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# Coworkers, Networks, and Job Search Outcomes

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# Coworkers, Networks, and Job Search Outcomes <sup>\*</sup>

**PRELIMINARY and INCOMPLETE,  
please do not cite without permission**

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## Abstract

Social networks are an important channel of information transmission in the labor market. In this paper investigate how displaced workers searching for new jobs benefit from information provided by their former coworkers. In line with the theoretical and empirical literature we find that the employment status networks members matters for the job finding rate. We further analyze the mechanisms through which employed contacts affect job search outcomes and find that (i) the types of firms at which the contacts work are important and (ii) contacts with similar characteristics as the displaced worker lead to better outcomes. Our findings strongly indicate that job referrals from network members are the main mechanism by which social contacts influence job search outcomes.

**JEL-Classification:** J63, J64, J65

**Keywords:** Networks, Labor Markets, Employment, Wages

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# 1 Introduction

Job matching process is complicated by an enormous degree of heterogeneity between workers and jobs. Information about suitable jobs are not always available and ex-ante worker's productivity is usually unknown. Personal relations, informal contacts, social networks potentially play a big role in overcoming these informational difficulties in labor market both for firms and job seekers. Early studies on networks in labor markets stated that about 50% of workers find their jobs through friends, family members, coworkers (Holzer (1988); Montgomery (1991)). These findings are also in line with recent trends. According to Jobvite, an online recruiting platform, the top source of job applications are job boards (42.9%) and career sites (32.1%). However, the main source of hiring shifts to employment referral programs which generates 39.9% of all hires<sup>1</sup>.

Given the significance of social networks in labor markets, there has been a growing interest in understanding how social networks operates in labor markets. In particular, both theoretical and empirical literature have been expanding since the pioneering studies by Rees (1966) and Granovetter (1973)<sup>2</sup>.

Looking at the existing literature, one can classify three perspectives that social networks can be at play in labor markets: job seeker side, firm side and social cost. Job seekers can use social network contacts to minimize search costs by obtaining information about vacancies from employed network members and firms use referrals while hiring as a signal for unknown productivity. Finally, if firms rely on networks to fill vacancies and if individuals rely on networks to find jobs, inequalities between different groups in the labor market can be fostered and can grow depending on the initial differences in the network employment rates(Calvo-Armengol and Jackson (2004)) therefore social networks might also explain inequalities or poverty trap Zenou (2013).

Jackson (2010) classifies theoretical studies under two headlines. First group of studies are based on a model of using referrals as a signal for unknown productivity of the potential hirings. Pioneering model of this strand is Montgomery (1991) where a model of employee selection is developed. Firms recruit new workers who are connected to their

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<sup>1</sup>These statistics are based data from 2007 to 2013 on a sample of firms that are Jobvite customers

<sup>2</sup>See Montgomery (1991), Ioannides and Loury (2004) for comprehensive surveys.

productive workers. Therefore, characteristics of incumbent members are relevant for job search outcomes and similar type workers refer each other.

Another group of theoretical papers that are mostly based on a model of information transmission in social networks(Calvo-Armengol and Jackson 2004). In these models, network consists of employed and unemployed workers and members receive randomly information about job opportunities. Unemployed workers keep information for themselves while employed workers pass on information to network members if they have a higher wage. Calvo-Armengol and Jackson (2004) suggest that unemployed workers who are connected in a social network with a high employment rate are more likely to find a job and should earn higher wages. In addition, they compare two groups with different employment rates and suggest that lower employment rates within a group will lead to a higher drop-out rate which will eventually cause a persistent inequality between two groups. Finally they also show that unemployment exhibits duration dependence. Similarly according to Loury (2006), workers are likely to earn higher wages if their contacts have good connections, are employed, receive higher wages, and help the employer by reducing the uncertainty about the productivity of the job seeker.

Empirical studies use quite heterogeneous data sources and various social network definitions. Some studies analyzed the social networks concerning the residential proximity using census data such as Topa (2001) and Bayer et al. (2008) while some studies considered the social ties such as family and friends using survey data such as Magruder (2010), Kramarz and Skans (2011) and Cappellari and Tatsiramos (2010) and ? used ethnicity based networks to show the network effects in labor market.

Using various definitions of social networks, it seems that there is a robust consensus that workers benefit from informal contacts when looking for a job and that social networks have a positive effect on the job finding rate (Corcoran et al. (1980); Holzer (1988); Mortensen and Vishwanath (1994); Pistaferri (1999); Topa (2001); Calvo-Armengol and Jackson (2004); Kramarz and Skans (2011); Bayer et al. (2008); Laschever (2009); Pellizzari (2010); Cappellari and Tatsiramos (2010); Cingano and Rosolia (2012); Goel and Lang (2009); Glitz (2012); Beaman (2012)). Some of these studies also elaborate the effect

of using networks on the quality of the subsequent matches (such as tenure and/or wage) with no clear consensus on the direction of the effect. Most of the studies use survey data where employees are asked about how they found their job in order to compare the jobs obtained through social networks and with those found through formal methods. Pistaferri (1999) uses the Bank of Italy Survey of Household Income and Wealth where applicants are asked how they found their jobs. He reports a positive effect of using informal connections on job offer arrival rate but a negative effect on earnings. Similarly, Bentolila et al. (2004) provide evidence for a positive effect on job finding but negative effect on earnings. They show that the social networks might induce mismatches between workers' productive advantage and their actual occupational choice using the "Multi-City Study of Urban Inequality, 1992-1994" survey conducted by the Inter-University Consortium for Political and Social Research. Pellizzari (2010) uses The European Community Household Panel (ECHP) which is a panel dataset of households covering all the 15 countries of the pre-enlargement European Union. Based on ECHP which contains individuals' job search strategies, he finds mixed evidence for the effect using personal contacts in different countries varying between a wage premium and a wage penalty. Antoninis (2006) suggests that the wage effect can be positive or negative depending on the type of tie. In particular, if the referee has a direct knowledge of worker's productivity, new recruits receive a higher starting wage. From the firm side, literature is very scarce and there are very few papers that mostly agreed that firms do not benefit from using social networks if workers are not properly incentivized

Some recent papers provide evidence for the effect of social networks consisting of past coworkers on job search: Cingano and Rosolia (2012), Glitz (2012) and Hensvik (2013). Cingano and Rosolia (2012) use a matched employer-employee data for two Italian provinces over the period 1975 to 1997 and estimate the effect of the network employment rate on unemployment duration. In order to overcome the selection bias into unemployment, they use firm closures and find that one standard deviation increase in the network employment rate leads to 8% reduction in unemployment duration. On the other hand, they only consider the displaced workers who find a job after the firm closure in order to analyze the unemployment duration. By using only the completed unemployment spells, they drop around 20% of the displaced workers from their sample. In other words, using only completed unemployment spells, they condition on the outcome of becoming

re-employed.

Glitz (2012) follows the same approach in terms of network definitions and empirical specification with two distinctive features from Cingano and Rosolia (2012). First, Glitz (2012) uses an administrative dataset for German workers in the 4 largest metropolitan areas where observations are recorded only annually. The second feature is that mass layoffs are used as an exogenous variation to the network employment rate as an additional identification strategy. As a result, Glitz (2012) suggests a strong positive effect of network employment rate on reemployment probabilities after displacement and no significant effect on wages.

Despite growing literature and interest in empirical tests of social network theories, there is limited evidence on channels through which social networks affect job search outcomes. Our aim is to empirically test some implications. We define the social networks as the group of past coworkers building on a 5 years history of overlapping spells at the same firm. We use data providing the entire work histories of the universe of private sector workers in Austria.

Our paper contributes to the existing studies on the role of networks consisting of past coworkers on job search outcomes by extending the perspective of the existing approaches. We use the Austrian Social Security Database (ASSD) which covers the universe of private sector workers covered by the social security system between 1980 and 2007. The ASSD provides daily information on employment and registered unemployment status, total annual earnings paid by each employer, and various individual characteristics of the workers as well as information on employers such as geographical location, industry, and size. Although we use the same network definitions as Cingano and Rosolia (2012) and Glitz (2012), we incorporate every worker that loses her job through a firm closure. In order to analyze the effect of network characteristics on the reemployment probability and unemployment duration, we apply both a linear probability model and a duration analysis in order not to drop displaced workers who do not find any jobs within the covered period.

More importantly, we incorporate firm heterogeneity into social network. We define

network employment rate according to firm characteristics... We also analyze whether similarity between workers and network members matter in terms of job search outcomes. Moreover we compare referral and non referral jobs.

Our empirical results show that a 10 percentage point increase in the network employment rate lead to a 3.2 percentage increase in the exit hazard, while being a blue collar worker increases the probability to find a job by about 14%. The Cox models and the Kaplan Meier estimates show furthermore that being female slows the process of exit into employment down, while a 10 percentage point increase in the share of females in the displaced workers network decreases the exit hazard by 1.2 percent. Consistently with theoretical predictions, we also find that a 10 percentage point increase in the network employment rate lead to a 2.5 percent decrease in the drop out hazard. For the match quality on the other hand we find that a 10 percentage point increase in the network employment rate leads to a 0.4 percentage point increase in the probability to have tenure of at least a year. Being a blue collar worker decreases the probability to last for a year or more at the re-entry job by about 8% while being female does not play a role for the match tenure. In contrast to the duration findings, the share of females in the displaced workers network increases the likelihood to stay at the re-entry job for at least a year.

The rest of the paper is organized as follows: First, we give a brief description of the data and the sample selection process as well as network formation process. We provide definitions of firm closures, job seekers, network characteristics and job search outcomes of interest. We then provide a descriptive analysis of individual characteristics, employment histories and network characteristics of the displaced workers as well as characteristics of firms where network members are employed. Following section presents the empirical specification and the identification and reports our results. We show how the employment rate of the displaced workers' past coworkers affect their reemployment probability and unemployment duration including a comprehensive set of control variables as well as full set of fixed effects for closing firms. We also look at the effect of network employment rate on wage growth for successful job seekers. In a subsection, we provide a heterogeneity analysis which divides job seekers in terms of individual characteristics and analyze the effect of similar network members. In the following subsection, we compare exits from

unemployment through referrals and without referrals. Finally, Section 6 concludes.

## 2 Data, Sample Construction, and Definitions

The data that we use in this paper comes from the Austrian Social Security Database (ASSD) which covers the universe of private sector workers covered by the social security system between 1980 and 2007. The ASSD provides daily information on employment, registered unemployment, total annual earnings paid by each employer, and various individual characteristics of the workers as well as information on employers such as geographical location, industry, and size. (For more information on the ASSD we refer the reader to Zweimüller et al. (2009))

### **Closing Firms and Displaced Workers:**

In the ASSD, the firms are associated with an employer identifier reported in every employment spell of the workers. Fink et al. (2010) identify entry and exit of firms using a worker flow approach that follows clusters of workers moving across entities. They show that their entry and exit definition is comparable to the official firm statistics of Austria in the covering period.

In order to use the firm closures as an exogenous entry to unemployment, we first created a sample of closing firms. We use the same strategy as Del Bono et al. (2012) to identify firm closures. To obtain our closing firm sample, we included firms that have only 3000 or less workers, in order to exclude very large firms, where individuals may not know each other. Given this sample of closing firms, we consider all blue and white collar workers who are displaced due to a closure with the following restrictions. First, we consider the displaced workers who were still employed within the last 3 months of activity of the closing firm. We chose to do so, because we also want to include those individuals that may be able to react quicker to the upcoming closure and thus leave within the last quarter of the firm operation. Second, we include workers who have at least 1 year tenure at the closing firm. This restriction makes sure that we only capture individuals which are really affected by the closure, and leaves out individuals that may



have just had a short term contract. Third, we excluded workers who were above age 55 at the time of displacement and workers who were below age 15 at the first entry to the system. These restrictions are necessary due to the early retirement schemes in Austria.<sup>3</sup>

In the following when we refer to the displacement spell, it is the last employment spell the individual had at the closing firm. In our sample of displaced workers, around 5% of the individuals were displaced due to a firm closure more than once in their employment history. For those workers, we considered the employment spells of the closing firms where they had the longest tenure as their displacement spell.

### **Network Formation:**

We define the network of a displaced worker based on the past coworkers that she worked with for at least a month within the past 5 years before the displacement.<sup>4</sup> The same network definition is used by Cingano and Rosolia (2012). Similarly, we exclude the co-displaced workers from the network and we consider the closures that occurred within the sub-period of 1980 and 2007 to have the data for the pre-displacement period of the network formation for all workers and since our focus lies in the job finding rate, we are interested where the displaced workers end up.

The final sample includes 165'658 displaced workers by 39'724 closing firms within our time frame. The closing firms are located in 10 main regions, where around 29% of them are located in the region of Vienna.

Table 1 shows the descriptive statistics of the individual characteristics and employment histories of the displaced workers as well as their network characteristics, separately for females (42%), males (58%) and the whole sample of displaced workers.

### **Outcome variables:**

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<sup>3</sup>After the age, tenure and firm size restrictions, we have 165658 displaced workers who were employed at a closing firm within the last 3 months of the firm's activity period.

<sup>4</sup>There are workers who have overlapping employment spells at that time. In order to take into account the overlapping spells with the displacement spell, we split the overlapping spells at the time of displacement and included the first part of this spell in the 5 year history of the network formation period.

As Job search outcomes we usually look at the time from losing ones job to becoming re-employed and the subsequent wage growth. In our sample, 47% of the displaced workers are observed as reemployed immediately after they lost their job. While we censor 18% of them at 12 months after the closure. 33% of the displaced workers are registered as unemployed after losing their jobs and the average time to reemployment is around 3 months including those individuals that do not find a job until a year after the closure. The panels 2n and 2o of Figure 3 show the distributions of time to reemployment since displacement. We measure wage growth as the difference between log wage at job lost and re-entry wage.

### **Network characteristics:**

The 3rd panel of Table 1 reports descriptive statistics of our network characteristic measures, starting with network size. To account for the demographics of the network we compute the share of female members, the share of Austrian members and different education and age groups as well as the share of blue collar members. Figure 3 shows the distributions of the network characteristics of our sample of displaced workers where the red lines indicate the 10th, 50th and 90th percentiles respectively. Moreover, we calculate the share of network members sharing the same characteristics such as gender, age, nationality, education, and occupation. Table 1 indicates a gender difference in job search outcomes and network characteristics. Here it is worth noticing that female workers have higher average time to next job. Furthermore, the network size and the employment rate is also lower for females.

The most relevant network characteristic in our analysis is obviously the share of employed network members. Figure 4 shows the employment and wages of the displaced workers before and after displacement on a quarterly basis. We divided our job seekers sample into four groups in terms of network employment rate quartiles. We aim at observing the differences in employment and/or wages of job seekers having different employment rates in their networks before and after job loss. The top two graphs illustrate the employment status of job seekers. Each line represents subgroups of job seekers in terms of different quartiles of network employment rate of job seekers. The one of the

right hand side shows female and male workers separately.

It seems that the workers with highest network employment rate are not necessarily more likely to be employed before job loss while the probability of employment after job loss is very much in line with network employment rate quartiles (i.e. highest network employment quartile is associated with highest probability of employment in first quarters after job loss and the lowest network employment rate is associated with lowest probability of reemployment while this relationship does not hold before job loss.) This descriptive finding suggests that the employment rate in the network is related to probability of reemployment after a job loss due to firm closure, while it is not necessarily correlated with the probability of employment before the closure. Moreover, the large differences in employment probabilities associated with network employment rate before job loss could indicate a significant heterogeneity. Hence, for a more comprehensive analysis, we decompose network employment rate according to network members' and their firms' characteristics.

As for employed network members, once we detect the firm they work at, we observe a significant variation in terms of certain firm characteristics. Some network members are employed at high wage firms, some others work at large firms, while some of them are working at firms that are currently hiring at the time of job search of the displaced worker. According to firm characteristics, we calculate following measures: share of network members employed in same industry, share of network members employed in above median wage firms and share of network members employed in hiring firms. All these characteristics are expected to have an impact on the relationship between networks and job search outcomes. For instance, the share of employed contacts at hiring firms could be more of a help as they can refer their friend or inform about the vacancy. Moreover, using network employment rate at hiring firms improves the identification of the effect on network on job search. We also create share of network members employed in firms that are hiring in quarter before the firm closure, quarter after and hiring in both quarters.<sup>5</sup> We also calculate the share of hires in firm size and take the average of this share within network.

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<sup>5</sup>We consider a firm as a hiring firm in a given quarter if the number of hires are greater than number of fires in that quarter.

In Figure 4, two graphs in the middle also illustrates the employment status of job seekers in each quarter before and after firm closure. On the left hand side, each line represents subgroups of job seekers in terms of different quartiles of network employment rate at hiring firms and the graph on the right hand side shows job seekers from different quartiles network employment rate at high wage firms. Finally two bottom graphs represents the wages of job seekers in each quarter before and after firm closure. The one on the left shows it for different quartiles of network employment rate while the one on the right hand side is for the subgroups of job seekers in terms of network employment rates at high wage firms

Employed network members also differ in terms of their individual characteristics. Gender, age, occupation, and nationality of the network members might play a role on functioning of networks in labor market. Moreover, as previous theoretical studies suggest, having similar characteristics also might affect have an impact such as same gender, occupation or age group workers might be more likely to help each other. According to individual characteristics of network members, we calculate the share of employed members for each characteristic such as gender, age, education, nationality and occupation. Table 1 reports summary statistics of all these variables for full sample as well as for female and male job seekers.

### **Referrals:**

Around 20% of our sample of displaced workers found a job at a firm where at least one of their past coworker is employed at. We assume that these workers find these jobs through referrals of their past coworkers. Table 2 reports the descriptive statistics for successful job searchers. This table also provides a separate descriptive analysis for the workers who find their jobs through referrals where we observe significant differences in individual characteristics and network characteristics.

### 3 Empirical Specification and Results

Our empirical analysis is based on the empirical test of the theoretical implications suggesting that social network characteristics may have an effect on subsequent labor market outcomes. In particular, we aim to test whether the network employment rate has a positive effect on labor market outcomes such as the reemployment probability, unemployment duration, and wage growth at the first job after displacement. In order to test these implications, we follow a similar empirical specification as Cingano and Rosolia (2012) with the following baseline equation:

$$y_i = \alpha + X_i\beta + ER_{it_0}\gamma + \theta\log(N_{it_0}) + e_{it_0} \quad (1)$$

where  $y_i$  is the outcome of interest (reemployment probability, unemployment duration, and quality of subsequent job (measured by wage growth at re-entry)),  $ER_{it_0}$  is the network employment rate and  $N_{it_0}$  is the overall size of the network, and all of these variables are measured at the starting date of the unemployment spell ( $t_0$ ) or equivalently stated at the date when the individual leaves the closing firm.  $X_i$  is a comprehensive set of both employment history and individual characteristics of displaced workers and average network characteristics.  $\gamma$  is the coefficient of interest and it is supposed to measure the causal effect of the specific network characteristics which are assumed to be orthogonal to the residuals.

In our first specification, we analyze the effect of the network employment rate on the reemployment probability, the dependent variable  $y_i$  is an indicator variable taking the value one if a displaced worker is observed as reemployed within a certain period of time after displacement.<sup>6</sup> We also use the difference in log wages between the wage at displacement and the wage at first employment thereafter as a job search outcome variable which measures the effect of network employment rate on the subsequent job quality.

For a more comprehensive analysis on networks and job search, as a second step, differently from Cingano and Rosolia (2012) we employ the semi parametric Cox Model

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<sup>6</sup>We specify the reemployment probabilities considering job finding within 3 months after displacement.

following Cox (1972) using the same set of control variables above.<sup>7</sup> This approach allows us to keep all displaced workers in our analysis without conditioning our sample on the outcome of exiting unemployment.

The main threat to identification of the causal effect of the network employment rate on labor market outcomes is an endogeneity problem. It arises from unobserved group level shocks and/or from the self selection of workers into particular firms based on unobservable characteristics. To overcome this endogeneity problem, we first include a full set of closing firm fixed effects. Furthermore, we include also a large set of individual controls such as wage at displacement date, wage at first labor market entry, relative employment duration until displacement, and the number of firms the worker has worked at during the network formation process. Finally, as we aim at understanding the mechanism behind the employed network members, we introduce firm heterogeneity measures. Moreover, the firms hiring decision is an additional exogenous variation in the network employment rate of job seekers.

Aside from the network employment rate results, we are able to introduce some heterogeneity in our network employment rate measure. First, we decompose the network employment effect with respect to firm characteristics such as whether the firm is in the same industry, whether the firm is a hiring firm, the share of hirings in firm size, and whether the firm is a high wage firm. Furthermore, we decompose the effect of employed contacts into the share of past coworkers working in the same and different industries, and occupations. We analyze the network composition in terms of gender, age, education, and nationality. Finally, we provide a closer look at the network composition in terms of sharing the same characteristics. (i.e. share of same gender or age group network members). In the following sections, we explain these estimations step by step.

### 3.1 Reemployment Probability

In this section, we present the results of the linear probability model of employment within 3 months after displacement based on equation 1. We consider the whole sample

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<sup>7</sup>Cingano and Rosolia (2012) consider only successful job seekers within a year and use duration as an outcome variable in a linear regression.

of displaced workers and analyze whether the network employment rate has an impact on the probability of their reemployment. In particular, our dependent variable is one if a displaced worker is reemployed within 3 months after displacement. Table 3 shows that network employment rate has a significant positive effect on the probability of reemployment. We control for the individual characteristics of the displaced worker as well as her employment history. All estimations include closing firm fixed effects. Table 3 presents evidence of a significant impact of the network employment rate on the reemployment probability after 3 months. This impact is mostly driven by network members that are employed in the same industry (column 2) and hiring firms (column 3 and 4) while the share of network members employed in above median wage firms (column 5) do not have a significant impact. Moreover, females and Austrian workers are less likely to find a job within 3 months while blue collar workers are more likely to be reemployed.

### 3.2 Exit Hazard

To test Calvo-Armengol and Jackson (2004) theoretical prediction that “Information passing leads to a positive correlation between employment status of agents who are directly or indirectly connected in the network within a period across time” we will use the Cox proportional hazard model. This translates into testing the empirical fact that an increase in the network employment rate leads to a decrease in unemployment duration. Since we include every displaced individual into our sample they become at risk from the displacement day onwards.<sup>8</sup> Furthermore, we restrict the sample in a sense that we censor all observations at 365 days, meaning that a displaced individual who did not find a new job after a year is treated as censored or as not having failed yet. We apply the same criteria to individuals that drop out of our sample for unknown reasons.<sup>9</sup> We treat individuals as censored after 12 months, even if they have not dropped out of the labor force.<sup>10</sup>

First we present the nonparametric estimates of the Kaplan Meier Survival Function in order to provide an overview of the data and the variation of the duration measures

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<sup>8</sup>Since our closing firm information is on a quarterly basis, we use the date that the person leaves the firm in the last 90 days, to identify how long she has been unemployed.

<sup>9</sup>A possible and plausible explanation for some of the dropouts is that they may have moved to Germany to get a job.

<sup>10</sup>Specific details on the implementation can be retrieved from the authors upon request, since we kept the spell that had the longest duration if that was an employment spell.

and some of the explanatory variables. Figure 5 looks at the different survival functions by gender. First graph clearly shows that males exit quicker to employment than females since they have a lower survival rate. Second graph of Figure 5 then looks at the different survival functions by network employment rate where we can see that higher network employment rate is associated with lower survival rate accordingly with the theory.

Tables 4 through 6 show estimated coefficients from Cox proportional hazard model. Table 4 presents the results of the specification with different measures of network characteristics. We also include controls for the individuals work history and demographic characteristics.<sup>11</sup> For identification purposes columns (1) through (6) are stratified by closing firm fixed effects. In column (1) of table 4, a 10 percentage point increase in the network employment rate leads to a 2.1 percent increase in the exit hazard from unemployment. In column (2) we add the network employment rate in same industry and this obviously leads to a drop in network employment rate coefficient but remaining significant. Higher share of network members employed in the same industry is associated with an increase in exit hazard and employed network members are still significantly helpful regardless they work in the same industry or not.

In column (3) we add the share of network members that are employed in a firm which is hiring in the same quarter of the job loss. It seems that higher share of network members at hiring firms leads to an increase of 0.8 percent in the exit hazard from unemployment. Similarly, column (4) shows that the higher share of new hirings in firms that network members work at leads to a higher exit hazard as well. Also Table 5 reports results for the analysis where we added different measures of hiring status of network members' firms. We included the share of network members employed at firms hiring in previous quarter and quarter after the job loss as well as firms hiring in both job loss quarter and following quarter. In these specifications, we see that only share of network members that are employed in firms hiring in the same quarter as job loss. It is also worth noticing that the coefficient of network employment rate remains significant in this columns even though the magnitude goes down significantly. This could be interpreted as following: While a considerable part of employed network members are helpful as they work in the same

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<sup>11</sup>The individual's work history contains all variables reported in summary statistics such as tenure at the closing firm, wage at displacement, unemployment durations in previous years, etc.



industry and they provide referrals or pass the vacancy information from their firm that is currently hiring, employed network members are still associated with a faster exit from unemployment which could be interpreted as information flow from other firms or other possible mechanisms.

In column (5) and (6) of Table 4 we included the share of network members employed in above median wage firms and at firms that are in the same quartile of the wage distribution as the firm that job searcher come from. Both of these variables remained insignificant in explaining the exit hazard from unemployment.

During job search process of displaced workers, network members can change their employment status or move to another firm and also firms' hiring decisions might change as well. In order to take into account time varying nature of network employment rate measures, we also conducted a duration analysis where we let the network employment rate measures vary across quarters. Table 6 reports these results which seems very consistent with our previous findings.

Notice also that the coefficient on the female dummy is significant at the 1% level throughout all specifications and negative, meaning that women exit unemployment slower than their male counterparts. Being a blue collar worker also increases the probability to find a job by about 12%. While marital status seems to be insignificant, age and nationality seems to play a role where younger group of job searchers and non-Austrians exit unemployment faster. Tenure at the closing firm, wage at displacement, unemployment duration before closure and the number of employment spells before the closure are all significantly different from zero but nevertheless very close to zero. Therefore they do not seem to play a major role in determining the exit to employment.

### **3.3 Wage Growth**

Table 7 analysis the theoretical prediction from Calvo-Armengol and Jackson (2004) that higher wage growth is associated with higher network employment rate. We find that network employment rate is positively associated with wage growth with a very low significance level for the sample of successful male job searchers. In columns (2) and (3)

where we include closing firm fixed effects, a 10 percentage point increase in the network employment rate leads to a 0.2 percentage point increase in the log wage growth from job loss to the daily wage at re-entry. This effect stays the same throughout the different specifications, where we introduce firm heterogeneity of network members in terms of hiring status where the network employment rate is separated as the share of members at hiring firms, the share of members employed in same industry firms. On the other hand, as it is shown in last two columns of Table 7, the effect of employment rate at high wage firms is higher and a lot more significant. Once we introduce firm heterogeneity in network employment rate in terms of average wages, we find a significant positive impact on wage growth from network members that are employed at high wage firms.

Table 8 restrict the analysis to male job searchers who are reemployed within 3 months period after job loss. While the network employment rate is found to be insignificant, here we can see that the higher the share of employed members in high wage firms in the network, the higher the observed wage growth. We find the same results for the share of members in hiring firms and same industry firms as the whole sample of successful male job searchers.

Table 9 reports the results for the sample of successful female job searchers. Similarly, network employment rate seems to be irrelevant for wage growth while network employment rate in high wage firms has a significant positive impact on wage growth for female job searchers. Differently from male counterparts, females seem to achieve higher growth in wages if they have contacts employed in same industry firms and hiring firms.

These results point into the direction that women may use networks in a different manner than males when it comes down to negotiating wages. Bertrand (2011) summarizes the gender preferences well and also offers some insights into the differences that exist in negotiation skills. It is also worth noting that some individual characteristics has different impacts on wage growth for female and male job searchers. While age is insignificant for females, it seems that younger male group of job searchers obtain higher wage growths. Moreover, being married has a positive impact for males while it is insignificant for females. Being a blue collar worker at the displacement date is more detrimental for

females to having a higher wage growth at reemployment.

### 3.4 Exit Hazard: Heterogeneity Analysis

In this section we take the analysis one step further and look at the heterogeneity in the effect of employed network members in terms of sharing similar characteristics such as age, gender, nationality, education, and occupation. Table 10 reports the estimated coefficients for different subsamples and decompose the network employment rate according to being in the same group or not. We see that both females and males benefit from employed network members from same gender and opposite gender while females benefit from male network members slightly more as shown in Column 1. Unemployed network members from same gender has no impact for males (Column 2) while there is a relatively smaller but still significant and positive impact for females (Column 1). Similarly blue collar workers and white collar workers benefit from employed contacts while the coefficients are larger in magnitude for white collars. For Austrian workers we find a positive impact of employed workers while the effect is not significant for non-Austrians.

Table 11 divides the sample into 4 age groups. Youngest workers (below 30) seem to benefit the most from their employed contacts from same age group and no impact from unemployed counterparts. Workers with age between 30 and 36 also benefit more from their employed contacts from same age group. On the other hand workers age between 36 and 45 seem to benefit more from employed contacts of opposite group rather than same age while oldest workers above 45 benefit from employed workers of both groups.

Finally, Table 12 shows the results for subsamples of different education levels. These results show that lowest education group workers benefit both from same and opposite group of employed network members while middle and high education groups mostly benefit from opposite group of employed network members and we do not find a significant effect for the highest education group.

### 3.5 Finding a Job Through Referrals

In this section, we present the estimation results from the linear probability model of reemployment through a referral after displacement. Our empirical approach is based on the following specification:

$$y_i = \alpha + X_i\beta + ER_{it_0}\gamma + \log(N_{it_0})\theta + XN_{it_0}\sigma + e_{it_0} \quad (2)$$

We consider the whole sample of displaced workers who are defined as successful job seekers and analyze whether network characteristics have an impact on the probability of their reemployment through a referral. In particular, our dependent variable takes value one if a successful job seeker displaced worker is observed as reemployed in a firm where there is at least one network member.

Obviously, network employment rate is positively associated with finding a job through referrals. Table 13 shows that the most important contribution to this probability comes from the network members that are employed in the same industry with the job searcher. Similar to the previous analysis, we control for individual characteristics of displaced workers as well as their employment history. All estimations include closing firm fixed effects. Another finding of these analysis is that females are less likely to find a job through referrals.

### 3.6 Exit Hazard: Referrals vs Non-Referrals

First, we present the nonparametric estimates of the Kaplan Meier Survival Function in order to provide an overview of the data and the variation of the duration measures and network characteristics. Figure 5 looks at the different survival functions by network employment rate. The second graph clearly shows that high network employment rate job searchers exit quicker to employment than those with low network employment rate since they have a lower survival rate. Third and fourth graphs in Figure 5 shows the survival functions by employment rate for non-referral jobs and referral jobs. There is a considerable difference between job searchers with low and high network employment rate for those exiting unemployment through referrals while for others this difference almost disappears.

In order to understand the mechanism behind the positive impact of employed network members, we run a separate analysis of semi-parametric Cox model for exit hazards to referral jobs and non-referral jobs. First, we fit a competing-risks model that treats referral job as the event of interest and a non-referral job as the competing event. Second we consider non-referral jobs as main incidence and referral jobs as competing event.

Table 14 shows the estimated coefficients from the fitted model. First two columns are the estimated coefficients from standard Cox model for comparison purposes. In order to compare the results for exiting.....

When we consider the incidence of exiting unemployment through referral jobs, a 10 percentage point increase in the share of employed members in network increases the exit hazard by 10.5 percent (Column 3). When we consider also the incidence of exiting through non-referral jobs as a competing event, the contribution of network employment rate falls to 8.9. In the case of considering non-referral jobs as main event, we find no significant impact of network employment rate on exit hazard (Column 5) while the effect of employed network members turn to be significant and negative when we consider referral jobs as competing event (Column 6).

## 4 Conclusion

A growing theoretical and empirical literature on the use of social networks in labor markets has provided various channels through which networks can affect labor markets. Although empirical studies have remained relatively scarce in order to test the implications of the theory with very little consensus on these channels.

In line with the inconclusive evidence on the effect of using networks in labor market, theoretical studies such as (Calvo-Armengol and Jackson, 2004) and Loury (2006) suggested that heterogeneity in the characteristics of social networks may lead to different impacts of social networks in terms of labor market outcomes. In order to empirically test these implications, we define the social networks as the group of past coworkers with whom they worked together at the same firm. We use data providing the entire work

histories of the universe of private sector workers in Austria.

We analyze the effect of network employment rate on the reemployment probability and unemployment duration as well as on wage growth at the first job after displacement. We find consistent evidence supporting the theoretical implications. According to our results, a 10 percentage point increase in the network employment rate lead to a 3.2 percentage increase in the exit hazard, while being a blue collar worker increases the probability to find a job by about 14%. The Cox models and the Kaplan Meier estimates show furthermore that being female slows the process of exit into employment down. We also find that a 10 percentage point increase in network employment rate leads to a ... increase in the wage growth at re-entry. While being a women decreases the entry wage, and also being a blue collar worker is detrimental to having a higher re-entry wage. For the share of females in a displaced workers network, we find that a 10 percentage point increase leads to a decrease in the re-entry wage by 0.08 percentage points.

## References

- ANTONINIS, M. (2006): “The wage effects from the use of personal contacts as hiring channels,” *mimeo*, 1–22.
- BAYER, P., S. ROSS, AND G. TOPA (2008): “Place of Work and Place of Residence: informal Hiring Networks and Labor Market Outcomes,” *Journal of Political Economy*, 116(6), 1150–1196.
- BEAMAN, L. A. (2012): “Social Networks and the Dynamics of Labour Market Outcomes: Evidence from Refugees Resettled in the U.S.” *Review of Economic Studies*, 79, 128–161.
- BENTOLILA, S., C. MICHELACCI, AND J. SUAREZ (2004): “Social Networks and Occupational Choice,” *mimeo*.
- BERTRAND, M. (2011): *New Perspectives on Gender*, Handbook of Labor Economics, Volume 4b, chap. 17, 1544–1582.
- CALVO-ARMENGOL, A. AND M. O. JACKSON (2004): “The Effects of Social networks on Employment and Inequality,” *The American Economic Review*, 94(3), 426–454.
- CAPPELLARI, L. AND K. TATSIRAMOS (2010): “Friends’ Networks and Job Finding Rates,” *DISCE Working Paper*, 1–37.
- CINGANO, F. AND A. ROSOLIA (2012): “People I know: Job Search and Social Networks,” *Journal of Labor Economics*, 30(2), 291–332.
- CORCORAN, M., L. DATCHER, AND G. DUNCAN (1980): *Information and Influence Networks in Labor Markets*, Five Thousand American Families vol. VIII.
- COX, D. (1972): “Regression Models and Life-Tables,” *Journal of the Royal Statistical Society. Series B (Methodological)*, 34(2), 187–220.
- DEL BONO, E., A. WEBER, AND R. WINTER-EBMER (2012): “Clash of Career and Family: Fertility Decisions after Job Displacement,” *Journal of European Economic Association*, 10(4), 659–683.

- FINK, M., E. KALKBRENNER, A. WEBER, AND C. ZUHLENER (2010): “Extracting Firm Information from Administrative Records: The ASSD Firm Panel,” *Nfn working paper No. 1004*, 1–25.
- GLITZ, A. (2012): “Coworker Networks in the Labour Market,” *mimeo*, 1–42.
- GOEL, D. AND K. LANG (2009): “Social Ties and the Job Search of Recent Immigrants,” *NBER Working Paper 15186*, 1–35.
- GRANOVETTER, M. S. (1973): “The Strength of Weak Ties,” *American Journal of Sociology*, 78(6), 1360–1380.
- HOLZER, H. J. (1988): “Search Method Use by Unemployed Youth,” *Journal of Labor Economics*, 6(1), 1–20.
- IOANNIDES, Y. M. AND L. D. LOURY (2004): “Job Information Networks, Neighborhood Effects, and Inequality,” *Journal of Economic Literature*, 42(4), 1056–1093.
- KRAMARZ, F. AND O. SKANS (2011): “When strong ties are strong: Networks and youth labor market entry,” *Uppsala Center for Labor Studies WP 2011:18*, 1–74.
- LASCHEVER, R. (2009): “The Doughboys Network: Social Interactions and the Employment of World War I Veterans,” *mimeo*, 1–54.
- LOURY, L. D. (2006): “Some Contacts Are More Equal than Others: Informal Networks, job Tenure and Wages,” *Journal Labor Economics*, 24(2), 299–318.
- MONTGOMERY, J. D. (1991): “Social Networks and Labor -Market Outcome: Toward an Economic Analysis,” *The American Economic Review*, 81(5), 10408–1418.
- MORTENSEN, D. T. AND T. VISHWANATH (1994): “Personal contacts and earnings It is who you know!” *Labour Economics*, 1, 187–201.
- PELLIZZARI, M. (2010): “Do Friends and Relatives Really Help in Getting a Good Job?” *ILRReview*, 63(3), 1–19.
- PISTAFERRI, L. (1999): “Informal networks in the Italian labor market,” *mimeo*, 1–21.
- REES, A. (1966): “Information Networks in Labor Markets,” *The American Economic Review*, 56(1/2), 559–566.



TOPA, G. (2001): “Social Interactions, Local Spillovers and Unemployment,” *The Review of Economic Studies*, 68(2), 261–295.

ZWEIMÜLLER, J., R. WINTER-EBMER, R. LALIVE, A. KUHN, J.-P. WUELLRICH, O. RUF, AND S. BÜCHI (2009): “Austrian Social Security Database,” *NRN: The Austrian Center for Labor Economics and the Analysis of the Welfare State*, Working Paper 0903.

# **A Appendix**

## **A.1 Replication of Previous Findings**

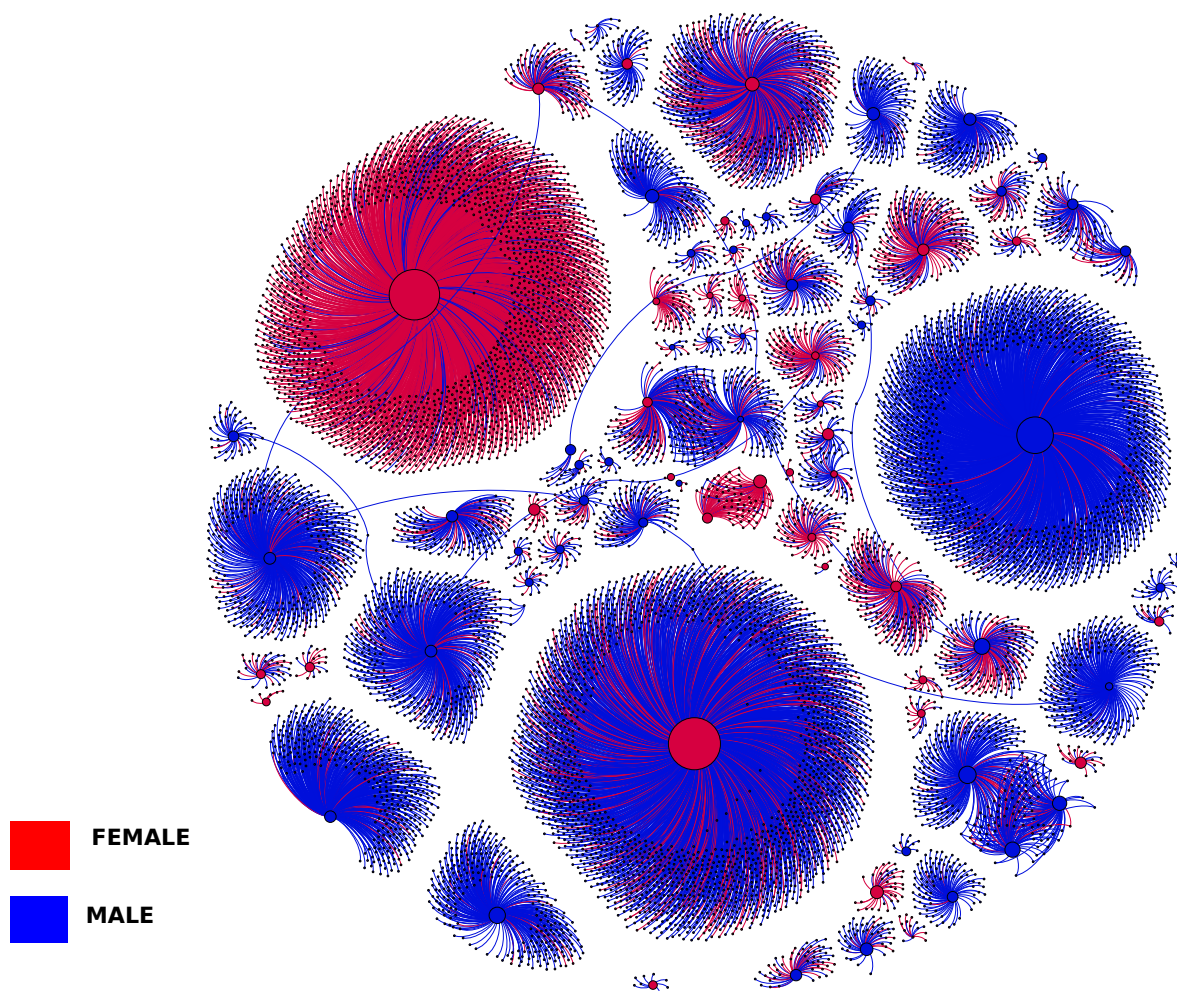
In this section we provide replication of estimations from previous studies to compare our results. Our findings are in line with previous findings in this literature. In particular...

## **A.2 Robustness Checks**

We have done a couple of robustness checks so far and all of the above results, especially those concerning the network employment rate are stable. First robustness check we conduct is to exclude some sectors such as construction, agriculture, gastronomy and tourism. Excluding these sectors we run the same analysis for exit hazard from unemployment as well as wage growth. Table 17 and Table 19 shows results for the sample excluding displaced workers coming from these sectors. Second robustness check was to exclude workers between age 50 and 55 as it could be considered as too close to retirement age. Similarly results are reported in Table 18 and Table 20.

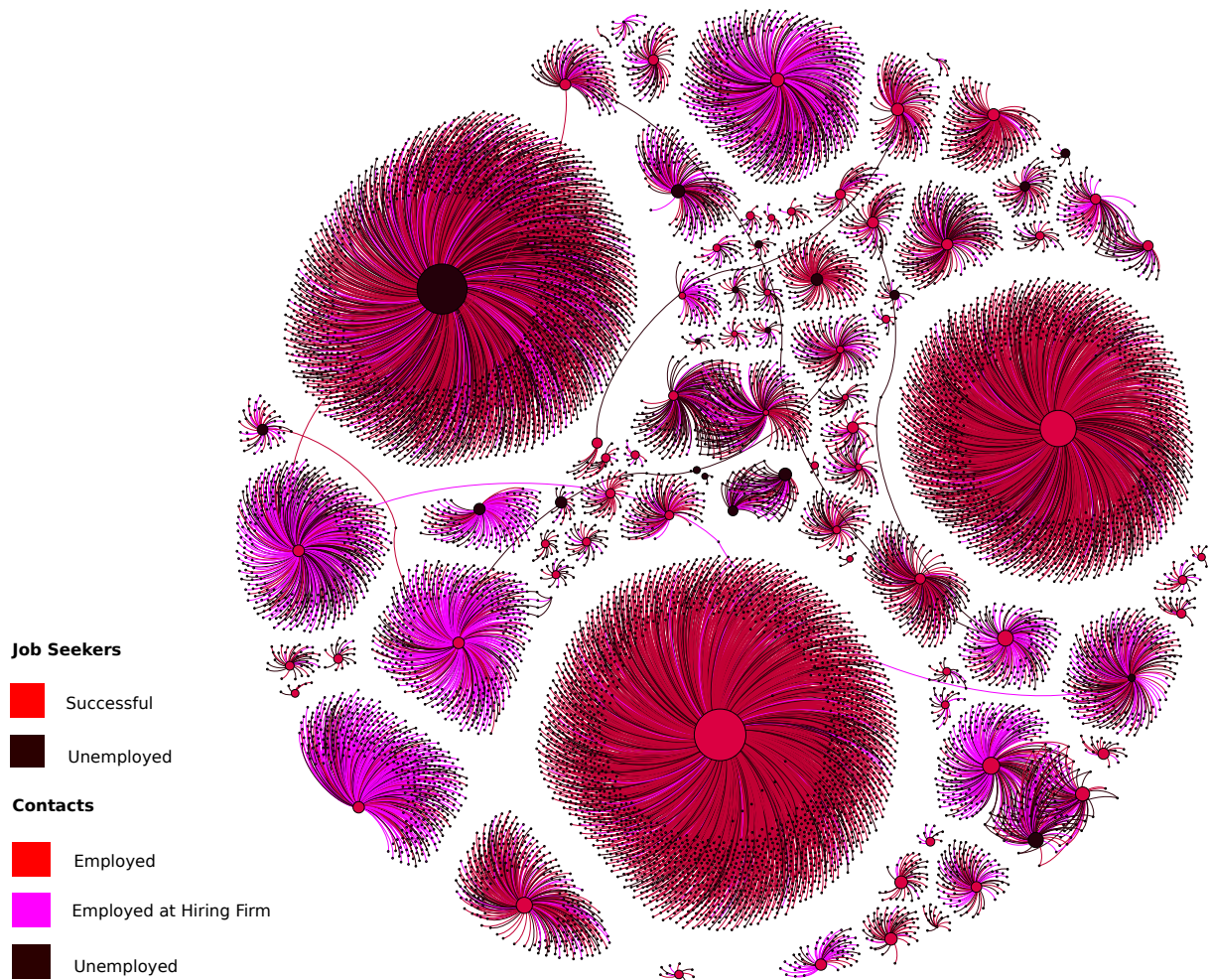
## B Figures and Tables

Figure 1: Job Seekers and Networks of Past Coworkers by Gender



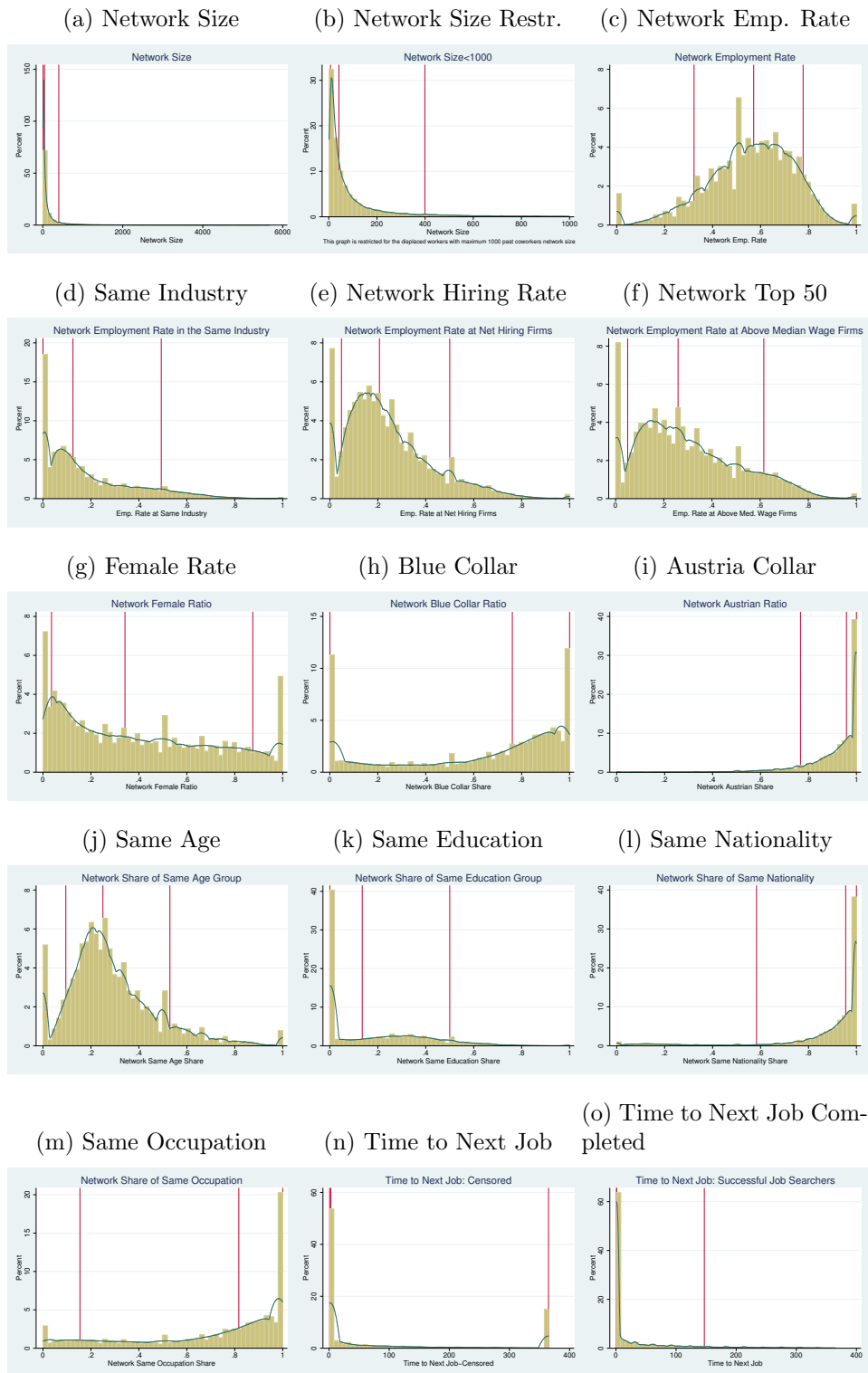
Note: This graph is obtained from a 1% random sample of workers lost their jobs at closing firms in 2000. It illustrates the displaced workers (in the middle) and their past coworkers as their connections. Blue (red) circles in the middle represents the male (female) job seekers while blue (red) connections around them are their male (female) contacts in their network.

Figure 2: Job Seekers and Networks of Past Coworkers by Employment Status



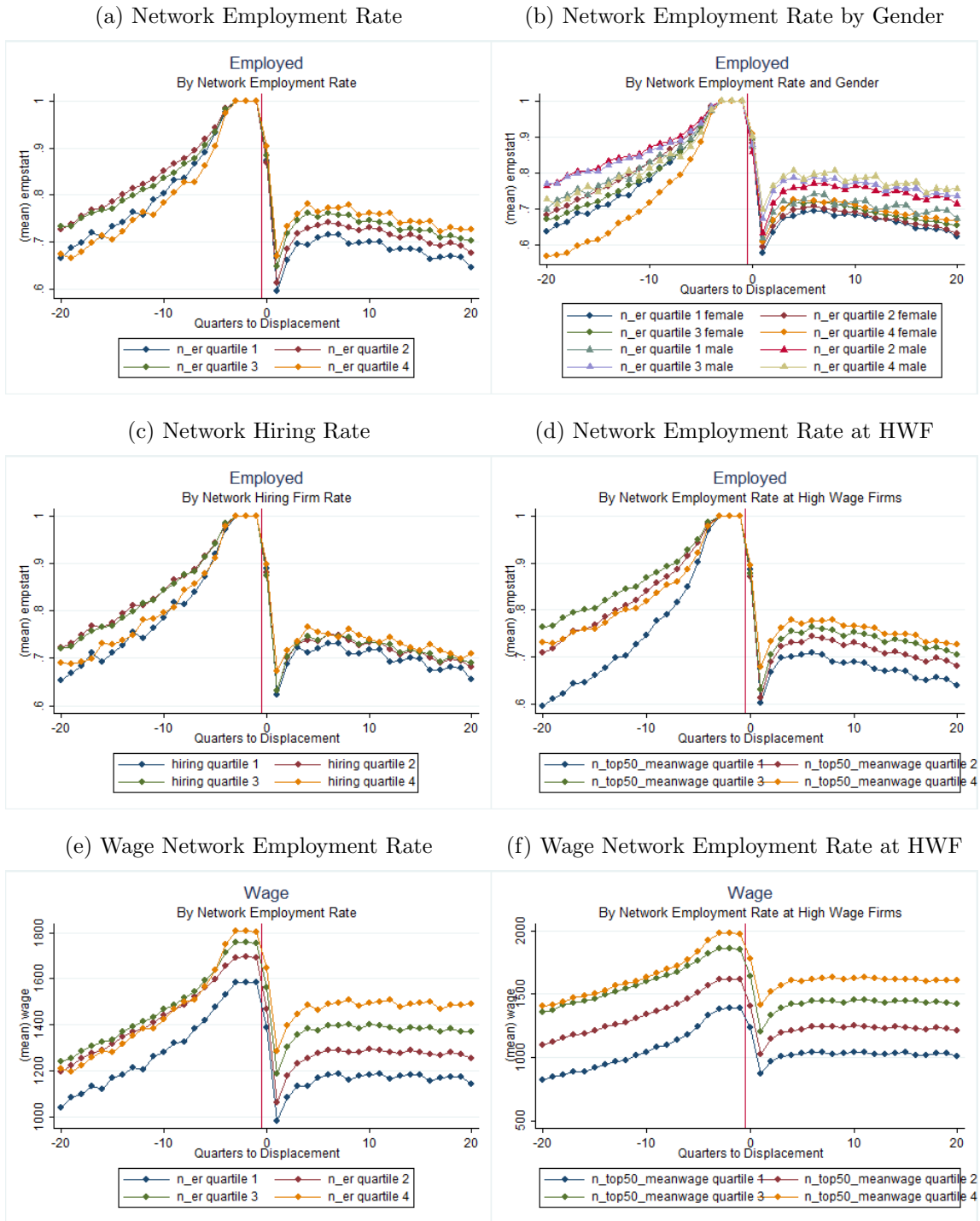
Note: This graph is obtained from a 1% random sample of workers lost their jobs at closing firms in 2000. It illustrates the displaced workers (in the middle) and their past coworkers as their connections. Red (black) circles in the middle represents the successful (still unemployed after 3 months) job seekers while red (black) connections around them are their employed (unemployed) contacts in their network. Pink connections are the network members who are employed at a firm that is currently hiring at the time of firm closure of job seeker.

Figure 3: Distribution of Network Characteristics



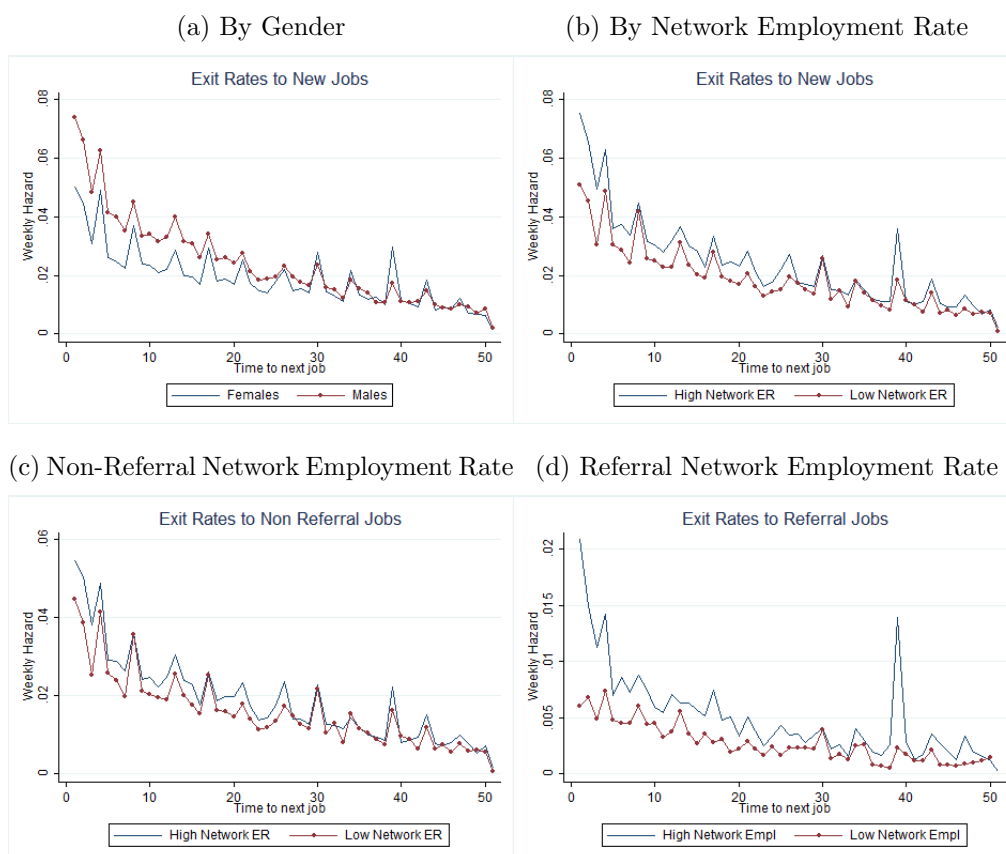
Note: These graphs are obtained from our full sample of displaced workers due to firm closures between years 1980 to 2007. Except for the last graph, they illustrate the distributions of variables measuring the characteristics of network members. Starting from number of contacts (network size), share of employed contacts (also employed in same industry and in above median wage firms), blue collar contacts, same age group, nationality and occupation contacts are shown. The last graph shows the distribution of duration of job seeking after firm closure for successful job seekers.

Figure 4: Employment and Wages Before and After Displacement, by Network Characteristics



Note: These graphs are obtained from our full sample of displaced workers due to firm closures between years 1980 to 2007. Top two graphs illustrate the employment status of job seekers in each quarter before and after firm closure. Each line represents subgroups of job seekers in terms of different quartiles of network employment rate of job seekers. The one of the right hand side shows female and male workers separately. Two graphs in the middle also illustrates the employment status of job seekers in each quarter before and after firm closure. On the left hand side, each line represents subgroups of job seekers in terms of different quartiles of network employment rate at hiring firms and the graph on the right hand side shows job seekers from different quartiles network employment rate at high wage firms. Finally two bottom graphs represents the wages of job seekers in each quarter before and after firm closure. The one on the left shows it for different quartiles of network employment rate while the one on the right hand side is for the subgroups of job seekers in terms of network employment rates at high wage firms.

Figure 5: Exit Rates to Jobs



Note: These graphs illustrate the exit rates to new jobs for our full sample of displaced workers due to firm closures between years 1980 to 2007. Horizontal axis shows the time to next job from job loss. First graph indicates the difference between female and male job seekers while the second one shows the two subgroups of job seekers with high vs low network employment rate. The third graph shows the exit to jobs obtained without using referrals from contacts for job seekers with high and low employment rate in their networks. Last graph shows the exit to jobs obtained through referrals for job seekers with low and high network employment rate.

Table 1: Summary Statistics: Workers Losing Jobs in Closing Firms

	Female		Male		All	
	mean	sd	mean	sd	mean	sd
Female					0.42	0.49
Age	36.14	10.20	36.78	9.40	36.51	9.75
Married	0.37	0.48	0.37	0.48	0.37	0.48
Austrian nationality	0.94	0.24	0.89	0.31	0.91	0.28
<b>Employment Characteristics</b>						
Blue Collar (job lost)	0.40	0.49	0.62	0.49	0.53	0.50
Average monthly wage (year before job loss)	1241.47	700.77	1789.80	818.05	1558.68	816.97
Claim Days (last 3 years)	24.53	74.60	25.49	70.84	25.09	72.45
Claim Days (last 5 years)	51.96	132.60	53.31	125.57	52.74	128.58
Tenure (job lost)	1757.55	1711.95	1720.31	1772.86	1736.01	1747.54
Work Days (last 2 years)	692.06	80.85	696.10	73.56	694.40	76.74
Work Days (last 5 years)	1492.55	430.15	1568.53	383.66	1536.50	405.65
Work Days (last 10 years)	2505.46	1054.81	2748.04	1007.08	2645.80	1034.43
Work Days (last 15 years)	3183.12	1612.05	3529.94	1607.56	3383.76	1618.54
<b>Outcome Variables</b>						
Time to Next Job	726.09	2128.51	552.84	1848.61	625.86	1973.29
Censored	0.18	0.38	0.13	0.33	0.15	0.36
Time to Next Job (incl. cens.)	100.02	142.25	78.81	127.58	87.75	134.36
Find New Job Immediately	0.47	0.50	0.48	0.50	0.47	0.50
Unemployed	0.35	0.48	0.31	0.46	0.33	0.47
<b>Network Characteristics</b>						
Network Size	133.99	318.71	173.15	350.88	156.64	338.25
<b>Share of Network Members:</b>						
Female	0.59	0.30	0.26	0.24	0.40	0.31
Blue collar	0.56	0.38	0.67	0.31	0.63	0.35
Austrian	0.93	0.10	0.91	0.12	0.92	0.11
Education1	0.29	0.19	0.29	0.18	0.29	0.18
Education2	0.24	0.17	0.26	0.16	0.25	0.16
Education3	0.04	0.07	0.03	0.05	0.04	0.06
Education4	0.03	0.06	0.02	0.04	0.02	0.05
Education5	0.02	0.05	0.02	0.05	0.02	0.05
Education6	0.02	0.06	0.02	0.04	0.02	0.05
Age Group1	0.38	0.22	0.32	0.19	0.35	0.21
Age Group2	0.21	0.12	0.22	0.11	0.21	0.12
Age Group3	0.18	0.12	0.19	0.11	0.19	0.11
Age Group4	0.24	0.17	0.26	0.16	0.25	0.17
Same Age Group	0.30	0.20	0.28	0.17	0.29	0.18
Same Educ Level	0.18	0.21	0.20	0.21	0.19	0.21
Same Gender	0.59	0.30	0.74	0.24	0.68	0.27
Same Nationality	0.89	0.21	0.84	0.25	0.86	0.23
Same Occupation	0.68	0.34	0.70	0.29	0.69	0.31
<b>Employed</b>	0.53	0.19	0.58	0.18	0.56	0.18
In Same Industry	0.18	0.19	0.20	0.19	0.19	0.19
In hiring firms	0.42	0.20	0.47	0.19	0.45	0.19
In net hiring firms	0.23	0.17	0.26	0.18	0.24	0.18
In net hiring firms in 2 quarters	0.09	0.12	0.10	0.12	0.10	0.12
In Above median Wage Firms	0.25	0.20	0.33	0.21	0.30	0.21
<b>Share of Employed Network Members</b>						
Female	0.30	0.20	0.13	0.14	0.20	0.18
Blue Collar	0.29	0.23	0.38	0.22	0.34	0.23
Austrian	0.49	0.19	0.52	0.18	0.51	0.19
Education1	0.15	0.12	0.17	0.12	0.16	0.12
Education2	0.14	0.12	0.17	0.12	0.15	0.12
Education3	0.02	0.05	0.02	0.03	0.02	0.04
Education4	0.02	0.04	0.01	0.03	0.01	0.03
Education5	0.01	0.03	0.02	0.03	0.01	0.03
Education6	0.01	0.04	0.01	0.03	0.01	0.03
Age Group1	0.19	0.14	0.18	0.13	0.19	0.13
Age Group2	0.12	0.09	0.14	0.09	0.13	0.09
Age Group3	0.11	0.09	0.13	0.09	0.12	0.09
Age Group4	0.11	0.11	0.13	0.11	0.12	0.11
Same Gender	0.30	0.20	0.44	0.21	0.38	0.21
Same Occupation	0.36	0.23	0.41	0.21	0.39	0.22
Same Nationality	0.47	0.21	0.49	0.22	0.48	0.21
Same Age Group	0.15	0.13	0.16	0.11	0.16	0.12
Same Education Level	0.10	0.13	0.12	0.14	0.11	0.13
Observations	69823		95835		165658	

Note: We report mean and standard deviations for the full sample of displaced workers due to firm closures in 1980-2007. First two columns are mean and standard deviations for females, 3rd and 4th columns represent the male sample while the last two columns represent the full sample.



Table 2: Summary Statistics: Successful Job Searchers

	Non-Referrals		Referrals		All	
	mean	sd	mean	sd	mean	sd
Female	0.43	0.50	0.31	0.46	0.41	0.49
Age	35.96	9.57	36.65	9.43	36.09	9.55
Married	0.37	0.48	0.40	0.49	0.37	0.48
Austrian nationality	0.91	0.29	0.90	0.30	0.91	0.29
<b>Employment Characteristics</b>						
Blue Collar (job lost)	0.54	0.50	0.58	0.49	0.55	0.50
Average monthly wage (year before job loss)	1541.37	798.71	1676.63	791.07	1567.43	799.03
Claim Days (last 3 years)	25.35	72.04	23.73	66.84	25.04	71.07
Claim Days (last 5 years)	52.81	127.08	50.88	117.98	52.44	125.38
Tenure (job lost)	1711.64	1694.64	1584.61	1630.53	1687.17	1683.22
Work Days (last 2 years)	694.23	76.74	703.40	63.48	696.00	74.45
Work Days (last 5 years)	1529.46	408.59	1597.48	348.63	1542.57	398.64
Work Days (last 10 years)	2616.03	1040.89	2780.98	962.55	2647.80	1028.32
Work Days (last 15 years)	3331.55	1620.72	3545.94	1554.40	3372.85	1610.38
<b>Outcome Variables</b>						
Time to Next Job	39.69	74.16	36.99	70.07	39.17	73.40
Censored	0.00	0.00	0.00	0.00	0.00	0.00
Time to Next Job (incl. cens.)	39.69	74.16	36.99	70.07	39.17	73.40
Find New Job Immediately	0.56	0.50	0.54	0.50	0.56	0.50
Unemployed	0.30	0.46	0.29	0.45	0.29	0.46
<b>Network Characteristics</b>						
Network Size	132.27	302.07	289.56	460.04	162.57	343.93
<b>Share of Network Members</b>						
Female	0.41	0.31	0.32	0.29	0.39	0.31
Blue Collar	0.63	0.35	0.66	0.31	0.63	0.34
Austrian	0.92	0.11	0.91	0.11	0.91	0.11
Education1	0.28	0.19	0.30	0.16	0.29	0.18
Education2	0.25	0.17	0.26	0.14	0.25	0.16
Education3	0.04	0.06	0.03	0.04	0.04	0.06
Education4	0.02	0.05	0.02	0.04	0.02	0.05
Education5	0.02	0.05	0.02	0.04	0.02	0.04
Education6	0.02	0.05	0.01	0.04	0.02	0.05
Age Group1	0.35	0.21	0.31	0.17	0.35	0.20
Age Group2	0.21	0.12	0.22	0.09	0.21	0.11
Age Group3	0.19	0.11	0.20	0.08	0.19	0.11
Age Group4	0.25	0.17	0.27	0.14	0.25	0.16
Same Age Group	0.29	0.19	0.28	0.15	0.29	0.18
Same Educ Level	0.19	0.21	0.20	0.20	0.19	0.21
Same Gender	0.67	0.27	0.73	0.25	0.68	0.27
Same Nationality	0.86	0.24	0.85	0.24	0.86	0.24
Same Occupation	0.70	0.31	0.70	0.29	0.70	0.31
<b>Employed</b>	0.55	0.19	0.62	0.15	0.56	0.18
In Same Industry	0.18	0.19	0.26	0.20	0.20	0.19
In hiring firms	0.44	0.19	0.52	0.18	0.46	0.19
In net hiring firms	0.23	0.17	0.29	0.19	0.25	0.18
In net hiring firms in 2quarters	0.09	0.11	0.13	0.15	0.10	0.12
In Above median Wage firms	0.29	0.20	0.38	0.22	0.30	0.21
<b>Share of Employed Network Members:</b>						
Female	0.21	0.18	0.18	0.17	0.20	0.18
Blue Collar	0.34	0.23	0.39	0.21	0.35	0.23
Austrian	0.50	0.19	0.56	0.16	0.51	0.18
Education1	0.16	0.12	0.18	0.11	0.16	0.12
Education2	0.15	0.12	0.17	0.11	0.16	0.12
Education3	0.02	0.04	0.02	0.03	0.02	0.04
Education4	0.01	0.03	0.01	0.02	0.01	0.03
Education5	0.01	0.03	0.02	0.03	0.01	0.03
Education6	0.01	0.03	0.01	0.02	0.01	0.03
Age Group1	0.19	0.14	0.18	0.11	0.19	0.13
Age Group2	0.13	0.09	0.14	0.07	0.13	0.09
Age Group3	0.12	0.09	0.14	0.07	0.12	0.09
Age Group4	0.12	0.11	0.15	0.10	0.13	0.11
Same Gender	0.38	0.21	0.46	0.20	0.39	0.21
Same Occupation	0.39	0.22	0.43	0.21	0.39	0.22
Same Nationality	0.47	0.21	0.52	0.20	0.48	0.21
Same Age Group	0.15	0.12	0.17	0.10	0.16	0.12
Same Educ Level	0.11	0.13	0.13	0.13	0.11	0.13
Observations	113807		27151		140958	

Note: We report mean and standard deviations for successful job seekers taken from the sample of displaced workers due to firm closures in 1980-2007. We include only successful job seekers without any restriction on time to reemployment. First two columns are mean and standard deviations for the sample of successful job seekers without referrals, 3rd and 4th columns represent the sample of successful job seekers through referrals while the last two represent the full sample of successful job seekers.

Table 3: Probability of Reemployment: Effect of Network Characteristics

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.005 (0.001)	0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)
Network Emp. Rate	0.081 (0.012)	0.029 (0.014)	0.013 (0.014)	0.025 (0.014)	0.009 (0.016)
Female	-0.014 (0.003)	-0.014 (0.003)	-0.014 (0.003)	-0.014 (0.003)	-0.014 (0.003)
Age Group1	0.107 (0.005)	0.107 (0.005)	0.107 (0.005)	0.107 (0.005)	0.107 (0.005)
Age Group2	0.080 (0.004)	0.079 (0.004)	0.079 (0.004)	0.079 (0.004)	0.079 (0.004)
Age Group3	0.070 (0.004)	0.070 (0.004)	0.070 (0.004)	0.070 (0.004)	0.070 (0.004)
Age Group4	0.063 (0.004)	0.062 (0.004)	0.062 (0.004)	0.062 (0.004)	0.062 (0.004)
Married	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)	0.003 (0.003)
Austrian Nationality	-0.034 (0.004)	-0.034 (0.004)	-0.034 (0.004)	-0.034 (0.004)	-0.034 (0.004)
Blue Collar at Job Lost	0.069 (0.004)	0.070 (0.004)	0.070 (0.004)	0.070 (0.004)	0.070 (0.004)
Emp. Rate at Same Industry		0.082 (0.012)	0.083 (0.012)	0.082 (0.012)	0.082 (0.012)
Emp. Rate at Net Hiring Firms			0.037 (0.010)		0.037 (0.010)
Emp. Rate at Net Hiring Firms at t and t+1				0.023 (0.013)	
Emp. Rate at Above Med. Wage Firms					0.006 (0.011)
Observations	165658	165658	165658	165658	165658

Source: ASSD, own calculations.

Note: Standard errors in parentheses. In all columns, the dependent variable is equal to 1 if the displaced worker is reemployed within 3 months after job loss. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 4: Job Finding Rate: Effect of Network Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	0.009 (0.002)	0.001 (0.003)	0.000 (0.003)	0.001 (0.003)	0.000 (0.003)	0.000 (0.003)
Network Emp. Rate	0.214 (0.021)	0.119 (0.025)	0.082 (0.026)	0.067 (0.026)	0.116 (0.027)	0.113 (0.032)
Female	-0.037 (0.006)	-0.037 (0.006)	-0.037 (0.006)	-0.037 (0.006)	-0.037 (0.006)	-0.037 (0.006)
Age Group1	0.241 (0.009)	0.240 (0.009)	0.240 (0.009)	0.241 (0.009)	0.240 (0.009)	0.240 (0.009)
Age Group2	0.192 (0.007)	0.192 (0.007)	0.192 (0.007)	0.192 (0.007)	0.192 (0.007)	0.192 (0.007)
Age Group3	0.178 (0.007)	0.178 (0.007)	0.178 (0.007)	0.178 (0.007)	0.178 (0.007)	0.178 (0.007)
Age Group4	0.167 (0.007)	0.167 (0.007)	0.167 (0.007)	0.167 (0.007)	0.167 (0.007)	0.167 (0.007)
Married	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)
Austrian Nationality	-0.075 (0.008)	-0.075 (0.008)	-0.075 (0.008)	-0.075 (0.008)	-0.075 (0.008)	-0.075 (0.008)
Blue Collar at Job Lost	0.122 (0.006)	0.123 (0.006)	0.122 (0.006)	0.122 (0.006)	0.123 (0.006)	0.123 (0.006)
Emp. Rate at Same Industry		0.149 (0.021)	0.152 (0.021)	0.175 (0.021)	0.149 (0.021)	0.149 (0.021)
Emp. Rate at Net Hiring Firms			0.085 (0.018)			
Network Av. Hiring Shares in Firm Size				0.291 (0.049)		
Emp. Rate at Above Med. Wage Firms					0.006 (0.019)	
Emp. Rate at Same/Higher Wage Firms						0.007 (0.025)
Observations	165658	165658	165658	165658	165658	165658

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 5: Job Finding Rate: Effect of Network Employment Rate at Hiring Firms

	(1)	(2)	(3)	(4)
Log Network Size	0.000 (0.003)	0.001 (0.003)	0.001 (0.003)	0.000 (0.003)
Network Emp. Rate	0.081 (0.026)	0.090 (0.026)	0.089 (0.027)	0.107 (0.025)
Emp. Rate at Same Industry	0.151 (0.021)	0.152 (0.021)	0.152 (0.021)	0.149 (0.021)
Emp. Rate at Net Hiring Firms	0.085 (0.018)	0.084 (0.018)	0.084 (0.018)	
Emp. Rate at Net Hiring Firms at t+1	0.006 (0.018)		0.008 (0.018)	
Emp. Rate at Net Hiring Firms at t-1		-0.026 (0.017)	-0.026 (0.017)	
Emp. Rate at Net Hiring Firms at t and t+1				0.076 (0.024)
Observations	165658	165658	165658	165658

Standard errors in parentheses

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column we add a different measure of network employment rate at hiring firms as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 6: Job Finding Rate: Effect of Time Varying Network Characteristics

	(1)	(2)	(3)
Log Network Size	0.011 (0.002)	0.001 (0.003)	0.001 (0.003)
Network Emp. Rate	0.186 (0.021)	0.085 (0.025)	0.041 (0.026)
Female	-0.037 (0.006)	-0.037 (0.006)	-0.037 (0.006)
Age Group1	0.241 (0.009)	0.240 (0.009)	0.240 (0.009)
Age Group2	0.192 (0.007)	0.192 (0.007)	0.192 (0.007)
Age Group3	0.179 (0.007)	0.178 (0.007)	0.178 (0.007)
Age Group4	0.167 (0.007)	0.167 (0.007)	0.167 (0.007)
Married	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)
Austrian Nationality	-0.075 (0.008)	-0.075 (0.008)	-0.075 (0.008)
Blue Collar at Job Lost	0.122 (0.006)	0.122 (0.006)	0.122 (0.006)
Emp. Rate at Same Industry		0.161 (0.021)	0.163 (0.021)
Emp. Rate at Net Hiring Firms			0.098 (0.018)
Observations	277435	277435	277435

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment where we allow network employment rates vary across quarters. In second and third columns, we add network employment rate in same industry and network employment rate at hiring firms and both variables as well as network employment rate vary across quarters. All estimations include closing firm FE as well as work force characteristics.

Table 7: Wage Growth: Effect of Network Characteristics, Only Men

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	0.001 (0.001)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.000 (0.002)	0.001 (0.002)
Network Emp. Rate	0.021 (0.013)	0.022 (0.015)	0.020 (0.016)	0.028 (0.016)	-0.010 (0.017)	-0.003 (0.018)
Age Group1	0.026 (0.005)	0.026 (0.005)	0.026 (0.005)	0.026 (0.005)	0.026 (0.005)	0.026 (0.005)
Age Group2	0.020 (0.004)	0.020 (0.004)	0.020 (0.004)	0.020 (0.004)	0.020 (0.004)	0.020 (0.004)
Age Group3	0.011 (0.003)	0.011 (0.003)	0.011 (0.003)	0.011 (0.003)	0.011 (0.003)	0.011 (0.003)
Age Group4	0.007 (0.003)	0.007 (0.003)	0.007 (0.003)	0.007 (0.003)	0.007 (0.003)	0.007 (0.003)
Married	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)
Austrian Nationality	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)	0.004 (0.004)
Blue Collar at Job Lost	0.000 (0.004)	0.000 (0.004)	0.000 (0.004)	0.000 (0.004)	0.001 (0.004)	0.000 (0.004)
Emp. Rate at Same Industry		-0.001 (0.011)	-0.001 (0.011)	-0.004 (0.012)	-0.009 (0.012)	-0.004 (0.011)
Emp. Rate at Net Hiring Firms			0.004 (0.010)			
Network Av. Hiring Shares in Firm Size				-0.034 (0.030)		
Emp. Rate at Above Med. Wage Firms					0.055 (0.012)	
Emp. Rate at Same/Higher Wage Firms						0.032 (0.013)
Observations	83504	83504	83504	83504	83504	83504

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from wage growth estimations. Dependent variable is the wage growth measured as the log difference of wage at job lost and re-entry wage. Estimation sample includes only male displaced workers due to firm closures in 1980-2007. We include only successful job seekers without any restriction on time to reemployment. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 8: Wage Growth: Effect of Network Characteristics, Only Successful Male Job Seeker within 3 months

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	-0.000 (0.001)	-0.000 (0.002)	-0.000 (0.002)	-0.000 (0.002)	-0.001 (0.002)	-0.000 (0.002)
Network Emp. Rate	0.017 (0.013)	0.018 (0.015)	0.014 (0.015)	0.026 (0.016)	-0.006 (0.016)	0.001 (0.018)
Age Group1	0.024 (0.005)	0.024 (0.005)	0.024 (0.005)	0.024 (0.005)	0.024 (0.005)	0.024 (0.005)
Age Group2	0.018 (0.004)	0.018 (0.004)	0.018 (0.004)	0.018 (0.004)	0.018 (0.004)	0.018 (0.004)
Age Group3	0.010 (0.003)	0.010 (0.003)	0.010 (0.003)	0.010 (0.003)	0.010 (0.003)	0.010 (0.003)
Age Group4	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)
Married	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)
Austrian Nationality	0.003 (0.004)	0.003 (0.004)	0.002 (0.004)	0.003 (0.004)	0.002 (0.004)	0.003 (0.004)
Blue Collar at Job Lost	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)	-0.005 (0.004)
Emp. Rate at Same Industry		-0.001 (0.011)	-0.001 (0.012)	-0.005 (0.012)	-0.008 (0.012)	-0.004 (0.012)
Emp. Rate at Net Hiring Firms			0.008 (0.011)			
Network Av. Hiring Shares in Firm Size				-0.042 (0.030)		
Emp. Rate at Above Med. Wage Firms					0.041 (0.012)	
Emp. Rate at Same/Higher Wage Firms						0.022 (0.013)
Observations	70689	70689	70689	70689	70689	70689

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from wage growth estimations. Dependent variable is the wage growth measured as the log difference of wage at job lost and re-entry wage. Estimation sample includes only male displaced workers due to firm closures in 1980-2007 who exit unemployment within 3 months after job loss. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 9: Wage Growth: Effect of Network Characteristics, Only Women

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	0.003 (0.002)	0.000 (0.002)	0.000 (0.002)	0.000 (0.002)	-0.001 (0.002)	0.000 (0.002)
Network Emp. Rate	0.019 (0.017)	-0.004 (0.019)	-0.019 (0.021)	-0.009 (0.021)	-0.026 (0.021)	-0.018 (0.028)
Age Group1	-0.001 (0.007)	-0.001 (0.007)	-0.001 (0.007)	-0.001 (0.007)	-0.001 (0.007)	-0.001 (0.007)
Age Group2	0.001 (0.006)	0.001 (0.006)	0.001 (0.006)	0.001 (0.006)	0.001 (0.006)	0.001 (0.006)
Age Group3	0.007 (0.006)	0.007 (0.006)	0.007 (0.006)	0.007 (0.006)	0.007 (0.006)	0.007 (0.006)
Age Group4	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)
Married	-0.009 (0.004)	-0.009 (0.004)	-0.009 (0.004)	-0.009 (0.004)	-0.009 (0.004)	-0.009 (0.004)
Austrian Nationality	0.018 (0.008)	0.018 (0.008)	0.018 (0.008)	0.018 (0.008)	0.018 (0.008)	0.018 (0.008)
Blue Collar at Job Lost	-0.022 (0.006)	-0.022 (0.006)	-0.022 (0.006)	-0.022 (0.006)	-0.021 (0.006)	-0.022 (0.006)
Emp. Rate at Same Industry		0.039 (0.017)	0.039 (0.017)	0.041 (0.018)	0.032 (0.017)	0.038 (0.017)
Emp. Rate at Net Hiring Firms			0.035 (0.015)			
Network Av. Hiring Shares in Firm Size				0.031 (0.045)		
Emp. Rate at Above Med. Wage Firms					0.047 (0.015)	
Emp. Rate at Same/Higher Wage Firms						0.016 (0.024)
Observations	57454	57454	57454	57454	57454	57454

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from wage growth estimations. Dependent variable is the wage growth measured as the log difference of wage at job lost and re-entry wage. Estimation sample includes only female displaced workers due to firm closures in 1980-2007. We include only successful job seekers without any restriction on time to reemployment. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.



Table 10: Job Finding: Effect of Similar Characteristics

	Female	Male	Blue Collar	White Collar	Austrian	Non-Austrian
Network Size	0.010 (0.004)	0.009 (0.003)	0.001 (0.004)	0.014 (0.003)	0.010 (0.002)	0.001 (0.011)
Employed Same Group	0.250 (0.047)	0.256 (0.046)	0.167 (0.055)	0.329 (0.042)	0.281 (0.089)	0.027 (0.147)
Employed Opposite Group	0.284 (0.059)	0.260 (0.067)	0.152 (0.076)	0.375 (0.060)	0.288 (0.117)	0.021 (0.124)
Unemployed Same Group	0.140 (0.053)	0.021 (0.055)	-0.029 (0.060)	0.160 (0.047)	0.069 (0.092)	-0.119 (0.221)
Observations	69823	95835	87244	78414	151133	14525

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column the estimation sample is a sub-group of displaced workers such as Female, Male, Blue Collar, White Collar, Austrian, and Non-Austrian. In each estimation, variables of interest are employment and unemployment rate of same or opposite subgroup in the network. All estimations include closing firm FE as well as work force characteristics.

Table 11: Job Finding: Effect of Similar Age Groups

	Below 29	29 to 36	36 to 44	Above 44
Network Size	0.019 (0.005)	0.006 (0.006)	0.010 (0.006)	-0.001 (0.007)
Employed Same Group	0.350 (0.065)	0.250 (0.091)	0.131 (0.095)	0.551 (0.096)
Employed Opposite Group	0.141 (0.061)	0.163 (0.065)	0.314 (0.067)	0.571 (0.090)
Unemployed Same Group	0.032 (0.071)	0.017 (0.120)	0.079 (0.140)	0.286 (0.102)
Observations	41207	37854	41327	45270

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column the estimation sample is a sub-group of displaced workers in terms of age groups such as below 29, between 30 and 36, between 36 and 44, and above 44. In each estimation, variables of interest are employment and unemployment rate of same or opposite subgroup in the network. All estimations include closing firm FE as well as work force characteristics.

Table 12: Job Finding: Effect of Similar Education Level

	Lowest	Middle	High	Highest
Network Size	0.015 (0.004)	-0.012 (0.005)	0.009 (0.005)	0.020 (0.012)
Employed Same Group	0.210 (0.054)	0.210 (0.074)	0.142 (0.066)	-0.033 (0.175)
Employed Opposite Group	0.211 (0.059)	0.325 (0.068)	0.263 (0.060)	0.024 (0.123)
Unemployed Same Group	0.148 (0.064)	-0.068 (0.092)	-0.194 (0.092)	-0.175 (0.207)
Observations	56626	44457	53437	11138

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from standard Cox Model for exiting unemployment. In each column the estimation sample is a sub-group of displaced workers in terms of education levels such as lowest, middle, high and highest education groups. In each estimation, variables of interest are employment and unemployment rate of same or opposite subgroup in the network. All estimations include closing firm FE as well as work force characteristics.

Table 13: Probability of Referrals: Effect of Network Characteristics

	(1)	(2)	(3)	(4)	(5)
Log Network Size	0.022 (0.001)	0.018 (0.001)	0.017 (0.001)	0.017 (0.001)	0.018 (0.001)
Network Emp. Rate	0.108 (0.011)	0.054 (0.012)	0.031 (0.012)	0.044 (0.012)	0.037 (0.013)
Female	-0.007 (0.003)	-0.007 (0.003)	-0.007 (0.003)	-0.007 (0.003)	-0.007 (0.003)
Age Group1	-0.008 (0.004)	-0.009 (0.004)	-0.008 (0.004)	-0.008 (0.004)	-0.008 (0.004)
Age Group2	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)
Age Group3	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)
Age Group4	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)
Married	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)
Austrian Nationality	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)	0.001 (0.004)
Blue Collar at Job Lost	0.013 (0.003)	0.013 (0.003)	0.013 (0.003)	0.013 (0.003)	0.013 (0.003)
Emp. Rate at Same Industry		0.082 (0.011)	0.082 (0.011)	0.081 (0.011)	0.084 (0.011)
Emp. Rate at Net Hiring Firms			0.055 (0.010)		0.055 (0.010)
Emp. Rate at Net Hiring Firms at t and t+1				0.059 (0.014)	
Emp. Rate at Above Med. Wage Firms					-0.012 (0.010)
Observations	117748	117748	117748	117748	117748

Source: ASSD, own calculations.

Note: Standard errors in parentheses. In all columns, the dependent variable is equal to 1 if the displaced worker is reemployed through a referral. (i.e. There is at least one past coworker at reemployment firm). In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 14: Competing Risk Models of Job Finding: Referral vs Non-Referral

	Exit to Job			Exit to Referral Job		Exit to Non-Referral Job	
	(1)	(2)	(3)	Baseline	CR	Baseline	CR
Log Network Size	0.053 (0.002)	0.048 (0.002)	0.048 (0.002)	0.355 (0.004)	0.357 (0.004)	-0.030 (0.002)	-0.082 (0.002)
Network Emp. Rate	0.168 (0.014)	0.131 (0.014)	0.109 (0.018)	1.054 (0.042)	0.890 (0.039)	-0.017 (0.016)	-0.115 (0.014)
Observations	165658	165658	165658	165658	165658	165658	165658

Source: ASSD, own calculations.

Note: Standard errors in parentheses. First three columns report results from standard Cox model. First column does not have any control other than gender. Second and third columns add demographic and employment history characteristics as well as industry, quarter, year and region fixed effects. Third column also includes network employment rate at net hiring firms and same industry firms. Fourth and fifth columns are based on exit hazards to referral jobs while last two columns are based on exit to non-referral jobs. Baseline estimations consider referral and non-referral job as main hazards while CR (Competing Risk) Cox Model estimations consider also the incidence of the competing events.

Table 15: Wage Growth: Effect of Referrals

	Male	Female	Male	Female
Referral	0.028 (0.004)	0.042 (0.007)	0.028 (0.004)	0.041 (0.007)
Age Group1	0.027 (0.005)	0.001 (0.007)	0.027 (0.005)	0.000 (0.007)
Age Group2	0.021 (0.004)	0.001 (0.006)	0.021 (0.004)	0.001 (0.006)
Age Group3	0.011 (0.003)	0.007 (0.006)	0.011 (0.003)	0.007 (0.006)
Age Group4	0.007 (0.003)	0.005 (0.005)	0.007 (0.003)	0.005 (0.005)
Married	0.005 (0.003)	-0.009 (0.004)	0.005 (0.003)	-0.009 (0.004)
Austrian Nationality	0.004 (0.004)	0.018 (0.008)	0.004 (0.004)	0.018 (0.008)
Blue Collar at Job Lost	-0.000 (0.004)	-0.022 (0.006)	-0.000 (0.004)	-0.022 (0.006)
Emp. Rate at Net Hiring Firms			0.009 (0.010)	0.036 (0.014)
Observations	83504	57454	83504	57454

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report results from wage growth estimations. Dependent variable is the wage growth measured as the log difference of wage at job lost and re-entry wage. In 1st and 3rd columns, estimation sample includes only male and 2nd and 4th columns includes only female displaced workers lost their jobs due to firm closures in 1980-2007. We include only successful job seekers without any restriction on time to reemployment. Variable of interest is referral which takes value 1 if the workers is reemployed through a referral. 3rd and 4th columns add also network employment rate at hiring firms as a measure of negotiation power of job seeker. All estimations include closing firm FE as well as work force characteristics.

Table 16: Reemployment Probabilities and Time to Next Job, Comparison to Other Studies

	(1)	(2)	(3)	(4)	rep5	rep6
Log Network Size	0.00425 (0.006)	0.00484 (0.006)	0.00755 (0.001)	0.00752 (0.001)	0.00587 (0.001)	0.00342 (0.001)
Network Emp. Rate	-0.508 (0.051)	-0.382 (0.054)	0.0547 (0.010)	0.0511 (0.011)	0.0633 (0.011)	0.0990 (0.012)
Female	0.0301 (0.014)	0.0305 (0.014)	-0.00588 (0.003)	-0.00589 (0.003)	-0.0121 (0.003)	-0.00908 (0.003)
Age Group2	-0.00334 (0.017)	-0.00325 (0.017)	0.0893 (0.004)	0.0893 (0.004)	0.0900 (0.004)	0.0470 (0.004)
Age Group3	-0.00645 (0.016)	-0.00599 (0.016)	0.0848 (0.003)	0.0848 (0.003)	0.0810 (0.004)	0.0439 (0.004)
Age Group4	0.00296 (0.015)	0.00328 (0.015)	0.0815 (0.003)	0.0815 (0.003)	0.0728 (0.003)	0.0414 (0.004)
Married	0.00740 (0.012)	0.00750 (0.012)	0.00413 (0.002)	0.00413 (0.002)	0.00301 (0.003)	0.00263 (0.003)
Austrian Nationality	0.109 (0.018)	0.109 (0.018)	-0.0255 (0.003)	-0.0255 (0.003)	-0.0359 (0.004)	-0.0347 (0.005)
Blue Collar at Job Lost	0.0951 (0.015)	0.0956 (0.015)	0.0706 (0.003)	0.0706 (0.003)	0.0776 (0.003)	0.0367 (0.004)
Emp. Rate at Net Hiring Firms		-0.295 (0.045)		0.00857 (0.008)		
Observations	140958	140958	165658	165658	165658	165658

Source: ASSD, own calculations.

Note: Standard errors in parentheses. In first and second columns, the dependent variable is log of time to next job and the sample consists of successful job searchers. In following columns, dependent variables are equal to 1 if the displaced worker is reemployed within 1, 6, and 12 months respectively. All estimations include closing firm FE as well as work force characteristics.

Table 17: Job Finding Rate: Effect of Network Characteristics: Robustness to Sector Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	0.011 (0.003)	0.002 (0.003)	0.002 (0.003)	0.003 (0.003)	0.002 (0.003)	0.002 (0.003)
Network Emp. Rate	0.239 (0.024)	0.144 (0.028)	0.105 (0.029)	0.096 (0.029)	0.143 (0.030)	0.138 (0.036)
Female	-0.043 (0.006)	-0.043 (0.006)	-0.043 (0.006)	-0.043 (0.006)	-0.043 (0.006)	-0.043 (0.006)
Age Group1	0.268 (0.010)	0.267 (0.010)	0.267 (0.010)	0.268 (0.010)	0.267 (0.010)	0.267 (0.010)
Age Group2	0.209 (0.009)	0.209 (0.009)	0.208 (0.009)	0.209 (0.009)	0.209 (0.009)	0.209 (0.009)
Age Group3	0.197 (0.008)	0.197 (0.008)	0.197 (0.008)	0.197 (0.008)	0.197 (0.008)	0.197 (0.008)
Age Group4	0.185 (0.008)	0.184 (0.008)	0.184 (0.008)	0.185 (0.008)	0.184 (0.008)	0.184 (0.008)
Married	0.001 (0.006)	0.002 (0.006)	0.002 (0.006)	0.002 (0.006)	0.002 (0.006)	0.002 (0.006)
Austrian Nationality	-0.074 (0.009)	-0.074 (0.009)	-0.074 (0.009)	-0.074 (0.009)	-0.074 (0.009)	-0.074 (0.009)
Blue Collar at Job Lost	0.097 (0.007)	0.098 (0.007)	0.098 (0.007)	0.098 (0.007)	0.098 (0.007)	0.098 (0.007)
Emp. Rate at Same Industry		0.148 (0.023)	0.150 (0.023)	0.172 (0.023)	0.148 (0.023)	0.148 (0.023)
Emp. Rate at Net Hiring Firms			0.089 (0.020)			
Network Av. Hiring Shares in Firm Size				0.286 (0.056)		
Emp. Rate at Above Med. Wage Firms					0.002 (0.021)	
Emp. Rate at Same/Higher Wage Firms						0.007 (0.027)
Observations	126451	126451	126451	126451	126451	126451

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report robustness results from standard Cox Model for exiting unemployment. Estimation sample includes displaced workers who lost their jobs at closing firms excluding construction and tourism sectors. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 18: Job Finding Rate: Effect of Network Characteristics: Robustness wrt Age Restriction

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	0.009 (0.002)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)
Network Emp. Rate	0.204 (0.022)	0.113 (0.025)	0.076 (0.027)	0.057 (0.027)	0.107 (0.027)	0.113 (0.033)
Female	-0.018 (0.006)	-0.018 (0.006)	-0.018 (0.006)	-0.018 (0.006)	-0.018 (0.006)	-0.018 (0.006)
Age Group1	0.170 (0.010)	0.169 (0.010)	0.169 (0.010)	0.169 (0.010)	0.169 (0.010)	0.169 (0.010)
Age Group2	0.117 (0.009)	0.117 (0.009)	0.117 (0.009)	0.117 (0.009)	0.117 (0.009)	0.117 (0.009)
Age Group3	0.100 (0.008)	0.100 (0.008)	0.099 (0.008)	0.099 (0.008)	0.100 (0.008)	0.100 (0.008)
Age Group4	0.083 (0.008)	0.083 (0.008)	0.083 (0.008)	0.084 (0.008)	0.083 (0.008)	0.083 (0.008)
Married	0.008 (0.005)	0.008 (0.005)	0.008 (0.005)	0.008 (0.005)	0.008 (0.005)	0.008 (0.005)
Austrian Nationality	-0.066 (0.008)	-0.066 (0.008)	-0.066 (0.008)	-0.066 (0.008)	-0.066 (0.008)	-0.066 (0.008)
Blue Collar at Job Lost	0.114 (0.007)	0.115 (0.007)	0.115 (0.007)	0.114 (0.007)	0.115 (0.007)	0.115 (0.007)
Emp. Rate at Same Industry		0.142 (0.021)	0.144 (0.021)	0.170 (0.022)	0.141 (0.021)	0.142 (0.021)
Emp. Rate at Net Hiring Firms			0.086 (0.019)			
Network Av. Hiring Shares in Firm Size				0.313 (0.050)		
Emp. Rate at Above Med. Wage Firms					0.012 (0.019)	
Emp. Rate at Same/Higher Wage Firms						-0.001 (0.026)
Observations	149733	149733	149733	149733	149733	149733

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report robustness results from standard Cox Model for exiting unemployment. Estimation sample includes displaced workers below age 50 instead of 55. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 19: Wage Growth: Effect of Network Characteristics: Robustness to Sectors, Only Men

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)	0.002 (0.002)
Network Emp. Rate	0.025 (0.015)	0.028 (0.017)	0.026 (0.018)	0.031 (0.018)	-0.005 (0.019)	0.010 (0.021)
Age Group1	0.028 (0.006)	0.028 (0.006)	0.028 (0.006)	0.028 (0.006)	0.028 (0.006)	0.028 (0.006)
Age Group2	0.020 (0.005)	0.020 (0.005)	0.020 (0.005)	0.020 (0.005)	0.020 (0.005)	0.020 (0.005)
Age Group3	0.011 (0.004)	0.011 (0.004)	0.011 (0.004)	0.011 (0.004)	0.011 (0.004)	0.011 (0.004)
Age Group4	0.007 (0.004)	0.007 (0.004)	0.007 (0.004)	0.007 (0.004)	0.007 (0.004)	0.007 (0.004)
Married	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)
Austrian Nationality	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)
Blue Collar at Job Lost	-0.001 (0.004)	-0.002 (0.004)	-0.002 (0.004)	-0.001 (0.004)	-0.001 (0.004)	-0.001 (0.004)
Emp. Rate at Same Industry		-0.005 (0.013)	-0.005 (0.013)	-0.006 (0.013)	-0.013 (0.013)	-0.007 (0.013)
Emp. Rate at Net Hiring Firms			0.006 (0.012)			
Network Av. Hiring Shares in Firm Size				-0.015 (0.036)		
Emp. Rate at Above Med. Wage Firms					0.055 (0.013)	
Emp. Rate at Same/Higher Wage Firms						0.024 (0.014)
Observations	60044	60044	60044	60044	60044	60044

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report robustness results from wage growth estimations. Dependent variable is the log difference of wage at job lost and re-entry wage. Estimation sample excludes displaced workers who lost their jobs at closing firms in construction and tourism sectors. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.

Table 20: Wage Growth: Effect of Network Characteristics: Robustness to Age, Only Men

	(1)	(2)	(3)	(4)	(5)	(6)
Log Network Size	0.001 (0.001)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)	0.000 (0.002)	0.001 (0.002)
Network Emp. Rate	0.021 (0.013)	0.023 (0.016)	0.021 (0.016)	0.029 (0.017)	-0.007 (0.017)	0.000 (0.019)
Age Group1	0.025 (0.006)	0.025 (0.006)	0.025 (0.006)	0.025 (0.006)	0.025 (0.006)	0.025 (0.006)
Age Group2	0.019 (0.005)	0.019 (0.005)	0.019 (0.005)	0.019 (0.005)	0.019 (0.005)	0.019 (0.005)
Age Group3	0.009 (0.004)	0.009 (0.004)	0.009 (0.004)	0.009 (0.004)	0.009 (0.004)	0.009 (0.004)
Age Group4	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)	0.005 (0.004)
Married	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)	0.006 (0.003)
Austrian Nationality	0.002 (0.004)	0.002 (0.004)	0.002 (0.004)	0.002 (0.004)	0.002 (0.004)	0.002 (0.004)
Blue Collar at Job Lost	-0.000 (0.004)	-0.000 (0.004)	-0.000 (0.004)	-0.000 (0.004)	0.000 (0.004)	-0.000 (0.004)
Emp. Rate at Same Industry		-0.003 (0.012)	-0.003 (0.012)	-0.005 (0.012)	-0.011 (0.012)	-0.005 (0.012)
Emp. Rate at Net Hiring Firms			0.005 (0.011)			
Network Av. Hiring Shares in Firm Size				-0.030 (0.031)		
Emp. Rate at Above Med. Wage Firms					0.053 (0.012)	
Emp. Rate at Same/Higher Wage Firms						0.029 (0.013)
Observations	76406	76406	76406	76406	76406	76406

Source: ASSD, own calculations.

Note: Standard errors in parentheses. All columns report robustness results from wage growth estimations. Dependent variable is the log difference of wage at job lost and re-entry wage. Estimation sample includes displaced workers below age 50 instead of 55. In each column we add a different measure of network employment rate as indicated. All estimations include closing firm FE as well as work force characteristics.