analysis, let *net* be a dummy treatment indicator with $net = 1$ for network-based job search and $net = 0$ for a job search based on other, formal means. Furthermore, let *lmo* be a variable representing monetary or non-monetary labor market outcomes in the new job. Following Rubin's Causal Model (RCM, see Rubin 1974; Holland 1986), two potential versions of the outcome variable have to be distinguished, depending on the job search strategy:

$$lmo = \begin{cases} lmo^0, \textit{ if } net = 0 \\ lmo^1, \textit{ if } net = 1 \end{cases} \tag{1}$$

Within this framework, one important causal effect is the average treatment effect on the treated (ATT):

$$\delta = E(lmo^1 \mid net = 1) - E(lmo^0 \mid net = 1) \tag{2}$$

Equation 2 compares the expected outcome in treatment status (network-based job search) for those who received the treatment with the so-called counterfactual, which is the expected outcome that the same persons would have experienced if they had not received the treatment (job search based on formal means). Outcome variables can be continuous (i. e., hourly wages), or they can be binary (i. e., job satisfaction). Assuming conditional mean independence (i. e. no unobserved confounders), the counterfactual expectation in Equation 2 can be replaced by a factual expectation of the job search outcomes for persons using formal methods, given covariates $\mathbf{x}$ (Holland 1986):

$$\delta = E_{\mathbf{x}}\Big(E(lmo^1 \mid net = 1,\mathbf{x}) - E(lmo^0 \mid net = 0,\mathbf{x})\Big) \tag{3}$$

A nonparametric estimator for the causal effect is the propensity score matching estimator (Rosenbaum & Rubin 1983, 1985; Heckman et al. 1998; Morgan & Harding, 2006), which estimates the ATT by matching persons with network-based job search to persons without network-based job search but with identical vectors of pre-treatment covariates $\mathbf{x}$, or, more precisely, the same propensity score $P(\mathbf{x})$[14].

The matching estimator is given by a weighted difference in means, with I_1 and I_0 indicating persons using network-based job search or not, respectively, and *CS* denoting the region of common support in the propensity score distributions of both groups:

$$\hat{\delta} = \frac{1}{n_1} \sum_{i \in I_1 \cap CS} lmo_i^1 - \frac{1}{n_1} \sum_{i \in I_1 \cap CS} \sum_{j \in I_0 \cap CS} w(i, j) lmo_j^0 \tag{4}$$

The number of individuals using network-based job search within the region of common support is n_1, and $w(i,j)$ is the weight given to observation j when matched to observation i. Depending on the choice of $w(i,j)$, different versions of the matching estimators can be constructed. We use single-nearest neighbor matching (SNNM) without replacement, i. e., observation j is chosen as a match for observation i when j is closest to i in terms of the absolute distance of propensity scores $\mid P(\mathbf{x}_i) - P(\mathbf{x}_j) \mid$. This algorithm is chosen because the sensitivity analysis (see below) is only possible when using SNNM.

To avoid any matches for which $P(\mathbf{x}_j)$ is both the nearest neighbor and very far from $P(\mathbf{x}_i)$, a maximum level of acceptable distance (caliper) has to be set.

Because the covariates are balanced nonparametrically, a weighted difference in means indicates the causal effect of networks on job search outcomes that are measured as dummy or continuous variables.

Note that the problem of unobserved heterogeneity arises if one or more influential variables cannot be included in the vector of the covariates $\mathbf{x}$. For example, an unobserved variable such as ability might influence wages and is simultaneously correlated with the chances of finding a job through networks. This correlation could be due to homophily (McPherson et al. 2001) if high-ability job seekers have a network consisting of high-ability persons who, in turn, refer them to higher-wage jobs. If longitudinal data are available, such unobserved fixed confounders can be taken into account by applying a panel fixed-effect estimator (e. g. Mouw 2006). Because only cross-sectional data are available to us, we perform a sensitivity analysis based on pro-

[14] Because of this, Equation (3) can also be written as $\delta = E_{P(\mathbf{x})}\Big(E(lmo^1 \mid net = 1,P(\mathbf{x})) - E(lmo^0 \mid net = 0,P(\mathbf{x}))\Big)$.

pensity score matching. Although a PSM on cross-sectional data cannot directly control for unobserved heterogeneity, it allows us to perform a sensitivity analysis to determine how strong the influence of any unobserved variables must be to cast doubt on the causal interpretation of network effects. The sensitivity analysis assumes that there is a relevant, unobserved confounder u that should have been included in the estimation of the propensity score (e. g., $u = 1$ for high-ability persons; $u = 0$ for low-ability persons):

$$P(x_i) = P(net = 1 \mid \mathbf{x}_i, u_i) = \left(1 + \exp-(\mathbf{x}_i'\boldsymbol{\beta} + \eta\, u_i)\right)^{-1} \quad (5)$$

Using a method developed by Rosenbaum (2002), we can vary the influence of this hypothetical variable (represented by the odds ratio (OR) e^{η}, where η is the respective coefficient) and determine whether any estimated effects are still significant. This test is a "worst-case scenario" (DiPrete & Gangl 2004: 15) because first, an unobserved relevant confounder u may not really exist, and second, the test assumes that the unobserved confounder leads to better job outcomes for every matched pair. However, the sensitivity test provides a good idea of how robust the results are with respect to any unobserved heterogeneity.

7 Empirical Analyses

As we have noted above, using the job-finding method as an indicator of network-based job search might lead to ambiguous results. Nevertheless, to illustrate this point, we first conduct the empirical analysis based on the standard approach, i. e., *net* = 1 if the accepted job was found with the help of one's network, and *net* = 0 if the job was found through other search channels.

Second, we will contrast these results with an analysis that will, as we have argued above, provide us with a more reliable estimate of the effect of network-based job searches. This analysis is based on job-searching method (*net* = 1 for job seekers who use networks as one of their search strategies, and *net* = 0 for job seekers who do not) rather than on the job-finding method.

In the following section, we will address the observed covariates that were used to estimate the propensity score and discuss whether matching was successful in terms of eliminating the influence of these covariates.

7.1 Estimating the Propensity Score

To ensure conditional independence, the logistic regression to estimate the propensity score must include all relevant covariates. Similar to regression analysis, we must focus only on those factors that are simultaneously correlated with the probability of network-based job search and with respective monetary or non-monetary labor market outcomes. Factors that exclusively influence labor market outcomes are not necessary to ensure unbiased estimation, but they can enhance the precision of the estimates. Additionally, factors that are only weakly correlated with either the treatment or the outcome should be excluded because they have limited use in reducing bias and can inflate the variance of the estimator (Imbens 2004).

To control for all necessary covariates, we identify three types of factors that are potentially important for finding a job through networks and labor market outcomes. First, we control for differences in job search behavior between the two groups; second, we take into account homophily in social network development (McPherson et al. 2001); third, we control for factors that influence an individual's degree of access to social capital (Boisjoly et al. 1995). The online appendix to this paper provides a more detailed discussion of the variables (free download at: www.zfs-online.org); Table A1 and A3 report the logistic regression to predict the propensity score for the case of job-finding method and job-search method, respectively, as well as multivariate tests of the matching quality; Table A2 and A4 provide results for bivariate balancing tests regarding the covariates.

Here, we focus on the case of job-finding method, but the same procedure was followed for the method of job search. We start with the logistic regression using all of the available covariates. In Table A1, Model 1, there are only a few covariates with significant effects on obtaining a job through networks (c.f., Lin 1999: 472, Fn2). Among all covariates, only job search behavior has a significant effect on whether an accepted job was found through networks. Intuitively, the more search methods one uses, the less likely it is that the accepted job will be found through networks. Additionally, whether one actively uses networks as a search method has a high influence on whether the accepted job was found through networks. This statement is not tautological because there are also persons who did not search actively through networks but still obtained a job referred to them by persons from their network. Other search channels do not influence the chances of obtaining a job through networks, except for "waiting for job offers from the employment agency". Model 2 restricts the covariates to those with a p-value lower than 0.6 because, similar to regression analysis, many irrelevant variables only inflate the standard errors of the matching estimator. A likelihood ratio test that compares Models 1 and 2 shows that the eliminated variables make no significant contribution to the model fit. The estimation of the propensity score is therefore based on Model 2.

Models 3 and 4 perform a simple multivariate test to determine whether matching eliminated the influence of the covariates. The test re-estimates Models 1 and 2 after the propensity score matching. As observed in Model 3, all formerly significant covariates become insignificant. Additionally, Model 4 ensures that, in the matched sample, the formerly irrelevant variables remain irrelevant. A more detailed analysis of the influence of covariates before and after matching can be found in Table A2. In Table A2, we show that, after matching persons in jobs found through networks and jobs found through regular methods, there are no significant bivariate differences in the means for any of the covariates used in the matching procedure.

In the case of job-search method (Table A3 and A4), the matching also sufficiently balances the covariates. Even if the bivariate tests sometimes result in a standardized bias larger than 5, none of the differences in means is statistically significant. Having established the quality of our matching procedure, we can use the matched sample to estimate the causal effect of the networks on labor market outcomes.

7.2 The Causal Effect of Networks on Labor Market Outcomes

Table 2 reports the results from SNNM without replacement and a very strict caliper of 0.005 for the standard approach, i. e. the job-finding method. First, let us consider the unadjusted differences in average job outcomes between persons in jobs found via networks and those in other jobs. Persons who found jobs through networks appear to have, on average, better job outcomes.

Because the differences are measured before controlling for any covariates, that is, without considering differences in the composition of the job seekers, they are what a "naïve" observer might see when comparing network jobs to other jobs. We see that jobs found through networks tend to be characterized by a monthly wage of approximately 100 Euros more than other jobs; hourly wages are, on average, approximately 80 Eurocents higher. This difference in wages reflects the common wisdom of beneficial networks. However, this finding is not complemented by a difference in wage satisfaction, which is approximately 5 percent but not statistically significant.

Assuming that the conditional independence assumption holds, the matching procedure eliminates all compositional differences between job seekers ending up in "network jobs" vs. those in other jobs. Differences in the means after matching can therefore usually be interpreted as causal effects. However, as has been argued above, the results are inherently ambiguous. Let us discuss the results in more detail.

Table 2 Job-finding via social networks and labor market outcomes

	Before matching			After matching		
	Difference in means	**Standard error**	**Number of treated / controls**	**Difference in means**	**Standard error**	**Number of treated / controls**
Hypothesis 1: Monetary outcome						
Monthly gross wages (euro)	99.925**	43.619	216 / 654	23.220	54.484	195 / 195
Hourly gross wages (euro)	0.782*	0.442	215 / 652	0.738	0.722	194 / 194
Satisfied with wage (Dummy, 1 if yes)	0.053	0.034	285 / 834	0.008	0.044	262 / 262
Hypothesis 2: Non-monetary outcomes						
Satisfied with job (Dummy, 1 if yes)	0.077***	0.027	285 / 834	0.065**	0.032	262 / 262
Satisfied with task (Dummy, 1 if yes)	0.046*	0.028	285 / 834	0.023	0.033	262 / 262
Permanent contract (Dummy, 1 if yes)	0.159*	0.092	285 / 834	0.198*	0.109	262 / 262

Single nearest neighbor matching, no replacement, caliper 0.005; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; propensity score matching performed in Stata using psmatch2 (Leuven & Sianesi 2003).

Table 3 Job-search via social networks and labor market outcomes

	Before matching			After matching		
	Difference in means	Standard error	Number of treated / controls	Difference in means	Standard error	Number of treated / controls
Hypothesis 1: Monetary outcome						
Monthly gross wages (Euro)	–99.925**	50.563	716 / 146	–37.213	71.297	137 / 137
Hourly gross wages (Euro)	0.082	0.513	713 / 146	–0.002	0.457	137 / 137
Satisfied with wage (Dummy, 1 if yes)	0.028	0.040	924 / 183	0.065	0.054	169 / 169
Hypothesis 2: Non-monetary outcomes						
Satisfied with job (Dummy, 1 if yes)	–0.022	0.032	924 / 183	0.012	0.042	169 / 169
Satisfied with task (Dummy, 1 if yes)	–0.022	0.033	924 / 183	0.006	0.042	169 / 169
Permanent contract (Dummy, 1 if yes)	0.046	0.109	924 / 183	0.071	0.142	169 / 169

Single nearest neighbor matching, no replacement, caliper 0.01; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; propensity score matching performed in Stata using psmatch2 (Leuven & Sianesi 2003).

From Table 2, we can see that the point estimates for monthly wages become smaller and statistically insignificant after matching. This is the case for monthly wages but not so much for hourly wages for which the point estimate remains virtually unchanged. This positive difference for hourly wages – even if it is not significant[15] – may indicate a positive causal effect of using networks if we are willing to assume that both the direct and indirect mechanisms are at work in our research population. However, the results are also in line with a situation in which formal search leads to more job offers but wages remain unaffected. Because all our survey participants were registered unemployed and eligible for placement services by the local employment agency, this situation is possible[16], albeit not very likely.

With regard to non-monetary outcomes, the situation is quite similar. Before matching, persons who located their jobs through networks tended to be more satisfied with their jobs and their specific job tasks. Additionally, persons who obtained their jobs through networks were significantly more likely to be employed with a permanent contract, with a difference of approximately 16 percent.

In contrast to monetary outcomes, effects on non-monetary outcomes remain partly significant even after controlling for observed covariates. The share of employees who are satisfied with their job is 6.5 percent higher in network jobs than in regular jobs. However, persons in network jobs are not more likely to be satisfied with the specific tasks in their jobs. Additionally, there is a significant positive effect of 20 percent on the likelihood of locating a job with a permanent contract. The problem here is the same as with the effect on wages: without accurate knowledge about the efficacy of the indirect and direct mechanisms, the positive differences might or might not reflect causal effects.

To alleviate these problems of ambiguity, we now conduct propensity score matching with a different treatment indicator, i. e. the job-searching method. In this case, the control group consists of persons who used any search strategy other than networks. Because of the small number of individuals in the control group, we had to broaden the caliper to 0.01 for single nearest neighbor matching without replacement.

The first and most striking difference compared to the results based on job-finding method is that, after matching, the point estimates are mostly close to zero (Table 3). For monetary outcomes, this result indicates that using networks as a job search strategy does not seem to lead to higher reservation wages, at least not among the low-skilled unemployed. The reason for this result may either be that networks do not increase the number of job offers for this population or that the number of job offers, contrary to job search theory, do not influence reservation wages. In either case, this null effect leads

[15] Interpreting results based on statistical significance without taking the size of point estimates into account has increasingly been criticized by statisticians (cf. Krämer 2011: 456). We therefore chose to take a more differentiated stand and not automatically disregard statistically insignificant but large coefficients.

[16] Cf. Pellizzari (2010) who argues that the strength of social networks derives from the weakness of local unemployment agencies.

us to conclude that the results from Table 2 were spurious correlations.

In addition to these effects on monetary outcomes, we also present the effects of a job search through networks on non-monetary outcomes in Table 3. There are no effects of network-based job search on job satisfaction or task satisfaction. Point estimates are close to zero. For permanent employment contracts, there is a positive but highly insignificant effect of 7 percentage points. This finding may indicate that network-based job search leads to better matches. This interpretation would be in line with results from Franzen & Hangartner (2006), who find higher job adequacy among individuals who relied on networks to find a job. Because the results for permanent employment contracts are statistically insignificant, these potentially positive effects of network-based job search should be interpreted with some caution.

All in all the results for non-monetary outcomes are similar to those for monetary outcomes. There are no causal effects of social networks on non-monetary outcomes either, and results obtained from the standard approach were indeed partly misleading.

7.3 Robustness With Regard to Unobserved Heterogeneity

In addition to the theoretical argument for rejecting the analysis based on job-finding method, Mouw (2003) also notes the problem of unobserved heterogeneity, especially in cross-sectional data. Setting aside Montgomery's critique for the moment, let us first consider the situation in which we have no unobserved influences. In this case, the positive correlation that we found after controlling for observed differences with propensity score matching (Table 2) can be interpreted as a causal effect of using networks on the corresponding outcome variable, e. g. wages or job satisfaction. However, with an unobserved variable such as ability or personality this correlation might be spurious. The conditions for this spuriousness are that ability (personality) has to have an influence on wages (or job satisfaction, etc.) and that it is either directly related to the chances of finding a job via networks or correlated with the characteristics of a person's network which in turn influence the probability of finding a job via networks. Like most surveys, our survey contains no such information on actual ability or personality. We therefore cannot control for such potentially important factors directly.

However, as we have shown in the methodological section, we can perform a sensitivity analysis with regard to the influence of unobserved confounders. To do so, we simulate an unobserved variable and vary its influence on obtaining a network or a regular job. We start with the job-finding method analysis. Results are shown in Table 4: The second column repeats the difference in means after matching from Table 2; moving from left to right, we first simulate a situation with no unobserved heterogeneity, which provides the results already reported in

Table 4 Job finding via social networks: robustness with regard to unobserved heterogeneity

		P-values for the causal effect, assuming …			
	Difference in means	**… no unobserved heterogeneity**	**… a low level (OR=1.1) of unobserved heterogeneity**	**… a medium level (OR=1.2) of unobserved heterogeneity**	**… a high level (OR=1.3) of unobserved heterogeneity**
Hypothesis 1: Monetary outcome					
Monthly gross wages (euro)	23.22	0.405	0.631	0.806	0.911
Hourly gross wages (euro)	0.738	0.219	0.421	0.627	0.790
Satisfied with wage (Dummy, 1 if yes)	0.008	0.465	0.389	0.217	0.108
Hypothesis 2: Non-monetary outcomes					
Satisfied with job (Dummy, 1 if yes)	0.065	0.030	0.070	0.134	0.221
Satisfied with task (Dummy, 1 if yes)	0.023	0.281	0.433	0.510	0.375
Permanent contract (Dummy, 1 if yes)	0.198	0.046	0.126	0.256	0.418

Single nearest neighbor matching, no replacement, calliper 0.005; p-values calculated in Stata using rbounds (Gangl 2004) for continuous outcomes and mhbounds (Becker & Calliendo 2006) for dichotomous outcomes.

Table 2, where there are positive but not significant effects on monetary outcomes and significant positive effects on job satisfaction and permanent contracts[17].

Next, we assume that we have unobserved heterogeneity of former job seekers in network and regular jobs (reflected by variable *u* in Equation 5). This unobserved heterogeneity can result from unobserved abilities that influence wages or from whether employers only offer a fixed-term contract. The heterogeneity might also result from personal characteristics that influence job satisfaction. If we assume that such a characteristic has only a small influence on whether job seekers end up in a job found via networks (OR=1.1), we find that the p-values for the effect on wages become even larger. As far as the non-monetary outcomes are concerned, the effect on job satisfaction would still be significant, with a p-value of 0.07, whereas the effect on fixed-term contracts, even if initially quite large, becomes insignificant. Under the assumption of a medium influence (OR = 1.2) of the unobserved variable *u*, the effect on job satisfaction becomes insignificant as well. The observed differences might therefore reflect causal effects; if, however, there is an important unobserved variable with only a small or medium influence, these differences must be regarded as spurious and not causal. Of course, our sensitivity analysis does not inform us as to whether such an important variable exists.

Because the positive effects of networks are rather sensitive to the influence of unobserved heterogeneity, the ambiguity induced by the problem of multiple job search methods is aggravated by an uncertainty of robustness with respect to such heterogeneity. In addition to delivering theoretically unambiguous results, the focus of our analysis on searching rather than on finding also has a distinct advantage with respect to the problem of unobserved heterogeneity. This advantage may not hold in general, but, at least in our case in which findings indicate null effects of social networks we have good reason to accept these results as causal. As we have established above, it is possible that those who use their network in searching for a job simply have a better network than those who do not utilize their contacts. If this were the case, results would be biased upward in the sense that the true effect would be overestimated. Faced with point estimates close to zero, an overestimation could only be the case if the actual effect of networks were negative and the positive bias had just the right size to suppress this negative effect. It is very unlikely that such a suppression effect would occur simultaneously across so many different outcome variables. In addition, such a suppression effect is substantially implausible: Because we are comparing job search via formal means to job search via both formal means and personal contacts, it is implausible that *additional* job offers could *reduce* the quality of accepted jobs. This is true even if those offers were drawn from an inferior wage distribution. Therefore, we argue that the results presented in Table 3 are very likely to indicate an accurate estimate of causal effects or, rather, of their absence.

8 Conclusions

Even decades after Granovetter's original analysis of the benefits of social networks in finding good jobs, the literature is still characterized by mixed evidence. Whereas some results seem to support Granovetter (1974) and report positive effects, others findings indicate negative effects or no effect at all. The conclusions that we draw from the preceding analysis are threefold:

First, our results indicate that the low-status unemployed in Germany experience no significant benefit from network-based job search with regard to either monetary outcomes (wages, wage satisfaction) or non-monetary outcomes (job/task satisfaction, permanent contract). Of course, we cannot say whether the low-status unemployed do profit in other regards, perhaps most notably with regard to shorter unemployment duration, as results in Brandt (2006) indicate. It is also unclear whether our results can be generalized to other labor market groups (cf. Franzen & Hangartner 2006) or other institutional settings (cf. Pellizzari 2010).

Second, our results indicate the importance to take Montgomery's (1992) critique into account. From the perspective of Montgomery's search-theoretical model, we showed that using the standard approach would have resulted in falsely assuming positive effects of network-based job search. This result is similar to Mouw's, who argues "that the best way to make sense of […] the apparent discrepancy between [different studies] is to consider Montgomery's (1992) sequential search model". Mouw (2003: 891) concludes that "intuition and anecdote aside, we have little empirical evidence showing that contacts matter".

Third, we showed that even if one considers the method of finding a job an adequate indicator for

[17] Please note that due to the use of a different test statistic, p-values differ slightly between Tables 2 and 4.

network-based job search, it is important to take into account unobserved heterogeneity. All positive effects of networks obtained via the standard approach were not sufficiently robust. In most cases small and medium sized influences of unobserved covariates were shown to be sufficient to explain higher job satisfaction and higher proportions of permanent employment contracts in jobs found via networks.

Taken together, our results lead us to believe that it is quite possible for at least some of the results presented in our initial review of recent studies to be misleading. Even if we are not the first to have stated this problem (cf. Montgomery 1992; Mouw 2003), we consider it an important point deserving of sustained attention. Whereas the problem of unobserved heterogeneity is taken into account more and more often, none of the above papers seems to have made any attempt to refute Montgomery's or Mouw's theory-based criticism.[18] In fact, the matter appears to be entirely ignored. By drawing attention to the problem and by providing an additional and easily implemented way to circumvent it, we hope to encourage future research to take the problem more seriously.

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[18] Chua (2011) is the only exception but see Krug (forthcoming) for a critical discussion of the paper.

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