Friends' Networks and Transitions into Employment[§]

Lorenzo Cappellari
Università Cattolica, Milan and IZA

Konstantinos Tatsiramos
IZA

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Abstract

We empirically investigate the effect of social interactions on labour market outcomes using a direct measure of social contacts based on information about individual's best friends and their characteristics. We examine the effect of the number of employed friends on the probability to enter into employment. We find that having employed friends increases the probability to find a job. These findings are robust to specifications that address the endogeneity of friends' employment status that may be induced by correlation with unobserved individual attributes. Investigating the mechanisms behind these effects, we find evidence of higher wages for those with more employed friends, which is consistent with networks acting as information transmission devices.

Keywords: Networks, Unemployment, Job-finding, 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 can provide an important source of information for job seekers.[1] Identifying social networks in the labor market is complicated for mainly two reasons. The first has to do with knowing the way in which individuals are connected to each other. In order to identify how others might affect an individual's employment outcomes one needs to have information on the contacts of individuals and their characteristics. The second reason is related to the possible presence of unobserved individual attributes that can be correlated between an individual and his or her contacts. The presence of such correlation can lead to serious bias in the estimated effect of social networks.[2]

In this paper, we estimate the effect of social networks on job finding probabilities addressing both of these issues. In particular, using the British Households Panel Survey (BHPS) we develop a direct measure of the relevant social network of each individual, which is based on information about each respondent's three best friends and their employment status. The idea behind the measure is that employed social contacts are better informed about job opportunities available in the market and pass this information to non-employed network members. Thence, differently from other papers in the literature that rely on indirect evidence on network derived from neighbourhoods data or linked employer-employee data, we can estimate network effects on job finding

[1] A number of studies document the widespread use of friends and relatives as a job search method (see Montgomery, 1991and Ioannides and Loury 2004 for reviews)

[2] This correlation of unobservables is the fundamental problem of identification of social interactions described as the reflection problem by Manski (1993, 2000).

[4] Belot and Ermisch (2009) is the only study we know, which is using the information on friends in the BHPS to examine the effet of frienship ties on geographical mobility.

probabilities using direct information on social ties.

This analysis offers direct evidence to recent theoretical work which examines the implications of networks on employment dynamics emphasizing the role of the employment status of the contacts in the network (Calvo-Armengol and Jackson, 2004; Bramoulle and Saint-Paul, 2009). In addition, by having access to panel data we can address the potential correlation between the quality of the network and unobserved heterogeneity by exploiting the panel variation of the employment status of friends across multiple non-employment spells for the same individuals estimating fixed effect models.[4]

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. 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 no employed friends. These results are robust to a number of specifications that address the potential endogeneity of the number of employed friends.

Our 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 consider more closely the source of variation of the employment status of friends over time for each individual. There are two different ways the employment status of friends might change over time: either because friends' employment status changes, or because friends are changing. We estimate specifications in which we control for the type of observed variation and we find that are results are robust.

Having established the significance of network effects, we further develop our analysis by investigating possible underlying mechanisms. We consider three different channels: 1) information transmission from the employed to the non-employed contacts, 2) peer-pressure or social norms and 3) leisure complementarities. To distinguish between these different channels we consider the relation of the number of employed friends with wages and satisfaction with leisure. We find that an additional employed friend among those who find a job is associated with a 5 percent increase in wages. The number of employed friends, however, has no effect on the satisfaction with leisure while being non-employed. We interpret these additional findings as suggestive evidence for the information transmission mechanism.

The remainder of the paper is organized as follows. Section 2 discusses how this paper is related to the social network theories of the labour market and the existing empirical literature. Section 3 describes the data and the empirical strategy. We report the main results in Section 4, the additional analysis on wages and satisfaction measures in Section 5 and conclude in Section 6.

2. Theoretical Framework and Empirical Literature

A number of theoretical contributions have modelled the impact of social interaction on employment transitions. Montgomery (1991 and 1994) develops models in which the probability of finding a job for an individual depends on the employment status of her contacts. Calvo-Armengol (2004) and Calvo-Armengol and Jackson (2004) emphasize the role of networks in transmitting information about jobs. Information passed from an employed to an unemployed individual increases the probability of becoming employed. Therefore, the better is the employment status of an individual's connections the more likely is to receive information about jobs, which leads to a positive correlation between the employment stauts of connected individuals in a network. Bramoullé and Saint-Paul (2009) develop a model in which social ties and job status co-evolve over time. By assuming that the probability of forming a new tie is greater between two employed individuals than between an employed and an unemployed one, workers accumulate social capital while employed. This social capital, which depletes during unemployment, increases the probability of finding a job.[5]

The empirical literature on the labour market effects of social networks has been growing substantially in recent years. While some authors rely on information on geographical proximity and neighbours of individuals to measure network effects, others have been using self-reported information on the use of informal contacts as a job finding mode. Moreover, a recent strand of literature exploits the availability of linked employer-employee data to look at the operation of networks. However, there is still no evidence based on *direct* information on network membership of the type we use in our paper.

Topa (2001) investigates the impact of social networks on aggregate unemployment across Census tracts in the Chicago area. In his paper, networks knots are given by tracts, and the network geometry is built according to tracts' neighbours. The model is estimated by minimum distance, by mapping the cross-sectional distribution of employment rates across neighbours derived by simulations of a structural model into its empirical counterpart. Selectivity issues are accounted for by controlling for observable heterogeneity across tracts and spatially correlated shocks. Theoretical predictions imply

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

that the job finding rate of the unemployed is increasing in the number of neighbours employed. Results indicate that local spill-overs are significantly positive, the increase in neighbouring employment rates being positively associated with the employment rate in a given tract. However, the inclusion of spatially correlated shocks greatly reduces the size of the effect.[6]

Bayer, Ross and Topa (2008) study the emergence and effects of work referrals within neighbours using Census data on residential and employment location. In this paper, a neighbour referral is empirically identified by couples of individuals living in the same block and working in the same firm. The underlying idea is that information on job openings at a given firm is passed through networks formed by individuals living in the same block, so that individuals sharing the residential block are more likely to work with the same firm. Issues of residential sorting are tackled by controlling for group-of-blocks fixed effects, which amounts at assuming that the relevant sorting (i.e. choice of residence) occurs at a higher level than the single block, while the relevant flow of information streams within a single block. They find that block co-residence (in different households) has a positive influence on the probability of working for the same employer, which they take as evidence of the operation of informal hiring networks within neighbours. However, the effect is diminished when individual fixed effects are controlled for in place of group-of-blocks ones. They next build measures of network quality based on the proportion of the co-working probabilities that is accounted for by co-residence within a block, and relate them to individual labour market outcomes while controlling for block-specific fixed effects, aimed at controlling for social interactions

[6] Page and Solon (2003) find that a relevant share of the neighbour correlation is due to large income differential between urban and non-urban areas combined with life-cycle persistence in urbanicity.

effects. The authors find significantly positive impacts of network quality on a range of labour market outcomes.

Variation in unemployment at the neighbour level has been exploited by van der Klaauw and van Ours (2003) to study exit rates from welfare into employment. In their paper the neighbour effects are interpreted in terms of spillover effects that could stem from either informal networks or social norms. The authors argue that by using variation across narrowly defined neighbours, spatially correlated unemployment shocks are not likely to drive their results, and use variation in house prices across neighbours to control for selection effects. They find that neighbour effects are relevant is speeding up the welfare-to-work transition, although only for subgroups of the population, namely young Dutch welfare recipients.

Welfare dependency and social networks are studied by Bertrand, Luttmer and Mullainathan (2000) who argue that neighbours alone can only provide an imperfect measure of networks. Using data from the US census, they supplement residential information with ethnic group language composition within the neighbours to derive measures of both network quantity and quality. They find that welfare receipt is strongly associated with network effects.

Other studies trying to assess the impact of informal networks of labour market outcomes have been based on self-reported use of contacts. Loury (2006) uses responses about of informal contacts in the NLSY to investigate their impacts on job tenure and wages. In principle, informal contacts effects may stem from improvement in match quality or from selection effects of workers with limited access to alternative search channels. She finds that wage effects may go either way depending upon what type of mechanism is at play behind the use of informal contacts. Another recent example is Pellizzari (2010) who uses information from self-reported use of contacts in the ECHP to address the impact of informal networks on labour market outcomes in a cross-country setup. Results are mixed in that both wage premia and penalties appear to be associated with contacts use across countries of the European Union. These wage gaps seem to be associated with the degree of efficiency of formal search methods: in countries where there are more labour market intermediaries, finding job through contacts is associated with wage gains, which suggests that in this countries informal networks may carry superior information about job opportunities.

Recently, researchers have been addressing the labour market effects of social networks with linked employer-employee data. Cingano and Rosolia (2006) use data from the Italian social security archive. They focus on displaced workers and define their contact networks as the set of individuals they have been working with prior to displacement. They relate a number of post-displacement outcomes such as unemployment duration and re-employment wages to measures of network quality, and find significant network effects. Population wide linked-employer employee data for Sweden have been used by Kramarz and Nordström Skans (2009) to assess the labour market impacts of a very specific type of social network, namely parental networks. They study the school-to-work transitions of young Swedish within educational cells defined at the class level, thereby being able to control for many confounding factors, and find that job referrals from parents are indeed very frequent, especially for males at the low end of the skill distribution. Wage effects of these networks are negative, but tend to be compensated by longer tenures in the first job found after leaving school. The intergenerational transmission of employers is studied by Corak and Piraino (2009) for Canada, who find strong association between fathers' and sons' employers, which is consistent, among others, with the operation of parental networks in the labour market. They find these effects to be particularly evident at the upper end of the fathers' earnings distribution.

As discussed at the start of this section, while the studies above are concerned with the operation of networks in the labour market or related spheres of economic activity, they all resort to some indirect measure of network in order to identify the effects of interest, either in terms of neighbours, self-reported information of linked employer-employee data structure. Indeed finding data that enable a direct observation of networks is not an easy task, and we are not aware of any paper using such direct information to study network effects in the labour market. Data on actual links within a network have been recently used by Calvo-Armengol, Patacchini and Zenou (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. They show that being located at (or close to) the centre of the network is beneficial to students' achievements. In a similar vein, in what follows we study network impacts using direct information on friendship ties.

3. Data and Empirical Strategy

3.1 Data

We use data from the British Households Panel Survey (BHPS) between 1992 and 2003. The BHPS is a representative sample of British households which follows individuals over time, allowing identification of individual yearly transitions across labour market states. In addition to this, the BHPS contains a special section on social networks that we exploit for estimating network effects on employment transitions. Namely, starting from wave 2 (1992) at each even wave respondents were asked 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 that is the closest to the BHPS respondent (the three best friends) and we are able to characterise the employment intensity within that portion.

Information on friends is retrieved at every even wave. Therefore we are able to relate the employment status of friends at wave t (t=1992, 1994, 1996….., 2002) to the employment transitions of BHPS respondents between waves t and t+1. We exploit the longitudinal dimension of the survey for integrating out individual specific effects. Unfortunately, no personal identifier is available for the three best friends, which prevents us from fully taking into account changes in friends' employment status over time. However, in our robustness checks we attempt at assessing friends' identity using demographic cells.

We select a sample of individuals in the 18-65 age range and not in full time education, whose three best friends also belong to the same age range. After deleting observations with missing information on some relevant explanatory variable (namely friends' employment status) we end up with a sample that covers 10,911 individuals (5,296 men and 5,615 women) with a total of 36,610 person-year observations.

Some relevant demographic information for our sample of BHPS respondent is presented in Panel A of Table 1, in connection with the demographic characteristics of the three best friends. The table 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) characterises 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' ages at 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 individuals make a transition from non-employment to employment from one year to another. 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 (including self-employment). As can be seen, the association are pretty 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. Clearly, and as discussed in Section 2, interpreting the findings of such regression models in causal terms is complicated by spurious correlation deriving from the fact that friendships tend to be formed by individuals with similar characteristics. Table 1 showed the relevance of such similarities when considering demographic traits, but it may well be that unobserved attributes such as productivity or effort in job search are also correlated across friends, which would translate in inconsistent parameter estimates of the effects of interest. To address these issues we exploit the longitudinal dimension of the data for taking into account respondents' unobserved heterogeneity. By observing the same individual in multiple spells of non-employment we are able to exploit the variation of the number of employed friends over time and the variation of the outcome. Based on this variation we are able to integrate out time invariant respondents' unobserved heterogeneity using panel data techniques. We also address the issue of time varying unobserved heterogeneity by checking the sensitivity of our fixed effects specifications to the inclusion of time varying regressors, and find that our findings on the effects of friends' employment status are not affected by such inclusion, suggesting that time varying heterogeneity is not the driver of our conclusions.

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 on values from 0 to 3. Our baseline specification is

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

where X 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 year of interview, living as a couple, having one, two or more children, having health problems, experiencing depression and being a smoker. The time invariant regressors include a gender dummy and education dummies. We also include in vector X the individual characteristics of each of the three friends that we have information; age and gender. The random variable α_i is the individual specific effect and $F(\cdot)$ is the distribution function that we use for integrating out the individual specific effects. For estimation we employ either probit or logit specifications. In the first case we treat the individual specific components as random effects, and also investigate robustness of the random effects to correlation with explanatory variables (the so called correlated random effect specification a-la-Mundlak, 1978, and Chamberlain, 1984). In the second case, we adopt a fixed effect logit approach. Finally, as an alternative way of accounting for time invariant unobserved heterogeneity, we estimate the transition equation jointly with an equation for the number of employed friends, and allow for correlated unobservables between the two equations using mass points.

4. Results

4.1 Baseline Specification

We first present the results of the baseline specification focusing on the effect of the number of employed friends on the transition into employment. The sample consists of a pooled sample of non-employment spells and the dependent variable is defined as one if the individual finds a job between year t (the reference period) and year t+1 and zero otherwise. Column 1 of Table 2 presents the estimates of the pooled probit regression without additional controls. We find that the number of employed friends exhibits a positive and significant effect on the transition into employment. The marginal effect suggests that having an additional employed friend increases the job finding probability by 6.4 percentage points (p.p). 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 5.6 p.p and after controlling for individual observed characteristics the marginal effect becomes 5.1 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. Taking into account the unconditional job finding rate of 20.28 percent, the effect of an additional employed friend is sizeable and corresponds to approximately a 25 percent increase.

Non-linear effects - The above analysis imposes a linearity assumption on the effect of the number of employed friends. We next estimate the baseline specification 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 suggest a non-linear effect. In particular, having one employed friend significantly increases the probability to enter employment in the next year by 5.2 p.p compared to have no employed friends, while having two or three employed friends increases the job finding probability by 8.9 p.p and 17.2 p.p, respectively.

Heterogeneity - We also investigate the heterogeneity of the effect of the number of employed friends by gender and age, considering three age groups (18-30, 31-50, 51-65). Controlling both for individual and friends characteristics we find a significant and positive effect of the number of employed friends for each age group and for both genders. The magnitude of the effect varies by age as shown in Table 3. For the younger age group (18-30) an additional employed friend increases the job finding probability by 7.4 p.p. The marginal effect for those aged 31-50 is 6.1 p.p and for the older group reduces to 1.2 p.p. As for gender, we find very similar positive marginal effects of 4.9 p.p for men and 5.2 p.p for women.

4.2 Robustness

The results presented so far establish the existence of a correlation between the employment status of friends. Individuals who have more employed friends are more likely to find a job. One concern with this finding is the potential endogeneity of the employment status of friends. It is likely that unobserved individual characteristics might affect both the probability to have friends who are employed and the own probability to become 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.

In order to address this endogeneity issue we need to exploit some variation in order to identify the causal effect of networks on the transitions into employment. Availability of panel data provides with this source of variation which can help us establish causality. 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. We estimate a number of different panel data models, which rely on different assumptions regarding the correlation between the error term and the regressors. We present in Table 4 both the linear specification with the number of employed friends and the non-linear specification with dummies for the number of employed friends.

Random effects - We first estimate a random effects model (RE), which assumes orthogonality between individual heterogeneity and the regressors. We also estimate a correlated random effect (CRE) in which we include the mean values of the time-varying regressors that relaxes the strong orthogonality assumption of the RE model. The results in Columns 1 and 2 of Table 4 show that after controlling for unobserved heterogeneity through RE or CRE the effect of the number of employed friends is very similar with the one estimated in the pooled probit regression of Table 2.

Fixed effects - Since the exogeneity assumption of the unobserved heterogneity with the observed regressors is very restrictive we further relax it by estimating a conditional fixed effects model (FE1). This estimator deals with the endogeneity issue by eliminating unobserved characteristics that are fixed over time. The sample size is reduced substantially due to conditioning on those individuals who are observed with multiple spells and with transitions from unemployment to employment over time. Column 3 of Table 4 shows the even after controlling for fixed effects the number of employed friends has a positive and significant effect on the job finding probability. The effect is lower (3.7 p.p) compared to the previous estimations, which suggests a positive correlation between unobserved individual heterogeneity and having employed friends that leads to an upward bias. Nevertheless, the effect remains significant and large. The non-linear specification in the lower panel shows that the effect is higher and significant when all friends are employed.

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, however, the case that time-varying characteristics might change when one becomes unemployed and that can be correlated with the characteristics of ones friends. For instance, it is possible that behavior such as smoking, drinking or depression might change upon entering unemployment, which might also affect the friendship ties of the unemployed. In order to test for the presence of such correlation we estimate our model by excluding all the time-varying covariates (FE-2). Our maintained assumption is that if observed time-varying regressors do not affect our estimates then unobserved time-varying regressors would not be correlated too. Column 4 in Table 4 shows that after excluding all the time-varying regressors the fixed-effect estimates remain unchanged.

The estimation of the fixed effects model relies on variation over multiple spells of the employment status of friends. This variation might have two sources. One is related to the change of the employment status of friends who remain the same over time. The second is due to changing friends over time that might lead to differences in their employment status. We try to separate the two sources by identifying those individuals for whom their friends remain the same over the observation period. So any variation of the employment status of their friends is due to transitions into and out of employment. We use the gender and age of friends to distinguish between stable and non-stable friends across two non-employment spells and we construct a dummy variable for having stable friends. We then estimate the fixed effects model controlling for the time varying covariate of having stable friends (FE-3). Column 5 shows that the main effect remains the same and the effect of having stable friends has no effect on the transition into employment.

Joint estimation - Finally, we estimate a semi-parametric two-equation model that accounts for the determinants of friends' employment status by means of an auxiliary equation that is estimated jointly with the transition model. The auxiliary equation specifies the endogenous choice of the number of employed friends as an ordered logit. This equation is estimated jointly with the main equation for the probability to find a job, which is specified as a logit. We allow unobserved heterogeneity to affect both endogenous variables and be correlated across equations. This model is semi-parametric because we do not impose a distributional assumption for unobserved heterogeneity. Instead, we model unobserved heterogeneity as a discrete distribution with two mass points for each random variable. Identification of this model relies again on the panel variation of the number of employed friends but contrary to the fixed effects it is estimated for the whole sample. The last column of Table 4 shows that the estimated marginal effect for the number of employed friend is very similar to the one estimated with fixed effects (top panel). In particular, an additional employed friend increases the probability to enter into employment by 3.2 p.p and is highly significant.

5. Mechanisms of network effect

The findings presented in the previous section suggest a significant network effect. In this section, we investigate the 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; Bramoulle 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, which leads them to lower their reservation wages and increase the probability to find a job. Lalive and Stutzer (2004) provide evidence that social norms ("worth ethic") speed up transitions out of unemployment. A third mechanism that might explain the findings is leisure complementarities. When an unemployed person has all friends 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 (2003) show effect of leisure coordination on happiness of couples. In what follows we will try to distinguish among these competing mechanisms that can explain the causal effect of employment of friends on job-finding.

Re-employment wages - Both for the peer-effect and leisure complementarities hypotheses we expect a lower reservation wage the higher is the number of employed friends. On the other hand, 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. We first investigate the effect of the number of employed friends on re-employment wages. Column 1 in Table 5 shows that the number of employed friends has a significant and positive effect on re-employment wages. An additional employed friend increases wage for those who become employed in the next year by 5.6 percent. In addition, having one (three) employed friend(s) compared to no employed friends increases wage by 11.8 (20.9) percent.

Satisfaction with leisure - Finally, as a way to assess the relevance of leisure complementarities as explanation of our findings, we exploit data on the satisfaction with the use of leisure that are available in the BHPS. If individuals derive utility from the fact that they have ‘someone to play with’ when they have time free from market work, then the fact that friends are employed should be negatively associated with the non-employed happiness towards their leisure, an association that we can actually estimate by regressing the satisfaction with leisure of the non-employed on the number of their employed friends. The findings also in this case are not suggesting that leisure complementarities might be able to explain the network effect that we find. As Column 2 of Table 5 shows the number of employed friends do not have any effect on satisfaction with leisure.

The findings of a wage gain with the number of employed friends and no effect on satisfaction with leisure support the information hypothesis against the social norm or leisure complementarities ones.

6. Conclusion

This paper investigates the effect of social interactions on labour market outcomes using a direct measure of social contacts based on individual's 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 probability to enter into employment. We provide evidence that employed friends increase the probability to find a job. An additional employed friend increases the probability to find 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 highest effects. These results are robust to a number of specifications that address the potential endogeneity of the number of employed friends due to correlation with unobserved individual attributes.

We also investigate the potential mechanisms through which employed friends might affect job finding probabilities, considering three mechanisms: information transmission, peer-effects or social norms, and leisure complementarities. To distinguish among these different channels we consider the relation of the number of employed friends with wages and satisfaction with leisure. We find that more employed friends is associated with wage gains, while there is no effect on satisfaction with leisure. We interpret this as evidence of the information transmission mechanism through which social networks operate.

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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

Table 2: Probit estimates - Dependent variable: Probability of finding a job

	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio	Coef.	M.E.	t-ratio
Number of Employed Friends	0.231	0.064	11.36	0.211	0.056	10.00	0.209	0.051	9.30			
One Employed Friend										0.203	0.052	2.50
Two Employed Friends										0.351	0.089	4.47
Three Employed Friends										0.627	0.172	7.76
Controls - Friends		No			Yes			Yes			Yes	
Controls - Individual		No			No			Yes			Yes	
Observations		6,516			6,516			6,516			6,516	

Table 3: Probit estimates – Heterogeneity

	Age 18-30		Age 31-50		Age 51-65		Men		Women	
	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio
Number of Employed Friends	0.074	5.20	0.061	6.15	0.012	2.92	0.049	5.04	0.052	7.95
Controls - Friends	Yes		Yes		Yes		Yes		Yes	
Controls - Individual	Yes		Yes		Yes		Yes		Yes	
Observations	1,552		2,582		2,371		1,945		4,571	

Table 4: Panel data estimates - Dependent variable: Probability of finding a job

	RE		CRE		FE- 1		FE- 2		FE- 3		Joint	
	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio
Number of Employed Friends	0.051	8.75	0.050	8.61	0.037	2.07	0.038	2.10	0.037	2.05	0.032	4.39
Controls - Friends	Yes		Yes		Yes		Yes		Yes		Yes	
Time Invariant Controls - Individual	Yes		Yes		Yes		Yes		Yes		Yes	
Time Variant Controls - Individual	Yes		Yes		Yes		No		Yes		Yes	
Observations	6,516		6,516		1,324		1,324		1,324		6,516	

	RE		CRE		FE- 1		FE- 2		FE- 3		Joint	
	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio	M.E.	t-ratio
One Employed Friend	0.058	2.43	0.057	2.42	0.081	1.37	0.086	1.46	0.081	1.36	0.045	2.19
Two Employed Friends	0.093	4.10	0.090	4.03	0.078	1.34	0.085	1.45	0.078	1.33	0.062	2.86
Three Employed Friends	0.188	6.50	0.183	6.40	0.142	2.23	0.145	2.29	0.140	2.21	0.110	4.30
Controls - Friends	Yes		Yes		Yes		Yes		Yes		Yes	
Time Invariant Controls - Individual	Yes		Yes		Yes		Yes		Yes		Yes	
Time Variant Controls - Individual	Yes		Yes		Yes		No		Yes		Yes	
Observations	6,516		6,516		1,324		1,324		1,324		6,516	

Table 5: Re-Employment Wages (logs), Leisure Satisfaction and Employment Status of Friends (OLS)

	Wages		Leisure Satisf.	
	Coef.	t-ratio	Coef.	t-ratio
Number of Employed Friends	0.056	3.50	0.018	0.55
Controls - Friends	Yes		Yes	
Controls - Individuals	Yes		Yes	
Observations	1,105		4,324	

	Wages		Leisure Satisf.	
	Coef.	t-ratio	Coef.	t-ratio
One Employed Friend	0.118	2.09	0.003	0.03
Two Employed Friends	0.187	3.46	0.002	0.02
Three Employed Friends	0.209	3.83	0.050	0.43
Controls - Friends	Yes		Yes	
Controls - Individuals	Yes		Yes	
Observations	1,105		4,324	