With a Little Help from My Friends?
Quality of Social Networks, Job Finding Rates and Job Match Quality[§]

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Abstract

This paper proposes a novel approach in estimating social network effects in the labor market using a direct measure of network quality based on the employment status of close friends. Using various identification strategies, we provide robust evidence that a higher number of employed friends increases job finding rates. We also find that better network quality has a matching effect for high-skilled workers and a mismatching effect for low-skilled workers. These findings shed light on the existing mixed evidence of network effects on labor market outcomes, highlighting heterogeneity by skill level and the importance of controlling for selection into employment.

Keywords: Social Contacts, Unemployment, Friendship Ties, Wages, Employment Stability

JEL: J64, J63, J21, J31, L14

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1. Introduction

Search in the labor market involves the acquisition of information by both employers and workers. Informal contacts through social networks have long been considered an important source of information in the job search process. Survey evidence gathered across countries and over time has consistently indicated that between one third and one half of job matches are created through friends and relatives.[1] By transmitting information, social contacts can help resolve the uncertainty about unobserved attributes for both sides of the market. Based on the belief that people tend to refer others who are similar to themselves, referrals through current employees can be used by firms as a screening device for the unobserved worker quality (Saloner, 1985; Montgomery, 1991; Galenianos, 2012), or can inform workers and firms about the quality of the match (Simon and Warner 1992; Mortensen and Vishwanath, 1994; Dustmann et al., 2011; Brown et al., 2012).[2] In both cases, by resolving the uncertainty in the matching process, referrals through social networks can be associated with better job matches through higher wages and lower job separations.

In this paper, we propose a novel approach in estimating social network effects in the labor market using longitudinal information on friendship ties and individual labor market outcomes from the British Household Panel Survey (BHPS). We construct a measure of network quality based on the employment status of the respondents' three closest friends and we examine its effects on job finding rates and job match quality. The proposed measure of network quality is related to a number of recent theoretical studies which model explicitly the structure of the network and consider the employment status of network members as the key ingredient for understanding the effectiveness of social contacts as a job search channel (e.g. Calvó-Armengol, 2004; Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009; Galeotti and Merlino, 2010). The main insight from this literature is that a higher employment rate within the network of social contacts increases the chances of a successful

[1] See Ioannides and Loury (2004) and Topa (2011) for extensive surveys of the existing literature.

[2] Saloner (1985) develops a model of screening using referees who compete with each other. The analysis of Montgomery (1991) is based on a model of adverse selection, while Galenianos (2012) develops an equilibrium search model. Mortensen and Vishwanath (1994), Fontaine (2007) and Cahuc and Fontaine (2009) also consider the role of social networks using an equilibrium search model. Simon and Warner (1992), Dustmann et al. (2011) and Brown et al. (2012) consider referrals as providing a productivity signal in a model of job matching and turnover and derive the implications for wages and job turnover.

job match for non-employed network members through the transmission of information about job opportunities. This generates a positive correlation between the employment rate in the network and the job finding rate of non-employed network members.[3]

There are two main objectives of the paper. The first is to estimate the effect of network quality on the transition from non-employment to employment. The second is to estimate the effect of network quality on job match quality (measured through wages and employment stability) among those who find a job, taking into account selection into employment. To our knowledge, this is the first study on the effect of friendship ties on labor market outcomes using longitudinal data, which addresses selection issues and offers direct empirical evidence to the recent theoretical literature emphasizing the importance of the employment rate within the network of social contacts.[4]

Previous empirical research on network effects is based either on survey information on the usage of informal search methods, such as friends and relatives, or on administrative records in which networks are defined indirectly using observable proxies, such as neighborhood, firm, or ethnicity. The approach proposed in this paper combines elements from these two strands of the literature for the definition of the relevant network and the measure of network quality.

Similar to studies based on survey data on the usage of friends and relatives as a search method, the relevant network is defined directly using friendship ties and not through the use of network proxies.[5] As noted by Topa (2011), one limitation of studies using surveys on the usage of informal channels is that the analysis is based on those who are already employed, which can be a selected group among those who are searching for a job. In addition, workers who report that they found their current job through friends and relatives are those who accepted the job opportunity offered through their informal contacts and may rejected other possible offers arriving from formal search channels (Montgomery, 1992). By

[3] See Jackson (2011) and Zenou (2012) for recent reviews of networks including labor markets.

[4] Positive correlations between friends' employment and unemployment exits in the BHPS have been reported by Hannan (1999).

[5] Holzer (1988) shows that there is a positive link between having more employed friends and searching for a job through friends; more employed friends lower the cost of using friends and relatives as a search method, which leads to a higher use of this search method.

modeling the transition into employment, we are able to take into account selection due to unobservables when estimating the effect of network quality on job match quality among those who find a job. This is important because focusing on the effect of network quality on labor market outcomes only for the sample of those employed might lead to biased estimates due to unobserved heterogeneity, which can vary by labor market status. The existing evidence for the effect of having found a job through friends and relatives on wages is mixed, with some studies finding positive effects (e.g. Simon and Warmer, 1992; Marmaros and Sacerdote, 2002; Loury, 2006), while others finding negative effects (e.g. Pistaferri, 1999; Bentolila et al., 2010, Goel and Lang, 2012), or both (Pellizzari, 2010).

Similar to studies using network proxies to define the relevant network, we observe the quality of the network through the employment rate of social contacts. As discussed above, theoretically this is considered to be the central measure of network effectiveness. Studies in this literature include Topa (2001), Weinberg et al. (2004), Bayer et al. (2008), Hellerstein et al. (2011) and Schmutte (2010), who use geographic proximity at the neighborhood level; Cingano and Rosolia (2012), who define networks at the firm level; Edin et al. (2003), Munshi (2003) and Beaman (2012), who define networks based on immigrants' ethnic origin; and Dustmann et al. (2011), who use information on both firms and ethnicity. Differently from these studies, we do not assume that agents are connected within the boundaries of the network proxy; rather, we directly observe network linkages through friendship ties.[6]

Identifying network effects on labor market outcomes can be challenging due to correlated effects that are induced by non-random selection into networks and the presence of common shocks.[7] We address the potential endogeneity of network quality by using three

[6] Kramarz and Nordström Skans (2011) investigate the role of fathers on the employment and earnings of their children, where the network defined at the family level is also directly observed. Wahba and Zenou (2005) consider the effect of network quality, which they proxy with the local unemployment rate or the number of family members in the labor force, on the probability of using friends and relatives for those employed but they do not consider labor market outcomes.

[7] Manski (1993) discusses these two issues in the context of social interactions (i.e. the effect of average group behavior on individual behavior). Moreover, his paper shows that estimation of the classical linear-in-means model of social interactions is also complicated by simultaneity issues, the so-called "reflection" problem. A large literature has developed focusing on the identification of social interactions (see e.g. Manski, 1993, Moffitt, 2001, Bramoullé et al., 2009, and the comprehensive review by Blume et al., 2011). In this paper we do not

different estimation strategies, each of which is based on a different set of identifying assumptions. The first is a fixed-effects estimator, which partials out time-invariant unobserved heterogeneity exploiting the availability in the data of multiple non-employment spells and time variation of network quality. The second is a semi-parametric correlated random effects estimator of the transition into employment, which also allows taking into account selection into non-employment and models the correlation of network quality with unobserved heterogeneity. The third is an instrumental variable (IV) estimator, which controls for non-random selection and other correlated effects due to all sources of unobserved heterogeneity, not only time-invariant ones.

We find that better network quality increases the transition probability from non-employment to employment. One additional employed friend increases the probability to find a job by about 3.1 percentage points, which is robust across various specifications and estimation methods employed to address the potential endogeneity of network quality. The magnitude of this effect corresponds to an increase in the job finding rate by as much as 15 percent. Regarding job match quality, we provide evidence that ignoring selection into employment can lead to seriously biased estimates, and that the effects vary by skill level and type of relationship. After controlling for selection, high-skilled individuals whose employed friends are non-relatives earn higher wages and experience more stable employment (a matching effect). In contrast, low-skilled individuals whose employed friends are relatives experience a wage penalty and lower employment stability (a mismatching effect).

The matching effect may be more important for high-skilled workers because heterogeneity in productivity driven by unobserved worker attributes can be more relevant for high than low-skilled individuals (Antoninis, 2006). More heterogeneity leads to increased uncertainty for the employer, which can be better resolved by referrals from close friends who are more likely to know the productivity of each other within their network, rather than by relatives who are less likely to be in the same occupation or profession (Tassier and Menczer, 2008). The mismatching effect may be more important for low-skilled workers because they

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estimate social interactions, but similarly to other recent papers on labor market networks, such as Dustmann et al. (2011) and Cingano and Rosolia (2012), we focus on the effect of network characteristics (the stock of employed social contacts) on individual employment dynamics.

are more likely to rely on relatives as a last resort due to limited access to job opportunities through other channels (Loury, 2006). Because relatives are less likely to be in the same occupation as the job-seeker, this can lead to a mismatch between the occupation and the abilities of the worker (Bentolila et al., 2010).

Our findings help shedding light on the mixed evidence of the existing literature on the use of social contacts as a search channel, highlighting heterogeneity by skill level and the importance of controlling for selection into employment. For example, Simon and Warner (1992) find a positive wage premium for a sample of high qualified individuals, which is consistent with our finding of a wage premium for high-skilled workers. On the other hand, Bentolila et al. (2010) find a wage penalty, which they explain by the mismatch argument between the occupation of the social contacts and the abilities of the worker. Also, Kramarz and Nordström Skans (2011) find that school graduates of lower ability are more likely to find a job through their parents but with a wage penalty. The evidence from these studies is consistent with the wage penalty we find for low-skilled workers with a better network quality of relatives.

While the portion of friends' network that is the closest to survey respondents is observed in the data, i.e. the three closest friends as reported by interviewees, information on weaker social contacts is not available from the survey. This type of limitation is common with a number of recent studies, which use self-reported information on friends derived from survey questionnaires where there is an upper bound on the total number of friends that can be reported (see e.g. Calvó-Armengol et al. 2009; and Conti et al. 2012). By observing only strong social ties it is not possible to consider whether weak ties matter more than strong ties, as discussed especially in sociology (see e.g. Granovetter, 1995). Indeed, if it is weak ties that matter for finding a job, then the approach taken in this paper based on strong ties would provide a lower bound to the network effect. In any case, the view that weak ties are what matters for finding a job and for labor market outcomes is not consensual and has been challenged by empirical papers producing evidence of strong ties effects (see e.g. Cingano and Rosolia, 2012 and Kramarz and Nordström Skans, 2011).

The remainder of the paper is organized as follows. Section 2 describes the data source, the sample, and presents some descriptive statistics. Section 3 discusses the empirical approach for identifying the effect of network quality on the transition into employment and the results are reported in Section 4. Section 5 presents the analysis and the results for the effect of network quality on job match quality. Section 6 concludes.

2. Data and Descriptive Statistics

2.1 Data

We exploit longitudinal data on friendship ties and individual labor market outcomes from the British Household Panel Survey (BHPS). The BHPS is an annual survey representative of British households running since 1991, which covers many aspects of life including social ones. Information about social networks is gathered through a special questionnaire section on ‘Social support networks’, which was introduced in 1992 and administered at each even wave since then. Survey participants are asked to report information on their three closest friends, with friends’ rankings chosen by the respondents.[8] Each respondent provides information for each of the 1st, 2nd and 3rd closest friend. The information includes gender, age, employment status, residential proximity, friendship duration (years knowing the person), frequency of contact and whether the friend is a relative.

Using the information on friends’ employment status we can distinguish between employed and non-employed friends. Aggregating the employment status over the three friends, we define network quality as the number of employed friends (varying from zero to three friends). In essence, what we observe is the part of the network closest to the BHPS respondent (the three closest friends) and the employment intensity within that portion.

The longitudinal design of the BHPS allows observation of the respondents’ labor market outcomes over time and thence of individual transitions across labor market states. BHPS respondents provide information on friends at each even-numbered wave; the employment status of friends at even-numbered waves can therefore be related to the employment transition of each respondent between even and an odd-numbered waves. The

[8] Questions on friends are introduced by the following general statement: "Here are a few questions about your friends. Please choose the three people you consider to be your closest friends. They should not include people who live with you but they can include relatives."

data are drawn between 1992 and 2007, the latter being the latest odd-numbered wave available in the BHPS, whereas the former is the first wave in which information on friends is available. We select a sample of respondents aged 18-65 who are not in full time education at any even-numbered wave and for whom we observe the employment status. In order to consider friends of working age, the sample is restricted to individuals with friends within the 18-65 age range.[9]

The BHPS is not the only data source that reports information on friends' networks. The German Socio-Economic Panel (GSOEP) also collects information on respondents' friends, including their labor market status. However, the questions on friends in the GSOEP questionnaire were not asked systematically as in the case of the BHPS and occurred only in 4 out of the now 29 waves of the survey. In the US, the Add Health Survey collected information on a cohort of school students and their friends within schools in 1994. Follow up surveys on the original cohort were conducted at approximately seven-year intervals. Relative to the BHPS, Add Health offers a wider coverage of the relevant network (up to 10 friends); however, its focus on a very specific cohort of adolescents and its sparse periodicity prevents its use for population-wide representative studies of yearly job finding rates and employment outcomes. Friends nominations are available also in the Wisconsin Longitudinal Study in which respondents were asked to name their three best friends when they were at high school.

2.2 Descriptive Statistics

The sample selection criteria described in the previous section lead to a sample of 35,518 observations (person spells), among which 7,213 are observed in non-employment. As shown in column 1 of Table 1, the mean number of employed friends is 2.4 in the full sample (Panel A) and 1.8 in the sample of non-employed (Panel B). The table also compares the mean number of employed friends between individuals who report having any new friend among

[9] Alternatively, restricting the sample of respondents to those aged 18-50 in order to avoid early retirement issues, or considering friends without an upper bound age restriction at 65, leads to very robust results compared to the ones presented in Sections 4 and 5. Information about all three friends is reported by the vast majority of respondents (92%) and the analysis is based on these cases. The results are also robust when including the few cases reporting less than three friends (adding dummies for missing friends in the set of controls).

their three closest friends to those who do not have any new friend.[10] The difference in the mean number of employed friends between the two groups of individuals is very small and it is not statistically different from zero (column 4). This suggests that, although the network of close friends is not fixed, new friends are not selected based on their employment status.

Based on the non-employed sample, the average yearly transition rate from non-employment to employment is 21.16 percent, which is increasing with the number of employed friends. While the transition rate is only about 10 percent for those with no employed friends, the job finding rate increases to about 16 percent with one employed friend, to 21 percent with two, and to almost 30 percent with three employed friends.

3. Empirical Approach

The aim of the paper is to identify the effect of network quality on the probability of finding a job and on job match quality (wages and employment stability). In this section, we focus on the estimation of the transition into employment, while we discuss the estimation for job match quality in Section 5.

The main issue that needs to be addressed is the potential endogeneity of network quality. Unobserved individual characteristics might be correlated both with the number of employed friends and the own probability of becoming employed. For instance, individuals who are more attached to the labor market might have a higher propensity to find a job and at the same time have friends who are more likely to be employed. This would lead to an upward bias in the effect of network quality. To address this endogeneity issue we consider three alternative estimation strategies, which rely on different identifying assumptions: a fixed effect estimator, a semi-parametric correlated random effects estimator and an instrumental variables (IV) estimator.

The transition probability from non-employment to employment is defined as:

$$p_{NE} \equiv \Pr(E_{i,t+1} = 1 \big| E_{i,t} = 0\big) = F(\alpha_{NE} + X'_{i,t}\beta_{NE} + \delta_{NE}NEF_{i,t} + \eta_{NEi}), \qquad (1)$$

[10] Each respondent answers the following question for each of the three friends: "About how long have you know him or her?" with possible answers "Less than 1 year ", "1-2 years", "3-10 years", "10 years or more". A friend is defined as "new" if he or she is known for less than 1 year.

where $t = 1992, 1994 \ldots 2006$, $E_{i,t}$ is a dummy indicator of respondent's i employment status in year t and $F(.)$ is a function which is either linear or logistic, the latter accounting for the limited dependent nature of the outcome variable. The employment dummy takes the value one for respondents who are either full-time employees, part-time employees or self-employed, and the value zero for those who are either unemployed (ILO definition), or out of the labor force. The main variable of interest is the number of employed friends of individual i in year t, denoted as $NEF_{i,t}$, which takes values from 0 to 3. The vector of individual characteristics $X_{i,t}$ includes time-varying and time-invariant regressors. The time-varying regressors include the local unemployment rate defined at the travel-to-work area (TTWA) level, splines of five age groups (18-24, 25-34, 35-44, 45-54, 55-65), splines for the elapsed duration in non-employment (at 20th, 40th, 60th, 80th percentile of the duration distribution), and dummies for the region of residence, the survey year, living as a couple, having one, two, three or more children, experiencing health problems, depression and being a smoker.[11] The time-invariant regressors include dummies for gender, education (highest qualification attained) and ethnicity (categorized in six groups). The vector $X_{i,t}$ also includes the available individual demographic characteristics for each of the three friends: splines of five age groups (18-24, 25-34, 35-44, 45-54, 55-65) and gender dummies.[12] Finally, η_{NEi} denotes time-invariant unobserved heterogeneity influencing the transition from non-employment to employment and α_{NE} is a constant term.

3.1 Fixed Effects

We first adopt a fixed effects estimator (either linear or logistic) for estimating equation (1), which eliminates the unobserved individual time-invariant effect η_{NEi}. The transition probability is estimated by considering individuals not in employment at time t and modeling their employment status in $t + 1$, where t is an even wave. To integrate out individual-specific effects, we pool the data across all even waves and we exploit the multiple non-

[11] In the UK, TTWAs are designed to represent local labor markets in terms of areas where the bulk of the resident population also work within the same area. There are 247 such areas.

[12] Table A1 contains descriptive statistics of all the covariates.

employment spells that are observed for about half of the non-employed respondents in the sample. This provides us with within-individual variation in the number of employed friends over time and across these spells, which is exploited to control for time-invariant unobserved heterogeneity that might be correlated with the main variable of interest, the number of employed friends.

In this context, fixed effect estimates can be biased for at least three reasons. First, bias can arise by selecting the sample based on the employment status ($E_{it} = 0$), which can be endogenous in the presence of serial correlation of the employment process, a form of initial conditions issue (Heckman, 1981). We deal with the endogenous selection in non-employment with the estimator which we present in Section 3.2. Second, individuals in the sample who experience multiple spells of non-employment are likely to be negatively selected in the sense of being less employable and, therefore, experience a lower transition into employment. In this sense, fixed effects provide a lower bound estimate of the network effect. Third, biased estimates can occur if the employment status of friends depends on past values of the dependent variable. For instance, if individuals with low values of η_{NEi} who remain non-employed are more likely to select their friends based on their employment status, then ignoring this dependence will bias the effect of the number of employed friends. While possible in principle, there are a number of reasons that this form of bias is less likely to be an important concern in our setting. First, we are focusing on networks of close friends who are more likely to be formed for purposes not related exclusively to job search. Second, the descriptive statistics of Table 1 suggest that non-employed respondents who change friends do not select their new friends based on their employment status, which confirms the conjecture that friendship formation among close friends is not driven by employment considerations. Finally, we provide evidence based on an instrumental variable estimator in which the employment status of friends varies exogenously. This addresses endogeneity both due to potential correlation with the unobserved determinants of the outcome, and with reverse causality coming from past values of the dependent variable. We discuss this in Section 3.3.

3.2 Semi-Parametric Random Effects

The second approach in estimating the transition into employment relies on a random effects estimator, which, rather than eliminating time-invariant unobserved heterogeneity through within-individual differencing, provides estimates of the parameters of its distribution. Differently from fixed effects, the sample is not selected based on the employment status (non-employment) of the respondent. Instead, we consider the full sample of respondents and we model selection into employment via the following initial condition equation:

$$p_N \equiv Pr(E_{i,t} = 0) = F(\alpha_N + X'_{i,t}\beta_N + \delta_N NEF_{i,t} + \theta_N u_{it-1} + \eta_{Ni}), \qquad (2)$$

where the lagged unemployment rate in the travel to work area (u_{it-1}) is included to proxy the accumulation of past unemployment shocks that may affect employment status prior to the transition. The term η_{Ni} denotes time-invariant unobserved heterogeneity influencing selection into non-employment.

Equations (1) and (2) are estimated jointly by maximum likelihood allowing for correlated unobserved heterogeneity across the two outcomes. The main advantage of this estimation approach is that it takes into account selection into employment, which can be endogenous due to the dynamic nature of the employment process. Consistency of random effects estimators is based on the assumption of independence between regressors and the unobservables, which amounts at assuming that the number of employed friends is exogenous. This assumption is relaxed by means of a correlated random effects specification, in which the random effects are allowed to depend on the time averages of time-varying regressors, including the number of employed friends and other individuals and friends' characteristics (see Mundlak, 1978; Chamberlain 1984) as follows:

$$\eta_{NEi} = \bar{X}_i'\lambda_{NE} + \omega_{NEi} \; ; \qquad \eta_{Ni} = \bar{X}_i'\lambda_E + \omega_{Ni} \; .$$

The vector $\bar{X}_i$ collects the individual averages of time varying regressors including the number of employed friends (*NEF*), which are computed across all panel waves and are, therefore, constant across transitions. After controlling for time averages (especially the mean number of employed friends each individual has over the years of the sample), the remaining unobservables ω are assumed to be orthogonal to the current number of employed friends and the other regressors.

One concern with this model might be that identification of the cross-equation correlation of unobservables is mainly driven by the functional form of the model. However, as discussed by Mroz and Savage (2006) this is more serious if the model includes only time-invariant variables. Exogenously time-varying regressors like the local unemployment rate provide a more robust source of identification. Identification is also enhanced by the variation coming through the multiple spells of non-employment that are observed in the data. Furthermore, we impose relatively mild assumptions on unobserved heterogeneity, which is modeled in a flexible way assuming a discrete distribution following Heckman and Singer (1984). More specifically, the unobserved heterogeneity is defined as a discrete distribution with the support points denoted by $(\omega_{NEm}, \omega_{Nm})$ and the corresponding probability mass given by $P(\omega_{NEi} = \omega_{NEm},\ \omega_{Ni} = \omega_{Nm}) = \pi_m$. Each unobserved factors is assumed to be time-invariant and individual specific for each outcome. The sample likelihood is given by

$$L = \prod_{i=1}^{N} \sum_{m=1}^{M} \pi_m l_{im}, \quad (3)$$

where the individual likelihood contribution l_{im}, given the observed and unobserved characteristics is given by

$$l_{im}(Z_i, \omega_{NEi}, \omega_{Ni}) = (p_{NEm})^{\tau_{ne}} (1 - p_{NEm})^{(1-\tau_{ne})} (p_{Nm})^{\tau_n} (1 - p_{Nm})^{(1-\tau_n)}, \quad (4)$$

where p_{NEm} and p_{Nm} denote probabilities evaluated at the mass points, τ_{ne} is a dummy for $E_{i,t+1} = 1$ in the sample with $E_{i,t} = 0$, τ_n is a dummy for $E_{i,t} = 0$, and Z_i includes the controls of equations (1) and (2) plus the individual averages of time-varying regressors. Since the specification for each equation includes a constant, for identification one mass point of each unobserved factor is normalized to zero. The function F in equations (1) and (2) is assumed to be logistic.

3.3 Symmetric Network – Instrumental Variables

The third approach to address the endogeneity of network quality in estimating the transition into employment is based on the IV method. Relative to the two previous approaches, with the IV method we can address the endogeneity due to non-random selection and other correlated effects coming from all sources of unobserved heterogeneity, not only time-invariant ones.

The IV estimator requires exogenous variation in the employment status of the respondent's friends, which is difficult to obtain because of the limited information on friends' characteristics in the BHPS. To circumvent this limitation and recover the required variation, we consider the transition equation (1) from the friends' perspective and estimate its symmetric version. That is, instead of estimating the effect of friends' employment status on the respondent's transition, the symmetric transition focuses on the effect of the employment status of the respondent on the employment transition of the *first closest non-employed friend*.[13] In this symmetric version, the potentially endogenous variable is now the employment status of the BHPS respondents, not that of their friends, and the wealth of information on respondents' characteristics can be exploited for deriving a valid instrument, as explained later in the section.

Strictly speaking, estimating this symmetric transition requires observation of friends' identity in order to follow their employment status over time, which is not provided by the data. To circumvent this limitation, the analysis is based on the first closest friend assuming that his or her identity is the same over the transition period. The plausibility of this assumption is assessed in Section 4.3 by investigating the sensitivity of the results for a fixed network of friends.

Let $FE_{i,t}$ be a dummy for whether the first closest friend is employed in year t, the symmetric transition equation is defined as:

$$p_{FE} \equiv Pr(FE_{i,t+2} = 1 \big| FE_{i,t} = 0) = F(\alpha_{FE} + X'_{i,t}\beta_{FE} + \delta_{FE}E_{i,t} + \eta_{FEi}). \qquad (5)$$

This transition is estimated on the sample of respondents whose first closest friend is non-employed at time t ($FE_{i,t} = 0$). The dependent variable is a dummy which takes the value one if the respondent's first friend makes a transition from non-employment to employment between time t and $t + 2$, and zero otherwise. We consider a 2-year transition because the information on friends in the survey is only available every two years. Equation (5) is similar to the transition equation (1) with the difference that it refers to the transition from non-employment to employment of the first closest friend and, therefore, it depends on the

[13] We thank Nikos Askitas for his suggestion to consider the symmetric model.

employment status of the respondent denoted by $E_{i,t}$. The vector X includes all available friend characteristics (age, gender), and the respondents' characteristics such as education, family structure, health status, experiencing depression, smoking and region of residence, which are included in the specification as proxies for the unobserved characteristics of the friend.

The advantage of focusing on the symmetric transition is that we can obtain a valid instrument for their potentially endogenous employment status ($E_{i,t}$) by exploiting the abundance of information about the respondents in the BHPS. We use two sources to construct the instrument. The first is whether the respondent experiences health problems. The second is the answer to the following question: "*Does your health limit the type of work or the amount of work you can do*?" The instrument for the potentially endogenous employment status of the respondent is the *onset* of a health problem, between the previous and the current interview, which limits the work activities of the respondent. The instrument, which is denoted by $WL_{i,t}$, is a dummy taking the value one for the respondents who experienced the onset of health related work limitations between $t-1$ and t, and zero otherwise. The instrumenting equation determining the endogenous employment status of the respondent is given by:

$$p_{E_{IV}} \equiv \Pr(E_{i,t} = 1) = F(\alpha_{E_{IV}} + X'_{i,t}\beta_{E_{IV}} + \theta_{E_{IV}} WL_{i,t} + \eta_{E_{IV}i}). \quad (6)$$

The onset of a health related work limitation is expected to have a negative effect on the probability of the respondent to be employed in the current period. The identifying assumption is that the onset of a health related work limitation for the respondent in the past period has no direct effect on the employment transition of the closest friend in the current period.

Due to the limited dependent nature of both the dependent variable and the instrumented variable, equations (5) and (6) are estimated jointly by maximum likelihood allowing for unrestricted correlation between the unobserved characteristics ($\eta_{FEi,}\eta_{E_{IV}i}$) using a discrete distribution. The construction of the likelihood is similar to the one for the random effects estimator presented in Section 3.2.

The identifying assumption of this estimator would be violated if the health status of the respondent and that of her first friend are correlated. In that case, the unobserved health status of the best friend would be correlated with the instrument (the onset of health limitations for the respondent).. We address this issue by including indicators for the current (at time t) level of respondent's health among the regressors in the transition equation. By controlling for the current health status we are able to capture the potential correlation in health between the respondent and the first friend.

4. Estimation Results - Transition into Employment

In this section we present the results for the effect of network quality on the transition into employment for the three empirical approaches: the linear fixed effects estimator (in Section 4.1), the semi-parametric random effects estimator (in Section 4.2) and the symmetric IV estimator (in Section 4.3). We start by presenting the estimates from a pooled OLS regression, which includes individual and friends characteristics but ignores the potential endogeneity of network quality and does not control for selection into non-employment. Estimating the transition equation (1) as a linear probability model, Table 2 shows that there is a positive and significant association between the number of employed friends and the transition into employment. The coefficient estimate suggests that one additional employed friend increases the job finding probability by 4 percentage points (p.p.).[14]

4.1 Fixed Effects Estimates

As discussed in Section 3.1, the first approach we adopt to address the endogeneity of network quality due to its potential correlation with unobserved heterogeneity is to estimate the transition equation (1) with fixed effects. Once we control for individual time-invariant unobserved heterogeneity, the coefficient of the number of employed friends in the linear fixed effects estimation in Table 2 is reduced from 0.040 to 0.018 (or an increase of 1.8 p.p. in the transition probability for an additional employed friend). Identification in the fixed effects

[14] Estimating a specification with dummies for the number of friends employed (one, two, or three employed friends relative to no employed friends) leads to results that are very much in line with the ones in the text.

estimator relies on individuals who are observed with at least two non-employment spells. As this group is likely to be less employable it is not surprising that the linear fixed effects estimate is much smaller than the one obtained from the pooled OLS.[15] A similar finding to the linear fixed effects estimator is obtained with the logit fixed effects estimator, which is identified out of the respondent's multiple non-employment spells among which at least one ends into employment. Although the fixed effects estimates can be downward biased because those who experience multiple spells of non-employment are likely to be negatively selected, they still suggest a positive and statistically significant effect of network quality on the transition into employment. That is, having more employed friends increases the chances of finding a job.

We perform a number of sensitivity checks with the fixed effects estimator. First, we allow for a differential effect of network quality among new friends, which allows separating the effect of network quality of a fixed network from a potentially endogenously changing network. We define as "new" those friends with a length of friendship of less than a year. Table 2 shows that the interaction of the number of employed friends with an indicator of having any new friends has no effect on the transition into employment.

Second, we include a full set of interactions of time-varying individual and friend characteristics with the gender dummy to capture unobserved heterogeneity in the data that varies over time and might be correlated with network quality. The main effect is not sensitive to the inclusion of these additional time-varying regressors.

Third, we consider the importance of common shocks for our results. Network formation may occur through residential proximity so that spatial correlation is an obvious source of common shocks. Similarly, when social contacts provide job referrals, network members are likely to share labor demand shocks. For example, a plant closure at the local area is a common shock that might affect the conditions for all members of the network. We consider the importance of local economic conditions for our findings in two ways. First, we find that the fixed effects estimates are not sensitive to the exclusion of the travel-to-work area unemployment rate (results of this sensitivity check are not reported and are available

[15] Indeed, the coefficient of NEF in the pooled OLS estimation for the sample of individuals with more than one spell is 0.024, which is substantially lower to the one from the full sample (0.040).

upon request). Second, we investigate how the network effect varies by the residential location and the frequency of contact among friends. Table A2 shows that what matters for the job finding probability is the strength of the friendship and not the location of the friends. The top panel of the table shows that the estimates for the number of employed friends with strong ties (frequency of contact at least once a week) and the number of employed friends who live close (less than 50 miles) are positive and statistically significant (coefficients of 0.023 and 0.020, respectively). The lower panel of table shows, however, that the location of friends is not a driving factor for our findings; the estimate for the number of employed friends who are strong ties is significant for both friends who reside in close distance and further away. In contrast, the effect of network quality among friends who do not interact frequently is insignificant for both friends who live close and for those who live far from the respondent. That is, stronger ties among close friends increase job finding rates irrespective of their location. Taking together, this evidence suggests the effect of network quality on job finding rates is not driven by local correlated shocks.

4.2 Semi-Parametric Random Effects Estimates

The second approach we adopt to identify the effect of network quality on the transition into employment is by way of the semi-parametric random effects estimator presented in Section 3.2, which allows for unobserved heterogeneity and takes into account selection in the initial state of non-employment.

To form a comparison to the fixed effects results, we first ignore the issue of selection into non-employment and we estimate a correlated random effects model, which controls for the mean number of employed friends and other time averages of time-varying covariates. Table 2 shows that the coefficient estimate for the number of employed friends is positive and statistically significant. The marginal effect suggests that an additional employed friend increases the transition probability into employment by 1.8 percentage points. This effect is similar in magnitude to the one obtained with fixed effects, which also does not take into account selection into non-employment.

We then estimate the full model of equation (3), which takes into account selection in non-employment through the initial condition. The effect of the number of employed friends remains positive and significant and the marginal effect increases to 3.1 percentage points. This effect is reported in the last estimation of Table 2. The magnitude of this effect lies between the one obtained from the pooled model, which ignores both unobserved heterogeneity and the initial condition (4 p.p.), and the fixed effects model, which controls for unobserved heterogeneity but ignores selection into non-employment (1.8 p.p.). Taking together these effects, we find robust evidence that network quality has a positive and significant effect on job finding rates. Our preferred estimate from the correlated random effects model, which controls for selection in non-employment, suggests that an additional employed friend increases the job finding probability by as much as 15 percent (marginal effect of 3.1 p.p. and unconditional exit rate of 21.16 percent).

4.3 Symmetric Network IV Estimates

The third approach for estimating the transition into employment is based on the symmetric model, in which the transition is defined on the sample of respondents whose first closest friend is non-employed at time t. The network effect is captured by the employment status of the respondent, which is potentially endogenous. We address this endogeneity by using as an instrument for the employment status of the respondent the onset of health related work limitations, which creates exogenous variation of network quality (see Section 3.3 for a discussion of the IV estimator and the identification assumption). Relative to the two previous approaches, the IV estimator deals with endogeneity due to all types of unobserved heterogeneity, not only time-invariant ones, and with potentially endogenous network formation driven by past outcomes.

Table 3 displays the results from the estimation of the symmetric transition for the sample of the non-employed first friends. We start by discussing the results without instrumenting for the endogenous employment status of the respondent. The first estimation in the top panel of Table 4 is based on a linear regression and shows a positive and statistically significant effect of the respondent’s employment status on the employment transition of the first closest friend. The marginal effect suggests a 9.2 p.p. increase in the transition probability of having an employed friend (referring to the respondent, which is denoted as "Friend Employed" in the table) compared to having a non-employed friend.[16] We next report the results of estimating the symmetric transition equation with fixed effects, similar to the analysis for the direct model of equation (1) discussed in Section 4.1. The effect of the respondent's employment status is reduced from 0.092 to 0.065, but it is still statistically significant at the 5 percent confidence level.

Turning to the IV results of Table 3, the coefficient estimate of the instrumental variable indicates that the instrument operates in the expected direction. The onset of health related work limitations between $t-1$ and t reduces the employment probability of the respondent at t, with the coefficient estimate being statistically significant at the 1 percent confidence level (t-ratio: 3.72). Considering the transition equation, we find a positive and statistically significant network effect. Having an employed friend increases the transition from non-employment to employment of the first closest friend by 7.5 percentage points. The marginal effect from the IV estimation (0.075) lies between the marginal effects from the linear fixed effects (0.065) and the linear pooled estimation (0.092).

In the last estimation of Table 3 we report the results from the specification in which we include the current health and depression indicators. If the current health status between the respondent and the first closest friend are correlated, this would violate the identification assumption of the IV estimator. By controlling for the current health indicators of the respondent, we are able to control for this potential correlation and check the robustness of our IV results. Since the current health and depression indicators are correlated with the onset of health limitations in the last year, we expect that including them in the specification will lead to a weaker instrument. This is the case as shown in the last column of Table 3. The coefficient and the marginal effect of the instrument are smaller in absolute terms and the level of significance is reduced. What is important, however, is that the main effect of interest

[16] A direct comparison with the marginal effects from the fixed effects and the semi-parametric random effects estimates cannot be made because the transition in the symmetric model is defined over the (t, t+2) interval, rather than (t, t+1) as in the fixed or random effects, and the variable of interest is a dummy for the employment status of the first friend rather than the number of employed friends.

remains practically unchanged as the effect of having an employed friend only slightly changes from a marginal effect of 0.075 to 0.073.[17]

As discussed in Section 3.3, the estimation of the symmetric model relies on the assumption that the identity of the first close friend remains constant between subsequent even waves. We investigate the sensitivity of our results to this assumption by considering only the subsample of non-employed first friends who remain fixed between time t and $t + 2$. There are two ways in which the network of three friends can change. The first is by having a new friend among any of the three close friends, where a new friend is defined as one with a length of friendship of less than 2 years. The second is by replacing one of the current friends with an existing friend who was not listed among the best three in the survey response. For the first case, we estimate the symmetric transition both when the first friend in $t + 2$ is not a new friend, and also when none of the three friends is a new friend, where the latter is a more restrictive condition allowing for changes in the ranking of friends across waves. For the second case, we estimate the transition when the length of friendship with the first closest friend is more than 10 years. This captures long-lasting friendships, which are more likely to remain fixed. Table A3 shows that in the sample without a new first friend the marginal effect is 0.078 and in the sample without any new friend the marginal effect is even higher (0.091). Similar findings are obtained when we consider only long friendships, which are not reported but are available from the authors. Overall, the IV estimates provide robust evidence of the existence of a network effect, which is consistent with the evidence obtained both from the fixed effects and the semi-parametric random effects estimators.

5. Match Quality

The above analysis shows that a better network quality increases job finding rates. In this section, we examine the effect of network quality on the quality of the matches formed by those who found a job, measuring match quality using labor market outcomes such as wages

[17] We also performed the estimation excluding each indicator – health or depression – in turn, reaching identical conclusions to those reported in the text. In addition, we have considered accidents as a potentially alternative way to model the onset of health related work limitation. However, the frequency of accidents in our sample is small so we could not pursue this further.

and employment stability. Theoretically, there are two main mechanisms through which social contacts and referrals are predicted to lead to higher initial wages. First, social contacts and referrals are used by employers as a screening device for the worker's unobserved productivity, based on the belief that current workers tend to refer others who are similar to themselves (Saloner, 1985; Montgomery, 1991; Galenianos, 2012). Second, referrals can inform workers and firms about the quality of the match (Simon and Warner, 1992; Dustmann et al., 2011; Brown et al., 2012). However, there may also be negative effects of informal networks: workers may rely on informal networks as a last resort, which can be associated with low-wage-offers due to limited access to job opportunities through other channels (Loury, 2006), or the quality of the information transmitted through the network may not match the abilities of the job-seeker (Bentolila et al., 2010).

The empirical literature so far has produced mixed results. Some studies find positive wage effects (e.g. Simon and Warmer, 1992; Marmaros and Sacerdote, 2002; Loury, 2006), while others find negative effects (e.g. Pistaferri, 1999; Bentolila et al., 2010, Goel and Lang, 2012). Furthermore, these effects are not limited to wages. To the extent that informal networks lead to better matches may well result in lower separation rates (Dustmann et al., 2011), and thus to higher employment stability.

5.1 Results on Wages

Given the longitudinal aspect of the data, we are able to follow individuals over time and investigate the effect of network quality on wages for those who find a job. The (log) wage equation is given by:

$$log(W_{i,t+1}) = \alpha_W + X'_{i,t+1}\beta_W + \delta_W NEF_{i,t} + \eta_{Wi} + \varepsilon_{i,t+1}, \quad \text{(7)}$$
$$if\ E_{i,t+1} = 1\ and\ E_{i,t} = 0$$

where the dependent variable $W_{i,t+1}$ denotes the hourly wage and the independent variables are defined similarly to equation (1) but measured at the time period $t + 1$. The specification includes η_{Wi}, which captures the effect of unobserved heterogeneity on wages. Network quality is measured by the number of employed friends (*NEF*) at time t; the time period in which the worker was non-employed.

The first estimate in the top row of Panel A in Table 4, which is based on the estimation of equation (7) by OLS, shows that the number of employed friends has a significant and positive effect on wages. An additional employed friend is associated with a 3.4 percent higher hourly wages. This effect is consistent with the theoretical literature which predicts a positive effect of informal contacts on the initial wage.

While this result suggests a positive network effect on wages one has to view it with caution because those who found a job are likely to be positively selected among the non-employed. To address this selection we estimate the wage equation jointly with the non-employment transition (1) and the initial condition equation (2), taking into account the correlation of unobserved heterogeneity across the three outcomes. By jointly estimating both the probability to be employed and the realized outcome we are able to separate the effect of interest from selection based both on observables and unobservables.[18] The selection-corrected estimate of the number of employed friends at time t on wages at time $t+1$ (first estimate in the top row of Panel B in Table 4) shows evidence of positive selection among those employed. The effect of network quality reduces from 3.4 percent to 1.7 percent and is not statistically significant.

We extend the previous analysis by considering possible heterogeneous network effects by skill level. Both the network effect and selection may differ by skill level. The matching effect of networks on wages is likely to be more important for skilled workers because there is more heterogeneity in productivity driven by unobserved worker attributes, which creates more uncertainty for the employer. High skilled workers are not only more likely to have friends of similar type but they are also more likely to know the productivity of their close friends, which is valued by employers as it reduces information asymmetry leading to a wage premium. That close friends are likely to know the productivity of each other within their network is because skilled close friends are more likely to be in the same profession or

[18] This model is the extension of the correlated random effects model of section 3.2 including the wage equation (7). We estimate the model using a discrete distribution of unobserved heterogeneity and correlated random effects as we did for the employment transition model. Estimating the wage equation with fixed effects is not feasible due to limited within-person variation of wages in the sample of individuals finding a job.

occupation (Tassier and Menczer, 2008).

In contrast, for less-skilled workers and jobs, employers face less uncertainty about the unobserved worker ability and productivity is not so sensitive to differences in individual ability (Antoninis, 2006). Therefore, employers may use referrals for low-skilled workers not as a screening device but rather as a way to reduce their hiring costs, in which case there should be no wage premium by finding a job through a referral.

The top part of Panel A in Table 4 reports the effects of network quality by skill level, where the wage equation is estimated by OLS ignoring selection into employment and endogeneity of network quality. We find that a higher network quality has a larger effect on wages for the high-skilled (4.7 percent and statistically significant) compared to the low-skilled (2.1 percent and statistically non-significant).[19] When we address selection and endogeneity we find that selection matters both for the high and the low-skilled but it is substantially more important for the low-skilled. Low-skilled workers are expected to face more difficulties to find a job and those who succeed are likely to be positively selected from the pool of the non-employed, so the positive selection should be more important for this group. The top part of Panel B in Table 4 shows for the high-skilled that an additional employed friend leads to a 4.4 percent increase in wages, which is significant at the 10 percent level. For the low-skilled, instead, there is no effect of network quality on wages. The finding that better network quality leads to increased wages for skilled workers, even after controlling for selection, is in line with the evidence provided by Simon and Warner (1992) who find that hiring through contacts for a sample of high qualified workers leads to a higher initial wage.

As discussed earlier, the empirical findings on the effect of searching through informal networks on wages is mixed. In a recent paper, Bentolila et al. (2010) find a negative effect of the use of social contacts on wages, which can be explained by the idea that social contacts may lead to a mismatch between the occupation and the abilities of the worker. This can occur because in general social contacts are not formed solely for the purpose of obtaining job information. Thence, they may help a worker to find a job but not necessarily in the

[19] High skilled are defined those individuals with A-levels and higher education.

occupation in which the worker is most productive. In the context of our analysis, which is based on the three closest friends, it is more likely that there is higher occupational overlap between close friendship networks, especially among the skilled, which leads to a matching effect and to higher wages when network quality is better. The mismatch hypothesis is more likely to hold when the informal contacts are relatives because they are less likely to be in the same profession or occupation compared to non-relative close friends (Tassier and Menczer, 2008).

In order to test the match vs. mismatch hypothesis we estimate separately the effect of network quality on wages among relatives and non-relatives.[20] The results in the low part of Panel A in Table 4, which are based on OLS, suggest that it is the number of employed non-relatives among high-skilled which matters for wages. After controlling for selection (low part of Panel B), we still find that high skilled individuals with more employed non-relatives earn higher wages, while there is a wage penalty for low skilled individuals with more employed relatives. These findings suggest a matching effect among high skilled with a better network quality of non-relatives, and a mismatching effect among low skilled with a better network quality of relatives.

The matching effect among high-skilled through non-relatives is consistent with the hypothesis that close friends can be more informative about match quality to the employers. The mismatching effect among low-skilled is consistent with the hypothesis that relatives are used as a last resort due to limited access to job opportunities through other channels (Loury, 2006), which can lead to a mismatch between the occupation and the abilities of the worker (Bentolila et al., 2010). The mismatching effect among low-skilled is also in line with the evidence by Kramarz and Nordström Skans (2011) who report that school graduates of lower ability are more likely to work in the firm in which their father is employed but with a wage penalty. Overall, these results help reconcile the mixed evidence of the previous literature on

[20] Each individual in the survey is asked if a reported friend is a relative or not. Reporting a relative or a non-relative among the three close friends is not related to the quality of the network. Indeed, for the sample of non-employed respondents there is no difference in the mean number of employed friends between those who ever report a relative as a friend and those who never report a relative among their friends.

the use of social contacts as a search channel on wages.[21]

It is important to note that while there is heterogeneity in the wage effects of network quality by skill level and by type of relationship, the effect of network quality on the probability of finding a job is positive and significant for both skill levels and irrespective of whether the friend is a relative or not. Table A4 presents the estimates for the transition from non-employment to employment, which indicate that a better network quality among non-relatives for the high-skilled has the highest effect (4.4 p.p.), followed by the one among relatives for the low-skilled (3.5 p.p.). Finally, Table A5 reports the estimates of the distribution of unobserved heterogeneity. Compared to the baseline, there is a group of individuals who are more likely to be observed as non-employed, are less likely to exit non-employment conditional on being non-employed, and receive lower wages once they exit employment. There is also another group, which is less likely to enter non-employment and is more likely to find a job with higher wages.

5.2 Results on Employment Stability

Finally, we examine the network effect and its heterogeneity by skill level for the probability of falling back into non-employment. If networks transmit information and lead to better matches, then those who find a job through informal contacts should also exhibit lower job separation rates and consequently better employment stability.[22] We estimate the following equation:

$$p_E \equiv \Pr(E_{i,t+2} = 0 \big| E_{i,t} = 0, E_{i,t+1} = 1\,) = F(\alpha_E + X'_{i,t+1}\beta_E + \delta_E NEF_{i,t} + \eta_{Ei}), \qquad (8)$$

which is the probability of being non-employed in $t+2$ for the sample of individuals who found a job between t and $t+1$. The specification is similar to the one used for the wage estimation in equation (7).

[21] Similar to the previous discussion on selection, a comparison of the estimates in Table 4 between Panel A (which ignores selection) and Panel B (which controls for selection) suggests that there is substantial positive selection among low skilled individuals. In the estimation of the correlated random effects model we control for the possible correlation of the measure of network quality (NEF) with the error term by including both the mean NEF for relatives and the mean NEF for non-relatives.

[22] We focus on employment stability and not on job stability because we cannot separate in the data promotions from job separations.

Panel A in Table 5 shows the estimates of equation (8) using a linear probability model. When we ignore selection and correlation of network quality with the error term, there is a negative effect of having better network quality on the probability to exit employment, which is significant both on average and by skill level, and independent of whether we consider network quality among relatives and non-relatives. Panel B reports the estimates when we control for selection into employment, which are based on the extension of the correlated random effects model of Section 3.2 including the transition equation (8). Because we estimate equation (8) using the logistic distribution we report both the coefficients and the marginal effects. There are two main results. First, after controlling for selection into employment and for endogeneity of network quality, the coefficient estimates of the number of employed friends are substantially lower and they become all insignificant. Second, although there is no effect of network quality on employment stability on average (first row of Panel B), there is still heterogeneity by skill level, where the effect for high-skilled is twice as large as the average effect. Furthermore, the lower part of Panel B suggests that the negative effect of better network quality for the high-skilled on the probability to exit employment is coming through the number of employed non-relatives. In contrast, for the low-skilled, we find that those with more employed relatives are more likely to exit employment. In terms of magnitude, these effects are less sizeable compared to the wage effects. An additional employed non-relative reduces the probability of employment exit for the high-skilled by 1 p.p., while an additional employed relative increases the probability of employment exit for the low-skilled by 0.4 p.p.

These effects, although imprecisely estimated and less sizeable, are qualitatively similar to those reported for wages and provide evidence for network heterogeneity, which generates either a matching or a mismatching effect depending on its nature. Better network quality of non-relatives is associated with higher wages and better employment stability among high-skilled (matching effect), while better network quality of relatives is associated with a wage penalty and lower employment stability among low-skilled (mismatching effect).

6. Conclusion

The labor market effects of social networks have received considerable attention in recent decades. We contribute empirically to this literature by developing a direct measure of network quality based on the number of employed close friends and we investigate its effect on job finding rates and on job match quality. This measure of network quality is motivated by the recent theoretical literature on network structure and employment dynamics, which emphasizes the employment status of network members as the key ingredient for the effectiveness of social contacts as a job search channel.

The literature on referrals has viewed networks as an information transmission mechanism leading to better matches. However, the quality of the information transmitted through the network may not match the abilities of the job-seeker, or networks may be used only as a last resort. In both cases, networks may increase job finding rates but may not necessarily lead to a good match. An alternative mechanism could be that, instead of transmitting information, better network quality creates pressure to network members to conform to the behavior of their peers. Therefore, a higher number of employed friends may increase the pressure to non-employed members to search more actively for a job leading to a higher job finding rate.

By considering both the transition to employment and the subsequent employment outcomes by skill level helps us to distinguish among these alternative explanations. Using various identification strategies, we provide robust evidence that one additional employed friend increases the job finding probability by about 3.1 percentage points, which corresponds to an increase in the job finding rate by as much as 15 percent. When we ignore selection into employment, we find that better network quality also leads to better matches, with higher initial wages and employment stability. After controlling for selection into employment, however, we find that better network quality increases job match quality only for high-skilled workers, while it leads to a mismatching effect for low-skilled workers, even though both skill groups experience higher job finding rates. More precisely, an additional employed friend among high-skilled leads to a wage premium (6.1 percent wage increase for each employed friend), while an additional employed relative among low-skilled leads to a wage penalty (4.3

percent wage loss for each employed relative). For employment stability, although the effects are less sizeable and imprecisely estimated, they suggest qualitatively also a matching effect for the high-skilled (higher employment stability) and a mismatching effect for the low-skilled (lower employment stability).

Clearly, a higher job finding rate through better network quality is consistent with both the information and peer-pressure mechanisms. However, our findings of a matching effect among the high-skilled through close friends, and a mismatching effect among the low-skilled through relatives, is consistent with the information mechanism in which friends pass better information than relatives and low-skilled workers are more likely to use relatives as a last resort. For the peer-pressure mechanism to explain these results it should hold that high-skilled conform to norms set by friends and the low-skilled conform to norms set by relatives. Furthermore, the norms should differ by skill level because we observe different match quality effects across skills.

The results of better network quality increasing job finding rates for all workers, but generating heterogeneity by skill level on match quality, help to reconcile the mixed evidence on the effect of social contacts on labor market outcomes reported by previous studies, and highlight the importance of controlling for selection into employment.

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Table 1. Mean Number of Employed Friends by Friendship Type

Panel A. Full Sample

	(1)	(2)	(3)	(4)
	All	With New Friends	Without New Friends	Diff (3)-(2)
	2.385	2.394	2.380	-0.015
		(0.010)	(0.005)	(0.011)
Number of Observations	35,518	6,906	28,612	

Panel B. Non-Employed Sample

	(1)	(2)	(3)	(4)
	All	With New Friends	Without New Friends	Diff (3)-(2)
	1.826	1.795	1.833	0.038
		(0.026)	(0.013)	(0.028)
Number of Observations	7,213	1,387	5,826	

Note: The table reports the mean number of employed friends for the full sample (Panel A) and for the sample of the non-employed (Panel B). Column (2) refers to the spells of individuals who have reported a new friend and column (3) to the spells of individuals who have not reported a new friend. A friend is defined as new if the length of friendship is less than 1 year. Standard errors are reported in parentheses.

Table 2. Number of Employed Friends and the Transition from Non-Employment to Employment

	Pooled OLS			Fixed Effects Linear			Fixed Effects Linear		
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
Number of Employed Friends	0.040	0.005	***	0.018	0.008	**	0.018	0.008	**
Number of Employed Friends * Having Any New Friend							-0.001	0.026	
Number of Observations	7,213			7,213			7,213		

	Fixed Effects Logit			Correlated Random Effects			Correlated RE with Initial Conditions		
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
Number of Employed Friends	0.187	0.080	**	0.155	0.061	**	0.252	0.063	***
				[0.018]			[0.031]		
Number of Observations	7,213			7,213			35,518		

Note: The sample consists of individuals aged 18-65 in the even years of the period 1992-2006 when information on their three closest friends is available. The sample is also restricted to friends aged 18-65. Other regressors include individual and friend time-varying covariates (five age groups, elapsed duration, dummies for living as a couple, number of children (1, 2 or more), having health problems, experiencing depression, smoking, time and region dummies, and five age groups for the age of each friend), individual and friend time-invariant covariates (dummies for female for individual and each of his or her friends, dummies for levels of education, ethnicity) and local economic conditions (local unemployment rate at travel-to-work area). Standard errors are clustered at the individual level. ***/**/* denote significance at the 1%/5%/10% level, respectively. For the correlated random effects the transition is defined using the logistic distribution, and average marginal effects are reported in squared brackets below the estimates.

Table 3. Transition from Non-Employment to Employment for the First Closest Friend

	Pooled OLS			Fixed Effects		
	Coef.	s.e.		Coef.	s.e.	
Friend Employed	0.092	0.014	***	0.065	0.026	**
Number of Observations	7,219			7,219		

	FIML IV W/out Current Health and Depression			FIML IV With Current Health and Depression		
	Coef.	s.e.		Coef.	s.e.	
Instrument: *Onset of Health Related Work Limitation*	-0.693	0.186	***	-0.450	0.188	**
	[-0.081]			[-0.052]		
Friend Employed	0.393	0.094	***	0.381	0.094	***
	[0.075]			[0.073]		
Number of Observations	7,219			7,219		

Note: The sample is defined over the non-employment spells of the respondents' first closest friend. The dependent variable is a dummy for the transition from non-employment to employment of the first closest friend. The variable of interest is "Friend Employed" which captures whether the respondent is employed or not. Other controls include all the available friend characteristics (year of birth, gender), and the respondents characteristics which are assumed to be correlated with friends characteristics that are not available in the BHPS, namely education, family structure, having currently health problems, experiencing depression, smoking and region of residence. The instrumental variable is a dummy which takes the value one if a respondent experienced a negative health shock that induced the onset of work limitation between t-1 and t, and zero otherwise. Since both the dependent and the endogenous variables are binary, the two equations are estimated jointly with Maximum Likelihood using a logistic distribution allowing for correlated unobserved heterogeneity across the two equations and the average marginal effects are reported in squared brackets below the estimates. ***/**/* denote significance at the 1%/5%/10% level, respectively.

Table 4. Number of Employed Friends and Hourly Wages by Skill Level and Friends' Relation

Panel A Pooled OLS

	All			High Skilled			Low Skilled	
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.
Number of Employed Friends	0.034	0.015	**	0.047	0.022	**	0.021	0.019
Number of Observations	1,150			1,150				

	All			High Skilled			Low Skilled	
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.
Number of Employed Relatives	-0.007	0.023		-0.009	0.034		-0.005	0.028
Number of Employed Non-Relatives	0.046	0.016	***	0.064	0.024	***	0.029	0.021
Number of Observations	1,130			1,130				

Panel B. FIML - Joint Estimation of Non-Employment Transition and Wages
Correlated Random Effects with Initial Conditions

	All			High Skilled			Low Skilled	
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.
Number of Employed Friends	0.017	0.021		0.044	0.025	*	-0.012	0.026
Number of Observations	35,518			35,518				

	All			High Skilled			Low Skilled	
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.
Number of Employed Relatives	-0.026	0.032		-0.014	0.040		-0.043	0.039
Number of Employed Non-Relatives	0.032	0.021		0.061	0.026	**	-0.001	0.026
Number of Observations	34,568			34,568				

Note: Panel A reports OLS results for the wage equation for the sample of those who make a transition from non-employment to employment. Panel B reports the estimation results of the wage equation when it is estimated jointly with the transition from non-employment into employment taking into account initial conditions and allowing for correlated random effects. Each row includes two estimations. The estimation on the left shows the effect of the number of employed friends on wages (All). The estimation on the right shows the effect of the number of employed friends by the skill level of the respondent (High Skilled vs. Low Skilled). High skilled are defined as those with A-levels or higher education. Finally, the second row in each panel shows the effect of the number of employed friends who are relatives vs. the number of employed friends who are non-relatives on wages.

Table 5. Number of Employed Friends and Employment Stability by Skill Level and Friends' Relation

Panel A Pooled OLS

	All			High Skilled			Low Skilled		
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
Number of Employed Friends	-0.041	0.014	***	-0.032	0.017	*	-0.049	0.021	**
Number of Observations	1,150			1,150					

	All			High Skilled			Low Skilled		
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
Number of Employed Relatives	-0.040	0.020	**	-0.027	0.025		-0.051	0.029	*
Number of Employed Non-Relatives	-0.041	0.015	***	-0.033	0.018	*	-0.048	0.022	**
Number of Observations	1,130			1,130					

Panel B. FIML - Joint Estimation of Non-Employment Transition and Employment Stability Correlated Random Effects with Initial Conditions

	All		High Skilled		Low Skilled	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Number of Employed Friends	-0.112	0.189	-0.205	0.236	-0.032	0.227
	[-0.006]		[-0.012]		[-0.002]	
Number of Observations	35,518		35,518			

	All		High Skilled		Low Skilled	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
Number of Employed Relatives	0.027	0.283	-0.006	0.357	0.059	0.335
	[0.002]		[-0.0003]		[0.004]	
Number of Employed Non-Relatives	-0.100	0.187	-0.171	0.232	-0.033	0.228
	[-0.006]		[-0.010]		[-0.002]	
Number of Observations	34,568		34,568			

Note: Panel A reports OLS results from a regression for the sample of those who have entered employment. The dependent variable is binary taking the value one if the individual returns back to non-employment within the next year and zero otherwise. Panel B reports the estimation results of the transition back to non-employment when it is estimated jointly with the transition from non-employment into employment taking into account initial conditions and allowing for correlated random effects. For this joint estimation the transitions are defined using the logistic distribution, and average marginal effects are reported in squared brackets below the estimates. Each row includes two estimations. The estimation on the left shows the effect of the number of employed friends on employment stability (All). The estimation on the right shows the effect of the number of employed friends by the skill level of the respondent (High Skilled vs. Low Skilled). High skilled are defined as those with A-levels or higher education. Finally, the second row in each panel shows the effect of the number of employed friends who are relatives vs. the number of employed friends who are non-relatives on employment stability. A negative (positive) coefficient indicates a lower (higher) exit probability from employment and higher (lower) employment stability.

Table A1. Sample Statistics

	Mean	St. Dev.
Number of Employed Friends	2.38	0.81
Age	39.11	11.98
Dummy for Female	0.53	0.50
Education (Ref: No Educ. Qualifications)		
Other Qualifications	0.08	0.28
O-Level	0.20	0.40
A-Level	0.13	0.33
Other Higher Education	0.29	0.46
Degree: First and Higher Education	0.15	0.36
Family Structure		
Dummy for Couples	0.75	0.44
Number of Children (*Ref: No Children*)		
One Child	0.17	0.37
Two Children	0.16	0.37
Three or More Children	0.06	0.24
Health Related Variables		
Dummy for Having Health Problems	0.52	0.50
Dummy for Experiencing Depresion	0.06	0.24
Dummy for Being a Smoker	0.28	0.45
Ethnicity (Ref: Other)		
White	0.95	0.23
Black African	0.004	0.06
Black Carribean	0.003	0.05
Indian	0.01	0.11
Pakistan	0.003	0.05
Travel-to-Work Unemployment Rate	4.41	3.46
Friends Characteristics		
Age of First Friend	39.40	12.06
Age of Second Friend	38.73	11.81
Age of Third Friend	38.49	11.87
Dummy for First Friend Female	0.55	0.50
Dummy for Second Friend Female	0.58	0.49
Dummy for Third Friend Female	0.57	0.50
Observations	35,518	

Note: The sample consists of individuals aged 18-65 in the even years of the period 1992-2006 when information on their three closest friends is available. The sample is also restricted to friends aged 18-65.

Table A2. Linear Fixed Effects Estimates for the Transition from Non-Employment into Employment by Contact Frequency and Residential Proximity

	Contact Frequency					Residential Proximity				
	Strong Ties			Weak Ties		Living Close			Living Far	
	Coef.	s.e.		Coef.	s.e.	Coef.	s.e.		Coef.	s.e.
Number of Employed Friends	0.023	0.008	***	0.005	0.012	0.020	0.008	**	0.001	0.022
Number of Observations	7,213					7,213				

	Contact Frequency and Residential Proximity									
	Strong Ties and Living Close			Weak Ties and Living Close		Strong Ties and Living Far			Weak Ties and Living Far	
	Coef.	s.e.		Coef.	s.e.	Coef.	s.e.		Coef.	s.e.
Number of Employed Friends	0.020	0.008	**	0.006	0.010	0.040	0.021	*	0.015	0.018
Number of Observations	7,213									

Note: For the sample and other regressors see the note in Table 2. “Strong ties” are defined as those in which the frequency of contact either by visiting, writing, or by telephone is at least once a week. “Weak ties” are defined as those in which the frequency of contact is less often than once a week. Friends “living close” are defined as those who live up to 50 miles away from the respondent, while “living far” if they live more than 50 miles away from the respondent.

Table A3. Transition from Non-Employment to Employment for the First Closest Friend - Sample with No New Friends

Panel A. Sample without a New First Friend

	Pooled OLS			Fixed Effects		
	Coef.	s.e.		Coef.	s.e.	
Friend Employed	0.093	0.014	***	0.069	0.027	***
Number of Observations	6,940			6,940		

	FIML IV W/out Current Health and Depression			FIML IV With Current Health and Depression		
	Coef.	s.e.		Coef.	s.e.	
Instrument: ***Onset of Health Related Work Limitation***	-0.440	0.195	**	-0.672	0.194	***
	[-0.050]			[-0.076]		
Friend Employed	0.405	0.101	***	0.409	0.102	***
	[0.078]			[0.078]		
Number of Observations	6,940			6,940		

Panel B. Sample without any New Friend

	Pooled OLS			Fixed Effects		
	Coef.	s.e.		Coef.	s.e.	
Friend Employed	0.098	0.020	***	0.080	0.044	*
Number of Observations	3,605			3,605		

	FIML IV W/out Current Health and Depression			FIML IV With Current Health and Depression		
	Coef.	s.e.		Coef.	s.e.	
Instrument: ***Onset of Health Related Work Limitation***	-0.602	0.275	**	-0.921	0.273	***
	[-0.062]			[-0.098]		
Friend Employed	0.471	0.114	***	0.505	0.128	***
	[0.091]			[0.098]		
Number of Observations	3,605			3,605		

Note: The estimation reported in this table is similar to the one of Table 4. Panel A is restricted to those individuals who do not report a new first friend in the next wave. Panel B is restricted to those individuals who do not report any new friend among their three closest friends in the next wave. A friend is defined as new if the length of friendship is less than 2 years. Average marginal effects are reported in square brackets.

Table A4. Number of Employed Friends and Transition from Non-Employment to Employment by Skill Level and Friends' Relation

	All			High Skilled			Low Skilled		
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
Number of Employed Friends	0.252	0.063	***	0.301	0.077	***	0.237	0.075	***
	[0.031]			[0.041]			[0.033]		
Number of Observations	35,518			35,518					

	All			High Skilled			Low Skilled		
	Coef.	s.e.		Coef.	s.e.		Coef.	s.e.	
Number of Employed Relatives	0.250	0.092	***	0.231	0.115	**	0.261	0.111	**
	[0.034]			[0.031]			[0.035]		
Number of Employed Non-Relatives	0.274	0.063	***	0.324	0.080	***	0.227	0.078	***
	[0.037]			[0.044]			[0.031]		
Number of Observations	34,568			34,568					

Note: The sample consists of individuals aged 18-65 in the even years of the period 1992-2006 when information on their three closest friends is available. The sample is also restricted to friends aged 18-65. Other regressors include individual and friend time-varying covariates (five age groups, elapsed duration, dummies for living as a couple, number of children (1, 2 or more), having health problems, experiencing depression, smoking, time and region dummies, and five age groups for the age of each friend), individual and friend time-invariant covariates (dummies for female for individual and each of his or her friends, dummies for levels of education, ethnicity) and local economic conditions (local unemployment rate at travel-to-work area). High skilled are defined as those with A-levels or higher education. ***/**/* denote significance at the 1%/5%/10% level, respectively. Average marginal effects are reported in square brackets.

Table A5. Distribution of Unobserved Heterogeneity

	Mass Point 1	s.e.		Mass Point 2	s.e.		Mass Point 3	s.e.	
Non-Employment Transition	-0.212	0.514		-2.135	0.137	***	2.359	0.179	***
Initial Conditions Equation	1.526	0.352	***	2.751	0.087	***	-2.865	0.089	***
Wage Equation	1.030	0.165	***	-0.288	0.053	***	0.096	0.055	*
Probability 1					0.44				
Probability 2					0.12				
Probability 3					0.44				

Note: These estimates of the discrete unobserved heterogeneity are from the estimation of the joint model of the transition from non-employment to employment, the wage equation and the initial conditions equation (the probability of being non-employed). There are three mass points for the unobserved term of each equation with three associated probabilities. The second and the third mass points are defined as deviation from the first.