Friends' Networks and Job Finding Rates[§]

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Abstract

We investigate the effect of social interactions on labor market outcomes using a direct measure of social contacts based on information about individuals' three best friends. We examine the effect of the number of employed friends on the transition from non-employment to employment and we find a significant positive effect of an additional employed friend on job finding rates. This evidence is robust to specifications that address the endogeneity of friends' employment status. We also find evidence of higher wages and employment stability for those with more employed friends, which is consistent with networks acting as an information transmission mechanism.

Keywords: Networks, Unemployment, Friendship ties

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1. Introduction

Search in the labor market involves the acquisition of information about available job opportunities, which requires time and effort. Social networks have for long been considered as an important source of information for job seekers (see e.g. Rees, 1966; Montgomery, 1991 in economics; and Granovetter, 1995; Petersen et al., 2010 in sociology). A number of early studies have documented the widespread use of friends and relatives as a job search method (see Montgomery, 1991 and Ioannides and Loury, 2004 for reviews). Recent studies have looked at the effect of social interactions on employment and wages using *indirect* measures, such as geographical proximity or group affiliation, to define the relevant social network (e.g. Topa, 2001; Munshi, 2003; Weinberg et al., 2004; Bayer et al., 2008; Dustmann et al., 2010).[1]

In this paper, we investigate the importance of network effects in the labor market using *direct information* on social interactions. We develop a measure of the relevant social network of each individual which is based on information from the British Household Panel Survey (BHPS) about each of the respondent's three best friends and their characteristics. Using this information, we can construct a measure of the quality of the network based on the employment status of the friends. To the best of our knowledge, this is the first paper that uses direct information on social interactions in estimating the effect of networks on labor market outcomes. Unlike previous research, we do not rely on the identification assumption that individuals within a given group – e.g. neighborhood or firm – actually know each other and are members of the same network, which is non-testable. The focus of our empirical analysis is to identify the effect of the number of employed friends on job finding rates based on the transition from non-employment to

[1] Ioannides and Topa (2010) review the recent literature on social interactions and job matching based on neighborhood effects.

employment across two years.[2] Due to the panel structure of our data, the measure of network quality – the number of employed friends – is predetermined at the time of the observed transition, which avoids the reflection problem (Manski, 1993).

Our analysis offers direct evidence to theoretical work which examines the implications of networks on employment dynamics (Montgomery, 1991; Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009; Galeotti and Merlino, 2010). The motivation behind using the number of employed friends as a measure of the quality of the social network is the assumption in these studies that employed social contacts are expected to be better informed about job opportunities available in the market and to pass this information to non-employed network members. The better, therefore, the employment status of an agent's connections, the more likely that is the agent to receive information about employment opportunities. This leads to a positive correlation between the employment status of the agents in a network. This prediction also has relevant policy implications, since the network may be seen as a social multiplier of labor market policies designed to bring the unemployed back into work.

Identification of social network effects is complicated for a number of reasons.[3] First, any effect of the number of employed friends on job finding rates might be due to the presence of correlated unobservables. Unobserved individual attributes can be correlated between an individual and his or her contacts because of positive sorting. For instance, more able and motivated individuals have better employment prospects and are more likely to have employed friends. Generally, social interactions are more likely to emerge among individuals that share some relevant traits – such as education or ethnicity – or are characterized by similar tastes or

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

[3] The identification of social interactions is discussed by Manski (1993, 2000), Moffitt (2001), Bramoullé et al. (2009) and in the comprehensive review by Blume et al. (2010).

constraints.[4] When these traits and tastes are unobservable to the researcher and correlated with the outcomes of interest the estimated effect will be biased and cannot be attributed to a network effect.

To deal with unobserved heterogeneity, our identification strategy exploits the panel dimension of our data, which provides variation in the employment status of friends and the outcomes for a given individual over time. This allows us to control for individual fixed effects. The main identification assumption is that any correlation between the number of employed friends and individual unobserved traits is due to traits that do not vary over time. This assumption rules out any correlation due to time-varying unobserved attributes. We investigate the sensitivity of our results to the inclusion of time-varying observed heterogeneity, and we show that our findings are robust. We also control for the local economic conditions using the unemployment rates in the travel-to-work area, thus addressing correlation in unobservables that may arise because of the presence of local economic shocks (e.g. a plant closing in the local area) that affect both the individual and his or her friends.

Another complication in the estimation of the network effects is that the composition and quality of the network might change in response to individual's labor market status. This feedback from being non-employed to the number of employed friends might arise if, for instance, staying longer out of employment leads to fewer contacts with those employed. We provide evidence that our findings are robust to the existence of an endogenous network and, if anything, they can be seen as a lower bound. We also find confirmation of robustness to endogeneity by estimating a 'reverse' version of our model where the employment transition of the first best friend is a function of the BHPS respondent's employment, and the latter is

[4] For a model of friendship formation stressing the role of 'types' similarities, see Currarini et al. (2009). An empirical investigation of friendship formation is provided by Marmaros and Sacerdote (2006).

instrumented using information on lagged health shocks.

Our results indicate the existence of significant network effects at the individual level. An additional employed friend increases the probability to find a job by 3.7 percentage points. Taking into account the unconditional yearly transition rate from non-employment to employment of 20.28 percent, the effect of an additional employed friend is sizeable and corresponds to an approximately 18 percent increase in the job finding rate. In addition, the job-finding rate increases with the number of employed friends, with individuals being 11 percentage points more likely to become employed when they have three employed friends than having none. We also find that an additional employed friend among those who find a job is associated with a 6.2 percent increase in wages and a reduction in the probability to exit from subsequent employment of 5.1 percentage points. We interpret these additional findings as suggestive evidence of networks operating as information transmission mechanisms.

The remainder of the paper is organized as follows. Section 2 discusses how this paper is related to the social network theories of the labor market and the existing empirical literature. Section 3 describes the data and the empirical strategy. We report the main results in Section 4, discuss our findings in relation to the potential mechanisms that can explain network effects in Section 5 and conclude in Section 6.

2. Theoretical Framework and Empirical Literature

The analysis in this paper offers direct empirical evidence on the role of employed contacts on job finding probabilities. A number of theoretical contributions have modeled the impact of social interactions on employment transitions. These studies emphasize the role of the employment status of the contacts in the network (Montgomery, 1991; Calvó-Armengol, 2004; Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009; Galeotti and Merlino, 2010).[5] Employed network members receive information about vacancies which they do not need for themselves and pass on to their unemployed contacts; they may be generally better informed about employment opportunities available in the market; or they may directly provide job referrals to employers. All these mechanisms imply a transmission of information between employed and unemployed network members that is beneficial to the job search process of the latter. Therefore, the core prediction from the theoretical literature is that the better the employment status of an individual's connections, the more likely he or she is to receive information about jobs, which leads to a positive correlation between the employment status of connected individuals in a network.

Our work relates to the growing empirical literature that tries to identify the labor market effects of social networks. A major challenge for most studies is the definition of the network due to the lack of information on social interactions.[6] One stream of literature relies on self-reported information about the use of contacts while searching for a job (see Loury, 2006 and Pellizzari, 2010 for recent examples in the literature). In this case, researchers have information on the existence of social ties, but typically do not observe the quality of such ties (in particular their employment status), which is key in understanding how networks operate. Moreover, the effect of informal contacts may stem from improvement in match quality or from selection effects of workers with limited access to alternative search channels.

Alternatively, research strategies based on geographical proximity and group affiliation have been proposed. A common trait of these studies is that in the absence of direct information on social ties, networks are assumed to operate along some observable dimensions, such as the

[5] Ioannides and Loury (2004) provide a comprehensive review of the literature.

[6] Data on actual links within a network have been recently used by Calvó-Armengol et al. (2009) to study educational outcomes. Using the US Add Health survey, they are able to construct complete network of friends in high schools and are then able to relate network characteristics to measures of educational success, separating network from peer effects.

neighborhood, the ethnic group or the firm. Practically, researchers generate clusters of agents based on group membership and assume that individuals are related to each other within these groups. Examples of studies that use geographic proximity at the neighborhood level to define networks include Topa (2001), Weinberg et al. (2004), Bayer et al. (2008), Hellerstein et al. (2008) and Schmutte (2010). These studies find significant effects of networks on employment and wages.[7] Studies that define networks based on group affiliation include Cingano and Rosolia (2006), who use data from the Italian social security archive and define contact networks at the firm level as the set of individuals who had been working together prior to displacement, Dustmann et al. (2010) who use German linked employer-employee data to study ethnicity based job referral networks, and Munshi (2003) who defines networks at the origin-community level to identify job networks among Mexican migrant in the U.S. labor market.

Finally, another empirical strategy relies on family networks identified from population-wide employer-employee data set. Kramarz and Nordström Skans (2009) study the school-to-work transitions of young Swedish and find that job referrals from parents are indeed very frequent, especially for males at the low end of the skill distribution. Although family networks define in a direct way the connection between network members they are more specific and refer to a subset of the potential social interactions that might be relevant.

3. Data and Empirical Strategy

3.1 Data

We use data from the British Household Panel Survey (BHPS) between 1992 and 2005. The BHPS is a representative sample of British households which follows individuals over time, allowing identification of yearly transitions across labor market states. In addition to this, the

[7] Van der Klaauw and van Ours (2003) use neighborhoods to study the effect of networks in the context of welfare transitions. Welfare dependency and social networks are also studied by Bertrand et al. (2000).

BHPS contains a special section on social networks, which we exploit for estimating network effects on job finding rates. Starting from wave 2 (1992), respondents were asked at each even-numbered wave to report information on their three best friends. Besides details about best friends' gender and age, the BHPS provides information on the employment status of friends. Therefore, we can observe that part of the network closest to the BHPS respondent (the three best friends), and we are able to characterize the employment intensity within that portion.

Since information on friends is retrieved at every even-numbered wave, we are able to relate the employment status of friends at wave t $(t = 1992, 1994, 1996, ..., 2004)$ to the employment transitions of BHPS respondents between waves t and $t+1$. We select a sample of individuals aged 18-65 and not in full time education at any even-numbered wave whose three best friends also belong to the same age range. This results in 10,911 individual observations (5,296 men and 5,615 women) with a total of 36,610 person-year observations. Since our focus is on yearly transitions from non-employment into employment (including self-employment) from one year to the next, we further select individuals who are not employed in the survey year and whose employment status in the subsequent year is observed.[8] Finally, we exclude individuals who do not report information on all three friends.[9] Our final estimating sample consists of 3,196 non-employed individuals with a total of 6,479 person-year observations. Half of the individuals are observed as non-employed more than once in the sample.

Some relevant demographic information for the estimating sample is presented in Panel A of Table 1, in connection with the demographic characteristics of the three best friends. The table

[8] For about 8 percent of those not employed in a given year the employment status is missing in the subsequent year. We assume that these observations are missing at random and exclude these panel attritors from the estimating sample. Cappellari and Jenkins (2008) show that in the BHPS panel attrition is ignorable for the estimation labor market transition models.

[9] In Section 4.3 we investigate the sensitivity to the exclusion of those individuals with missing information on their friends.

shows that there is a certain extent of assortative mating among friends in terms of both gender and age. The proportion of women whose first best friend is a woman is 83 percent, and a similar incidence (81 percent) characterizes men. As we move from the first to the third best friends, assortative mating remains high among women (79 percent have the third best friend who is of the same gender), while it decreases somehow more evidently for men, where the proportion of cases whose third best friend is men is 71 percent. We can observe patterns of assortative mating among friends also in the case of age, where the average age of friends grows with the age of the respondent. Note, however, that we have truncated the distribution of friends' age between 18 and 65, which explains why the ordering between respondents and their friends' ages reverts as we consider older respondents in our sample.

In Panel B of Table 1 we provide some summary statistics on the job finding probabilities in the sample. On average, about 20 percent of non-employed individuals make a transition from non-employment to employment from one year to another.[10] The lower part of Table 1 provides evidence on the association between the number of employed individuals in the group of the three best friends and transitions from non-employment to employment. As can be seen, the association is strong, with the exit rate from non-employment that more than triples when moving from zero to three employed friends. Moreover, patterns appear to be rather similar for women and men.

3.2 Empirical Strategy

We model the associations singled out in Table 1 by means of regression models for the probability of transitions from non-employment into employment.

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[10] The year-to-year job finding rate is much higher for the unemployed (42 percent) and lower for the inactive (15 percent).

Let E_{it} be a dummy indicator of respondent's i employment status in year t, and let NEF_{it} denote the number of employed friends of individual i in year t, a variable that can take values from 0 to 3. The employment dummy takes on value one for respondents that are either full-time employees, part-time employees or self-employed, and value zero for those who are either unemployed (ILO definition) or out of the labor force. Our baseline specification is

$$\Pr(E_{i,t+1} \mid E_{i,t} = 0) = F(X_{i,t}^{'}\beta_1 + \delta NEF_{i,t} + u_i) \qquad (1)$$

where $X_{i,t}$ is a vector of controls. The vector of individual characteristics includes time-varying and time-invariant regressors. The time-varying regressors include the local unemployment rate defined at the travel-to-work area level, age and dummies for the region of residence, the survey year, living as a couple, having one, two or more children, experiencing health problems, depression and being a smoker. The time-invariant regressors include a gender dummy, education (highest qualification attained) and ethnicity (categorized in nine groups) dummies. We also include in vector X the individual characteristics of each of the three friends for which we have information; age and gender.

We estimate the transition equation in (1) by forming a sample of non-employed individuals at each even wave (*t*=1992, 1994, 1996,…, 2004). For estimation we adopt a fixed effect logit approach, which eliminates the unobserved effect u_i, which is fixed over time. In our sample, we observe multiple non-employment spells for each individual with the number of employed friends varying over time and across these spells. We use this variation to control for individual unobserved heterogeneity that might be correlated with the main variable of interest, the number of employed friends. The sample size is reduced due to the conditioning of the fixed effects logit estimator on those individuals who are observed with multiple spells and with transitions from non-employment to employment over time. Individuals who do not experience a transition to employment over their observed spells or who always make a transition do not contribute to the likelihood.

The presence of unobserved heterogeneity induces serial correlation in the employment process, which may imply that sample selection is endogenous. Note, however, that we integrate out time-invariant unobserved heterogeneity using the fixed effect logit estimator. Moreover, to the extent that those found out of employment in a given year have an unobserved propensity to find a job that is lower than the average in the population, any remaining bias is likely to produce attenuation in the effect under estimation.

4. Results

4.1 Empirical Correlations

We first present some regression-based correlations between the number of employed friends and the transition into employment to have a benchmark for comparison with the fixed effect estimates that follow. Column 1 of Table 2 presents the estimates of a pooled logit regression without additional controls. We find that the number of employed friends exhibits a positive and significant association with the transition into employment. The marginal effect of the number of employed friends on the job finding probability is 6.4 percentage points (p.p).[11] In Columns 2 and 3 we investigate the sensitivity of this finding to the inclusion of individual and friends' characteristics. With the inclusion of friends' characteristics (age and gender) the marginal effect reduces to 5.9 p.p and after controlling for individual observed characteristics, the marginal effect becomes 6.0 p.p. This suggests that only a small part of the effect is due to a correlation

[11] Marginal effects for both the pooled logit and the fixed effect logit of the next section are computed as $\beta_{nef}\, p(1-p)$, where β_{nef} is the estimated coefficient on the number of friends, while p is the average sample predicted probability.

between the number of employed friends and observed characteristics. Estimating the same pooled logit model separately for the unemployed and inactive, we find that an additional employed friend increases the job finding rate by 7.0 p.p. for the unemployed and by 5.0 p.p. for the inactive.

Non-linear effects **–** The above analysis imposes a linearity assumption on the effect of the number of employed friends. We next estimate the pooled logit model allowing for a non-linear effect by defining dummies for having one, two or three employed friends. The results presented in Column 4 of Table 2 show that having one employed friend significantly increases the probability to enter employment in the next year by 6.2 p.p compared to having no employed friends, while having two or three employed friends increases the job finding probability by 10.3 p.p and 18.1 p.p, respectively. We also experimented with quadratic trends and with specifications accounting for the effect of one additional employed friend, and found no clear evidence of convexities in the network effect.

4.2 Fixed Effects Estimates

The results presented so far establish the existence of a correlation between the employment status of friends. Non-employed individuals who have more employed friends are more likely to find a job. One concern with this finding is that unobserved individual characteristics might affect both the probability of having friends who are employed 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 on the effect of the number of employed friends. As discussed in Section 3, we address this by estimating equation (1) using a fixed effect logit approach.

The first column of the top panel (FE-1) of Table 3 shows that even after controlling for fixed effects the coefficient of the number of employed friends indicates a positive and significant effect on job finding probability. An additional employed friend increases the transition probability by 3.7 p.p. This effect is lower compared to the pooled estimation, which suggests a positive correlation between unobserved individual heterogeneity and having employed friends, which leads to an upward bias. Nevertheless, the effect remains significant and large. Taking into account the unconditional job finding rate of 20.28 percent, the effect of an additional employed friend is sizeable and corresponds to an approximately 18 percent increase in the job finding rate. This finding is consistent with the core prediction from the theoretical literature that the better the employment status of an individual's connections, the better his or her employment prospects (Calvó-Armengol, 2004; Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009; Galeotti and Merlino, 2010).

The non-linear specification of the FE-1 estimation in the lower panel of Table 3 shows that the effect is higher – and significant – when all friends are employed. This finding is consistent with the theoretical predictions of Calvó-Armengol and Jackson (2004), according to which, more employed contacts reduce the competition within the network, so we should expect a larger effect. To the contrary, when the network has more unemployed friends, then any new information about job vacancies that might arrive is more likely to be kept by the individual who receives it and less likely to be passed on to other members of the network.

4.3 Sensitivity Analysis

In this section, we investigate the sensitivity of our main results with respect to the inclusion of time-varying covariates, the local economic conditions and the missing information on friends.

Time-varying covariates – The fixed effect estimation (FE-1) assumes that only fixed unobserved individual characteristics can be correlated with the employment status of friends. It could be the case, however, that time-varying characteristics might change when one enters non-employment and this change might be correlated with friends' characteristics. For instance, it is possible that behavior such as smoking, drinking or depression might change upon entering non-employment, which might also affect the friendship ties of the non-employed. In order to test for the presence of such a correlation, we estimate our model by excluding all the time-varying covariates. Our maintained assumption is that if observed and unobserved time-varying heterogeneity are correlated, then finding that our estimates are not sensitive to time-varying regressors would signal that they are also likely to be robust to time-varying unobserved heterogeneity. The second column of Table 3 (FE-2) shows that after excluding all the time-varying regressors the fixed-effect estimate is very similar (marginal effect of 0.038) with the one that includes the time-varying regressors (marginal effect of 0.037).

Local economic conditions – Correlation in unobservables may also arise because of the presence of local economic shocks (e.g. a plant closing in the local area) that affect both the individual and his or her friends. We consider the importance of local economic conditions for our findings in two ways. First, we estimate our baseline model excluding the local unemployment rate, which is defined at the travel-to-work area. The coefficient estimate from FE-3 in Table 3 remains the same compared to the main specification (FE-1), which suggests that our main finding is not sensitive to the local economic conditions. Second, we estimate our baseline model including, as an additional control, the percentage of benefit claimants by occupation and region. The idea is that individuals who work in the same occupation as their friends are more likely to be subject to correlated shocks that might not be completely captured by an aggregate local unemployment rate. The percentage of benefit claimants by occupation in the region of residence captures those local occupational specific shocks that might affect members of the same network. We only have this information for the years 1996-2000, so we perform this estimation with the relevant sub-sample.[12] Due to the reduced sample size, we are not able to estimate the model with fixed effects. Based on the estimation on the pooled sample, we find that after controlling for the percent of benefit claimants, the marginal effect of the number of employed friends on the sub-sample of observations within 1996-2000 remains unchanged at 0.04 (4 p.p).

Missing friends **–** We also check the sensitivity of our main findings to the missing information on friends. Every individual in the survey is asked to provide information on his or her three best friends; but not everyone reports information on three friends and even when all three friends are observed there might be missing information on some of their characteristics. Considering the sample which includes those with missing information on their friends, we include dummy variables by the type of information that is missing for each friend as additional controls (i.e. missing age, gender, employment). The estimation FE-4 in Table 3 shows that main effect of the number of employed friends is unchanged when we consider this larger sample. The marginal effect is slightly larger (0.041 instead of 0.037 of FE-1) and is statistically significant.

4.4 Selection and Feedback Effects

We now consider the situation in which the network is endogenous, so that the composition of the network may change in response to individual's labor market status. The estimation of the

[12] This information is obtained from the Nomis official labor market statistics of the UK Office of National Statistics (www.nomisweb.co.uk).

fixed effects model relies on variation over time of the employment status of friends, assuming no feedback effects. This, rules out the case of a feedback from being non-employed to the number of employed friends, which might arise if, for example, staying longer out of employment leads to fewer contacts with employed people. In addition, given that our sample is based on the stock of non-employed at time *t* with differences in the length of elapsed duration, this feedback might lead to dynamic selection with those having a shorter duration also having more employed friends. This type of selection might result in a spurious correlation between the number of employed friends and job finding rates as those with shorter duration in non-employment are also more likely to find a job.

Starting from the possible selection due to stock-sampling, we examine the effect of the elapsed duration in non-employment on the number of employed friends. Although this does not address selection in a regression framework, it provides evidence as to whether those with longer non-employment spells have systematically fewer employed friends. Given the panel structure of our data, we estimate a linear fixed effects model, which eliminates the unobserved individual characteristics that might be correlated with both the number of employed friends and the length of time in non-employment. The top panel of Table 4 shows that the elapsed duration in months in non-employment is not statistically significant in explaining the number of employed friends. This provides sufficient evidence that our sample is not selected in way that might lead to a spurious relation between number of employed friends and job finding rates.[13] We also investigate the sensitivity of our estimates from equation (1) to the inclusion of the length of time in the current labor market state for the sample of non-employed. The estimation FE-5 in Table 3 shows that controlling for the length out of employment increases the marginal effect from 0.037

[13] The OLS result (not reported) is negative and significantly different from zero, which suggests that any correlation is due to unobserved characteristics.

to 0.042. This suggests that any correlation between the length of time in non-employment and the number of employed friends is likely to lead to a downward bias.

In order to address feedback effects we estimate equation (1) using lagged values of the number of employed friends. If feedback effects from non-employment spells may induce depletion in the stock of friends in the base year of a transition, using the number of employed friends in the year before provides a measure of networks that is less prone to this type of effect. The coefficient estimate from the fixed effect logit in the second panel of Table 4 using the lagged number of employed friends is larger compared to the estimate from Table 3 (FE-1), which refers to the current number of friends. The estimated marginal effect is 6.3 p.p. (3.7 p.p. in Table 3), which suggests that our main estimates from Table 3 can again be seen as a lower bound of the effect of networks on job finding rates.

4.5 Sources of Variation of Network Quality

The estimation of the fixed effects model relies on variation over time of the employment status of friends. This variation might have two sources. The first is related to changes of the employment status of friends who remain the same over time. The second is due to changes of friends over time that might lead to differences in the quality of the network because of endogenous changes in the composition of the network. We investigate the sensitivity of our findings to these sources of variation by restricting the analysis only to those individuals for whom their friends remain the same over the relevant observation period. With this restriction, any variation of the employment status of the friends is due to their transitions into and out of employment and not to respondents changing friends as a way to possibly improve the quality of the network. Unfortunately, no personal identifier is available for the three best friends, which prevents us from taking fully into account changes in friends' employment status over time. Since we do not observe an identifier for the friends we use observed characteristics such as gender and year of birth of all three friends to distinguish between stable and non-stable friends across two consecutive non-employment spells. In addition, we consider individuals for whom the duration of friendship with each of the three friends is longer than 3 years.[14] To check the sensitivity of our results we estimate our baseline specification for various subsamples, which are based on different definitions of stable networks. A network is stable when for all three friends the observed characteristics (gender and year of birth) do not change across the two waves within which the transitions occur, and the duration of friendship with all friends is longer than 3 years.

The first column of Table 5 reports for ease of comparison the estimated effect of the baseline model with a marginal effect of 0.037 (FE-1 from Table 3). The second column shows the estimated effect for the sample of individuals with all friends having the same gender across two waves, which results in a significant marginal effect of 0.05. The sample in the third column is restricted to those individuals with all friends having the same year of birth across two waves, which leads to a marginal effect of 0.046 that is significant at the 10% level. When the sample is restricted to long friendships (above 3 years) in Column 4 the estimated marginal effect is 0.038 but not significantly different from zero due to large reduction in the sample size. Finally, we report the results when we combine the restrictions based on gender and year of birth (Combined 1) and when we combine the three restrictions - same gender, year of birth and long friendships (Combined 2). In both case, although there is a loss in efficiency due to significant drop in the sample size, we observe that the main effect remains positive and above the results from the baseline model. Overall, the estimated marginal effects in Columns 2-5 vary from 0.038 to

[14] The information on the duration of friendship in the BHPS is provided in the following categories: less than 1 year, 1-3 years, 3-10 years and more than 10 years. If there is a new friendship formed in period t then the duration of friendship should be less than 3 years in period $t+1$.

0.073.

4.6 Reverse Network Effect

So far we have dealt with network endogeneity using the fixed effects estimator. In principle, one alternative possibility to assess endogeneity would be to use valid instruments for the employment status of the respondents' friends. Relative to fixed effects, instrumental variables would control for all sources of unobserved heterogeneity, not only time-invariant ones. However, such a strategy is not viable in our case because in the BHPS the amount of information about friends is rather limited. The situation is rosier if we reverse the model and consider it from the friends' perspective, i.e. estimating the effect of the respondents' employment status on the transitions - from non-employment to employment - of the friends.[15] In that case we can exploit the abundance of information on respondents in the BHPS, and use as instruments for the potentially endogenous employment status those respondents' characteristics that can legitimately be thought of as having no direct effect on friends' transitions. Strictly speaking, estimating such a model requires observation of friends' identity in order to follow their employment status over time, something that our data do not provide. To circumvent such limitation, we focus on the first best friend and assume that his or her identity is the same over two consecutive even waves, i.e. waves in which information on friends is available. We discuss the consequences of this assumption along with the estimation results.

The reverse model is estimated on the sample of respondents whose first best friend is non-employed at time *t*. The dependent variable in the model is a dummy which takes the value of one if the respondent's best friend makes a transition to employment between time *t* and *t+2*,

[15] We thank Nikos Askitas for his suggestion to consider the reverse network effect by looking on the transition of friends as a function of respondents' employment status.

and zero otherwise. We consider 2-year transitions because we observe information about friends every two years. The conditioning set in the 'reverse' model is formed by the respondents' employment status in the base year of each transition (year *t*), all available friends characteristics (age, gender), and some of the respondents' characteristics which are presumably correlated with friends' characteristics that are not available in the BHPS, namely education, family structure and region of residence.

We instrument respondent's employment exploiting information on whether health status limits the type and amount of work he or she can undertake; more specifically, we use the change in this variable between years *t-1* and *t* to instrument respondent's employment in year *t*. The instrumental variable is a dummy which takes on value one for respondents who experienced a negative health shock that induced the onset of work limitation between *t-1* and *t*, and value zero otherwise. Our identification assumption, therefore, is that the change in respondents' health status between *t-1* and *t* has no effect on the friend's transition between *t* and *t+2* besides the one exerted through the respondent's employment status in *t*. Due to the limited dependent nature of both the dependent variable and the instrumented variable, we implement the model with a simultaneous system of two logit equations, using a discrete distribution with two mass points for each unobserved factor, which are allowed to be correlated across equations, to approximate the joint distribution of unobserved heterogeneity. The system is estimated on pooled transitions without fixed effects, the latter would require assuming that friends' identity is constant through all BHPS waves.

Results are reported in Table 6. In order to provide a benchmark for the results of the 'reverse' model, we show in the first column the estimates of the 'direct' model. This is the model for respondents' transitions as a function of friends' status similar to Table 3, in which the network effect is captured by the employment status of the first best friend only and the employment transition is analyzed over a two-year window. We account for the potential network endogeneity in the direct model using fixed effects, as in Table 3. The estimated marginal effect on friend's employment status is 0.092, which is statistically significant at the 5 percent confidence level and suggests that having the best friend employed leads to a 9.2 percentage points increase in the job finding probability.

We next consider the 'reverse' model. The estimate of the coefficient on the instrumental variable (change in health conditions that induces limitations to work between *t-1* and *t*) indicates that it operates in the expected direction reducing the probability of the respondent to be employed and it is strong in a statistical sense (F-test equals 15.13). Considering the transition equation, we find a positive and significant causal (conditional on the identification assumption) network effect, which is sizeable. In particular, having an employed friend (the respondent) increases the transition into employment of the best friend by 11 percentage points. This effect is larger than the one from the direct model in the first column, and one reason could be that the assumption that the identity of the best friend is the same between *t* and *t+2* is inducing an over-estimation of friends' transitions into employment, which is correlated with the respondent's status. We address this possibility in the last column of the Table 6, by restricting the estimation sample to cases for which the characteristics of the first best friend –gender and year of birth— are constant across the two years in which the transition occurs and the duration of the friendship is longer than three years. The last column shows that the estimated network effect is now a 8.2 percentage points increase in the job finding probability, which is remarkably close to the effect estimated with the 'direct' model in the first column.

4.7. Labor market outcomes

Given the panel dimension of our data, we are able to investigate the effect of networks on labor market outcomes for those who find a job. We consider re-employment wages and the stability in employment by modeling the probability of exiting from employment back to non-employment over the next year.

Column 1 in Table 7 shows that the number of employed friends has a significant and positive effect on re-employment wages. An additional employed friend increases wages for those who become employed in the next year by 6.2 percent. In addition, having one (three) employed friend(s) compared to having no employed friends increases wages by 11.6 (22.2) percent. The second column of Table 7 shows that an additional employed friend not only increases wages but also reduces the probability to exit subsequent employment by 5.1 p.p. As shown in the lower panel of Table 7, having one employed friend does not lead to a significant difference in exit rates, but those who have two or three friends employed compared to none are significantly more likely to remain employed. While both these results suggest positive network effects on labor market outcomes one has to view them with some caution as those who find a job might be positively selected among the non-employed.

5. Mechanisms of Network Effects

There are a number of potential mechanisms through which employed friends might affect job finding probabilities. The first mechanism is related to information transmission of available jobs from the employed to the non-employed contacts of the network (e.g. Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009). The second is related to peer-effects and social norms. Social norms might exert pressure on the unemployed workers to find a job. Stutzer and

Lalive (2004) provide evidence that social norms (‘worth ethic’) speed up transitions out of unemployment. To the extent that the relevant social group is formed by the best friends, our findings may reflect the pressure that employed friends exert on non-employed network members. A third mechanism that might explain the findings is leisure complementarities. When the friends of an unemployed person are all employed, this will lower the value of leisure if enjoying leisure requires the presence of others, which might lower the reservation wage. Jenkins and Osberg (2004) show the effect of leisure coordination on the happiness of couples.

As a way to assess the relevance of peer-pressure and leisure complementarities as explanations of our findings, we exploit data on life satisfaction and satisfaction with the use of leisure, which are available in the BHPS. If non-employed individuals experience pressure from having all their friends employed or derive disutility from the fact that they have ‘nobody to play with’ when they have time free from market work, we should expect a negative association between the number of employed friends and satisfaction with life in general and leisure. We can actually estimate these associations by regressing life satisfaction and satisfaction with leisure of the non-employed on the number of their employed friends. The findings in Table 8 – both for the OLS and FE estimations – suggest that the number of employed friends does not have any effect on either measures of satisfaction.

In addition, for both the peer-effect and leisure complementarities hypotheses, we expect a lower reservation wage when the number of employed friends is higher. In fact, according to both interpretations, employed friends make non-employment spells more painful, so that non-employed network members should try to speed up the exit from non-employment, which can be done by lowering reservation wages and increasing search effort. In turn, lower reservation wages should correspond to lower wages upon re-employment. Conversely, the information hypothesis would suggest that the number of employed friends should lead to better employment opportunities and higher wages, to the extent that networks convey superior information on job offers relative to alternative job search channels.[16] The evidence that the number of employed friends increases wages and the stability in employment that we provided in Section 4.7 is, therefore, suggestive of networks operating as information transmission mechanisms.

6. Conclusion

This paper investigates the effect of social interactions on labor market outcomes using a direct measure of social contacts based on individuals' best friends and their characteristics. Using data from the BHPS, we identify the effect of social networks by examining the effect of the number of employed friends on the transition from non-employment to employment. We provide evidence that employed friends increase the probability of finding a job. An additional employed friend increases the probability of finding a job by 3.7 percentage points, which is a sizeable effect. In addition, having all friends employed compared to no employed friends leads to the greatest effects. These results are robust to a number of specifications that address the potential endogeneity of the number of employed friends due to correlated unobservables and feedback effects.

We also investigate the impact of friends' networks on labor market outcomes other than employment transitions, finding that employed friends are associated with higher wages and more stable matches upon re-employment. We use this evidence and additional findings on the effects of friends' employment on life satisfaction and satisfaction with leisure to conclude that

[16] Ioannides and Soetevent (2006) show in a calibrated matching model with random social network that on average workers who are better connected socially experience lower unemployment rates and receive higher wages.

the network effects are due to information transmission rather than to alternative mechanisms such as peer effects and leisure complementarities.

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Table 1: Summary Statistics.

Panel a): Demographic characteristics of sample respondents and their three best friends

	Friends' characteristics					
	First Best Friend		Second Best Friend		Third Best Friend	
Own Characteristics	Man	Woman	Man	Woman	Man	Woman
Man	81.16	18.84	75.66	24.34	71.6	28.4
Woman	16.94	83.06	16.26	83.74	20.78	79.22
	Age					
	Mean	S.D	Mean	S.D	Mean	S.D
18 to 24	23.49	7.44	23.38	7.23	23.42	7.14
25 to 29	30.57	9.17	30.3	8.56	29.57	7.78
30 to 34	34.7	8.81	34.04	8.27	33.76	8.44
35 to 39	38.21	8.18	37.38	7.88	37.28	8.18
40 to 44	41.87	7.95	40.81	7.76	40.9	8.03
45 to 49	44.66	8.04	43.59	8.52	43.54	8.86
50 to 54	47.1	9.6	47.16	10.01	46.61	10.23
55 to 65	51.3	10.52	50.01	11.09	49.55	10.86

Panel b): Number of employed friends and exit rates from non-employment

	Full sample	Men	Women
Unconditional Exit rate	20.28	22.52	19.34
Number of Employed Friends			
0	9.77	12.57	8.82
1	15.44	17.83	14.63
2	20.66	19.88	20.96
3	28.28	30.47	26.95

Notes: The sample consists of non-employed individuals in the even years between 1992-2005 for which information on friends is observed.

Table 2: Coefficients and Marginal Effects from Pooled Estimations.

	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
		(1)			(2)			(3)			(4)	
Number of Employed Friends	0.399	0.064	10.86	0.367	0.059	9.67	0.373	0.060	9.16			
One Employed Friend										0.384	0.062	2.53
Two Employed Friends										0.639	0.103	4.35
Three Employed Friends										1.126	0.181	7.50
Controls - Friends		No			Yes			Yes			Yes	
Controls - Individual		No			No			Yes			Yes	
Log-Likelihood		-3,181.36			-3,010.68			-2,742.21			-2,740.89	
Number of Individuals		3,196			3,196			3,196			3,196	
Number of Observations		6,479			6,479			6,479			6,479	

Notes: Logit regressions for the transition from non-employment to employment. Coefficients, marginal effects and their t-ratio are reported. The sample consists of non-employed individuals in the even years between 1992-2005 for which information on friends is observed. Other regressors include individual and friend time-varying covariates (age, dummies for living as a couple, number of children (1, 2 or more), having health problems, experiencing depression, smoking, time and region dummies, and 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. The full specification is reported in Table A1.

Table 3: Coefficients and Marginal Effects from Fixed Effects Estimations.

	FE-1			FE-2			FE-3			FE-4			FE-5		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Number of Employed Friends	0.166	0.037	2.04	0.171	0.038	2.10	0.166	0.037	2.04	0.191	0.041	2.57	0.188	0.042	2.26
Log-Likelihood	-450.04			-453.21			-450.11			-608.53			-437.81		
Number of Observations	1,324			1,324			1,324			1,787			1,307		

	FE-1			FE-2			FE-3			FE-4			FE-5		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
One Employed Friend	0.371	0.082	1.39	0.389	0.086	1.46	0.371	0.082	1.39	0.347	0.074	1.63	0.388	0.086	1.42
Two Employed Friends	0.357	0.079	1.35	0.383	0.085	1.45	0.360	0.080	1.36	0.382	0.081	1.72	0.411	0.091	1.52
Three Employed Friends	0.636	0.141	2.21	0.656	0.145	2.29	0.636	0.141	2.21	0.678	0.144	2.74	0.694	0.154	2.37
Log-Likelihood	-449.32			-452.50			-449.40			-607.82			-437.21		
Number of Observations	1,324			1,324			1,324			1,787			1,307		

Notes: Fixed effect regressions for the transition from non-employment to employment. Other regressors include individual and friend time-varying covariates (age, local unemployment rate at travel-to-work area, dummies for living as a couple, number of kids (1, 2 or more), having health problems, experiencing depression, smoking, time dummies, and age of each friend. FE-1 is the main specification with the full set of covariates and FE-2 is estimated without individual time-varying covariates. FE-3 is estimated without the local unemployment rate. Estimation FE-4 is based on the sample of individuals which includes those who have missing information on their friends. Dummy variables defined by the type of information missing are included as additional regressors. Estimation FE-5 includes a control for the length of the non-employment spell. The full specification of FE-1 is reported in Table A1.

Table 4: Coefficients and Marginal Effects from Fixed Effects Estimations - Selection and Feedback Effects.

	FE		
Dependent Variable: Number of Employed Friends			
	Coef.	t-ratio	
Duration in Non-Employment (in months)	-0.0004	-1.31	
Number of Observations	6,423		
	FE		
Dependent Variable: Job Finding Probability			
	Coef.	M.E	t-ratio
Lag Number of Employed Friends	0.276	0.063	2.57
Number of Observations	795		

Note: The top panel reports the coefficient estimate of the linear fixed-effects regression of the number of employed friends on the duration in non-employment. The second panel reports the estimate of the conditional fixed-effects regression of the probability of finding a job on the lag number of employed friends. Both estimations include all the other controls.

Table 5. Coefficients and Marginal Effects from Fixed Effects Estimations - Same Friends.

	Baseline			Same Gender			Same Year of Birth			Length of Friendship (3+ yrs)			Combined 1			Combined 2		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Number of Employed Friends	0.166	0.037	2.04	0.216	0.050	1.94	0.198	0.046	1.64	0.161	0.038	1.31	0.223	0.053	1.49	0.297	0.073	1.35
Log-Likelihood	-450.04			-259.41			-231.88			-211.41			-145.66			-68.31		
Number of Observations	1,324			768			701			616			449			223		

Notes: The baseline refers to the results of the main model (FE-1) of Table 3. The remaining fixed effect estimations are based on samples for which the friends remain the same between the current wave and the next wave. We use three definitions of having the same friends. The first one relies on the friends having the same gender. The second relies on having the same year of birth and the third one consider only those for which the duration of friendship is longer than 3 years. Combined 1 conditions the sample on friends having the same gender and year of birth, while combined 2 conditions on the three definitions. Standard errors are clustered at the individual level.

Table 6. Coefficients and Marginal Effects from Fixed Effects and IV Estimations - Symmetric Network Effects.

	Direct - 2 year transition Fixed Effects			Reverse - IV1			Reverse - IV2		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Instrument	-	-	-	-0.945	-0.208	-3.89	-1.638	-0.371	-3.30
Friend Employed	0.407	0.092	2.06	0.498	0.110	5.08	0.659	0.082	3.50
Number of Observations		797			5,631			1,733	

Notes: All estimations focus on the employment status of the best friend. The first estimation is a fixed effects logit estimation similar to the one in Table 3 in which the sample consists of the non-employment spells of respondents. The differences from the estimation in Table 3 are two: 1) the focus is only on the employment status of the best friend, which is captured by the coefficient and marginal effects of the variable "Friend Employed" and 2) the dependent variable is a dummy for the transition into employment from year t to year t+2 instead of a 1-year transition. In the reverse model, the sample is defined over the non-employment spells of respondents' best friend. The dependent variable is a dummy for the transition of the best friend from non-employment to employment. Since we have information on friends only every second wave, the transition for the reverse model is defined as a 2-year transition. The main effect of interest is the employment status of the friend (the respondent), which means that the variable "Friend Employed" captures whether the respondent is employed or not. The conditioning set in the reverse model is formed by the respondents' employment status in the base year of each transition (year t), all available friends characteristics (year of birth, gender), and some of the respondents' characteristics which are presumably correlated with friends' characteristics that are not available in the BHPS, namely education, family structure and region of residence. The instrumental variable is a dummy which takes the value of one if a respondent experienced a negative health shock that induced the onset of work limitation between t-1 and t, and zero otherwise. Reverse IV-1 is estimated on the full sample, while in Reverse IV-2 the estimation sample is restricted to cases for which the characteristics of the first best friend – gender and year of birth – are constant and the duration of the friendship is longer than three years.

Table 7. Coefficients and Marginal Effects - Labor Market Outcomes.

	Wages		Exit Employment		
	Coef.	t-ratio	Coef.	M.E.	t-ratio
Number of Employed Friends	0.062	4.10	-0.350	-0.051	-3.58
Number of Observations	1,093		1,062		

	Wages		Exit Employment		
	Coef.	t-ratio	Coef.	M.E.	t-ratio
One Employed Friend	0.116	2.04	-0.316	-0.046	-0.89
Two Employed Friends	0.201	3.76	-0.632	-0.093	-1.84
Three Employed Friends	0.222	4.20	-1.034	-0.152	-2.86
Number of Observations	1,093		1,062		

Notes: The estimation in the first column is a linear regression of log wages for the sample of those who make a transition from non-employment to employment. The estimation in the second column is a logit regression for the probability to exit from employment in the following year for the sample of those who make a transition from non-employment to employment.

Table 8. OLS and Fixed Effects Coefficient Estimates - Life and Leisure Satisfaction.

	Life Sat. - OLS		Life Sat. - FE		Leis. Sat. - OLS		Leis. Sat. - FE	
	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Number of Employed Friends	-0.011	-0.45	0.012	0.42	0.000	0.00	-0.009	-0.24
Number of Individuals	2,230		2,230		2,231		2,231	
Number of Observations	4,116		4,116		4,117		4,117	

	Life Sat. - OLS		Life Sat. - FE		Leis. Sat. - OLS		Leis. Sat. - FE	
	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
One Employed Friend	-0.034	-0.40	-0.154	-1.87	-0.065	-0.64	-0.035	-0.34
Two Employed Friends	-0.071	-0.86	-0.035	-0.42	-0.068	-0.69	-0.020	-0.19
Three Employed Friends	-0.040	-0.45	-0.057	-0.60	-0.029	-0.27	-0.043	-0.37
Number of Individuals	2,230		2,230		2,231		2,231	
Number of Observations	4,116		4,116		4,117		4,117	

Notes: Linear and fixed-effects regressions. The dependent variable is life satisfaction (Life Sat.) and leisure satisfaction (Leis. Sat.). Other regressors include the ones reported in the first column of Table 1.

Table A1. Pooled and Fixed Effects Full Specification Estimates.

	Pooled Logit			Fixed Effects		
	Coef.	S.Error	t-ratio	Coef.	S.Error	t-ratio
Number of Employed Friends	0.373	0.041	9.16	0.166	0.082	2.04
Individual Characteristics						
Female	-0.598	0.137	-4.38			
Age	-0.068	0.005	-13.21	0.060	0.303	0.20
Having Health Problems	-0.360	0.076	-4.73	-0.154	0.172	-0.90
Experiencing Depression	-0.528	0.131	-4.02	-0.586	0.256	-2.29
Smoking	0.008	0.085	0.09	0.064	0.277	0.23
Family Characteristics						
In Couple	0.221	0.096	2.29	0.290	0.254	1.14
One Child	-0.151	0.111	-1.36	-0.146	0.277	-0.52
Two Children	-0.156	0.109	-1.44	-0.018	0.301	-0.06
Three or more Children	-0.447	0.130	-3.43	-0.186	0.369	-0.50
Level of Education						
Other Qualifications	0.383	0.142	2.69			
O-Level	0.259	0.125	2.08			
A-Level	0.476	0.143	3.33			
Other Higher Education	0.727	0.121	6.01			
University Degree	0.990	0.153	6.46			
Regions						
Inner London	-0.910	0.496	-1.84			
Outer London	-0.629	0.478	-1.32			
Rest of South East	-0.343	0.450	-0.76			
South West	-0.386	0.460	-0.84			
East Anglia	-0.412	0.472	-0.87			
East Midlands	-0.611	0.453	-1.35			
West Midlands Conurbation	-0.679	0.488	-1.39			
Rest of West Midlands	-0.565	0.473	-1.19			
Greater Manchester	-0.494	0.489	-1.01			
Merseyside	-1.378	0.522	-2.64			
Rest of North West	-0.674	0.477	-1.41			
South Yorkshire	-0.920	0.506	-1.82			
West Yorkshire	-0.886	0.482	-1.84			
Rest of Yorkshire	-0.513	0.481	-1.07			
Tyne and Wear	-0.884	0.504	-1.75			
Rest of North	-0.558	0.475	-1.18			
Wales	-0.611	0.467	-1.31			
Scotland	-0.542	0.464	-1.17			

Ethnicity						
White	-1.310	1.458	-0.90			
Black Carribean	-1.672	1.560	-1.07			
Black African	-1.355	1.586	-0.85			
Black Other	-0.426	1.694	-0.25			
Indian	-1.280	1.500	-0.85			
Pakistani	-2.337	1.572	-1.49			
Bangladeshi	-2.066	1.603	-1.29			
Other	-1.292	1.553	-0.83			
Local Unemployment Rate	-0.025	0.015	-1.66	0.026	0.070	0.37
w4	0.072	0.116	0.63	0.426	0.640	0.67
w6	-0.142	0.158	-0.90	0.452	1.250	0.36
w8	-0.190	0.200	-0.95	0.493	1.868	0.26
w10	-0.030	0.212	-0.14	0.357	2.465	0.14
w12	-0.216	0.225	-0.96	-0.225	3.067	-0.07
w14	-0.207	0.233	-0.89	-0.116	3.666	-0.03
Friends' Characteristics						
Age of Friend 1	0.006	0.004	1.64	0.015	0.008	1.87
Age of Friend 2	0.001	0.004	0.24	0.007	0.008	0.78
Age of Friend 3	-0.001	0.004	-0.17	0.005	0.008	0.65
Friend 1 - Male	0.044	0.101	0.43			
Friend 2 - Male	-0.162	0.095	-1.71			
Friend 3 - Male	-0.165	0.086	-1.92			
Constant	2.842	1.557	1.83			
Log-Likelihood		-2,742.21			-450.04	
Number of Individuals		3,196			437	
Number of Observations		6,479			1,324	

Notes: The pooled logit estimation refers to the estimation in the third column of Table 2. The fixed effects estimation refers to the estimation in the first column of Table 3 (FE-1).