Coworker Networks in the Labour Market

Albrecht Glitz[1]

Universitat Pompeu Fabra

April 2011

PRELIMINARY - PLEASE DO NOT CIRCULATE

Abstract

This paper studies the role of networks consisting of former coworkers for individual labour market outcomes. I analyse how the provision of labour market relevant information by former coworkers affects the employment probabilities and, if hired, the starting wages of workers who have previously become unemployed as the result of a firm closure. While there is ample empirical evidence for the importance of friends and families for the job search process, little is known about the role of coworkers. This is somewhat surprising since these individuals are more likely to be both better acquainted with the job-related skills of a worker and more knowledgeable about potential job openings fitting this worker's profile. The empirical strategy applied in this paper builds on the substantial theoretical work that exists on the effect of social networks on employment and wages (see, for example, Topa, 2001, or Calvó-Armengol and Jackson, 2004, 2007). The empirical analysis is based on German administrative data that comprise the universe of workers who were employed in Germany between 1980 and 2001, and allow me to obtain a full picture of the employment histories of both unemployed workers and their coworkers.

Key Words: Networks, Labour Markets, Employment, Unemployment, Wages

[1]I am grateful to Marco Hafner and Johannes Ludsteck from the Institute for Employment Research for invaluable support with the data. I thank the Barcelona GSE Research Network, the Government of Catalonia, and the Spanish Ministry of Science (Project No. ECO2008-06395-C05-01) for their support.

1 Introduction

In many economic and social situations, individual agents do not act autonomously but as members of a group. This observation has encouraged substantial theoretical and empirical research on the role of social networks in recent years. While the theoretical literature has developed sophisticated models of interactions of agents in a large number of different settings, the empirical work has so far mostly focused on relatively few, tightly defined environments such as classrooms (Ammermueller and Pischke, 2006, Cipollone and Rosolia, 2007), universities (DeGiorgi et al., 2009), individual firms (Bandiera et al., 2009, Mas and Moretti, 2009) and neighbourhoods (Bayer et al., 2008). This focus is to a large extent due to the often prohibitively high demands on data without which the identification of the relevant networks and an analysis of their functionality is impossible. In particular, the analysis of the role of networks in the labour market has suffered from these restrictions due to the relatively broad scope of the environment and the potentially complicated and often unobserved network structures.

One of the key questions of interest in the labour market context is whether and to what extent a worker's labour market outcomes, especially employment and wages, are affected by the network he or she is operating in. To answer this question, most research so far has proceeded by either analysing survey data in which workers state whether they have heard about a particular job through a friend or relative (see Ioannides and Loury, 2004, for a survey of the literature), or by relating the presence of other individuals that are likely to have an influence on the worker in question - for instance due to similar observable characteristics such as ethnicity (for example Edin et al., 2003 or Damm, 2009) - to his or her labour market outcomes. While survey data have the advantage of providing direct information about the actual use of network contacts, they typically lack information on the characteristics of the relevant network contacts, which makes an analysis of the factors underlying the working of the network difficult. Using average characteristics of an exogenously determined reference group such as neighbours or individuals with the same ethnicity as an indirect measure of network quality provides better indication of the potential mechanisms but leaves the actual channel through which information is transmitted unexplored.

In this paper, I take a novel approach to the definition of networks in the labour market context. Using German data on individuals' entire work histories, I define a given worker's network as the group of all coworkers with which he has, at some point, worked together in the same firm. I first give a descriptive overview of the key features of these coworker-based networks. Based on an analysis of mobility patterns, I then provide evidence suggesting that the strength of the link between any two workers is heterogenous and depends in an intuitive way on a number of variables describing the worker-coworker relationship. In the main part of the empirical analysis, I then analyse in detail the role coworker-based networks play for the labour market outcomes of workers who were exogenously displaced as the result of a firm closure.

The empirical results show that coworker networks are an important feature of the labour market. The median number of coworkers a worker has worked with over a period of five years is 48. In the year after the firm closure, around 20 percent of all displaced workers end up working in a firm where at least one of these former coworkers is already present. The strength of the link between a worker and a given coworker, which may explain the observed mobility patterns, is a negative function of the time that passed since the workers were separated and a positive function of the time they worked together, the wage gap between them and the age difference between them. In addition, the strength of a link is stronger between ethnic minority workers and between women. The analysis of the labour market outcomes after displacement shows that being embedded in a larger network has a positive effect on the employment probability one year after displacement but no effect on starting wages in the new job.

The way to identify the relevant network in the labour market context is not straightforward. In the literature, the focus has been on individuals with the same ethnicity, neighbours, or family members and friends as particularly more recent surveys often collect information about these contacts and their role in the job search activities of workers (see, for example, Loury, 2006, Cappellari and Tatsiramos, 2010, or Goel and Lang, 2010). However, an important group of individuals has so far received relatively little attention: the group of coworkers (an important exception is the study by Cingano and Rosolia, 2009). There are two main reasons for why studying this group may potentially better capture the relevant information transmission mechanism in the labour market context than any of the aforementioned groups. First, since unemployed workers typically search for a job in a profession related to the one they previously worked in, coworkers are likely to have better knowledge of the job-specific abilities of the worker and be more aware of potential job openings than friends or family members who, although wanting to help, may lack the attachment to the relevant labour market segment (see Antoninis, 2006). Second, and in contrast to most other network definitions, one can be fairly certain that coworkers, given a sufficiently small firm size, actually know each other. This is not trivial as in many studies of network effects actual personal contact between individual network members cannot be verified.

Taking full advantage of social security data that cover the universe of workers in the German labour market between 1980 and 2001, I am able to identify precisely each single coworker a worker has ever worked with in the same firm in the past as well as these coworkers' individual characteristics and, most crucially, labour market status at the time the worker is displaced. This allows a detailed investigation of how coworker characteristics and in particular their own labour market status affect the job finding probability and wages a worker obtains after being exogenously displaced as the result of a firm closure.[2]

[2]Of course, in addition to coworkers there are a number of alternative information channels, formal and informal, through which a worker may hear about job openings which I do not consider here but which one may think as

This main empirical analysis in this paper is closely related to the theoretical work of Calvó-Armengol and Jackson (2004) and (2007). Their work sets out in detail, how an individual agent's employment status and wage rate is related to the characteristics of the network he is part of. The basic idea is that every worker receives information about a job opportunity at an exogenously given rate. If the worker is employed and the new job opportunity does not dominate his current wage, the worker passes the information on to one of his unemployed network contacts. An unemployed worker will therefore obtain more information about potential job openings - and hence be more likely to find a well-paid job - the larger his network and the higher the employment rate of his contacts. I test this basic prediction by defining a network based on coworkership and estimating the effect of the employment rate in a given worker's network on the employment probability and wages of this worker in the years after an exogenous displacement due to a firm closure.

The remainder of the paper is organised as follows. In the next section, I discuss the theoretical model underlying the empirical analysis, summarise its key predictions, and explain its empirical implementation. In Section 3, I describe the data source and sample preparation. In Section 4, I present comprehensive descriptive evidence on the main features of coworker-based networks. In Section 5, I examine the heterogeneity in the strength of network links. Section 6 provides the main empirical results. Section 7 concludes.

2 Theoretical Model and Empirical Implementation

The model underlying the empirical analysis in this paper is based on the theoretical work on networks in labour markets by Calvó-Armengol and Jackson (2004, 2007). In their model, a network consists of a group of agents that are path-connected. Two agents are path-connected

being orthogonal to the coworker channel that is at the core of this paper.

if there exists a sequence of links that form a path between them. The focus of this paper is on coworker relationships and, primarily, on directly connected workers: a given worker is directly connected to another worker if and only if both workers have worked together at the same firm. In most specifications, I implicitly assume that the strength of each direct connection is constant. I will relax this assumption and analyse the possible factors influencing the strength of a link between two workers in Section 5.

The mechanism the theoretical model set-up by Calvó-Armengol and Jackson captures is the following. In the first phase of each period, an agent hears about a new job opportunity and the wage associated with it with an exogenous probability. If the agent is unemployed then he will accept the job. If the agent is employed and the new wage offer does not dominate the agent's current wage, he will randomly select one of his unemployed direct contacts and pass the information about the new job on to this contact. If an unemployed worker receives more than one job offer, he will accept the one that offers the highest wage. As a consequence, unemployed workers that are embedded in a strong network are more likely to find a new job and receive higher wages than workers embedded in a weak network. In the context of this paper, the prediction is that the larger a displaced worker's network and the higher the employment rate in this network, the higher the probability of finding a new job and the higher the starting wages in the new job.

To capture this relationship, I estimate a linear in means model of the following form:

$$y_i = \alpha + \mathbf{x}_i'\gamma + \beta_1 ER_i + \beta_2 NS_i + NC_i'\delta + u_i, \tag{1}$$

where $\mathbf{x}_i$ is a set of individual characteristics of displaced worker i, and ER_i, NS_i and NC_i represent the employment rate, number (network size), and a vector of average characteristics (network characteristics) of displaced worker i's former coworkers. The dependent variable is either an indicator variable taking the value of one if a worker is observed working in the year after the firm closure, or the log daily wage in the new job. Theory predicts that $\beta_1 > 0$ and $\beta_2 > 0$.

As is well known in the literature on social interaction effects, identification of the parameters of interest in the linear in means model is difficult due to the issues of reflection and endogeneity (see Manski, 1993). The typical reflection problem arises because within a closed network, for example a classroom, every individual agent's behaviour affects every other agent's behaviour, which makes it impossible to distinguish endogenous effects – the effect of the aggregate network outcome on an individual agent's outcome – from exogenous effects – the effect of the average network characteristics on an individual agent's outcome. As Manski (1993) and DeGiorgi et al. (2009) show, however, as long as the groups of direct contacts are individual-specific, i.e. there are at least some direct contacts of a given agent that are not at the same time direct contacts of all the other agents he is connected with, identification of both the endogenous and the exogenous effects is possible. In the present framework, the groups of former coworkers differ across individuals due to the heterogenous employment histories of the workers. Only workers that have worked with exactly the same set of coworkers in the years between 1990 and 1994 would have the same group of direct contacts.

The problem of endogeneity could arise in the present context either due to unobserved group level shocks that affect the outcomes of all workers who work (or worked) together in the same firm, or through unobserved individual level heterogeneity, for example due to workers' self-selection into particular firms based on unobservable characteristics. To overcome these issues, I include fixed effects for the closing firms in the estimation of Equation (1) which should account to a large extent for any unobserved firm level shocks or heterogeneity. Identification is then coming from variation in the employment rate, size, and characteristics of the coworker networks across workers who are being displaced from the same firm in 1995. To account for any additional unobserved heterogeneity on the individual level, I include a large set of individual control variables, including education, potential work experience, gender, immigrant status, and the last wage observed in or before 1989.[3]

Finally, in an extension of the basic model, I also include the employment rate and size of each displaced worker's two-link away contacts as additional regressors. Two-link away contacts are all those workers who worked together with one of the direct contacts of a given worker between 1990 and 1994 but never with the worker himself. As predicted by the theoretical model described above, these workers – and in particular the unemployed subset among them – are competitors for the job information a given coworker receives. The more unemployed contacts a former coworker has, the less likely it is that he will pass on any information about a job opening to the displaced worker in question. In the extended specification, the model is given by

$$y_i = \alpha + \mathbf{x}_i'\gamma + \beta_1 ER_{i1} + \beta_2 NS_{i1} + NC_{i1}'\delta + \beta_3 ER_{i2} + \beta_4 NS_{i2} + u_i, \tag{2}$$

where the subscripts 1 and 2 refer to the one-link (direct) and two-link away contacts, respectively.

3 Data and Sample Preparation

The data used in the analysis are based on social security records and comprise every worker in Germany who is subject to social security contributions.[4] They cover more than two decades, from 1980 to 2001, and are recorded annually on the 30^{th} of June. The social security records contain

[3]The reason to control for the last wage in or before 1989 rather than the last wage observed in 1995 is that the network measures are calculated based on the period 1990 to 1994 and are likely to already affect the observed wage in 1995. To avoid what Angrist and Pischke (2008) call a "bad control", I condition on the wage prior to the network building period.

[4]The main groups not included in the data are civil servants, the self-employed, and military personnel. In 2001, 77.2% of all workers in the German economy were covered by social security and are hence recorded in the data (Bundesagentur für Arbeit, 2004).

unique worker and firm identifiers as well as an unusually wide array of background characteristics, such as education[5], occupation, industry, and citizenship. From this data base, I have initially selected all workers working in one of the three largest metropolitan areas in Germany: Hamburg, Frankfurt, and Munich.

In a first step, I construct a panel data set of firms using the unique firm identifiers. The base year for my analysis is the year 1995.[6] For this year, I obtain a list of all firms that exist in 1995 but do not exist anymore in 1996 (18,438 firms or 8.4% of all active firms in 1995). From this set of firms, I then select all firms that had between 5 and 50 workers in the last year of business (2,307 firms or 12.5% of the sample of closing firms) and for whom the maximum share of displaced workers who end up working together in another firm in the year after the firm closure is smaller than 50% (leaving 710 firms or 30.8% of the sample of closing firms with between 5 and 50 employees).[7] This is the sample of closing firms on which the analysis is based.

In the next step, I collect information about all workers who are working in these firms in 1995, the year of the firm closure. I call these workers "displaced workers". In addition to these workers' individual characteristics such as gender, education, age, and nationality, I obtain characteristics of all the workers each displaced worker has ever worked with in the same firm, including variables related to their common employment spell such as the time (in years) the workers worked together and the duration (in years) since separation. I call these workers "coworkers".

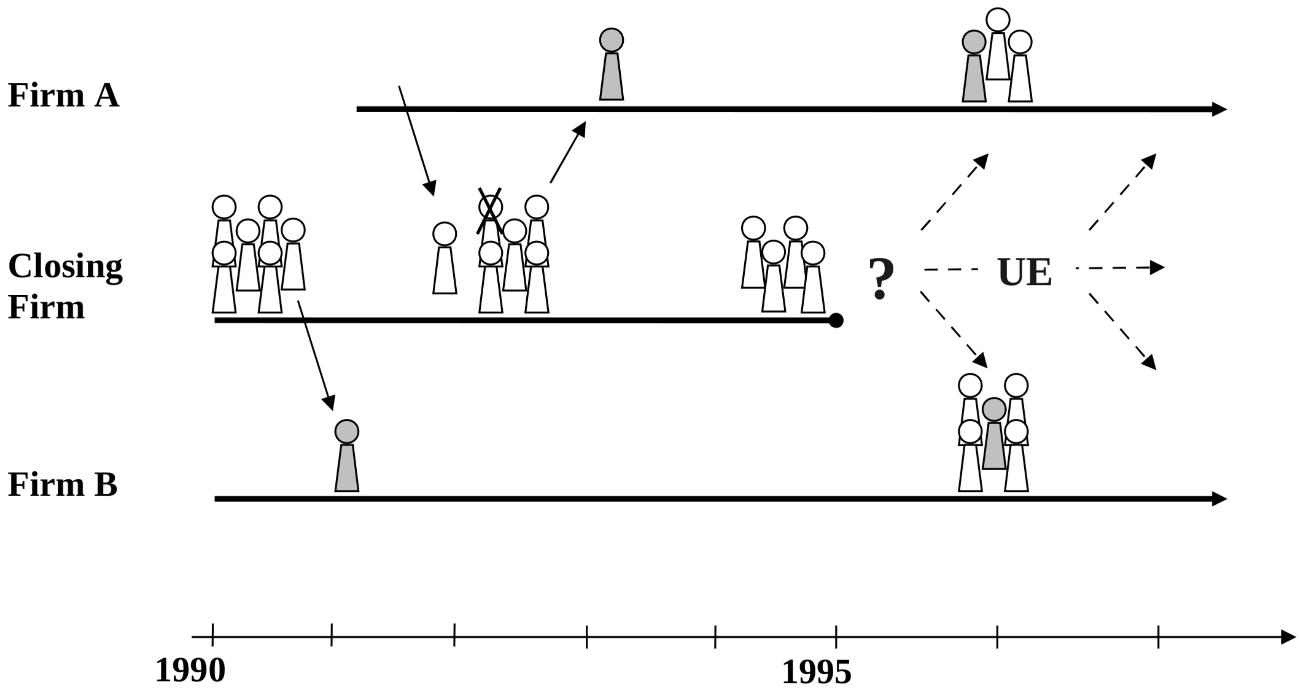
For the main empirical analysis, I only consider coworkers who worked together with a given

[5]To improve the consistency of the education variable in our data, I apply the imputation algorithm suggested by Fitzenberger et al. (2006).

[6]This year is chosen for no particular reason. It does provide a sufficiently long pre- and post-bust period which allows controlling a the labour market histories of the workers as well as the long-run effects of being in a network.

[7]The motivation for this sample selection is the following. I exclude very small firms since these are often family-run and provide not sufficient variation in network structure within firms. I exclude firms whose majority of the workforce continuous to work together in a new firm after the firm closure to rule out firms that simply change their legal status, for example through mergers, in which case they would receive a new firm identifier and hence appear as new firms in the data. This latter selection rule may lead to an underestimation of the network effects although it appears unlikely that networks themselves are strong enough to induce half of a firm's workforce to move together to the same firm.

Figure 1: Work Histories



displaced worker between 1990 and 1994. Consequently, other contemporaneously displaced workers are not in the set of coworkers of a given displaced worker. This is reasonable as these workers become unemployed at the same time as the displaced worker and are hence unable to provide any information about new job opportunities. The restriction to coworker relationships established over the preceding five years is partly driven by data processing constraints but can be motivated by a gradually depreciating network quality over time such that any contact that was last active (in the form of working together) before 1990 has ceased to provide any information to the displaced workers in 1995. Figure 1 illustrates the general data set-up.

4 Descriptive Evidence

Table 1 shows descriptive statistics for the sample of displaced workers. Overall, there are 5,427 workers who become unemployed as the result of 681 firm closures in the Hamburg, Frankfurt and Munich metropolitan areas in 1995.[8] Around two-thirds of these workers are men, and around 11 percent are foreign citizens. Most of the displaced workers in the sample have medium education which in the German context refers to vocational training. Around 10 percent do not have vocational training or have missing information about their educational attainment, and about 7 percent of workers have university education. In terms of the sectoral composition, the largest share of displaced workers worked in their last job in professional, medical and business services, basic manufacturing or wholesale. While a relatively large fraction of men worked in the construction sector, women worked predominantly in the services and the retail sector.

Table 2 provides information about some key variables for the period before the firm closure (top panel) and the year after the firm closure (bottom panel). Between 1980 and 1995, the displaced workers spent on average 12.4 years working. On average, they worked in 3.5 different firms, spending around 3.4 years in each of them. Over the entire pre-firm closure period from 1980 to 1994, the median number of coworkers a displaced worker worked with was 220. In the last five years prior to the firm closures in 1995, the period on which the calculations of the network characteristics are based, the median number of coworkers a displaced worker worked with was 48.[9] On average, a displaced worker worked 4.2 years with his former coworkers although there is substantial variation. The average tenure in the firm that eventually closes down in 1995 is about 5 years and the average daily wage earned in 1995 is around 69 Euros.

[8]The sample described in Table 1 refers to the actual sample of firms that is later used in the estimations. Some of the original 710 firms in the sample are not used in the estimation because of missing data for some of the worker's covariates.

[9]Note that the mean number of coworkers is substantially higher, 686 coworkers when looking at the last five years, due to some extreme outliers. For example, the maximum number of coworkers a displaced worker in the sample had between 1990 and 1994 is 48,135.

The lower panel of Table 2 shows that the average employment rate across the coworker networks is 58.6 percent. Of the workers who were displaced in 1995, 70.1 percent were working again in 1996 and of those, 28.7 percent end up working in a firm where a former coworker is already present. On average, a displaced worker working in 1996 works with 3.9 percent of his former coworkers. A comparison of the wage levels shows that those displaced workers who do end up working again with at least one of their former coworkers earn substantially more, around 3.5 Euros, than those workers who work without any of their former coworkers. Conditional on working in 1996, daily wages of the displaced workers only drop relatively mildly and only for men, by around 0.6 percent. Interestingly, men who work with at least one of their former coworkers earn around 0.7 percent more than before while those who work without any former coworker earn 1.2 percent less. In contrast, women earn 1 percent less if they work with a former coworker but 0.6 percent more if they work in a firm without a former coworker present.

5 Strength of a Network Link

In the standard calculation of the employment rate for a given coworker network, the strength of the link between the displaced worker and his coworkers is implicitly assumed to be constant. This may not well reflect reality where the strength of the link between two workers is likely to depend on a number of observable characteristics of both workers as well as features of their common work experience. For example, individual characteristics that may affect the strength of the connection could be the two agents' relative educational attainment and wage rate, their nationalities and their age. Features of the common work experience that may have an effect on the strength of the connection could be, for instance, the time they worked together and the time that has elapsed since separation.

There are a number of ways in which one could specify the strength of a link between a worker and his former coworkers. One is to exogenously choose one or several characteristics of the relationship that are likely to play an important role for the strength of the link, such as the time worked together or whether worker and coworker have the same nationality, and use these to obtain a weighted average of the coworkers' employment status. I follow a more systematic approach by exploiting the information inherent in the decisions of displaced workers to start working at firms where former coworkers are already working. Suppose that the strength of the relationship between any two workers i and j can be written as

$$S_{ij}^{*} = \mathbf{x}_{ij}'\beta + \epsilon_{ij},$$

where $\epsilon_{ij},\ j = 1, ..., NS_i$, represent unobservable preferences of worker i for coworker j which are assumed to be independent of the vector of observable characteristics $\mathbf{x}_{ij}$. Every worker now chooses to follow the coworker with whom they have established the strongest relationship over their common employment spell. Following McFadden (1974), I assume that the stochastic components ϵ_{ij} are independently identically distributed following the extreme value distribution so that

$$P(y_i = k|\mathbf{x}_i) = \frac{\exp(\mathbf{x}_{ik}'\beta)}{\sum_{j \in N_i} \exp(\mathbf{x}_{ij}'\beta)},$$

where y_i is a variable taking the value k if worker i is observed working together with coworker k in the year after the firm closure, and N_i is the set of worker i's former coworkers.

I estimate this conditional logit model on the subset of coworkers that are working in 1996. I then use the estimated coefficient vector $\widehat{\beta}$ to predict the probabilities that a displaced worker follows one of his coworkers in the year after the firm closure, including out of sample prediction for those coworkers that are not employed in the year after the firm closure. These predicted probabilities capture the strength of the link between two workers and are then used as weights in the calculation of the network-specific employment rates. The vector $\mathbf{x}_{ij}$ includes the time each worker-coworker pair worked together, the time since separation, their relative wage, relative age, relative education, an indicator for the same sex, and an indicator for the same nationality.[10]

Table 3 shows the corresponding coefficient estimates from the conditional logit model. The main results in the second column show that the more time has passed since the separation of the workers, the lower is the probability of a displaced worker following his or her coworker: one additional year since separation reduces the relative probability of following a particular coworker by around 35 percent. On the other hand, the longer the duration of cowork, the higher is the probability of following a particular coworker: an additional year of cowork increases the relative probability of following a coworker by 1.9 percent. The results with respect to the average relative wages between the displaced worker and his coworkers during the time of their coworkership show that the higher the wage of the coworker, the more likely a worker is to follow this coworker. Since the two point estimates are relatively similar in magnitude, the effect is roughly linear in actual relative wages.[11] The results for the age difference, however, show a non-linear relationship. While a younger displaced worker is more likely to follow his older former coworker the greater the age difference, the mobility choice of a worker who is older than his coworkers is unaffected by

[10]Given the large sample size, it is not possible to estimate this model using the exact maximum likelihood function. Instead, I take advantage of the fact that the conditional logit model is closely related to the Cox model known primarily from the analysis of duration data. In fact, after appropriately setting up the data and specifying the correct way to handle ties, estimating a Cox model is identical to estimating a conditional logit model (in STATA by specifying the exact partial-likelihood method for ties). If can be shown that as long as ties – in the present context a tie would arise if a given worker follows more than one coworker – are not too frequent, the Cox model evaluator with the Breslow method specified to handle ties leads to good results at much lower computation costs.

[11]The reason for the particular specification chosen is that, a priori, it is not clear whether one should expect a linear relationship between relative wages and relative age, and the probability of following a coworker. It could very well be that what matters is similarity between the workers in these dimensions, in which case the coefficients on both interactions would show a negative sign.

the absolute age differences between them. The remaining results show that while a coworker's nationality has no effect on the strength of the link for a German displaced worker, foreign displaced workers are much more likely to follow another foreign coworker than a German coworker: holding all else constant, the probability of following a foreign coworker is about 31 percent ($e^{0.269} - 1$) higher than the probability of following a German coworker.

6 Empirical Results

In this section, I investigate how the employment rate and size of a displaced worker's network affect his employment probability and wages one year after the displacement. Table 4 shows the results of a linear probability model for being employed based on Equation (1) (columns (1)-(4)) and Equation (2) (columns (5)-(8)). Column (1) in Table 4 shows small positive effects of both the employment rate and the number of coworkers (measured in logs) on the probability of being employed one year after the exogenous displacement. However, both estimates are statistically not significant. Including a full set of fixed effects for the closing firms in column (2) has only a small effect on the point estimates which remain statistically not significant. In column (3) and column (4), instead of firm fixed effects I include firm/education and firm/occupation group fixed effects, respectively. Identification now comes from variation in the employment rate and size of coworker networks across worker with the same education or occupation coming out of the same firms. Again, point estimates remain relatively unchanged. In columns (5) to (8), I now extend the estimation by including the number and employment rate of all two-link away contacts of a given displaced worker as additional covariates. As described in Section 2, unemployed two-link away contacts effectively compete with the displaced workers for information about job opportunities from the direct contacts. Hence, a lower employment rate and larger number of two-link away contacts should, all else equal, reduce the probability of working for a given displaced worker. The results provide some evidence for this hypothesis. When controlling for firm/education and firm/occupation fixed effects, the point estimates suggest that a 10 percent increase in the number of direct contacts increases the probability of finding a job within a year by 0.2 percentage points. On the other hand, a 10 percent increase in the number of two-link away contacts leads to a decrease of the employment probability of between 0.1 and 0.2 percent. The coefficients on the employment rates of the coworkers and two-link away contacts have the right sign but are statistically not significant.

Table 5 shows the corresponding results for the log wages in the new jobs of the displaced workers. Overall, there is no evidence that a higher employment rate and larger coworker network have any effect on the starting wages of recently displaced workers in their new firms. All estimates, with the exception of the effect of the two-link away employment rate, are not only statistically not significant but also close to zero in magnitude.

Table 6 reports the results for the employment probability but this time using the coworkers' weighted employment rate based on the results from the conditional logit model estimation reported in Table 3, column (2). As expected, the coefficients are somewhat more accurately estimated though only statistically significant in the specifications without fixed effects, with a parameter value of between 0.067 and 0.078, implying that a 10 percentage point increase in the coworkers' employment rate leads to a 0.7 to 0.8 percentage point increase in the probability of working in the year after the firm closure.

7 Conclusion

This paper diverges from the existing literature on the role of social networks by defining networks based on coworkership. Coworkers are likely to play an important role in the exchange of labour market relevant information between individuals. They are likely to possess good knowledge of a given worker's specific skills and to be more aware of job opportunities appropriate for the worker in question. Using data on the universe of workers in Germany's social security system, I show that coworker networks play an important role for the decision of workers where to start a new job. About 20 percent of all workers who lose their job as the result of a firm closure end up working in a new firm where at least one of their former coworkers is already present. Key factors determining which of the potential coworkers a displaced worker is going to follow are the duration of cowork, the time since separation and, for non-German citizens, the ethnicity of the coworker. A systematic analysis that takes account of unobserved correlated group level effects and individual sorting into firms through the inclusion of a detailed set of fixed effects and control variables shows that the size of a worker's network at the time of becoming unemployed due to a firm closure has a positive effect on his employment probability one year after displacement. However, there is no effect of neither network size nor the employment rate on the starting wages in the new firms. In future work, I will look more closely at the heterogeneity of these effects across different subgroups of the population, e.g. in terms of education and immigrant status, as well as the long-run effects beyond the first year after displacement.

References

Ammermueller, A. and J.-S. Pischke (2006). Peer effects in european primary schools: Evidence from pirls. NBER Working Paper 12180.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. New Jersey: Princeton University Press.

Antoninis, M. (2006). The wage effects from the use of personal contacts as hiring channels. *Journal of Economic Behavior & Organization 59*(1), 133–146.

Bandiera, O., I. Barankay, and I. Rasul (2009). Social connections and incentives in the workplace: Evidence from personnel data. *Econometrica 77*(4), 1047–1094.

Bayer, P., S. E. Ross, and G. Topa (2008). Place ofwork and place of residence: Informal hiring networks and labor market outcomes. *Journal of Political Economy 116*(6), 1150–1196.

Bundesagentur für Arbeit (2004). Arbeitsmarkt 2003. Amtliche Nachrichten der Bundesagentur für Arbeit.

Calvó-Armengol, A. and M. O. Jackson (2004). The effects of social networks on employment and inequality. *American Economic Review 94*(3), 426–454.

Calvó-Armengol, A. and M. O. Jackson (2007). Networks in labor markets: Wage and employment dynamics and inequality. *Journal of Economic Theory 132*(1), 27–46.

Cappellari, L. and K. Tatsiramos (2010). Friends networks and job finding rates. IZA Working Paper No. 5240.

Cingano, F. and A. Rosolia (2009). People i know: Workplace networks and job search outcomes. Bank of Italy Working Paper No. 600.

Cipollone, P. and A. Rosolia (2007). Social interactions in high school: Lessons from an earthquake. *American Economic Review 97*(3), 948–965.

Damm, A. P. (2009). Ethnic enclaves and immigrant labor market outcomes: Quasi-experimental evidence. *Journal of Labor Economics 27*(2), 281–314.

DeGiorgi, G., M. Pellizzari, and S. Redaelli (2009). Be as careful of the company you keep as of the books you read. peer effects in education and on the labor markets. NBER Working Paper No. 14948.

Edin, P.-A., P. Fredriksson, and O. Åslund (2003). Ethnic enclaves and the economic success of immigrants - evidence from a natural experiment. *Quarterly Journal of Economics 118*(1), 329–357.

Fitzenberger, B., A. Osikominu, and R. Völter (2006). Imputation rules to improve the education variable in the iab employment subsample. *Schmollers Jahrbuch : Journal of Applied Social Science Studies / Zeitschrift fr Wirtschafts- und Sozialwissenschaften 126*(3), 405–436.

Goel, D. and K. Lang (2010). Social ties and the job search of recent immigrants. CReAM Discussion Paper No. 22/10.

Ioannides, Y. M. and L. D. Loury (2004). Job information networks, neighborhood effects, and inequality. *Journal of Economic Literature 42*(4), 1056–1093.

Loury, L. D. (2006). Some contacts are more equal than others: Informal networks, job tenure, and wages. *Journal of Labor Economics 24*(2), 299–318.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies 60*(3), 531–542.

Mas, A. and E. Moretti (2009). Peers at work. *American Economic Review 99*(1), 112–145.

McFadden, D. L. (1974). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*, Chapter 4, pp. 105142. New York: Academic Press.

Topa, G. (2001). Social interactions, local spillovers and unemployment. *Review of Economic Studies 68*(2), 261–295.

Table 1: Summary Statistics - Worker Sample

	All	Men	Women
Number	5,427	3,575	1,852
Share Foreign	11.2	13.3	7.1
Average Age	40.1	40.6	39.3
Share in Hamburg	34.2	33.5	35.6
Share in Frankfurt	31.8	31.4	32.6
Share in Munich	33.9	35.1	31.8
Educational Attainment			
Share missing	1.7	1.7	1.6
Share low education	8.1	7.7	8.9
Share medium education	83.0	82.0	84.7
Share high education	7.3	8.5	4.9
Industry			
Agriculture	1.5	1.4	1.7
Construction	8.9	12.3	2.3
Manufacturing, low tech	6.8	8.8	3.1
Manufacturing, basic	13.4	16.4	7.7
Manufacturing, high tech	3.0	3.1	2.8
Communications, transport & utilities	11.5	11.8	11.0
Wholesale	13.4	13.6	12.9
Retail	10.5	8.0	15.1
Prof., med. and business services	18.6	16.5	22.6
Education & Welfare	1.1	0.6	2.1
Public administration	0.8	0.4	1.6
Other services	10.6	7.2	17.2

Note: The table reports descriptive statistics of the sample of workers that become unemployed as the result of a firm closure (681 firms) in the Hamburg, Frankfurt and Munich metropolitan area in the year 1995. The firm sample consists of firms that have between 5 and 50 employees in the year of the firm closure.
Source : Social Security Data, Hamburg, Frankfurt, Munich 1995

Table 2: Summary Statistics - Before and After the Firm Closure

	All		Men		Women	
	Mean	Std	Mean	Std	Mean	Std
Before the firm closure						
No. of firms worked at	3.56	1.93	3.68	2.02	3.34	1.72
No. of all coworkers, median	220	7,697	236	8,473	186	5,899
No. of coworkers in last 5 years, median	48	3,993	50	4,537	42	2,635
Duration of cowork	4.23	3.38	4.44	3.50	3.61	2.89
Time in the labour market	13.79	3.02	14.01	2.91	13.34	3.18
Overall work experience	12.39	3.65	12.70	3.59	11.79	3.68
Firm tenure	3.40	3.49	3.38	3.52	3.43	3.44
Firm tenure in bust firm (last spell)	4.97	4.74	4.99	4.81	4.92	4.61
Wage in bust firm (uncensored) in t	69.03	27.86	75.70	25.18	57.52	28.51
Log wage in bust firm (uncensored) in t	4.18	0.46	4.29	0.36	3.99	0.56
After the firm closure						
Share of coworkers working in t	0.586	0.183	0.586	0.181	0.586	0.186
Share DW working in t+1	0.701	0.458	0.717	0.450	0.669	0.471
Share of DW working with ≥ 1 coworker	0.201	0.401	0.228	0.419	0.150	0.357
Share of working DW working with ≥ 1 coworker	0.287	0.452	0.317	0.466	0.224	0.417
Share of working coworkers a working DW is working with in t+1	0.039	0.114	0.043	0.120	0.029	0.101
No. of coworkers a working DW is working with in t+1, median	0	817	0	888	0	646
Wage of working DW working with ≥ 1 coworker	73.58	26.21	77.40	23.63	64.54	29.63
Wage of working DW working with 0 coworkers	70.00	25.18	75.01	23.29	61.57	25.99
Δ log wage of working DW	-0.003	0.330	-0.006	0.245	0.002	0.445
Δ log wage of working DW working with ≥ 1 coworker	0.002	0.311	0.007	0.217	-0.010	0.461
Δ log wage of working DW working with 0 coworkers	-0.005	0.337	-0.012	0.255	0.006	0.440

Note: DW stands for Displaced Workers. Unless otherwise specified, coworkers always refers to the set of coworkers in the last 5 years and do not include coworkers that are themselvesdisplaced workers. Descriptives for the pre- and post-firm closure period are calculated only for the 5,427 workers who had coworkers that were not themselves displaced workers.
Source : Social Security Data, Hamburg, Frankfurt, Munich 1995

Table 3: Conditional Logit Estimation

	(1)	(2)
	Conditional Logit	
Years Since Separation	-0.443	-0.433
	(0.042)***	(0.044)***
Duration of Cowork	0.016	0.019
	(0.005)***	(0.005)***
Higher Wage X Absolute Relative Wage	-0.199	-0.227
	(0.041)***	(0.079)***
Lower Wage X Absolute Relative Wage	0.093	0.206
	(0.115)	(0.133)
Older X Absolute Age Difference	-0.001	-0.000
	(0.003)	(0.003)
Younger X Absolute Age Difference	0.008	0.008
	(0.002)***	(0.002)***
German X Same Nationality		-0.016
		(0.015)
Foreign X Same Nationality		0.269
		(0.120)**
Men X Same Gender		-0.143
		(0.075)*
Women X Same Gender		0.133
		(0.035)***
Worker Edu X Coworker Edu		yes
Log Pseudo Likelihood	-1,736,727.5	-1,735,994.3
Observations	5,083,311	5,083,311

Note: Conditional logit results show coefficient estimates, not marginal effects.
Standard errors are clustered at the bust firm level.

Table 4: Linear Probability Model of Working in Year after the Firm Closure

	1	2	3	4	5	6	7	8
		OLS				OLS		
Employment rate coworkers	**0.055**	**0.041**	**0.060**	**0.055**	**0.070**	**0.047**	**0.064**	**0.061**
	[0.042]	**[0.062]**	**[0.065]**	**[0.064]**	**[0.043]**	**[0.062]**	**[0.065]**	**[0.064]**
Log number of coworkers	**0.006**	**0.008**	**0.009**	**0.009**	**0.013***	**0.019****	**0.017***	**0.023****
	[0.004]	**[0.005]**	**[0.006]**	**[0.006]**	**[0.007]**	**[0.009]**	**[0.009]**	**[0.010]**
Employment rate 2-link away contacts					**-0.181***	**-0.010**	**0.031**	**0.100**
					[0.100]	**[0.185]**	**[0.192]**	**[0.214]**
Log number of 2-link away contacts					**-0.007**	**-0.016**	**-0.013**	**-0.024***
					[0.006]	**[0.012]**	**[0.012]**	**[0.013]**
Experience	0.005**	0.005**	0.007**	0.004	0.006**	0.005**	0.007**	0.004
	[0.002]	[0.003]	[0.003]	[0.003]	[0.002]	[0.003]	[0.003]	[0.003]
Experience squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Medium education	0.032*	0.029	0.018	0.024	0.033*	0.029	0.018	0.024
	[0.018]	[0.020]	[0.024]	[0.021]	[0.018]	[0.020]	[0.024]	[0.021]
High education	-0.042	-0.096**	-0.094	-0.083*	-0.038	-0.093**	-0.094	-0.080*
	[0.040]	[0.041]	[0.071]	[0.043]	[0.040]	[0.041]	[0.071]	[0.043]
Female	-0.059***	-0.084***	-0.086***	-0.061***	-0.058***	-0.084***	-0.086***	-0.062***
	[0.017]	[0.019]	[0.020]	[0.022]	[0.017]	[0.019]	[0.020]	[0.022]
Immigrant	-0.007	0.008	0.021	0.025	-0.006	0.01	0.023	0.027
	[0.021]	[0.024]	[0.025]	[0.026]	[0.021]	[0.024]	[0.025]	[0.026]
Age coworkers	-0.011	0	0.003	0.006	-0.011	0	0.003	0.005
	[0.010]	[0.013]	[0.014]	[0.013]	[0.010]	[0.013]	[0.014]	[0.013]
Age squared coworkers	0	0	0	0	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Share coworkers medium education	-0.045	-0.037	-0.064	-0.031	-0.04	-0.036	-0.063	-0.028
	[0.039]	[0.048]	[0.051]	[0.053]	[0.039]	[0.048]	[0.050]	[0.053]
Share coworkers high education	0.061	-0.074	-0.091	-0.085	0.064	-0.07	-0.084	-0.079
	[0.081]	[0.089]	[0.101]	[0.094]	[0.080]	[0.090]	[0.101]	[0.094]
Share female coworkers	0.048	-0.024	-0.018	0.005	0.048	-0.022	-0.016	0.007
	[0.032]	[0.040]	[0.043]	[0.044]	[0.031]	[0.040]	[0.043]	[0.044]
Share immigrant coworkers	-0.036	-0.087	-0.087	-0.056	-0.034	-0.078	-0.078	-0.044
	[0.055]	[0.074]	[0.078]	[0.082]	[0.055]	[0.074]	[0.078]	[0.083]
Last firm fixed effects		yes				yes		
Last firm/edu fixed effects			yes				yes	
Last firm/occposition fixed effects				yes				yes
Observations	5,427	5,393	5,157	4,917	5,426	5,392	5,155	4,916
R-squared								
Number of groups		647	807	926		647	806	926

Note : All worker and coworker control variables are measured in 1989. Additional controls included in all specifications are industry dummies for the year 1989 and the last wage observed before or in 1989 interacted with the year in which it was observed. Standard errors are robust and clustered at the bust firm level. A (*) denotes statistical significance at the 10% level, a (**) at the 5% level, and a (***) at the 1% level.

Source : Social Security Data, Hamburg, Frankfurt, Munich 1995

Table 5: Linear Probability Model of Log Wage in Year after the Firm Closure (conditional on working)

	1	2	3	4	5	6	7	8
		OLS				OLS		
Employment rate coworkers	**0.042**	**0.001**	**-0.003**	**0.007**	**0.029**	**-0.001**	**-0.005**	**0.003**
	[0.047]	**[0.058]**	**[0.057]**	**[0.054]**	**[0.047]**	**[0.057]**	**[0.057]**	**[0.053]**
Log number of coworkers	**0.013*** **	**0.008**	**0.003**	**0.002**	**-0.012**	**0.005**	**0.001**	**-0.001**
	[0.005]	**[0.005]**	**[0.005]**	**[0.005]**	**[0.008]**	**[0.009]**	**[0.009]**	**[0.009]**
Employment rate 2-link away contacts					**0.033**	**0.191**	**0.199**	**0.241**
					[0.125]	**[0.153]**	**[0.162]**	**[0.147]**
Log number of 2-link away contacts					**0.029*** **	**0.001**	**-0.001**	**0.000**
					[0.007]	**[0.011]**	**[0.011]**	**[0.012]**
Experience	-0.009***	-0.002	-0.001	0.003	-0.009***	-0.002	-0.001	0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Experience squared	0	0	0	-0.000**	0	0	0	-0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Medium education	-0.061***	-0.025	-0.075***	-0.017	-0.062***	-0.025	-0.074***	-0.016
	[0.019]	[0.018]	[0.022]	[0.019]	[0.019]	[0.018]	[0.022]	[0.019]
High education	0.035	0.008	-0.274***	0.05	0.035	0.006	-0.277***	0.049
	[0.054]	[0.060]	[0.074]	[0.057]	[0.055]	[0.060]	[0.074]	[0.057]
Female	-0.115***	-0.178***	-0.181***	-0.155***	-0.116***	-0.179***	-0.181***	-0.155***
	[0.024]	[0.029]	[0.032]	[0.023]	[0.024]	[0.029]	[0.032]	[0.023]
Immigrant	-0.054**	-0.028	-0.033	0.004	-0.050**	-0.028	-0.033	0.004
	[0.023]	[0.024]	[0.025]	[0.025]	[0.023]	[0.024]	[0.025]	[0.025]
Age coworkers	-0.051***	-0.049***	-0.041***	-0.038***	-0.053***	-0.049***	-0.041***	-0.038***
	[0.012]	[0.013]	[0.013]	[0.014]	[0.012]	[0.013]	[0.013]	[0.014]
Age squared coworkers	0.001***	0.001***	0.000***	0.000**	0.001***	0.001***	0.000***	0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Share coworkers medium education	0.159***	0.126***	0.140***	0.088**	0.165***	0.124***	0.139***	0.087*
	[0.044]	[0.044]	[0.044]	[0.044]	[0.045]	[0.044]	[0.044]	[0.044]
Share coworkers high education	0.300***	0.095	0.179*	0.051	0.295***	0.092	0.179*	0.046
	[0.106]	[0.108]	[0.107]	[0.111]	[0.105]	[0.108]	[0.108]	[0.111]
Share female coworkers	-0.076*	0.027	0.027	-0.048	-0.07	0.025	0.026	-0.049
	[0.043]	[0.043]	[0.046]	[0.041]	[0.043]	[0.043]	[0.046]	[0.041]
Share immigrant coworkers	-0.085	0.001	0.002	-0.033	-0.079	-0.005	-0.003	-0.04
	[0.062]	[0.067]	[0.071]	[0.070]	[0.062]	[0.067]	[0.072]	[0.070]
Last firm fixed effects		yes				yes		
Last firm/edu fixed effects			yes				yes	
Last firm/occposition fixed effects				yes				yes
Observations	3,361	3,286	3,085	2,896	3,361	3,286	3,085	2,896
R-squared								
Number of groups		588	627	718		588	627	718

Note : All worker and coworker control variables are measured in 1989. Additional controls included in all specifications are industry dummies for the year 1989 and the last wage observed before or in 1989 interacted with the year in which it was observed. Standard errors are robust and clustered at the bust firm level. A (*) denotes statistical significance at the 10% level, a (**) at the 5% level, and a (***) at the 1% level.
Source : Social Security Data, Hamburg, Frankfurt, Munich 1995

Table 6: Linear Probability Model of Working in Year after the Firm Closure

	1	2	3	4	5	6	7	8
	OLS				OLS			
Weighted employment rate coworkers	**0.067***	**0.060**	**0.072**	**0.060**	**0.078****	**0.066**	**0.076**	**0.066**
	[0.036]	**[0.057]**	**[0.059]**	**[0.060]**	**[0.037]**	**[0.057]**	**[0.059]**	**[0.060]**
Log number of coworkers	**0.005**	**0.007**	**0.008**	**0.008**	**0.012***	**0.018***	**0.016***	**0.023****
	[0.004]	**[0.005]**	**[0.006]**	**[0.006]**	**[0.007]**	**[0.009]**	**[0.010]**	**[0.010]**
Employment rate 2-link away contacts					**-0.182***	**-0.001**	**0.043**	**0.110**
					[0.100]	**[0.186]**	**[0.193]**	**[0.215]**
Log number of 2-link away contacts					**-0.007**	**-0.016**	**-0.013**	**-0.024***
					[0.006]	**[0.012]**	**[0.012]**	**[0.013]**
Last firm fixed effects		yes				yes		
Last firm/edu fixed effects			yes				yes	
Last firm/occposition fixed effects				yes				yes
Observations	5,422	5,387	5,151	4,912	5,421	5,386	5,149	4,911
R-squared								
Number of groups		646	806	925		646	806	925

Note : All worker and coworker control variables are measured in 1989. Additional controls included in all specifications are industry dummies for the year 1989 and the last wage observed before or in 1989 interacted with the year in which it was observed. Employment rates of coworkers are weighted by the predicted weights from the conditional logit model based on the results in Table 3, Column (2). Standard errors are robust and clustered at the bust firm level. A (*) denotes statistical significance at the 10% level, a (**) at the 5% level, and a (***) at the 1% level.
Source : Social Security Data, Hamburg, Frankfurt, Munich 1995