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Friends' networks and job finding rates

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Non-technical summary

Searching for a job involves the acquisition of information about available employment opportunities, and this requires time and effort. Social networks have been considered an important source of information for job seekers by economists and sociologists for a long time. In this paper, we investigate the importance of network effects in the labor market exploiting information on close friends. We construct a measure of the quality of the network based on friends' employment status using information from the British Household Panel Survey (BHPS) on each of the respondent's three best friends and their characteristics. The focus of our empirical analysis is to identify the effect of friends' employment on individual's job finding rates.

There are three main contributions of our study. To the best of our knowledge, this is the first paper that uses direct information on social interactions in estimating their effect on labor market outcomes. Unlike previous research, our definition of 'peers' does not rely on the assumption that individuals within a given group – e.g. neighbourhood or firm – interact with each other and are members of the same network, which is non-testable. The second contribution is that our study provides empirical evidence on alternative mechanisms through which social interactions might operate. We consider three ways in which peers might affect job finding probabilities: by transmitting information on available jobs, by exerting pressure due to social norms, or through the existence of leisure complementarities. The third contribution is that we can separate the effect of friendship networks from that of family networks.

We provide evidence that employed friends increase the probability of finding a job. An additional employed friend increases the job finding probability by as much as 13 percent or 3.3 percentage points. In addition, having all friends employed compared to no employed friends leads to the greatest effects, which suggests the presence of competition among the contacts. These results are robust to alternative analytical strategies. 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 the network effects are due to information transmission rather than to alternative mechanisms such as pressure due to social norms and leisure complementarities. Finally, we provide evidence which suggests that it is the behaviour of the contacts in the network rather than their characteristics that matters and that friends' networks matter above and beyond family networks. This has relevant policy implications, since the transmission of information through social interactions may act as a social multiplier of labour market programs.

Friends' Networks and Job Finding Rates§

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Abstract

Social interactions have important consequences for labour market outcomes. Yet the growing literature has relied on indirect definitions of networks. We present the first evidence based on direct information on friends' networks. We address issues of correlated effects with instrumental variables and panel data. We find large network effects, which persist even after controlling for family networks. One additional employed friend increases a person's job finding probability by approximately 13 percent. This is a result of endogenous social interactions. We also provide the first evidence that network effects operate through information transmission rather than through social norms or leisure complementarities.

Keywords: social interactions, 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 Ioannides and Loury, 2004 for a comprehensive review). Recent studies have looked at the effect of social interactions on employment and wages relying on *indirect* measures, such as geographic proximity or group affiliation, to define the relevant social network (e.g. Topa, 2001; Munshi, 2003; Weinberg et al., 2004; Bayer et al., 2008; Beaman, 2010; Dustmann et al., 2010).[1]

In this paper, we investigate the importance of network effects in the labor market exploiting *direct information* on close friends. We construct a measure of the quality of the network based on friends' employment status, using information from the British Household Panel Survey (BHPS) on each of the respondent's three best friends and their characteristics. The focus of our empirical analysis is to identify the effect of friends' employment on individual's job finding rates. We find that an additional employed friend increases a person's job finding probability by as much as 13 percent. Our analysis offers direct evidence to the theoretical work which examines the implications of networks on employment dynamics (e.g. Montgomery, 1991; Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009).[2]

There are three main contributions of our study. To the best of our knowledge, this is the first paper that uses direct information on social interactions in estimating their effect on labor

[1] Ioannides and Topa (2010) and Ross (2009) review the recent literature on social interactions and job matching based on neighborhood effects.
[2] We discuss the theoretical and empirical literature in Section 2.

market outcomes.[3] Unlike previous research, our peer definition does not rely on the identification assumption that individuals within a given group – e.g. neighborhood or firm – interact with each other and are members of the same network, which is non-testable. The second contribution is that our study provides empirical evidence on alternative mechanisms by which social interactions might operate. We consider three ways in which peers might affect job finding probabilities: by transmitting information on available jobs, by exerting pressure due to social norms, or by the existence of leisure complementarities. Our findings suggest that network effects originate from the transmission of information. The third contribution is that we can separate the effect of friendship networks from that of family networks. We provide evidence that friends are important in increasing a person's job finding probabilities even after controlling for the quality of family networks, spouse's employment status and spouse's friends network.

Having access to direct information on social interactions through close friends offers a stronger signal compared to previous studies in which the reference group is defined using indirect information. This might come at the cost of greater threats to identification due to correlated effects. There are three types of correlated effects that might be relevant to our analysis: non-random selection, simultaneity and common shocks.[4]

Any effect of the number of employed friends on job finding rates might be due to non-random selection into networks. 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 may have better employment prospects and may be more likely to have employed friends. Generally, social interactions are more likely to emerge among individuals

[3] Positive correlations between friends' employment and unemployment exits in the BHPS have been reported by Hannan (1999).
[4] 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. (2011).

that share some relevant traits – such as education or ethnicity – or are characterized by similar tastes or constraints.[5] 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 social interaction effect.

Our identification strategy relies both on instrumental variables (IV) and on fixed effects regressions, which exploit the panel dimension of our data. Relative to fixed effects, instrumental variables control for non-random selection and endogeneity of the quality of the network that is both due to fixed and time-varying characteristics. Our IV strategy instruments the potentially endogenous friend's employment status with lagged health shocks that limit work activities. The identifying assumption is that health shocks affect the employment status of the friend but are uncorrelated with the error term that determines the person's transition into employment. We show robust IV estimates even after controlling for the current level of health status, which captures the potential correlation of friends' health.

For both fixed effects and IV estimations, we deal with the second threat to identification – simultaneity – by using a predetermined measure of the quality of the network. In particular, we consider the effect of the employment status of friends (level) on the change of the person's employment status, which is defined as the transition from non-employment to employment. However, correlation over time in outcomes due to persistence might imply that the use of predetermined measures does not suffice to circumvent the simultaneity bias. We address the issue of simultaneity through persistence by showing robust results when we control for elapsed duration and when we endogenize initial conditions (i.e. the probability of being non-employed at the starting point of the transition).

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

Correlated unobservables can operate not only at the individual level but also at the local level due to common shocks, inducing a third potential threat to identification for our analysis. 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 address this threat to identification in three ways. First, we control for the local economic conditions using the unemployment rates in the travel-to-work area, which capture the conditions in the local labor markets. Second, we investigate the importance of the quality of the network by friends' residential proximity. If common local shocks drive the results, we would expect friends who live closer to matter more. We provide evidence which shows that the number of employed friends matters but not friends' residential distance from the respondent. Third, we estimate placebo regressions using a conditional random assignment methodology. For each individual within cells defined by age, level of education, gender, region of residence and year, we assign the quality of the network of a randomly chosen person. Following this random assignment we are able to test whether there are correlated effects within the dimensions used to construct the cells. We find that employed friends in these placebo regressions have no effect on the transition probability into employment.

Another potential source of bias stems from the fact that we are observing a stock sample of non-employed, which might be affected by feedback effects from outcomes to covariates. 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. To address this concern, we consider the effect of elapsed duration in non-employment on the number of employed friends. We find no difference in the quality of the network for the same individual at different lengths of non-employment, which provides evidence that our sample is not selected in way that might lead to a feedback effect from employment transitions to the number of employed friends.

Network effects have relevant policy implications since the impact of labor market programs may spill over from participants to non-participants through the social interaction, a sort of social multiplier. However, the effectiveness of the multiplier depends on whether network effects operate through the behavior or the characteristics of the peers, the former being the vehicle for social spillovers (Moffitt, 2001). Manski (1993) distinguished endogenous (i.e. behavioral) and contextual network effects and discussed the issues related to their separate identification in linear-in-means models, the so called "reflection problem". In this paper, we isolate endogenous effects by fixing the network demographic composition over time. By doing this, the fixed effects estimator addresses also network specific unobserved heterogeneity on top of individual specific one. Therefore, the remaining effects would be due to changes in the behavior of social contacts over time, not changes in their characteristics. We find that endogenous effects account for almost all of the network effects on job finding rates. We reach similar conclusions when we fix the composition of the network in the model estimated by IV.

The final part of the paper investigates the possible explanations of network effects. Information transmission is the key ingredient in much of the theoretical literature (e.g. Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009), but alternative mechanisms based on social norms or leisure complementarities are also able to predict a positive effect of friends' employment on job finding rates. However, these mechanisms generate different predictions in terms of re-employment wages and match quality. While the information mechanism should increase the efficiency of matching and lead to better paid and more stable jobs, both social norms and leisure complementarities imply a reduction in reservation wages that should eventually translate into lower wages upon re-employment and possibly worse matches, which are not supported by our data. We investigate the issue further by designing a test of social norms and leisure complementarities based on satisfaction data, in particular general satisfaction and satisfaction with leisure. While one would expect the satisfaction of the non-employed to be a negative function of the number of employed friends due to social norms or a diminished value of leisure, we are not able to find any effect, which leads us to conclude in favor of information transmission as the mechanism operating behind network effects.

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). 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 paper also relates to the search and matching literature that incorporates social networks (e.g. Mortensen and Vishwanath, 1994; Fontaine, 2007; Cahuc and Fontaine, 2009; Galenianos, 2010).

With respect to the empirical literature, our work relates to the growing number of studies that aim 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 (e.g. Loury, 2006; Goel and Lang, 2009; Bentolila et al.,2010; 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 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

[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.

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. Studies that define networks based on group affiliation include: Munshi (2003), who defines networks at the origin-community level to identify job networks among Mexican migrant in the U.S. labor market; 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; Laschever (2009), who examines the effect of networks on employment based on veteran groups; Beaman (2010) who examines the effect of network size of refugees resettled in the U.S. and Dustmann et al. (2011), who use German linked employer-employee data to study ethnicity based job referral networks.[7]

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 between 1992 and 2007. 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 BHPS

[7] The role of social networks has also been examined in other settings including: Bertrand et al. (2000) on welfare dependency; Van der Klaauw and van Ours (2003) on welfare transitions; and Bandiera et al. (2010) on individual performance at the workplace.

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, residence and relation to the respondent, 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 $(t = 1992, 1994, 1996, ..., 2006)$ to the employment transitions of BHPS respondents between waves t and $t+1$. We select a sample of individuals aged 18-65 not in full time education and not retired at any even-numbered wave whose three best friends also belong to the same age range. This results in 11,933 individual observations (5,795 men and 6,138 women) with a total of 45,365 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 2,737 non-employed individuals with a total of 5,612 person-year observations. Half of the individuals are observed as non-employed more than once in the sample.

[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 of labor market transition models.

[9] We tested the sensitivity of our main findings to the inclusion of these individuals with missing information on friends by way of dummy variables for the missing data. The results are not affected so in what follows we focus on the sample without missing data.

Table 1a: 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	81.10	18.90	75.81	24.19	71.41	28.59
Woman	17.61	82.39	16.55	83.45	21.41	78.59
	Age					
	Mean	S.D	Mean	S.D	Mean	S.D
18 to 24	20.75	5.28	20.75	5.26	21.09	5.93
25 to 29	24.92	7.88	24.81	7.67	24.66	7.46
30 to 34	30.54	9.12	30.24	8.46	29.57	7.83
35 to 39	34.68	8.81	33.95	8.29	33.74	8.45
40 to 44	38.20	8.13	37.47	8.01	37.27	8.22
45 to 49	41.92	7.90	40.81	7.77	40.89	8.05
50 to 54	44.72	8.03	43.55	8.59	43.48	8.91
55 to 65	47.56	9.73	47.40	10.00	47.11	10.09

Notes: The sample consists of non-employed individuals in the even years between 1992-2007 for which information on friends is observed.

Some relevant demographic information for the estimating sample is presented in Table 1a, in connection with the demographic characteristics of the three best friends. The table shows that there is a certain degree of assortative mating among friends in terms of both gender and age. The proportion of women whose first best friend is a woman is 82 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 (almost 79 percent have the third best friend who is of the same gender), while it decreases somewhat 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 Table 1b, we illustrate the evolution of our network indicator – the number of employed friends – over waves of the BHPS. The distribution of network employment is skewed to the right, and the most frequent occurrence is having two friends employed. Nonetheless, a substantial number of cases report having no friends in employment, between 8 and 13 percent depending upon the wave.

Table 1b: Distribution of Number of Employed Friends by Wave.

	Number of Employed Friends			
Wave	0	1	2	3
2	12.77	25.45	37.95	23.84
4	12.31	28.27	34.71	24.71
6	10.28	23.82	36.73	29.17
8	10.99	24.25	37.63	27.12
10	8.41	22.21	37.71	31.67
12	9.12	21.22	36.87	32.79
14	8.00	23.36	33.12	35.52
16	11.20	18.90	36.45	33.44
18	10.14	19.93	36.30	33.63
Total	10.59	23.58	36.48	29.35

Notes: The sample consists of non-employed individuals in the even years between 1992-2007 for which information on friends is observed.

Finally, in Table 1c we provide some summary statistics on the job finding probabilities in the sample. On average, about 26 percent of non-employed individuals make a transition from non-employment to employment from one year to another.[10] The lower part of the table 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

[10] The year-to-year job finding rate is much higher for the unemployed (45.53 percent) and lower for the inactive (19.90 percent).

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 both women and men.

Table 1c: Number of Employed Friends and Exit Rates from Non-Employment.

	Full sample	Men	Women
Unconditional Exit rate	25.93	30.96	24.10
Number of Employed Friends			
0	12.83	15.86	11.87
1	19.96	25.57	18.30
2	26.19	28.40	25.49
3	35.00	39.90	32.47

Notes: The sample consists of non-employed individuals in the even years between 1992-2007 for which information on friends is observed.

3.2 Empirical Strategy

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

Let $E_{i,t}$ be a dummy indicator of respondent's *i* employment status in year *t*, and let $NEF_{i,t}$ 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. We estimate the following transition equation:

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

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 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 dummies for gender, education (highest qualification attained) and ethnicity (categorized in nine groups). 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 (1) by forming a sample of non-employed individuals at each even wave $(t = 1992,\ 1994,\ 1996, ..., 2006)$. In order to address the threats to identification discussed in the introduction, as a *first strategy* we adopt a fixed effects logit estimator, eliminating the unobserved effect u_i, which is fixed over time. As we noted in Section 3.1, in our sample we observe multiple non-employment spells for about half of the non-employed respondents 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. We present the fixed effects results along with a battery of robustness checks to the various identifying assumptions in Section 4.2.

Our *second identification strategy* is based on an instrumental variables approach. In this case, rather than integrating out unobserved heterogeneity potentially correlated with network effects, we model such correlation exploiting exogenous variation. We estimate a reverse version of equation (1) in which the employment transitions of the best friend are a function of the employment status of the BHPS respondent, and instrument the latter using lagged health shocks. We explain the details of the reverse model and report its results in Section 4.3.

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 main analyses 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 7.5 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 remains stable at 7.5 p.p and after controlling for individual observed characteristics, the marginal effect becomes 6.9 p.p. This suggests that only a small part of the effect is due to a correlation 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 7.4 p.p. for the unemployed and by 5.9 p.p. for the inactive (results not shown).

[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.

Table 2: Transition into Employment from Pooled Estimation.

	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	0.396	0.075	10.75	0.393	0.075	10.47	0.362	0.069	9.07			
One Employed Friend										0.377	0.072	2.58
Two Employed Friends										0.638	0.121	4.49
Three Employed Friends										1.095	0.208	7.52
Controls - Friends		No			Yes			Yes			Yes	
Controls - Individual		No			No			Yes			Yes	
Log-Likelihood		-3,117.40			-3,041.63			-2,809.82			-2,808.82	
Number of Individuals		2,737			2,737			2,737			2,737	
Number of Observations		5,612			5,612			5,612			5,612	

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 1992-2006 for which we have information on their friends. 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.

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 7.2 p.p compared to having no employed friends, while having two or three employed friends increases the job finding probability by 12.1 p.p and 20.8 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 Endogenous Network Formation

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 3.2, our first approach in addressing this source of endogeneity is by estimating the transition equation (1) using a fixed effects logit estimator.

The first column 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 the job finding probability. An additional employed friend increases the transition probability by 3.3

p.p. This effect is lower compared to the pooled estimation, which suggests a positive correlation between unobserved individual heterogeneity and having employed friends, leading to an upward bias.

Table 3: Transition into Employment from Fixed Effects Estimation.

	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
		(1)			(2)	
Number of Employed Friends	0.155	0.033	2.05			
One Employed Friend				0.414	0.089	1.61
Two Employed Friends				0.414	0.089	1.63
Three Employed Friends				0.627	0.135	2.32
Log-Likelihood		-510.81			-510.06	
Number of Observations		1,498			1,498	
Number of Individuals		467			467	

Notes: Fixed effects logit 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. Standard errors are clustered at the individual level. The full specification for the first column is reported in Table A1.

Nevertheless, the effect remains significant and large. Taking into account the unconditional job finding rate of 25.93 percent, the effect of an additional employed friend is sizeable and corresponds to an approximately 13 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 (e.g. Calvó-Armengol, 2004; Calvó-Armengol and Jackson, 2004; Bramoullé and Saint-Paul, 2009). 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.

We consider the non-linear specification of the effect in the second column of Table 3, which shows that the effect is higher − and significant − when all friends are employed. The cumulative impact of having all three friends employed is higher than that implied by the linear specification – compare 13.5 p.p. with three times 3.3 p.p. – which is consistent with convex network effects. However, formal tests rejected the hypothesis of convex effects, as in the case of the pooled estimation.[12]

4.2.1 Robustness of Fixed Effects Estimation

The validity of the fixed effects estimator is based on the assumption of time invariant unobserved heterogeneity and strict exogeneity, the latter implying no feedback from past labor market trajectories to the employment status of friends. In this section we address the two assumptions in turn.

Time-varying covariates – The fixed effects estimation assumes that only fixed unobserved heterogeneity can be correlated with the employment status of friends. It could be the case, however, that time-varying characteristics might change when one enters in 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 the transition equation (1) 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.

[12] Coefficient estimates of other covariates are presented in Table A1.

Table 4: Transition into Employment - Robustness of Fixed Effects Estimates.

	Dependent Variable: Transition into Employment												Dependent Variable: Number of Employed Friends	
	(1) Baseline			(2) Exclude Time-Varying Regressors			(3) Include Elapsed Duration			(4) Endogenous Initial Conditions			(5) Duration in Non-Employment	
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	t-ratio
Number of Employed Friends	0.155	0.033	2.05	0.157	0.034	2.10	0.158	0.034	2.07	0.459	0.038	9.94		
Non-Employment Duration (months)													-0.0004	-0.74
Number of Observations	1,498			1,498			1,467			33,361			1,475	
Number of Individuals	467			467			461			8,565			466	

Notes: Columns (1)-(4) are fixed effects logit regressions for the transition from non-employment to employment. The first column is the baseline model of Table 3 (column 1). The second column shows the result for the estimation without individual time-varying covariates. The third column includes as a regressor the elapsed duration (in months) in non-employment until the time of the interview. The fourth column reports the estimate for the number of employed friends when we take into account initial conditions. The last column reports the coefficient estimate of the linear fixed effects regression of the number of employed friends on the duration in non-employment. Standard errors are clustered at the individual level.

The second column of Table 4 shows that, after excluding all the time-varying regressors, the fixed effects estimate is very similar (marginal effect of 0.034) with the one that includes the time-varying regressors (baseline marginal effect of 0.033 in the first column of Table 4).

Feedback effect – The estimation of the fixed effects model relies on variation over time of the employment status of friends, assuming strict exogeneity. 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 since those with shorter duration in non-employment are also more likely to find a job.

To address these issues, we examine the effect of the elapsed duration in non-employment on the number of employed friends. Although this does not consider feedback effects jointly in a model with the transition of interest, 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 last column 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 evidence that our sample is not selected in way that might lead to a feedback effect from employment transitions to the number of employed friends.[13]

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

4.2.2 Simultaneity through Persistence

Reverse causality through simultaneity is another source of bias in the estimation of social interactions. In our model, we circumvent the issue by using a measure of the quality of the network that predates the individual outcome, namely the number of employed friends in the base year of the individual transition from non-employment into employment. However, to the extent that there is persistence in individual employment trajectories, this strategy may not suffice for isolating the estimates from simultaneity bias. In this section, we provide evidence on the robustness of the results to persistence.

Elapsed duration **–** We start by augmenting our specification with a measure of persistence, namely the elapsed duration in non-employment. The third column in Table 4 shows that controlling for the length out of employment in our fixed effects estimation leaves the effect unaltered, 3.4 p.p. to be compared with 3.3. p.p. in the baseline specification. Reverse causality through simultaneity would instead result in an upward bias, since the direct and inverse effects would operate in the same direction and reinforce each other.

Endogenous initial conditions – Our last assessment of the issues generated by persistence in employment dynamics is based on modeling selection into non-employment in the base year of the transition investigated. Allowing for the endogeneity of initial conditions is a way for modeling serial correlation in the employment process (see e.g. Cappellari and Jenkins 2008). We achieve this by augmenting the transition equation (1) with an equation for employment in the base year:

$$\Pr(E_{i,t}) = F(X_{i,t}^{'}\gamma_1 + Z_i^{'}\gamma_2 + \gamma_3 NEF_{i,t} + \nu_i)\,. \qquad (2)$$

Following suggestions by Heckman (1981), we approximate the initial condition using a vector of characteristics pre-dating labor market entry (Z_i) which are assumed to affect the initial condition but not the transition. In particular, the vector Z includes indicators of parental education.[14] The endogeneity of initial conditions is allowed for by estimating the joint distribution of individual effects of equations (1) and (2), $G(u_i\ v_i)$, using a discrete approximation with two mass points and unrestricted correlation.

Results from the model with endogenous initial conditions estimated by maximum likelihood are reported in the fourth column of Table 4. If our main findings were driven by simultaneity induced by employment persistence, we should observe the effect to weaken once persistence is explicitly modeled. Conversely, we obtain a marginal effect of 0.038, which aligns pretty closely with the baseline. This is remarkable considering that the treatment of unobserved heterogeneity (and consequently the estimating sample) differs markedly in the two cases; explicit modeling versus elimination via fixed effects.[15]

4.2.3 Common Shocks

Commons shocks represent a further threat to identification. 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. We consider the importance of local economic conditions for our findings in two ways.

[14] Note that although potentially relevant in affecting one's network, parental education is time invariant and therefore orthogonal to the within individual variation that we exploit to identify network effects in equation (1).

[15] We further investigated the impact of persistent dynamics by considering only those non-employment spells for which we observed the starting point in the data. Persistence should be less relevant in these fresh spells compared to the overall sample: was simultaneity – induced by persistence – the driver of our baseline findings, we should observe the effect to weaken in the fresh spells sample. Working with fresh spells led to a considerable reduction of the sample size, therefore we estimated the model as a pooled logit. We obtained an estimated effect of 8.4 p.p. (to be compared with the baseline estimate for pooled estimation of 6.9 p.p. in Table 2), i.e. it was not consistent with the hypothesis of simultaneity through persistence.

Table 5: Transition into Employment - Robustness of Fixed Effects Estimation to Common Shocks.

	(1) Exclude Local Unemployment Rate			(2) Residential Distance of Friends			(3) Placebo Regression		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Number of Employed Friends	0.155	0.033	2.05	0.168	0.041	1.83	0.008	0.002	0.11
Distance of Friends									
Number of Employed Friends x Number of Friends in 5+ miles				-0.086	-0.018	-0.56			
Number of Observations	1,498			1,465			1,498		
Number of Individuals	467			459			467		

Notes: Fixed effects logit regressions for the transition from non-employment to employment. The first column excludes from the baseline regression the unemployment rate at the travel-to-work area. The second column allows for an interaction of the number of employed friends with the number of friends residing more than 5 miles away from the respondent. Column (3) is a placebo regression following a conditional random assignment methodology, which assigns the number of employed friends of a random person who belongs in the same cell as the respondent. The cell is defined by age, gender, level of education, region of residence and year of interview.

Local unemployment rate – First, we estimate our baseline model excluding the local unemployment rate, which is defined at the travel-to-work area. The coefficient estimate of the number of employed friends from the first column of Table 5 remains unaffected compared to the baseline specification, which suggests that our main finding is not sensitive to the local economic conditions.[16]

Residential proximity – We further investigate the robustness to common shocks by addressing the impact of friends' residential location. We exploit information in the BHPS about how far each of the three friends live from the respondent and we distinguish local friends – those living within five miles from the respondent – from distant ones. If common local shocks drive the results, we would expect friends who live closer to matter more. We estimate the transition equation by fixed effects interacting the number of employed friends with the number of distant friends. Results are reported in the second column of Table 5 and point towards a non significant impact of residential proximity on network effects.

Placebo regression – We also assess whether network effects are driven by correlated effects by means of a conditional random assignment exercise and placebo network measures. Specifically, we form cells defined by year of interview, gender, age, level of education and region of residence and we derive placebo network measures by endowing individuals within those cells with the network measure of a different cell member randomly selected. In this way, we are able to test whether there are correlated effects within the dimensions used to construct

[16] We have experimented also 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 had this information for the years 1996-2000, so we performed this estimation with the relevant sub-sample. Due to the reduced sample size, we were not able to estimate the model with fixed effects. Based on the estimation on the pooled sample, we found that after controlling for the percent of benefit claimants, the effect of the number of employed friends on the sub-sample of observations within 1996-2000 remained unchanged at 6 p.p.

the cells. The result of the placebo regression in column (3) of Table 5 very clearly indicates that reshuffling the treatment-outcome association within the relevant cells is enough to eliminate any network effect, which provides support for the validity of our findings. Reading this result in conjunction with the other evidence in Table 5 suggests that correlated effects are not the driver of the network effects that we find.

4.3 Best Friend's Transition into Employment – IV Estimation of Reverse Network Effect

So far we have dealt with network endogeneity using the fixed effects estimator. An alternative identification strategy is to use valid instruments for the quality of the network. Relative to fixed effects, instrumental variables control for non-random selection and other correlated effects due to all sources of unobserved heterogeneity, not only time-invariant ones. The IV approach requires exogenous variation in the quality of the network. To recover such variation, we consider the transition probability in equation (1) from the friends' perspective: we estimate a reverse version of the model in which the respondents' employment status affects the employment transitions of their friends.[17] By doing so, we can exploit the abundance of information on respondents in the BHPS, and use as instruments for the potentially endogenous respondents' employment status those respondents' characteristics that can plausibly be thought of as having no direct effect on friends' transition. In particular, we use health shocks that limit respondents' work activities; we discuss the underlying identification assumption below.[18]

[17] We thank Nikos Askitas for his suggestion to consider the transition of non-employed friends into employment as a function of respondents' employment status.

[18] Estimating the 'direct' model of equation (1) by IV using health shocks is not feasible due to the lack of information on health related shocks of the respondents' friends. We have experimented, however, with two alternative IV strategies. First, we considered the unemployment rate at the neighboring local areas within the region of residence as an instrument for the number of employed friends. Although there is a strong negative correlation between the two, once we control for regional fixed effects the remaining within-region variation is not sufficiently strong. Second, we considered the unemployment rates by occupation as instruments for the employment status of friends. Friends in occupations different from the one of the respondent will be less likely to be employed when the

Strictly speaking, estimating the reverse 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. Later on, in Section 4.4., we assess the plausibility of this assumption.

The 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*, and zero otherwise. We consider 2-year transitions because we observe information on 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, health status, experiencing depression, smoking and region of residence.

Our identifying assumption is that health related shocks that lead to work limitations occurring to the respondent between *t*-1 and *t* have no effect on their best friend's transition between *t* and *t+2*. The assumption would be violated if there was correlation in health among friends that is not captured by the respondent's general health indicators included in the main model, inducing a direct effect of respondent's changes in work limitations on friends' employment transitions. We address the issue of assortative mating in health by considering the sensitivity of the IV estimates to the exclusion of indicators of respondent's general health and depression, which should magnify any bias deriving from the unobserved health status of friends.

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unemployment rate of their occupation is higher. Due to data limitations in the information on occupation, which is only observed for the best friend, we could not pursue this further.

Table 6: Best Friend's Transition into Employment (Reverse Model) with Instrumental Variables Estimation.

	(1) Baseline - 2-Year Fixed Effects			(2) Reverse Model			(3) Reverse - IV With Current Health and Depression			(4) Reverse - IV W/out Current Health and Depression			(5) Reverse Model Placebo Regression		
	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
Instrument: ***Work Limiting Health Shock***							-0.422	-0.082	-2.11	-0.629	-0.118	-3.16			
Friend Employed	0.501	0.107	3.15	0.457	0.114	7.24	0.399	0.098	3.98	0.401	0.099	3.98	-0.051	-0.013	-0.75
Number of Observations		1,154			6,630			6,630			6,630			6,630	
Number of Individuals		358			3,656			3,656			3,656			3,656	

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 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 and region of residence. The second column is a pooled logit estimation of the probability for the best friend to become employed on the respondent's employment status. The instrumental variable in columns (3) and (4) 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. Column (5) is a placebo regression for the reverse model following the same conditional random assignment method to assign the employment status of a random person within the same cell as in column (3) of Table 5.

Due to the limited dependent nature of both the dependent variable and the instrumented variable, we estimate the model with a simultaneous system of two logit equations by maximum likelihood. Let FE_{it} be a dummy for whether the first best friend is employed in year t and WL_{it} a dummy for whether the respondent experienced the occurrence of health problems limiting work activity between t-1 and t. Our IV strategy is summarized by the following equations:

$$\Pr(FE_{i,t+2} \mid FE_{i,t} = 0) = F(X'_{i,t}\lambda_1 + \lambda_2 E_{i,t} + \varepsilon_i) \qquad (3a)$$

$$\Pr(E_{i,t}) = F(X'_{i,t}\eta_1 + \eta_2 WL_{i.t} + \mu_i) \qquad (3b)$$

Equation (3*a*) is similar to the transition equation (1) with the difference that it refers to the best friends' transition from non-employment to employment and therefore depends on the respondent's employment status $E_{i,t}$. We allow for correlation in the unobservables ($\varepsilon_{i,}$ μ_i) using a discrete distribution with two mass points and unrestricted correlation across equations.

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 from the transition equation (1). This is the model for respondent's transition as a function of friend's' 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 0.107, which is statistically significant at the 5 percent confidence level: having the best friend employed leads to a 10.7 p.p. increase in the probability of finding a job over the two year window.

We next consider the 'reverse' model. The second column of Table 6 reports the estimates obtained without using instrumental variables, which point towards a substantial effect of the respondent's employment on the friend's employment transition, 11.4 p.p. and statistically significant. The third column of the table reports IV estimates. 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 statistically significant. Considering the transition equation, we find a positive and sizeable network effect, which is statistically significant. Having an employed friend (the respondent) increases the transition into employment of the first best friend by 9.8 p.p. In the fourth column of the table we show results obtained manufacturing some unobserved heterogeneity potentially correlated with the instrument and headline employment transitions through the exclusion of indicators of respondent's current health and depression. It is evident that this exclusion affects substantially the marginal effect in the instrumenting equation, but there is practically no impact on the marginal effect in the headline equation. This evidence suggests that respondent's health indicators are not correlated with the employment transitions of their friends, supporting the validity of lagged health shocks as an instrument. [19] Overall, the IV estimates suggest a causal network effect, which is consistent with the evidence obtained with the fixed effects.[20] Finally, we estimate a placebo regression for the reverse model in which we randomly permute the employment status of the respondent using a conditional random assignment methodology similar to the one for the fixed effects estimates in section 4.2.3. Column (5) of Table 6 shows that the network effect vanishes once we assign the network quality of a random person.

[19] We also experimented 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 shocks that limit working ability. However, the frequency of accidents in our sample is small so we could not pursue further with this approach.

[20] Coefficient estimates of all the parameters in equations 3*a* and 3*b* are presented in Table A1.

Table 7: Transition into Employment – Friends vs. Family Networks.

	(1) Relatives vs. Non-Relatives			(2) Only Spouse's Network			(3) Own and Spouse's Network			(4) Including Spouse's Employment Status		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Own Network												
Number of Employed Friends - Non Relatives	0.154	0.033	1.91				0.153	0.033	1.89	0.153	0.033	1.89
Number of Employed Friends - Relatives	0.156	0.033	1.28				0.153	0.033	1.26	0.131	0.028	1.06
Spouse's Network												
Spouse's Number of Employed Friends				0.078	0.017	0.71	0.069	0.015	0.62	0.006	0.001	0.05
Spouse Employed										0.936	0.201	3.45
Number of Observations		1,498			1,498			1,498			1,498	
Number of Individuals		467			467			467			467	

Notes: Column (1) distinguishes the effect of employed best friends that are relatives of the respondent from that of non relatives. Remaining columns of the table consider the number of employed friends of the spouse of the respondent. For those without a spouse we control with a dummy variable for the missing values. Column (2) includes only the number of employed friends of the spouse. Column (3) controls for both the respondent and the spouse number of employed friends. Column (4) includes as an additional control whether the spouse is employed. Standard errors are clustered at the individual level.

4.4 Family Networks

The previous analyses provide robust evidence for the importance of friends' networks on job finding. However, not only friends but also family may be a source of information in the job search process. To the extent that the quality of the networks is correlated between friends and family, the effect of friends may be partly capturing the effect of the family and it is important to identify them separately for drawing conclusions on the relevance of friends networks.

Relying on our survey information we can derive some measures of family networks. First, we exploit information on whether the best friend is a relative and distinguish the effect of the number of employed friends that are relatives from that of the number of employed friends that are non-relatives.[21] Although this strategy offers only an incomplete outlook on family networks – i.e. we only have information on those relatives that are indicated as friends by the respondent – it serves the purpose of assessing the robustness of our findings to the confounding effects of family ties. Results are in the first column of Table 7. The effect of the number of employed relatives on job finding is strikingly identical to the one of friends that are non relatives, 3.3 p.p., although estimated with lower precision. The effect of the number of employed friends that are non-relatives, on the other hand, is statistically significant at conventional levels of confidence, supporting the robustness of the findings discussed in the previous Sections.

Our second approach for assessing robustness to family ties exploits the household structure of the BHPS, namely we derive information on the employment status of the respondent's spouse (which may reflect assortative mating on top of family networks) and on the spouse's number of employed friends. The second column of Table 7 reports the effect of spouse's number of employed friends on the respondent's job finding probability. Compared to

[21] About 20 percent of BHPS respondents indicate a relative as best friend, which is most frequently a sibling (8 percent), a parent or a child (5 percent each).

the effect of own network of 3.3 p.p. from Table 3, spouse's network exhibits a smaller effect (1.7 p.p.), which is not significantly different from zero. In the third column, we control for both the spouse network and the family network (using the strategy of column (1) for the latter) and find no relevant change in results. Finally, in the fourth column we also control for the employment status of the spouse. While this latter control exhibits a very large and positive effect, the effect of the spouse's friends becomes zero, and the estimated effect of the number of employed friends that are relatives loses size and precision. The important point is that the effect of the number of employed friends that are non-relatives remains sizeable and significant, which suggests that friends matter on top of family networks.

4.5 Separating Endogenous from Exogenous (contextual) Effects

In his seminal paper, Manski (1993) identified two different ways in which peers can affect each other, either through their behavior (endogenous effects) or their attributes (exogenous or contextual effects). Distinguishing between the two sources of social interactions is important for our analysis since in the presence of endogenous effects labor market programs affecting the behavior of the unemployed may multiply their effects besides program participants through social spillovers (Moffitt, 2001).

With this aim, we focus our attention on the sources of variation generating the effects estimated in the previous subsections. This variation might have two sources. The first, is related to changes of the employment status of friends who remain the same over time, and is therefore associated to endogenous network effects. The second, is due to changes in the composition of the network, the contextual effect.

Table 8: Separating Endogenous from Exogenous (contextual) Effects.
Fixed Effects Logit Estimates for Transition into Employment with a Fixed Network.

	FE-1			FE-2			FE-3			FE-4		
	Baseline			Same Gender			Same Year of Birth			Same Gender and Year of Birth		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Number of Employed Friends	0.155	0.033	2.05	0.150	0.034	1.43	0.166	0.037	1.53	0.154	0.036	1.10
Log-Likelihood	-510.81			-289.67			-275.41			-165.97		
Number of Observations	1,498			864			818			521		
Number of Individuals	467			293			281			190		

	FE-1			FE-2			FE-3			FE-4		
	Baseline			Same Gender			Same Year of Birth			Same Gender and Year of Birth		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
One Employed Friend	0.414	0.089	1.61	0.496	0.111	1.39	0.249	0.056	0.71	0.674	0.156	1.46
Two Employed Friends	0.414	0.089	1.63	0.510	0.114	1.42	0.278	0.063	0.82	0.463	0.107	1.03
Three Employed Friends	0.627	0.135	2.32	0.674	0.151	1.74	0.572	0.129	1.53	0.809	0.187	1.63
Log-Likelihood	-510.81			-289.12			-275.12			-164.84		
Number of Observations	1,498			864			818			521		
Number of Individuals	467			293			281			190		

Notes: The first column (FE-1) is the baseline model of Table 3 (column 1). The remaining fixed effects estimations are based on samples for which the friends remain the same between the current and the next wave. We use two indicators of having the same friends. The first one relies on the friends having the same gender (FE-2). The second relies on having the same year of birth (FE-3). The last column (FE-4) conditions the sample on friends having the same gender and year of birth. Standard errors are clustered at the individual level.

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, thence abstracting from contextual effects. 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 over time. Since we do not observe an identifier for the friends, we use gender and year of birth of all three friends to distinguish between stable and non-stable networks. A network is stable when, for all three friends, gender and year of birth do not change across two consecutive non-employment spells. Note that by restricting the estimating sample to stable networks the fixed effects estimator not only addresses time invariant unobserved heterogeneity related to the individual, but also the one that is related to the network.

The upper panel of Table 8 reports results from models that adopt a linear specification of network effects, whereas those obtained using dummy variables specifications are in the lower panel. The first column (FE-1) reports for ease of comparison the effect estimated in the baseline model of Table 3, with a marginal effect of 0.033 (3.3 p.p.) for the linear specification. The second column (FE-2) shows the estimated effect for the sample of individuals with all friends having the same gender across two waves, which results in a marginal effect of 0.034 (3.4 p.p.). Estimating the model on stable networks reduces the sample size considerably, resulting in lower precision. Columns 3 and 4 of Table 8 report the results obtained on stable networks defined using friends' year of birth or the combination of gender and year of birth, yielding conclusions about the size and precision of marginal effects that are in line with those reached in column 2. The substantial stability of the marginal effects when moving from the baseline to the stable network sample is consistent with a predominance of endogenous network effects in driving our results.

Table 9: Separating Endogenous from Exogenous (contextual) Effects.
Best Friend's Transition into Employment for a Fixed Network with Instrumental Variables Estimation.

	(1) Reverse Model			(2) Reverse - IV With Current Health and Depression			(3) Reverse - IV W/out Current Health and Depression		
	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Instrument: *Work Limiting Health Shock*				-0.733	-0.149	-2.23	-1.040	-0.198	-3.22
Friend Employed	0.438	0.108	4.63	0.423	0.095	2.35	0.365	0.086	2.06
Number of Observations	3,037			3,037			3,037		
Number of Individuals	1,888			1,888			1,888		

Notes: The results are based on the instrumental variable estimation similar to Table 6 estimated on the sample for which the characteristics of the first best friend – gender and year of birth – are constant across the two waves.

Results in the lower panel of Table 8, which allows for non-linearity also go in the same direction. In particular, we find similarly with Table 3 that when all friends are employed the effect on the job finding probability is the highest and is statistically significant at the 10 percent confidence level.

In Table 9 we conduct another exercise of network stability, this time considering the IV estimation of the 'reverse' model. Recall that we estimated this model assuming that the identity of the first best friend was constant between subsequent even waves, something that we cannot observe due to data limitations. Imposing network stability in this model is, therefore, also a way of making that assumption weaker. The estimated marginal effects are only 1 p.p. lower compared with their counterparts estimated on the overall sample and are statistically significant, pointing to the prevalence of endogenous network effects also in the IV estimation.

4.6. Labor market outcomes – Wages and Employment Stability

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 hourly wages and the stability in employment, the latter being modeled as the probability of exiting from employment back to non-employment over the next year. Both exercises are conditional on exiting non-employment between t and t+1; we therefore use pooled estimators rather than fixed effects due to the limited size of the resulting samples.

Column 1 in Table 10 shows that the number of employed friends has a significant and positive effect on re-employment wages. An additional employed friend increases hourly wages for those who become employed in the next year by 4.8 percent. In addition, having one (three) employed friend(s) compared to having no employed friends increases hourly wages by 11.6 (22.2) percent. The second column of Table 10 shows that an additional employed friend not only increases wages but also reduces the probability to exit subsequent employment by 3.3 p.p.

Table 10. Labor Market Outcomes after Transition into Employment. OLS Regression for Wages and Logistic Regression for the Probability to Exit from Employment back to Non-Employment.

	Hourly Wages		Exit from Employment		
	Coef.	t-ratio	Coef.	M.E.	t-ratio
Number of Employed Friends	0.048	3.23	-0.241	-0.033	-2.82
Number of Observations	1,163		1,322		

	Hourly Wages		Exit from Employment		
	Coef.	t-ratio	Coef.	M.E.	t-ratio
One Employed Friend	0.106	1.85	-0.023	-0.003	-0.07
Two Employed Friends	0.174	3.20	-0.253	-0.035	-0.78
Three Employed Friends	0.184	3.42	-0.591	-0.082	-1.80
Number of Observations	1,163		1,322		

Notes: The estimation in the first column is a linear regression of log hourly 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.

As shown in the lower panel of Table 10, 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). This is the idea behind much of the theoretical and empirical literature on social networks in the labor market. However, there may be other forces at play. One 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. Another alternative 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.

In this section, we propose a new test for assessing 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 11 – both for the OLS and FE estimations – suggest that the number of employed friends does not have any effect on either measures of satisfaction.

Table 11. Life and Leisure Satisfaction.
OLS and Fixed Effects Coefficient Estimates.

	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	0.012	0.46	0.015	0.52	0.002	0.05	-0.016	-0.44
Number of Individuals	2,009		2,129		2,009		2,130	
Number of Observations	3,779		3,937		3,781		3,940	

	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	-0.017	-0.18	-0.114	-1.29	-0.023	-0.21	0.002	0.02
Two Employed Friends	0.019	0.22	0.014	0.16	0.002	0.02	0.020	0.18
Three Employed Friends	0.019	0.20	-0.036	-0.36	-0.009	-0.08	-0.052	-0.42
Number of Individuals	2,009		2,129		2,009		2,130	
Number of Observations	3,779		3,937		3,781		3,940	

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 A1.

In addition, for both the social norms 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 and worse matches. Conversely, the information hypothesis suggests 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.[22] The evidence that we provide in Section 4.6 that the number of employed friends increases wages and the stability in employment 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 examine the effect of network quality - measured by friends' employment status - 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 job finding probability by as much as 13 percent or 3.3 percentage points. In addition, having all friends employed compared to no employed friends leads to the greatest effects, which suggests the presence of competition among the contacts. These results are robust to alternative identification strategies based on fixed effects and instrumental variables estimations.

We also investigate the impact of friends' networks on labor market outcomes other than employment transitions, finding that employed friends are associated with

[22] 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.

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 the network effects are due to information transmission rather than to alternative mechanisms such as pressure due to social norms and leisure complementarities. Finally, we provide evidence which suggests that it is the behavior of the contacts in the network rather than their characteristics that matters and that friends networks matters on top of family networks. This has relevant policy implications, since the transmission of information through social interactions may act as a social multiplier of labor market programs.

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Table A1. Pooled, Fixed Effects and IV Full Specification Estimates.

	Pooled Logit			Fixed Effects			IV-Auxilliary Equation			IV-Transition Equation		
	Coef.	S.Error	t-ratio	Coef.	S.Error	t-ratio	Coef.	S.Error	t-ratio	Coef.	S.Error	t-ratio
Number of Employed Friends	0.362	0.040	9.07	0.155	0.075	2.05						
IV Model												
Friend Employed										0.399	0.100	3.98
Instrument:												
Work Limiting Health Shock							-0.422	0.200	-2.11			
Individual Characteristics												
Female	-0.594	0.132	-4.48									
Age	-0.046	0.005	-8.52	-0.131	0.272	-0.48						
Having Health Problems	-0.409	0.076	-5.42	-0.193	0.170	-1.13	-0.484	0.106	-4.57	-0.066	0.061	-1.08
Smoking	-0.071	0.082	-0.86	0.033	0.268	0.12	-0.413	0.120	-3.44	0.066	0.068	0.98
Experiencing Depression	-0.629	0.127	-4.97	-0.617	0.241	-2.56	-1.352	0.163	-8.32	-0.229	0.108	-2.11
Family Characteristics												
In Couple	0.216	0.091	2.37	0.075	0.230	0.33	0.216	0.126	1.71	-0.114	0.073	-1.57
One Child	-0.320	0.102	-3.14	-0.107	0.250	-0.43	-0.966	0.139	-6.93	0.008	0.084	0.09
Two Children	-0.333	0.102	-3.25	-0.076	0.266	-0.29	-1.140	0.136	-8.38	0.042	0.084	0.50
Three or more Children	-0.641	0.123	-5.21	-0.162	0.326	-0.50	-1.857	0.192	-9.68	0.086	0.115	0.75
Level of Education												
Other Qualifications	0.459	0.139	3.30				0.542	0.211	2.57	0.151	0.122	1.23
O-Level	0.376	0.123	3.07				1.256	0.182	6.89	0.283	0.101	2.80
A-Level	0.532	0.142	3.74				1.617	0.216	7.49	0.282	0.118	2.39
Other Higher Education	0.807	0.122	6.62				2.163	0.180	12.04	0.258	0.101	2.56
University Degree	1.036	0.155	6.69				1.982	0.214	9.26	0.419	0.119	3.53
Regions												
Inner London	-0.833	0.438	-1.90				-0.279	0.702	-0.40	0.059	0.427	0.14
Outer London	-0.663	0.419	-1.58				1.203	0.428	2.81	-0.253	0.261	-0.97
Rest of South East	-0.285	0.387	-0.74				1.275	0.389	3.28	-0.519	0.235	-2.21
South West	-0.201	0.393	-0.51				1.005	0.339	2.96	-0.168	0.215	-0.78
East Anglia	-0.428	0.412	-1.04				0.538	0.364	1.48	-0.344	0.224	-1.53
East Midlands	-0.468	0.392	-1.19				-0.629	0.382	-1.65	-0.464	0.250	-1.86
West Midlands Conurbation	-0.525	0.425	-1.23				0.701	0.374	1.87	-0.207	0.224	-0.93
Rest of West Midlands	-0.388	0.411	-0.95				0.194	0.525	0.37	-0.374	0.256	-1.46
Greater Manchester	-0.300	0.431	-0.70				0.818	0.408	2.01	-0.178	0.240	-0.74
Merseyside	-1.225	0.452	-2.71				1.106	0.429	2.58	-0.381	0.255	-1.49
Rest of North West	-0.592	0.418	-1.42				-0.009	0.388	-0.02	-0.299	0.240	-1.25
South Yorkshire	-0.833	0.450	-1.85				1.518	0.501	3.03	-0.291	0.270	-1.08
West Yorkshire	-0.739	0.434	-1.70				0.652	0.485	1.34	-0.321	0.261	-1.23
Rest of Yorkshire	-0.471	0.423	-1.11				0.307	0.484	0.63	-0.011	0.260	-0.04
Tyne and Wear	-0.876	0.452	-1.94				0.205	0.478	0.43	-0.078	0.277	-0.28
Rest of North	-0.567	0.418	-1.36				-0.058	0.381	-0.15	-0.349	0.238	-1.47
Wales	-0.578	0.408	-1.42				0.081	0.387	0.21	-0.658	0.234	-2.81
Scotland	-0.541	0.401	-1.35				0.688	0.355	1.94	-0.203	0.222	-0.92

Ethnicity												
White	-1.356	1.333	-1.02				1.675	1.136	1.47	0.284	0.564	0.50
Black Carribean	-1.989	1.403	-1.42				0.999	1.505	0.66	1.452	0.780	1.86
Black African	-1.451	1.483	-0.98				-0.407	1.651	-0.25	0.660	0.886	0.75
Black Other	-1.019	1.521	-0.67				0.757	1.780	0.43	1.694	1.006	1.68
Indian	-1.469	1.371	-1.07				0.925	1.214	0.76	0.325	0.611	0.53
Pakistani	-2.050	1.419	-1.44				0.534	1.334	0.40	0.575	0.704	0.82
Bangladeshi	-2.269	1.473	-1.54									
Other	-1.435	1.426	-1.01				1.518	1.373	1.11	-0.128	0.703	-0.18
Local Unemployment Rate	-0.040	0.023	-1.70	-0.023	0.057	-0.40	-0.047	0.033	-1.44	-0.038	0.020	-1.89
w4	0.014	0.114	0.12	0.648	0.578	1.12	-0.090	0.151	-0.60	0.134	0.104	1.28
w6	-0.185	0.148	-1.25	0.969	1.121	0.86	0.153	0.200	0.77	0.043	0.131	0.33
w8	-0.183	0.185	-0.99	1.411	1.674	0.84	0.102	0.248	0.41	-0.082	0.158	-0.51
w10	-0.062	0.196	-0.32	1.690	2.214	0.76	0.040	0.268	0.15	-0.193	0.173	-1.12
w12	-0.316	0.207	-1.52	1.477	2.747	0.54	0.171	0.279	0.61	-0.230	0.178	-1.29
w14	-0.223	0.215	-1.03	1.884	3.291	0.57	0.206	0.296	0.70	-0.207	0.187	-1.11
w16	-0.632	0.261	-2.42	2.066	3.841	0.54	0.029	0.355	0.08	-0.270	0.226	-1.20
FriendsÕCharacteristics												
Age of Friend 1	0.004	0.004	1.18	0.014	0.008	1.77	0.008	0.004	2.11	-0.035	0.002	-15.62
Age of Friend 2	-0.002	0.004	-0.61	0.008	0.008	0.94						
Age of Friend 3	-0.001	0.004	-0.14	0.000	0.008	-0.05						
Friend 1 - Male	0.086	0.096	0.90				0.430	0.127	3.39	0.247	0.069	3.57
Friend 2 - Male	-0.205	0.092	-2.23									
Friend 3 - Male	-0.114	0.086	-1.32									
Constant	2.481	1.414	1.76				-4.032	1.252	-3.22	0.832	0.652	1.28
Mass Point 2							3.898	0.144	27.10	2.062	0.410	5.02
Number of Individuals		2,737			467			2,737			2,737	
Number of Observations		5,612			1,498			5,612			5,612	

Notes: The pooled logit estimation refers to the estimation in column 3 of Table 2. The fixed effects estimation refers to the estimation in the first column of Table 3. The IV estimation refers to column 3 of Table 7.