COWORKERS, NETWORKS, AND JOB-SEARCH OUTCOMES AMONG DISPLACED WORKERS

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This article examines the mechanisms by which social networks affect the labor market outcomes of displaced workers. The authors draw on administrative records for the universe of private-sector employment in Austria to identify work-related networks among former coworkers. They analyze the importance of social networks for both job seekers and hiring firms. For job seekers, results indicate that having a high share of former coworkers who are currently employed in expanding firms improves job-finding success. For firms seeking to hire new employees, the authors find that a firm is twice as likely to hire a displaced worker with a former-coworker link to one of their current employees than to hire a worker displaced from the same closing firm but without a link. These results suggest that information about job opportunities and demand-side conditions is transmitted in work-related networks between workers and firms.

The labor market is characterized by an enormous degree of heterogeneity among workers and jobs, which makes the matching process between the two highly complex. Personal relations, informal contacts, and social networks have long been recognized as major factors in overcoming informational difficulties (Rees 1966; Granovetter 1974). Survey evidence across countries indicates that 30 to 50% of workers have found their jobs with the help of friends, family members, or coworkers. Recent survey evidence from

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Austria shows that 72% of unemployed job seekers search for new jobs through friends and relatives, and one-third of them report finding a job through social contacts (Eppel, Mahringer, and Weber 2014). Employers, on the other side of the market, tend to rely heavily on employee referrals and word of mouth in recruitment.[1]

The literature examines two main mechanisms of information transmission in labor market networks. The first investigates the exchange of information about job opportunities among social contacts. Following this idea, Calvo-Armengol and Jackson (2004) designed a model of social networks in which employed network members pass job-related information to their unemployed contacts. Empirical tests of this mechanism typically examine how the properties of social networks affect job-search outcomes (Cingano and Rosolia 2012; Schmutte 2015; Glitz 2017). The second mechanism is motivated by employers' hiring strategies, in which social networks generate job referrals for specific vacancies; for example, when a worker recommends an unemployed contact to their employer for a potential hire. Models of referral hiring are based on the intuition that in a market with adverse selection, employers enjoy an informational advantage by hiring referred applicants (Montgomery 1991; Simon and Warner 1992; Dustmann, Glitz, Shönberg, and Brücker 2016). In this spirit, the empirical literature tests whether hiring probabilities, productivity, or profits differ between referral and non-referral workers (Kramarz and Skans 2014; Hensvik and Skans 2016; Eliason, Hensvik, Kramarz, and Skans 2019).

In this article we bring together differing perspectives on information transmission mechanisms while acknowledging that in the job-matching process, both workers and employers make use of social networks. This approach provides insights into the importance of job-related information about demand-side conditions, and of job referrals on job-search outcomes. Our setting focuses on workers who are displaced by closing firms and, consequently, forced to search for new jobs. We define their social networks as the former coworkers with whom they shared a workplace over the past five years before displacement, an approach also taken by Cingano and Rosolia (2012), Glitz (2017), and Eliason et al. (2019). The setup is implemented in the Austrian Social Security Database (ASSD), which covers the universe of private sector workers over a period of 30 years and offers a large sample and very detailed information on networks and labor market outcomes.

Our analysis then proceeds through three main steps. We start with an approach that adopts the job seeker's perspective to investigate how the properties of a displaced worker's social network affect their job-search outcomes. If information about job opportunities is passed on from employed to unemployed network members, the share of employed network members should have an impact on job-finding rates. In the second step, we investigate whether the type of firms in which former coworkers are employed

[1]For surveys of the recent literature, see Ioannides and Loury (2004) and Topa (2011).

matters for job-search outcomes. We focus on the firms' industries and demand-side factors, such as the firms' wage levels and employment growth. If demand-side factors are relevant for search outcomes, they should operate through information transmission of demand-side conditions or directly through the job-referral channel, as a contact in an expanding firm will be especially effective if this firm offers a job to the displaced job seeker. Exploiting detailed daily information on the jobless durations, we also investigate changes in the importance of social networks over the jobless spell. This analysis provides insights into the quality of job offers generated through social contacts. On one hand, if social contacts give access to promising job offers above the reservation wage, they should lead to rapid transitions into employment. On the other hand, if unsuccessful job seekers turn to social contacts as a last resort, the network effects should play out only later in the jobless spell.[2]

To confirm the intuition that information about the demand side or about specific vacancies matters, in the third step of our analysis we switch to the perspective of the hiring firm. The concept of former-coworker networks allows us to construct a network between firms by linking each closing firm to a set of connected firms in which the former coworkers of displaced workers are employed. Based on this firm network, we examine the hiring probabilities of displaced workers. In particular, we compare the hiring probabilities of displaced workers with and without a direct link to a former coworker in the connected firm (Kramarz and Skans 2014; Eliason et al. 2019). Although we lack information on actual employee referrals, we take the existence of an individual's former coworker in a connected firm as a proxy for a referral. Results of the hiring analysis will thus provide additional information on the importance of referral hirings.

A key concern in the empirical analysis of social networks is the endogeneity of network characteristics with respect to outcomes, for example because of non-random selection into networks. If individuals select into networks based on shared unobserved characteristics, a clear identification strategy is necessary to distinguish causal network effects from spurious correlation of the outcomes among network members. We define social networks by former coworkers because such networks are not formed with the primary objective of generating information about job opportunities. Nevertheless, coworker networks are determined by shared employment histories, and are thus not generated randomly with respect to labor market outcomes. Our strategy is to isolate demand-side variation in network characteristics from employment history components, which we can control with a detailed set of variables. Even if former coworkers are similar to the displaced worker, the type of firms in which they are employed should be driven by random variation. In addition, we restrict our analysis to variation at the closing-firm level. The counterfactual experiment is thus determined

[2]We are grateful to an anonymous referee for this comment.

by displaced workers from the same closing firm whose network characteristics differ. In the analysis of hiring probabilities, we compare displaced workers from the same closing firm, in which one person has a link to a former coworker in the connected firm and the other person does not.

Our analysis leads to the following main findings. *First*, we confirm previous evidence that the share of employed network members increases job-finding rates (Cingano and Rosolia 2012; Glitz 2017). In the Austrian application, an increase in the share of employed network members by one standard deviation increases the job-finding hazard by 4%, or the probability of finding a new job within three months by 1.3 percentage points. *Second*, the type of firms in which network members are employed matters for job-search outcomes. The share of network members employed in expanding firms increases the job-finding rate, whereas the share of network members employed in high-wage firms leads to higher wages in the new job. *Third*, we find that employed former coworkers boost job-finding rates early in the unemployment spell and the impact decreases greatly after the first half-year of joblessness, which suggests that social contacts generate high-quality job offers. *Fourth*, connected firms are important for the employment prospects of displaced workers, as 24% of them find a new job in a connected firm. *Fifth*, the analysis of hires in connected firms provides evidence in favor of the referral hiring channel. Displaced workers with a link to a former coworker in a connected firm are more than twice as likely to be hired by that firm. *Sixth*, some evidence of heterogeneity of network effects across groups of workers is apparent. Older workers, white-collar workers, and job seekers with Austrian nationality particularly benefit from former-coworker networks. Results from heterogeneity analysis at the job-seeker side and the hiring side confirm each other. On the job-seeker side, we find that coworkers employed in expanding firms or in high-wage firms reduce search durations. From the demand-side perspective, hires are more likely if the link is with a former coworker who is employed in an expanding or high-wage firm.

In addition to the literature on job-search networks, which we review in more detail in the next section, our article is also related to the literature on job displacement, which documents strong and persistent adverse effects in terms of employment stability and earnings from job displacement (Jacobson, LaLonde, and Sullivan 1993; Von Wachter, Song, and Manchester 2009; Davis and von Wachter 2011; Fink, Kalkbrenner, and Weber 2014). It will therefore be interesting, perhaps, to shed light on the extent to which these losses can be mitigated by social network effects.

Theoretical Background and Empirical Literature

The job searcher's perspective is adopted in the model of information transmission in social networks described by Calvo-Armengol and Jackson (2004). In this framework, a social network consists of a group of employed and unemployed workers in which network members randomly receive information about job opportunities. Unemployed workers keep this information to themselves and take the job, whereas employed members pass on the information to one of their unemployed contacts. This mechanism ensures that unemployed network members have two sources of job information: the information they gather themselves and the information transferred through their employed contacts. In a network with many employed members, unemployed workers will find jobs more quickly than in networks with mostly unemployed members in which each worker has to rely on the information they gather on their own. Thus the model predicts that the share of employed network members has a positive impact on the job-finding rates of job seekers. Information traded in the network is general information about job opportunities along with information on demand-side conditions such as the type of firms that offer attractive jobs or the favorable wage offers.

Models that incorporate the firms' interests are based on a setting in which employers face uncertainty about the productivity of applicants when they make the recruitment decision and a worker's productivity is only revealed over time (Jovanovic 1979). Employee referrals help employers recruit because they provide additional information about the applicant that would otherwise not be available. Simon and Warner (1992)—and, more recently, Galenianos (2013) and Dustmann et al. (2016)—developed models in which employers can hire either through referrals or on the open market, and derived predictions about starting wages, wage growth, and job turnover that can be tested empirically. Montgomery (1991) took a slightly different approach based on the assumption of homophily, stating that workers are more likely to have ties to individuals who are similar to themselves. Once the type of a worker is revealed, the employer will thus only hire referrals from highly productive workers, as the referred workers are more likely to be highly productive types themselves. The type of information that is shared among network members in the referral models is very specific. Employed contacts encourage their job-seeking network members to apply for a vacancy at their firms. Predictions from models of referral hiring imply that the types of firms in which employed network members are working should be reflected in the job-search outcomes. In addition, we should see job-seeking network members who join their employed contacts in the same firms.

A third alternative mechanism by which social contacts affect search outcomes is primarily discussed in the literature on peer effects. Instead of exchanging job-related information, social networks might directly affect workers' preferences for work or leisure (Marmaros and Sacerdote 2002; Bandiera, Barankay, and Rasul 2009; Mas and Moretti 2009). In a network of mostly employed members, an unemployed worker who wants to be similar to her peers will be subject to social pressure to search harder for a job. If this mechanism is at play, we expect to find strong impacts from the employment status of network members on job-search outcomes, while the types of network members' firms or the availability of vacancies at the firms would not be relevant. Cappellari and Tatsiramos (2015) investigated networks of close friends of unemployed workers, who are likely to have common preferences, and find that the number of employed friends has a positive effect on job finding and match quality.

The popularity of informal job-search methods among job seekers, and the large share of jobs that are generated by personal contacts, has been documented in numerous studies; Ioannides and Loury (2004) and Topa (2011) provided excellent surveys of this literature.[3] More recently, two studies have tested predictions from the model of Calvo-Armengol and Jackson (2004) in networks that are based on former coworkers and in a setting very similar to ours. Cingano and Rosolia (2012) and Glitz (2017) showed that for Italy and Germany, the share of employed coworkers has a positive impact on the job-finding rates of displaced workers. Glitz (2017) applied an instrumental variable (IV) strategy to account for network endogeneity and by exploiting variation in the employment rate of former coworkers from mass layoffs, he found even stronger network effects. We replicate the findings by Cingano and Rosolia (2012) and Glitz (2017) for Austria. We also investigate the effect of the type of firm in which former coworkers are employed. This approach resembles Schmutte (2015), whose evidence is consistent with the hypothesis that workers in higher-paying firms are better sources of job information. In addition, we analyze the impact of employed former coworkers over the spell of joblessness to distinguish between desirable and less desirable job offers.

The widespread use of referral hiring techniques by employers is well documented on the basis of survey evidence of employers' hiring strategies; see, for example, Marsden (2001), Holzer (1987), and Topa (2011) for an overview.[4] In addition, studies based on evidence from personnel records of large firms have shown that referred applicants are more likely to be invited for job interviews, and also more likely to get hired than are non-referred applicants (Castilla 2005; Brown et al. 2016). Burks et al. (2015) used very detailed data from nine large firms in various industries with application records and productivity measures, which allowed them to compare the predictions from theoretical models of employer hiring. They found that no single model is fully confirmed by the data.

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[3]Pellizzari (2010) presented a comparison of job-search channels across European countries. Oyer and Schaefer (2011) provided a survey from personnel economics literature on firms' hiring strategies, including accessing employees' social networks.

[4]According to studies that use firm-specific data from large companies with employee referral programs, up to 50% of non-entry-level jobs are filled by referrals (Castilla 2005; Burks, Cowgill, Hoffman, and Housman 2015; Brown, Setren, and Topa 2016). Using firm-level surveys, Hensvik and Skans (2014) showed that two-thirds of firms in Sweden used informal channels to fill their vacancies. A central point of interest, therefore, is how social networks operate in the labor market and how they influence outcomes.

Furthermore, several studies provide indirect evidence on the importance of the referral hiring mechanism. These findings are based on various definitions of social networks. In the context of the literature on neighborhood effects, Bayer, Ross, and Topa (2008), Hellerstein, McInerney, and Neumark (2011), and Hawranek and Schanne (2014) found that individuals who live in the same residential location are also more likely to work in the same firms as individuals living in neighboring locations. Hellerstein, Kutzbach, and Neumark (2016) studied residential networks further by focusing on the impact of networks on re-employment of displaced workers from mass layoffs during the Great Recession in the United States. Schmutte (2015) found that workers who live in a census block with a high share of neighbors working in high-paying jobs are more likely to switch jobs and move to better-paying firms themselves. Defining networks along ethnic minority group dimensions, Dustmann et al. (2016) showed that firms with a high share of migrant workers are more likely to hire additional workers of the same ethnicity. In the same context, Åslund, Hensvik, and Skans (2014) and Giuliano, Levine, and Leonard (2009) found that immigrant managers are substantially more likely to hire immigrant workers than native workers. Also, Munshi (2003) studies Mexican immigrant networks based on origin communities and suggests a positive impact on labor market outcomes in the United States.

Using family-based networks, Kramarz and Skans (2014) found that high school graduates are more likely to find their first jobs in a parent's firm. Hensvik, Müller, and Skans (2017) also studied labor market entrants and documented countercyclical effects of contacts to employers from summer jobs, who recall young workers to regular jobs after high school graduation. Hensvik and Skans (2016) defined work-related networks by former coworkers and showed that firms are more likely to hire a former coworker of one of their incumbent employees than a random applicant from the open market. This effect is even stronger for high-ability incumbent employees, which confirms Montgomery's (1991) prediction about referrals from highly productive workers. Two recent papers by Eliason, Hensvik, Kramarz, and Skans (2017, 2019) focused on the probability that displaced workers from establishment closures are hired by connected firms, thereby adopting distinct definitions of social connections. Eliason et al. (2019) compared the effectiveness of family networks, coworker networks, networks of former classmates, and neighborhood networks in generating hires in connected firms. Their results showed that family contacts are most productive, followed by former-coworker contacts, while the other types of contacts seem to transmit little job-relevant information. Eliason et al. (2017) extended the analysis to study the impacts of hires through social networks on firm outcomes such as total hires and value added. Using displaced workers from establishment closures as exogenous variation in the pool of connected applicants, they showed that connected hires lead to an increase in firm-level production. Our analysis on demand-side impacts is related to Eliason et al. (2019), who also compared the hiring probabilities of displaced workers with and without a direct link to a former coworker in the connected firm. Our heterogeneity analysis allows us to directly compare predictions from the job-seeker analysis with the demand-side analysis. In particular, we find that coworkers employed in expanding firms or in high-wage firms reduce search durations. This is confirmed by the finding that hires are more likely if the link is with a former coworker who is employed in expanding or high-wage firms.

Data and Network Definitions

Our empirical analysis is based on the Austrian Social Security Database (ASSD), which covers the universe of private sector workers in Austria from 1972 to 2012 (Zweimüller et al. 2009). The data provide detailed daily information on employment, unemployment, and other states relevant for social security such as sickness, retirement, or maternity leave. Earnings paid by each employer are recorded at an annual level. We refer to the average monthly earnings by employer and year as the monthly wage; note, however, that we cannot measure working time. The matched employer–employee structure of the ASSD is defined by employer identifiers, which are linked to individual employment spells.[5] To measure workforce characteristics at the firm level, we organize the data in a quarterly panel, collapsing it along employer identifiers. We then define firm-exit dates as the last quarter date in which a firm employs at least one worker. We use a worker-flow approach to distinguish firm closures from other exit events such as mergers or institutional changes in the employer identifier. This approach is explained in detail in Fink et al. (2010). The main definition is that a closure is restricted to the exit of an employer identifier in which less than 50% of the previous year's workforce jointly move to the same new employer identifier. Because this approach is not meaningful for very small firms, we restrict closures to firms with at least five employees in the past year.

Our sample of displaced workers consists of individuals displaced by firm closures from 1980 to 2007. We make four restrictions to this sample. First, we consider only blue-collar or white-collar workers who are still employed in the quarter of firm exit. We refer to this quarter alternatively as the firm-closure quarter or the displacement quarter. Second, we restrict the sample to workers with at least one year of tenure at the closing firm. Third, we focus on workers who are between 20 and 55 years of age at displacement. Fourth, we consider only firm closures that involve at least two displaced individuals. We require that the closing firm has at least five employees during the previous

[5]The ASSD does not provide a clear definition of the business unit associated to an employer identifier; it can be either a single establishment or a firm consisting of multiple establishments. In Austria business units are typically small and consist of only one establishment. We therefore refer to employer identifiers as "firms" in the remainder of the text. For a detailed discussion and analysis, see Fink, Kalkbrenner, Weber, and Zulehner (2010).

year. Because of restrictions on the characteristics of displaced workers, however, the number of displaced workers may be lower than the total number of workers employed during the past year. The resulting sample includes 151,432 workers displaced from 27,960 closing firms, which means that on average we observe 5.4 workers displaced by the same closing firm.[6]

Displaced Workers and Coworker Networks

For each displaced worker, we define the social network as the set of all individuals who shared a workplace with her over the past five years before the displacement quarter. Thus, we require that the employment spells of the contacts overlap for at least 30 days. We further exclude links with former coworkers that were established in very large firms with more than 3,000 employees. This restriction facilitates the computational tractability but more importantly it restricts the size of the networks and excludes very large networks, which offer limited information about interpersonal information flows. Finally, we also exclude from the network co-displaced workers, that is, those who were displaced by the same firm-closure event. These workers will form the comparison group at the closing-firm level.

Table 1 presents summary statistics of individual and network characteristics of our sample of displaced workers. The average worker's age at displacement is 36.8 years, 41% are females, 91% are of Austrian nationality, and 53% hold a blue-collar contract at time of displacement. The average displaced worker's tenure—4.9 years—is slightly below the length of the time window over which the network is formed, but the distribution of job tenure is right-skewed and the median is at 2.9 years. Typically, displaced workers experience interruptions in their labor market careers over the five-year window. On average, a displaced worker experienced one job change over the past five years, worked for 4.3 out of the five years, and spent 50 days in unemployment. Firms in the Austrian labor market are generally small, which is also reflected in size of firms in which displaced workers were employed during the five-year window. The average firm size over the last 19 quarters prior to displacement is 50, and the median firm size is approximately 20. In the displacement quarter, closing firms are even smaller and a displaced worker has 13 co-displaced workers on average and 7 at the median.

[6]Because our sample is based on the universe of Austrian private sector workers, and because of the long time frame, our sample of closing firms and displaced individuals is larger than the samples used in previous studies. Glitz (2017) used establishment closures in the Hamburg, Cologne, Frankfurt, and Munich metropolitan areas in the years 1995 and 1996. This leaves him with 10,916 displaced male workers from 1,814 establishments. Cingano and Rosolia (2012) focused on two Italian provinces (Treviso and Vicenza) and observed 9,121 displaced and re-employed individuals from 1,195 firm closures in the manufacturing sector over the years 1980 to 1994. The displaced workers of Cingano and Rosolia (2012) had to have been employed in the closing firm in the final month of activity. Eliason et al. (2019) identified plant closures in Sweden between 1990 and 2006, which should result in a larger sample size. They did not report the number of closing plants or displaced workers, however.

Table 1. Summary Statistics: Displaced Workers

	Mean	*Median*	*Std. Dev.*
Individual characteristics			
Female	0.41		0.49
Age	36.8	36.0	9.5
Blue-collar worker	0.53		0.50
Austrian nationality	0.91		0.28
Tenure (in years)	4.87	2.92	4.84
Employed over past 5 years	4.27	4.90	1.06
Unemployed over past 5 years	0.14	0.00	0.35
Number of firms over past 5 years	1.92	2	1.20
Average firm size over past 5 years	50.29	19.28	105.4
Size of closing firm in final quarter	13.71	7	20.52
Network characteristics			
Network size	158.3	44	339.0
Share of network members who are			
Female	0.40	0.34	0.31
Blue-collar workers	0.62	0.76	0.35
Austrian nationality	0.92	0.96	0.11
Same gender as displaced worker	0.68	0.75	0.27
Same age group	0.28	0.25	0.18
Same occupation	0.69	0.81	0.31
Same nationality	0.86	0.95	0.23
Contacts from closing firm	0.61	0.74	0.40
Still employed at old firm	0.08	0.00	0.16
Network employment characteristics			
Share of network members who are			
Employed	0.56	0.57	0.18
Employed in the same industry	0.19	0.13	0.19
Employed in net hiring firms	0.24	0.21	0.18
Employed in above-median-wage firms	0.30	0.26	0.21
Observations	151,432		

Notes: Sample includes workers displaced from firm closures in 1980 to 2007. "Employed in the same industry" refers to the share of network members who are employed in the same two-digit industry as the closing firm. "Employed in net hiring firms" refers to the share of network members who are employed in firms that increase their absolute employment level during the quarter of displacement. "Employed in above-median-wage firms" refers to the share of network members who are employed in firms that pay average wages above the median of the firm-level distribution.

The employment history characteristics of displaced workers indicate that the size of coworker networks is typically determined by rapid employment turnover of both the displaced workers and their former coworkers, rather than by stable employment spells in large firms. The average network size of almost 160 former coworkers is thus approximately three times as large as the average firm size over the past five years; the median network size is smaller, with 44 former coworkers.[7]

[7]The co-displaced workers, whom we exclude from the network, are in general only a small fraction of all former coworkers. For the average displaced worker the group of co-displaced workers amounts to roughly 20% of all former coworkers over the past five years. The median is lower with 14%. The network can include co-workers in the closing firm who left the firm before the final quarter.

In general, coworker networks are diverse: on average approximately 40% of network members are female, a share of 62% are blue-collar workers, and a share of 92% have Austrian nationality. When we compare displaced workers to the members of their networks, we see that about 68% of them have the same gender as the displaced worker, which indicates a slight selection into networks by gender; 86% of network members share the same nationality with the displaced worker; 69% hold the same job type; and 28% are in the same age group. We split displaced workers into four age groups of about equal size.

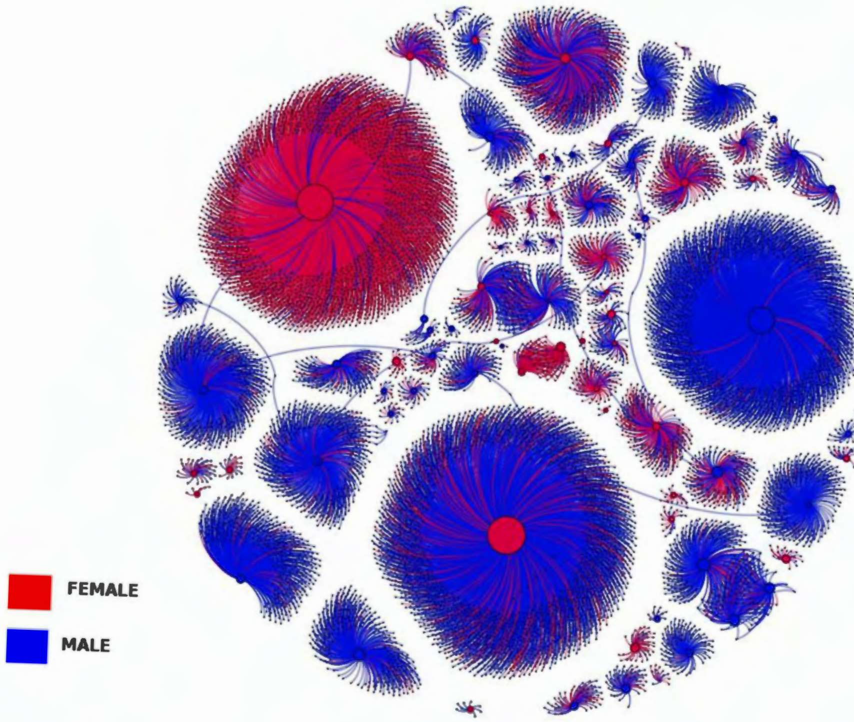
Our network definition includes all coworkers who shared a workplace with the displaced worker over the past five years. This definition includes contacts formed in the closing firm and contacts from previous or "old" firms, in which the worker was employed before the displacement job spell. On average, the majority of former coworkers, or 61%, are from the closing firm, even after the exclusion of co-displaced workers. This can be explained, in part, by the 43% of displaced workers who only held a job with the closing firm over the past five years. For workers with multiple job spells over the past five years, the share of contacts formed in the closing firm is 33%.

Next, we turn to the employment characteristics of network members and focus on the jobs that network members hold in the displacement quarter. At the time of firm closure, on average 56% of the network members hold a job.[8] Among former coworkers, 8% are "stayers" who were contacted in firms other than the closing firm and who still hold the same job in the displacement quarter. If we compare the industry of the closing firm with the industries of the firms in which network members are employed, we find that only 19% of the contacts' industries overlap at the two-digit level. To classify industries we use a two-digit Nomenclature of Economic Activities (NACE) classification, which covers approximately 60 distinct industries.

We construct two additional measures that provide information about employment dynamics and wage levels of the firms in which network members are employed. First, we are interested whether network members hold jobs in expanding firms, approximated by the firms' employment growth over the displacement quarter. We find that on average 24% of the network members are employed in "net hiring firms," defined as firms with an absolute increase in the number of blue- and white-collar workers in the displacement quarter. Second, we look at the share of network members who are employed in "high-wage firms." To approximate the firms' wage level, we compute average wages of male employees in every quarter and define high-wage firms as those having an average wage above the overall median. According to this measure, we see that a relatively high share of 30% of

[8]The share of employed coworkers is similar to the value reported by Glitz (2017) for Germany, but lower than the corresponding number in Cingano and Rosolia (2012). The network employment rate does not vary strongly by the type of former coworker. Specifically, coworkers contacted during the final year before firm closure are not more or less likely to be employed than are coworkers who overlapped in the earlier years.

Figure 1. Former-Coworker Networks



Notes: The figure is based on a 1% random sample of 85 workers who lost their jobs at closing firms in 2000. It illustrates displaced workers (in the center) and their former coworkers as their connections. Blue (red) circles in the middle represent male (female) job seekers, while blue (red) connections around them are their male (female) contacts in their network. (Colors are viewable in the online version of the article.)

network members are employed in firms that pay above median wages to their average employees. We compute average male wages in firms with at least 3 three male employees in a certain quarter. Firms with fewer employees are then categorized into the low-wage group. We focus on male wages to avoid problems with part-time workers, who are predominantly female.

Figure 1 shows an example of the structure of the coworker networks. To construct this graph, we selected a 1% random subsample of 85 workers who were displaced in the year 2000. The displaced worker is shown at the center of each coworker network and the edges represent links to the former coworkers. We see that the sizes of the networks vary greatly; the largest includes approximately 2,000 contacts and the smallest has only a single contact. Some displaced workers have networks that overlap, while other networks are isolated. This discrepancy is potentially attributable to the random draw of displaced workers from the full population. In general, networks of two individuals who are displaced from the same firm will overlap to a certain extent. Unless their employment careers are identical during

Table 2. Firm Characteristics

	Mean	*Median*	*Std. Dev.*
Closing firms			
Number of displaced workers	5.4	4	6.7
Firm size at maximum	23.9	13	51.4
Firm age at closure (years)	10.0	7.5	8.4
Above median wage	0.31		0.46
Vienna	0.31		0.46
Manufacturing	0.19	0.39	
Construction	0.16	0.37	
Sales	0.24		0.43
Tourism	0.14		0.34
Service	0.19		0.39
Firm network characteristics (per closing firm)			
Number of connected firms	175.3	55	317.9
Average size	154.4	147.5	97.8
Average above median wage	0.48		0.19
Share same industry	0.23	0.16	0.21
Share same region	0.55	0.60	0.30
Number of closing firms	27,960		
Number of connected firms	352,995		
Per closing-connected-firm pair			
Individuals with links	1.98	1.00	4.59

Notes: Sample includes firms closing in the years 1980 to 2007. Firm characteristics are measured at quarterly dates. The firm network for each closing firm consists of a set of connected firms in which former coworkers of the displaced individuals are employed at the firm-closure date. For the share of connected firms in the same industry, industries are defined at the two-digit level. Regions are defined at the level of 35 NUTS-3 districts. "Average above median wage" means that the average worker receives a wage that is above the median in the distribution of average wages among all firms. NUTS, Nomenclature of Territorial Units for Statistics.

the past five years, however, the networks will only partially overlap. Colors in the graph (viewable in the online version of this article) represent the gender of displaced workers and network members. The figure suggests the presence of gender segregation in networks, as some of them consist predominantly of men or of women.

Closing Firms and Firm Networks

At the firm level we construct networks by linking each closing firm to a network of connected firms, which builds on the individual-level former-coworker networks. In particular, we define the set of connected firms as the firms in which the former coworkers of displaced individuals are employed at the closure date. One way to think of the set of connected firms is as a proxy of the local labor market, which offers new job opportunities to the displaced worker. Based on this definition our set of 27,960 closing firms is connected to 352,995 firms that span a large fraction of the overall market.

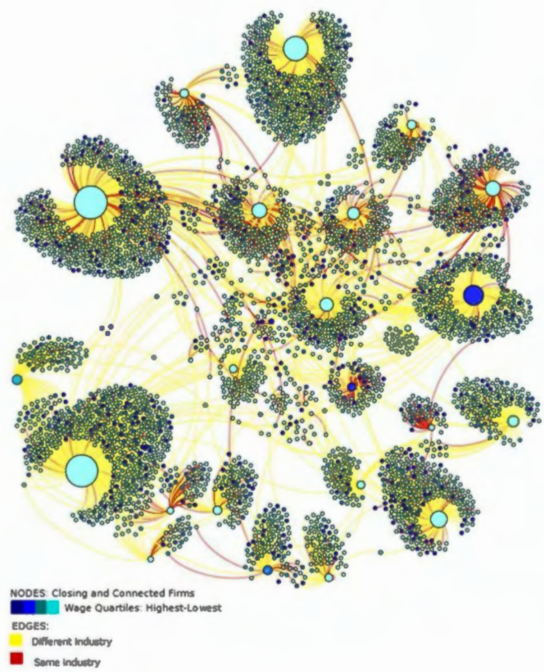
Table 2 presents the main characteristics of closing firms and their networks of connected firms. As mentioned above, closing firms in the ASSD are fairly small. Among all firms who lay off at least two workers in the closing quarter, the average number of displaced workers is 5.4 and the median is 4 workers. During their lifetime, these firms, too, were not large. In the quarter with its maximum size, the average closing firm employed 24 workers, and the median firm employed 13. On average, closing firms stayed in the market for 10 years. Closing firms also pay low wages; in the quarter of firm closure only 31% of firms pay average wages above the median among all firms in the market. Of closing firms, 30% operated in Vienna and they are fairly equally distributed across industries. Because of the seasonal nature of the construction and tourism sectors in Austria, we later check whether our results are robust to excluding these industries. (See Table A.6 in the Online Appendix.)

Next, we turn to the firm networks of closing firms. On average a closing firm has former coworker links to 175 connected firms; the median number of connected firms is 55. The average size of connected firms is much larger than the size of closing firms and 48% of connected firms pay above median wages to their average employees. Of note, firm networks are not segregated by industries, but the typical firm network spans a variety of industries. On average a closing firm is linked to 27.7 connected firms in the same industry, the median is 7. This finding suggests that on average only about one-third of the links from the closing to connected firms are among firms in the same two-digit industry. At the regional level, firm networks are slightly more segregated with about 55% of linked firms operating in the same region as the closing firm.[9] At the level of pairs of closing and connected firms, there are on average two displaced workers with links to former coworkers who are employed in the connected firm at the displacement quarter.

Figure 2 shows an example of a firm network. The figure is based on a random subsample of 60 firms that closed in the year 2000. At the center of each network we see the closing firms, and edges represent links to connected firms. The color (viewable in the online version of this article) of the links represent industry connections: a red edge means that the pair of closing and connected firms is in the same industry; a yellow edge denotes that the industries differ. The nodes are colored by the wage quartiles of the firms, with a lighter blue color representing a lower quartile firm. The small sample indicates that closing firms are mostly low-wage firms, though there are more high-wage firms with darker colors among the connected firms. If we compare the network structure between Figure 1 and Figure 2, it appears that multiple links from one connected firm to several closing firms are more prevalent within the firm network than in workers' networks.

[9]This value is based on the three-digit Nomenclature of Territorial Units for Statistics (NUTS) regional classification, which covers approximately 30 regions.

Figure 2. Firm Networks



Notes: The figure is based on a random sample of 60 firms closing in the year 2000. At the center of each network are the closing firms; edges represent links to connected firms. The color of the edge represents industry connections: A red edge means that the pair of closing and connected firms are in the same industry, while a yellow edge represents different industries. Nodes are colored by the wage quartiles of the firms, with a lighter blue representing a lower-quartile firm. (Colors are viewable in the online version of the article.)

Job-Search Outcomes

Descriptive statistics of job-search outcomes of displaced workers are shown in Table 3. Approximately 85% of the displaced workers in our sample find a new job within one year after the displacement date. The average time to find a new job is 83 days, censored at 365 days, whereas the median is 2 days. This finding reflects the fact that not all displaced workers are out of employment after the layoff. About 47% transit to a new job immediately after leaving the closing firm and 33% of displaced workers are registered as unemployed.

To examine job-search outcomes in more detail, we focus on the subset of successful job seekers who find a job within the first year after job displacement. The average time between displacement and the start of the new job is 38 days for this group, and more than half of successful searchers find a new job immediately. On average, the change in log wage between the pre- and post-displacement jobs is close to zero, but some variation exists. In comparing pre- and post-displacement industries and regions, we find that approximately 50% of the workers find new jobs in the same

Table 3. Job-Search Outcomes

	Mean	*Median*	*Std. Dev.*
All job seekers (N = 151,432)			
Find new job in one year	0.86		0.34
Time to next job in days (censored at 365)	83.19	2	131.32
New job immediately	0.49		0.50
Unemployed	0.33	137	0.47
Links to firm network			
Number of connected firms	373.8	137	655.9
Number of connected firms with link	58.2	22	110.7
Share of connected firms with link	0.40	0.24	0.37
Hired by connected firm	0.21		0.40
Successful job seekers (N = 130,477)			
Time to next job in days	37.93	1	72.20
Log wage gain	0.009	0.015	0.301
New job in same industry	0.52		0.50
New job in same region	0.80		2.83
New job in old firm	0.07		0.25
Links to firm network			
Number of connected firms	383.0	150	636.8
Number of connected firms with link	60.7	24	110.7
Share of connected firms with link	0.39	0.24	0.36
Hired by connected firm	0.24		0.43
Hired by connected firm with link	0.19		0.39

Notes: Sample includes workers displaced from firm closures in 1980 to 2007. Successful job seekers are defined as displaced workers who find a new job within 365 days. A job in an old firm refers to a firm in which the displaced worker was employed during the past five years. The firm network for each closing firm consists of a set of connected firms in which former coworkers of the displaced individuals are employed at the firm-closure date. Industries are defined at the two-digit NACE level. Regions are defined at the level of 35 NUTS-3 districts. NACE, Statistical Classification of Economic Activities in the European Community; NUTS, Nomenclature of Territorial Units for Statistics.

industry and 80% find a new job in the same region. We also check whether displaced workers return to an employer for whom they had worked during the past five years, which is the case for about 7% of the sample.[10]

Next, we consider individual links to the connected firms within the firm network. We discuss the numbers for successful job searchers, but as it can be seen in Table 3 the statistics are similar for the full sample of displaced workers. On average, a displaced worker has access to a relatively large number of more than 380 connected firms via all former coworkers of the group of workers displaced by the same firm-closure event. For 60 of the 380 firms, the displaced worker is connected through a direct link to one of their own former coworkers. The share of connected firms to which the average displaced worker holds a direct link is approximately 40% of all connected firms. Finally, we look at the job matches that form within firm networks.

[10]The share of stayers, that is, contacts formed in old firms who remain in the same job until the displacement date, is very similar to the share of displaced workers returning to an old firm. Displaced workers who return to an old firm where they worked before have a higher share of stayers in their network (19%) than do workers who find a job in a new firm (8%).

We see that 24% of successful displaced workers find a new job in one of the firms that are connected to the closing firm and 19% find a new job in a connected firm to which they have a personal link.[11] These numbers suggest that referral hirings are potentially an important channel of information transmission in the coworker networks. We examine this channel more closely in the empirical analysis.

Empirical Analysis of Job Seekers

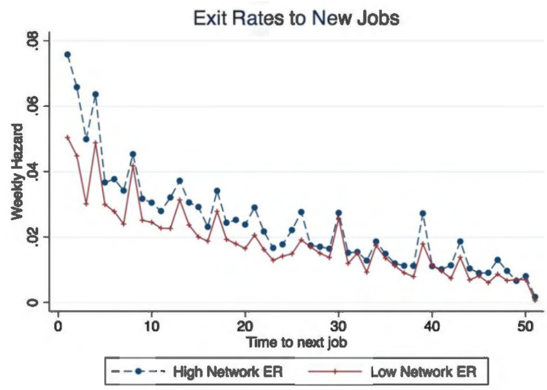
The empirical analysis proceeds in two parts to exploit both the job-search dimension and the hiring dimension of coworker networks. From the job searcher's perspective, we start by investigating the effects of network characteristics on job-finding rates and wage growth after job displacement. Our main identification strategy consists of comparing workers who were displaced from the same closing firms but who have different networks. This approach will give us a first indication of whether coworker networks have an impact on job-search outcomes. The second part of our analysis aims to narrow the channel by which information is transmitted among network members. We exploit the firm dimension of coworker networks and investigate the probability that a displaced worker finds a job in a firm that is connected to the closing firm. Therefore, we focus on the role of the displaced worker, the connected firm, and a potential link to a former coworker in the connected firm to identify the magnitude of the social tie effect.

How Do Social Networks Affect Job-Finding Rates?

The model of information transmission in social networks of Calvo-Armengol and Jackson (2004) predicts that the share of network members who are employed is crucial for the job-finding success of unemployed workers. To get a first impression of this connection in our sample, we present weekly hazard rates into new jobs over the first year after displacement in Figure 3. We specifically focus on two subsamples of the total population: displaced workers with a share of employed former coworkers in the top quartile of the distribution—which we denote as workers with a "high network employment rate"—and displaced workers with a share of employed former coworkers in the bottom quartile of the distribution, denoted as "low network employment rate." The figure shows declining patterns in weekly exit hazard rates for both groups, but—especially during the initial weeks of job search—the exit rate of individuals with a high network employment rate is clearly above the exit rate of individuals with a low network employment rate. After approximately 5 to 6 months of job search, the two

[11]The firm network does not necessarily include old firms in which displaced workers were employed before joining the closing firm. This is only the case if the network includes stayers, or if other contacts have joined one of the old firms before the displacement quarter.

Figure 3. New Job Hazards by Network Employment Rate



Notes: The graph plots weekly hazard rates into new jobs over the first year after displacement for two subsamples: displaced workers with a share of employed former coworkers in the top quartile of the distribution, denoted as "High network ER," and displaced workers with a share of employed former coworkers in the bottom quartile of the distribution, denoted as "Low network ER." ER, employment rate.

lines in the graph converge and we observe hardly any difference in exit hazard rates.

To see whether the graphic representation also holds after controlling for individual characteristics and closing-firm effects, we estimate proportional hazard models for the risk of finding a new job in the first year after displacement. These models include unrestricted daily baseline hazards at the closing-firm level; a set of individual-level covariates *X*, such as age, gender, nationality, and detailed labor market and earnings history characteristics; and variables that capture events during the five years of network formation, such as average firm size and number of employer changes. The main regressors of interest are a set of network characteristics *NW*.

Specifically, we model the discrete hazard function $h(T|X_{ij}, NW_{ij})$ as the probability that individual i displaced from firm j finds a job after T days, given that she has not exited to a job up to day $T-1$, as

$$h(T|X_{ij}, NW_{ij}) = \lambda_j(T)\exp(\alpha X_{ij} + \beta NW_{ij}) \tag{1}$$

where the baseline function $\lambda_j(T)$ specifies the closing-firm-specific hazard rates when all covariates are set to 0, and α and β are the vectors of coefficients to be estimated. Observations with durations longer than 365 days are treated as right-censored.

Table 4 presents the estimation results. Columns (1) to (5) present estimates from separate regressions that include different sets of network characteristics.[12] All models control for log network size to account for network heterogeneity in terms of the number of contacts. After controlling for

[12]A table with a full set of covariates is available on request.

Table 4. Effect of Network Characteristics on Job-Finding Rates

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Log network size	0.016	0.009	0.008	0.008	0.008
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Share of network members					
Employed	0.195	0.109	0.071	0.097	0.099
	(0.028)	(0.032)	(0.034)	(0.032)	(0.034)
Employed in same industry		0.134	0.136	0.133	0.131
		(0.025)	(0.025)	(0.025)	(0.026)
Employed at net hiring firms			0.086		
			(0.021)		
Employed at net hiring firms in two quarters				0.074	
				(0.029)	
Employed at above-median-wage firms					0.017
					(0.022)
Observations	151,432	151,432	151,432	151,432	151,432

Notes: Estimation results from Cox regressions in which the dependent variable is the hazard to a new job in days. Standard errors are in parentheses and clustered at the closing-firm level. The estimation sample includes workers displaced from firm closures in 1980 to 2007. In each column we add a different measure of the network employment rate, as indicated. All specifications control for the following covariates: gender, age (quintiles), marital status, Austrian nationality, education (5 groups), blue-collar occupation, tenure in last job (quintiles), employment days in past two years, days employed in past five years (quintiles), days employed in past 15 years (quintiles), days claiming unemployment insurance (UI) in past three and past five years, wage before job loss (quintiles), number of employers in past five years, average firm size over past five years (quintiles). All specifications allow for closing-firm-specific baseline hazards.

average firm size and employment turnover of displaced workers during the five years of network formation, we find that larger networks lead to faster job take-ups. The coefficient in the first specification indicates that an increase in network size by one standard deviation increases the job exit rate by about 3%. After controlling for additional network characteristics, the size effect drops to about half in columns (2) to (5).

In line with the graphic results from Figure 3, the share of former coworkers who are employed in the displacement quarter has a large and significant impact on the job-finding rate. The magnitude of the effect in column (1) implies that a one standard deviation increase in the share of employed former coworkers increases the exit rate to jobs by about 4%. This result is similar in magnitude to the effect reported by Cingano and Rosolia (2012), but somewhat smaller than the IV estimates of Glitz (2017).

The remaining model specifications in Table 4 include variables that represent the types of firms in which former coworkers are employed. Column (2) controls for the share of former coworkers who are working in firms operating in the same industry as the closing firm. It turns out that former coworkers in same-industry firms are almost twice as effective—compared to other employed coworkers—in helping their former coworkers find new jobs.

The next specification in column (3) takes into account demand-side factors from the firms in which former coworkers are employed. Social contacts in expanding firms might be more helpful for displaced workers because these firms typically have vacancies. This intuition is confirmed by the regression coefficient. The share of former coworkers employed in net hiring firms—defined as firms that are growing in the quarter of job displacement—further increases the exit rate to new jobs. Column (4) examines whether this effect also holds for the share of former coworkers who are employed in firms that were growing over the two last quarters before displacement to ensure that the hiring of a former coworker is not the only reason for the employment growth in these firms.[13] As the estimated magnitude of the coefficient remains the same and is statistically significant, we conclude that former coworkers employed in expanding firms are potentially an important source of information about vacancies in their firms.

The final specification in column (5) examines the effect of former coworkers who are employed in firms that pay above-median wages to their average male employees. Here the coefficient is small and insignificant, and we do not observe an impact on the job-finding rate.

The Effects of Network Characteristics over the Jobless Spell

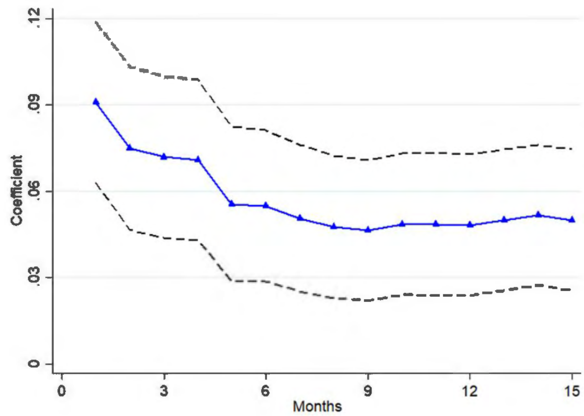
We have seen in Figure 3 that the gap in job-finding rates narrows over the jobless spell between individuals with high and low shares of employed contacts. Is this time pattern driven by dynamic selection on observed characteristics or are network contacts more effective in the earlier stages of job search? To address this question we first estimate hazard rate models that take into account changes in network characteristics over time. The specifications in Table 4 are based on network characteristics measured in the displacement quarter. For job seekers who are still out of work for a longer period after displacement, however, network characteristics at a later date may be more relevant. Online Appendix Table A.1, therefore, presents results from hazard models that allow for time-varying network characteristics in the first quarters after job displacement. Qualitatively and quantitatively, these results do not differ from the estimations with fixed network characteristics.

Second, we estimate a series of linear probability models, for which the dependent variable is an indicator equal to 1 if the individual finds a job within n months, with $n \leq 15$. Figure 4 presents the coefficient estimates and confidence intervals on the network employment rate for specifications with the same set of covariates as column (1) in Table 4.[14] The pattern in

[13]Eliason et al. (2017) found that job displacements in connected firms have a positive impact of firm growth in future periods. Our measure of firm growth in the connected firm refers to the period prior to displacement.

[14]Table A.2 in the Online Appendix presents results from a full set of regressions for the probability of finding a new job within three months. The coefficient from the specification in column (1) implies that a one standard deviation increase in the share of employed network members increases the probability of finding a job within three months by 1.3 percentage points from a base mean of 72%.

Figure 4. Effect of Networks on Probability of Finding a Job over Job-Search Duration



Notes: The graph plots the coefficients with confidence intervals of share of employed contacts in networks in the estimations of probability of finding jobs over job-search duration. The coefficient is the highest for the probability of finding a job in the first months after the job loss and declines over time.

the estimated coefficients confirms the impression from gaps observed in the descriptive exit rates. The share of employed network members has the strongest impact on job-finding rates in the first months after job displacement. Thereafter it gradually declines and stabilizes after approximately six months. This finding suggests that after this period the positive impact of network characteristics on job-finding rates is more or less exhausted. Social contacts thus seem to lead to jobs with highly desired characteristics, rather than providing the last resort for job seekers (Loury 2006).[15]

In a companion paper based on the same data and network definitions, Nimczik (2014) introduced link intensity as a network characteristic. His results based on weighting network contacts by the time spent in the same workplace together with the displaced worker implied that short-time contacts are most effective for increasing job-finding rates. This finding is in line with the common observation that weak ties have a disproportionately large impact on information transmission (see Granovetter 1973).

Robustness Checks

In the Online Appendix we present several additional tests for the robustness of our results. First, we check robustness with respect to the network definition. We have mentioned above that on average 61% of all former-coworker contacts were formed in the closing firm. To assess whether these contacts are driving our results, we modify the network definition and first exclude all former coworkers who were contacted during the final year

[15]This finding does not confirm Bentolila, Michelacci, and Suarez et al. (2010), who compared jobs formed by social contacts to all other jobs and showed that contacts reduce unemployment duration but they are associated with wage discounts.

before job displacement, and second, we exclude all former coworkers from the job spell prior to displacement. Results are shown in Online Appendix Tables A.3 and A.4. Note that our main findings are very robust to the network definition. Coefficient estimates in Table A.3 are almost identical with Table 4 and results for the network excluding all former coworkers from the closing firm are slightly stronger than those with the full network definition. If we exclude all former coworkers contacted in the closing firm from the network, the sample is reduced to displaced workers with more than one job spell over the past five years. In addition, our estimation strategy requires that we observe at least two displaced workers per closing firm.

Next, we check the impact of stayers on job-finding rates. Stayers are former coworkers from old firms who still hold the same job when their contact gets displaced. These stayers could help their displaced former coworker to get re-hired by the old firm. We include the share of stayers in the network in the specifications estimating the effects on job-finding rates to see whether they are driving our main results. Online Appendix Table A.5 shows that, as expected, the share of stayers has a positive impact on job-finding rates across all specifications. But the overall effect of the network employment rate remains strong and significant. The share of stayers is, by construction, strongly correlated to the share of former coworkers employed in the same industry, which is reflected by the insignificant coefficients on this variable in Online Appendix Table A.5. An important question concerns the motives for a displaced worker to return to an old firm, where she worked before displacement. Is this move driven by firm characteristics, such as firm-specific human capital acquired during previous employment, or is it driven by personal contacts through former coworkers. The positive impact of the share of stayers on job-finding rates suggests that the second mechanism is important. But our setup does not allow us to draw causal conclusions as unobserved workplace characteristics might be driving both the probability that former coworkers stay and the probability that former employees return.

Because of the seasonal nature of the Austrian labor market, it is challenging to distinguish true firm closures from seasonal fluctuations in highly seasonal industries such as construction or tourism based on our data-driven definition. We therefore check whether the main results are robust to excluding firm closures in the construction, hotel, and agriculture sectors (see Online Appendix Table A.6). We find that our results are robust to the exclusion of seasonal industries. Second, because we allow contacts to form in firms with up to 3,000 employees, some of the displaced workers in our sample have very large networks. To check for the sensitivity of our results with respect to very large networks, we present specifications for subsamples, in which we restrict the maximum network size to 1,000 and to 500. Alternatively, we restrict the size of the average size firm in which the displaced worker was employed during the past five years before displacement to less than 100. Table A.7 in the Online Appendix shows that these

Table 5. Wage Growth: Effect of Network Characteristics

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Log network size	0.006	0.005	0.005	0.005	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Share of network members					
Employed	0.026	0.013	0.007	0.012	–0.015
	(0.011)	(0.012)	(0.013)	(0.012)	(0.014)
Employed in same industry		0.020	0.020	0.020	0.012
		(0.010)	(0.010)	(0.010)	(0.010)
Employed at net hiring firms			0.014		
			(0.009)		
Employed at net hiring firms in two quarters				0.008	
				(0.012)	
Employed at above-median-wage firms					0.052
					(0.009)
Observations	130,477	130,477	130,477	130,477	130,477

Notes: Estimation results from linear regressions in which the dependent variable is the difference in log wages between the last job and the new job. The sample is restricted to workers displaced from firm closures in 1980 to 2007 who find a new job within 365 days of firm closure. Standard errors in parentheses and clustered at the closing-firm level. In each column we add a different measure of network employment rate, as indicated. All estimations include closing-firm fixed effects. For a list of additional covariates, see Table 4.

restrictions exclude only few observations from the total sample and the main results remain unchanged.

How Do Social Networks Affect Wages in the New Jobs?

After having established the importance of network characteristics for the job-finding rate, we investigate whether coworker networks also have an impact on characteristics of the new jobs. We focus on the sample of successful job seekers—who find a new job in the first year after displacement—and compare their pre- and post-displacement wages. Specifically, we estimate the following regression model:

$$y_{ij} = X_{ij}\alpha + NW_{ij}\beta + \gamma_j + u_{ij} \tag{2}$$

where y_{ij} denotes the difference in log wages before and after displacement and γ_j controls for closing-firm fixed effects. The effects of individual and network characteristics are given by the parameters α and β. The restriction to workers who find a new job within one year after displacement applies to approximately 14% of the full sample. We have shown in the previous section that the impact of network characteristics on job-finding rates die out after about half a year. Thus the restriction to successful job seekers should not lead to any bias.

We present estimation results in Table 5. In contrast to the effects on job-finding rates, network characteristics have relatively small and often insignificant effects on wage growth. Increasing the network employment rate or the share of former coworkers employed in the same industry by one standard deviation in specifications (1) and (2), respectively, results in an additional wage increase by approximately 0.5 percentage points. The most important determinant of wage growth is the share of network members who are employed in above-median-wage firms. Increasing this share by one standard deviation raises the average wage gain by one percentage point. This result suggests that former coworkers who are now employed in higher-paying firms are better sources of job information because either they provide information about attractive jobs they did not take themselves, or they generate job referrals (Schmutte 2015).

Heterogeneity of Network Effects on Search Outcomes

In this section, we examine whether network effects are heterogeneous for distinct groups of displaced workers. We are particularly interested in two questions. First, we want to examine the sources for heterogeneity. Do the effects of social networks differ because of individual traits or because individuals in distinct groups form separate networks? Second, we investigate whether former coworkers with similar characteristics have stronger impacts on the job-finding rate. We start with a detailed heterogeneity analysis by gender and then discuss heterogeneity along other dimensions.

Heterogeneity by Gender

To address the first question, we start with estimating hazard rate models similar to Equation (1) separately for men and women. Table 6, panel A, presents two model specifications for the male and female samples. Comparing columns (1) and (2), we see that the effects of network characteristics differ by gender. Male displaced workers are more likely to benefit from employed former coworkers than females. Is this because men rely more on the help of former coworkers when searching for jobs or is it because they have different networks? To answer this question we use a probability weighting strategy and reweight the female sample such that average network characteristics in the reweighted female sample are equal to average network characteristics among males (DiNardo, Fortin, and Lemieux 1996).[16] Column (3) shows estimates based on the reweighted female sample that are very close to the coefficient estimates for the male sample. This result indicates that if women had networks with similar characteristics as males their job-finding rates would be similarly affected. Columns (4) to (6) repeat the estimations for a model that controls for additional network characteristics.

[16]Network characteristics included in the balancing procedure are: network size, number of network members who are female, Austrian nationals, blue-collar workers, members of four education and four age groups, the share of employed network members, share of network members employed in the same industry, in hiring firms, or in high-wage firms.

Table 6. Effects of Network Characteristics by Gender

	Male	*Female*	*Female, weighted*	*Male*	*Female*	*Female, weighted*
Panel A: Job-finding rate	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Log network size	0.017	0.017	0.015	0.011	0.009	–0.000
	(0.006)	(0.011)	(0.011)	(0.007)	(0.012)	(0.012)
Share of network members						
Employed	0.222	0.147	0.234	0.114	0.025	0.028
	(0.038)	(0.051)	(0.071)	(0.046)	(0.059)	(0.086)
Employed in same industry				0.091	0.148	0.251
				(0.034)	(0.045)	(0.063)
Employed at net hiring firms				0.105	0.075	0.098
				(0.029)	(0.038)	(0.056)
Observations	88,666	62,766	62,766	88,666	62,766	62,766
Panel B: Wage growth	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Log network size	0.002	0.009	0.011	0.002	0.006	0.007
	(0.003)	(0.004)	(0.006)	(0.003)	(0.004)	(0.006)
Share of network members						
Employed	0.025	0.016	–0.007	–0.008	–0.028	–0.062
	(0.015)	(0.020)	(0.034)	(0.020)	(0.025)	(0.040)
Employed in same industry				–0.008	0.034	0.067
				(0.013)	(0.021)	(0.031)
Employed at above-median-wage firms				0.055	0.042	0.015
				(0.013)	(0.018)	(0.027)
Observations	78,110	52,367	52,367	78,110	52,367	52,367

Notes: In panel A, estimation results from Cox regressions in which the dependent variable is the hazard to a new job in days. Standard errors are in parentheses and clustered at the closing-firm level. The estimation sample includes male and female workers displaced from firm closures in 1980 to 2007 in separate columns. In panel B, estimation results from linear regressions in which the dependent variable is the difference in log wages between the last job and the new job. The sample is restricted to male and female workers displaced from firm closures in 1980 to 2007 who find a new job within 365 days of firm closure in separate columns. Columns (3) and (6) in both panels include the estimations on the female sample with weights estimated to equalize the mean network characteristics of women and men. Standard errors are in parentheses and clustered at the closing-firm level. In each column we add a different measure of network employment rate, as indicated. All estimations include closing-firm fixed effects. For a list of additional covariates, see Table 4.

In this case, the interpretation is less clear. Women benefit more from former coworkers who are employed in the same industry than males, and even more so if they have networks with more male characteristics. For men, on the other hand, all types of employed network members matter. The share of former coworkers employed in expanding firms has a positive impact of roughly the same magnitude on job-finding rates of both men and women. Reweighting females makes the genders even more similar in this respect. Panel B adds the analysis of wage growth by gender. Here we find fewer significant coefficient estimates. The results do not suggest that female wage outcomes would benefit if their networks were similar to the male networks. The strongest impact of wage growth for both groups is attributable to former coworkers who are employed in high-wage firms. But

Table 7. Job Finding: Effect of Similar Characteristics

	Female (1)	*Male* (2)	*Blue collar* (3)	*White collar* (4)	*Austrian* (5)	*Non-Austrian* (6)
Log network size	0.027	0.026	–0.002	0.052	0.033	–0.034
	(0.016)	(0.009)	(0.010)	(0.015)	(0.009)	(0.026)
Share of network members						
Employed in same group	0.047	0.048	0.020	0.080	0.059	0.005
	(0.012)	(0.012)	(0.012)	(0.013)	(0.021)	(0.020)
Employed in opposite group	0.055	0.033	0.014	0.087	0.023	0.003
	(0.016)	(0.012)	(0.013)	(0.016)	(0.010)	(0.026)
Unemployed in same group	0.031	0.004	–0.009	0.040	0.024	–0.010
	(0.017)	(0.011)	(0.014)	(0.014)	(0.021)	(0.023)
Observations	62,766	88,666	80,604	70,828	138,010	13,422

Notes: Estimation results from Cox regressions in which the dependent variable is the hazard to a new job in days. Standard errors are in parentheses and clustered at the closing-firm level. The columns present estimation results for different subsamples of workers displaced from firm closures in 1980 to 2007. "Employed in same group" refers to the share of network members from the same group as the column head who are employed at the time of firm closure. Employment share variables are standardized with a mean of 0 and a standard deviation that is equal. All estimations allow for closing-firm-specific baseline hazards. For a list of additional covariates, see Table 4.

if women's networks were more similar to men's they would gain less. Overall, we can conclude that differences in network effects are to a certain extent driven by the distinct networks both genders establish in the five years prior to job displacement. But the differences in search outcomes seem to be driven also by factors that are directly attributable to gender.

Second, we turn to the issue of homophily to examine whether it is important to have social contacts who are of the same type as oneself. We estimate hazard rate models with controls for log network size and share of employed network members. In particular, we divide network members into four categories: employed network members of the same population group, employed network members of the opposite population group, non-employed network members of the same population group, and non-employed network members of the opposite population group; the latter serves as the reference group. Estimation results by gender are shown in columns (1) and (2) of Table 7. To facilitate comparison of the estimated effects across columns and across groups of network members, we standardize covariates such that coefficient estimates correspond to the effects of a one standard deviation increase in the independent variable. The first column reports the result for female displaced workers: Females benefit from employed female or male former coworkers to a similar extent. An increase in employed former coworkers of either gender by one standard deviation increases the job-finding rate by 5 to 6%. Even non-employed female network members are more important for the job-finding success of women than non-employed male network members. In comparison, males, shown in column (2), mostly benefit from employed male former coworkers, while employed female network members are slightly less important.

Non-employed contacts of either gender do not have any effect on the job-finding rate of male displaced workers.

Heterogeneity by Other Characteristics

How important are differences in network effects on search outcomes among other groups and could they be equalized by changing networks? We look at differences by occupation, for blue- and white-collar workers, by citizenship, and by age groups. Online Appendix Tables A.8 to A.10 present results for effects on job-finding rates and Tables A.11 to A.13 present corresponding results for wage growth. Overall, these results indicate that heterogeneity between groups is primarily due to group-level differences and not due to differences in network characteristics. Differences in the effects of the network employment rate on job-finding rates across groups are mostly explained by the differences in the effectiveness of varying types of employed former coworkers. For example, white-collar workers mainly benefit from employed network members in the same industry, whereas blue-collar workers benefit more from network members employed in expanding firms. Similarly, employed network members in the same industry are only effective in generating job offers for older workers, but not for the young.

When we compare the effects of network characteristics on wage growth, we find much less heterogeneity across groups. The important and extremely robust finding here is that network members who are employed in high-wage firms generate high-wage offers for all types of workers. The coefficients on this variable are significant in all specifications and of roughly the same magnitude across all groups; they change very little with reweighting. Again, this finding is in line with Schmutte's (2015) conclusion that higher-paying firms are better sources of job information. Does the similarity to network members matter? We compare network effects by occupation in columns (3) and (4) of Table 7 and note that employed former coworkers of the same type are not more important in generating job offers for either group. The results confirm that the impacts of employed former coworkers on the job-finding rates of white-collar workers are much stronger than for blue-collar workers. An increase in the share of employed former coworkers by one standard deviation corresponds to a shift in the hazard rate by 8 to 9% for white-collar workers, but to an increase of only approximately 2% for blue-collar workers.

Cutting the sample by nationality reveals that job information seems to be primarily traded among Austrian workers. The job-finding rates of displaced workers with Austrian nationality are more than twice as highly correlated to the share of employed Austrian former coworkers than to employed former coworkers of other nationalities. For displaced workers with non-Austrian nationality, we do not find any significant network effects. This sample is rather small and heterogeneous, however, as it includes all individuals with non-Austrian nationality.

Table 8. Job Finding: Effect of Similar Age Groups

	Below 29	*29 to 36*	*36 to 43*	*Above 43*
Log network size	0.078	–0.001	0.019	–0.009
	(0.031)	(0.017)	(0.016)	(0.017)
Share of network members				
Employed in same group	0.060	0.021	0.013	0.054
	(0.018)	(0.011)	(0.011)	(0.014)
Employed age < 29		0.022	0.048	0.084
		(0.014)	(0.015)	(0.019)
Employed age 29 to 35	0.002		0.019	0.036
	(0.012)		(0.012)	(0.014)
Employed age 36 to 43	0.020	0.012		0.041
	(0.012)	(0.011)		(0.014)
Employed age > 43	0.022	0.013	0.024	
	(0.015)	(0.013)	(0.012)	
Unemployed in same group	0.014	0.001	0.006	0.042
	(0.019)	(0.013)	(0.014)	(0.018)
Observations	36,030	35,244	38,404	41,754

Notes: Estimation results from Cox regressions in which the dependent variable is the hazard to a new job in days. Standard errors are in parentheses and clustered at the closing-firm level. The columns present estimation results for different subsamples of workers displaced from firm closures in 1980 to 2007. "Employed in same group" refers to the share of network members from the same group as the column head who are employed at the time of firm closure. Employment share variables are standardized with a mean of 0 and a standard deviation that is equal. All estimations allow for closing-firm-specific baseline hazards. For a list of additional covariates, see Table 4.

Table 8 reports network effects on job-finding rates by age groups. Here the results also indicate some heterogeneity. Overall, the workers in the oldest and youngest age groups seem to be most affected by the employment rate among former coworkers, whereas prime-age workers appear to be less reliant on their networks for finding a new job.

Empirical Analysis of Hiring in Connected Firms

Results so far confirm that network characteristics are strongly related to the job-search outcomes of displaced workers. In line with Cingano and Rosolia (2012) and Glitz (2017), we find that the share of employed former coworkers has a positive impact on job-finding rates. But which mechanism drives these results? Our findings provide suggestive evidence that job referrals might be an important channel, and that the type of firms in which former coworkers are employed matters. In particular, former coworkers employed in the same industry as the closing firm or employed in expanding firms have a positive impact on job-finding rates. In addition, we find wage gains in the new job for displaced workers whose former coworkers are employed in high-wage firms. Arguably, firm type should matter for search outcomes if network information leads to jobs in these expanding or high-wage firms. Alternatively, the network contacts might just be better informed about general demand-side conditions.

The next part of the analysis further examines the importance of the referral channel. We exploit the firm dimension of the coworker network and ask: What is the effect of a link to a former coworker employed at firm l on the probability that the displaced individual i is hired at l? We start by specifying the following regression model:

$$P_{i,j,l} = \beta L_{il} + \gamma_{jl} + \epsilon_{il} \tag{3}$$

where $P_{i,j,l}$ denotes the probability that individual i, displaced from firm j, is hired by firm l; L_{il} is an indicator equal to 1 if the individual has a link to a former coworker who is employed at l. Thus, β measures the network effect. To avoid spurious correlation in unobservable characteristics of the worker and the firm, which might occur if firm l is generally more likely to hire workers of i's type, we control for fixed effects γ_{jl} at the pair level of closing and hiring firms. The counterfactual analysis that identifies the network effect β thus compares two workers displaced by the same closing firm j in which one of them has a link to a former coworker employed in firm l and the other does not.

The variation in L_{il} that contributes to identification of the network effect comes from variation in connections to firm l among individuals displaced from the same closing firm j. In particular, observations that involve a hiring firm l without former-coworker ties to any of the displaced workers from j do not contribute to identification. This fact reduces the analysis to hiring probabilities within the set of connected firms. Among the connected firms, identification relies on those firms to which only a subset of displaced workers have a link. As we have seen in the summary statistics in Tables 2 and 3, ample variation in the fraction of displaced workers with a link to a connected firm exist in our data.

To make estimation of the model tractable, we apply a fixed-effects transformation suggested by Kramarz and Thesmar (2013) and applied by Kramarz and Skans (2014). In particular, we collapse Equation (3) at the closing-connected-firm level and consider the share of linked individuals displaced from closing firm j who are hired by connected firm l, $R_{j,l}^{Link}$, given by

$$R_{j,l}^{Link} = \frac{\sum_i P_{ijl} * L_{il}}{\sum_i L_{il}} = \beta + \gamma_{jl} + u_{il}^{Link}$$

and the share of non-linked individuals displaced from closing firm j, who are hired by connected firm l, $R_{j,l}^{noLink}$, given by

$$R_{j,l}^{noLink} = \frac{\sum_i P_{ijl} * (1 - L_{il})}{\sum_i (1 - L_{il})} = \gamma_{jl} + u_{il}^{noLink}$$

The difference between these two expressions determines the coefficient of interest β as

Table 9. Probability of Finding a New Job in a Connected Firm

	All	*Vienna*	*Same industry*	*Year* > *1995*	*# Layoffs* > *10*
coefficient β	0.067	0.050	0.149	0.056	0.053
	(0.003)	(0.004)	(0.009)	(0.003)	(0.005)
	24.96	12.82	15.78	17.2	9.9
$R_{j,l}^{Link}$	0.115	0.095	0.283	0.100	0.109
	(0.001)	(0.002)	(0.004)	(0.001)	(0.002)
$R_{j,l}^{noLink}$	0.047	0.045	0.134	0.044	0.056
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Ratio	2.41	2.11	2.11	2.27	1.94
Observations	5,711,461	2,299,824	1,055,871	3,491,092	2,430,651

Notes: Estimations for the probability of finding a new job in a connected firm from linear probability models. The parameter β measures the effect of having a direct link via a former coworker. Observations are pairs of closing and connected firms. For the definition of the dependent variable, see Equation (4). The columns present estimation results for different subsamples. All estimations are weighted by the number of links between closing and connected firms. Standard errors are in parentheses and clustered at the closing-firm level. Coefficients and standard errors are multiplied by 100.

$$G_{i,j} = R_{j,l}^{Link} - R_{j,l}^{noLink} = \beta + u_{il} \tag{4}$$

Ordinary least squares (OLS) estimates of Equation (4) are consistent as long as ϵ_{il} is uncorrelated with L_{il} in Equation (3), which holds true if all unobserved heterogeneity is captured by the closing-connected-firm fixed effect.

We present our estimation results in Table 9.[17] In the table we multiply all coefficients and standard errors by 100 so they can be interpreted as percentages. The first column presents the estimate of β and its components for the full sample. The parameter on the link indicator variable is estimated with high precision. A link to a former coworker in l increased the probability of being hired there by 0.067 percentage points. To interpret the magnitude of the link effect, we compare the share of linked workers who get hired, $R_{j,l}^{Link}$, with the share of non-linked workers who get hired, $R_{j,l}^{noLink}$. The ratio between the two is 2.4 for the full sample, which means that workers with a direct link are more than twice as likely to be hired by the connected firm than are similar workers without a link from the same closing firm.

To determine if the result for the overall sample is driven by certain subgroups, we repeat the estimation for various subsamples in the remaining columns of Table 9. Although the coefficient estimate of the link effect varies across groups—for example, β is higher in pairs of closing-connected firms in the same industry—the ratio between the share hired with a link and the share hired without a link remains relatively stable around a value

[17]Standard errors are clustered at the closing-firm-level. Estimations are weighted by the number of links between the closing and connected firm. Unweighted results are shown in Table A.14 in the Online Appendix.

of 2. For example, both linked and non-linked individuals have a higher probability of being hired by a connected firm in the same industry. We also confirm that the link effect does not change over time, by region, or for larger closing firms, which potentially have more variation in links across connected firms.

We next investigate whether hiring probabilities and link effects are heterogeneous by types of displaced workers or types of connected firms. Following Kramarz and Skans (2014), we extend the basic model in Equation (3) to include covariates X_i to capture individual job searcher characteristics and an interaction term between X_i and the link indicator L_{il}:

$$P_{i,j,l} = \beta^0 L_{il} + \beta^x L_{il} X_i + \delta X_i + \gamma_{jl} + \epsilon_{il} \tag{5}$$

The fixed-effects transformation to eliminate closing-connected-firm fixed effects results in the following regression equation:

$$G_{i,j} = R_{j,l}^{Link} - R_{j,l}^{noLink} = \beta^0 L_{il} + \beta^x \bar{X}_{jl}^{Link} + \delta\left(\bar{X}_{jl}^{Link} - \bar{X}_{jl}^{noLink}\right) + u_{il} \tag{6}$$

where $\bar{X}_{jl}^{Link}$denotes mean value of X_i for individuals displaced from closing firm j with links to connected firm l, and $\bar{X}_{jl}^{noLink}$ is the equivalent for individuals without links.

Table 10 presents estimation results with coefficients and standard errors multiplied by 100. Panels A1 and A2 focus on heterogeneity by worker characteristics, including the same population groups that we investigated in the job-search analysis in Tables 7 and 8. Panel A1 presents results from separate regressions that entered one covariate at a time plus the interaction with a link dummy. Panel A2 shows results from a regression model that includes the full set of worker-specific covariates simultaneously.

Note that the heterogeneity in hiring probabilities for workers with a link to the connected firm resembles our results on the job seeker's side. We find no difference in hiring probabilities by gender. Blue-collar workers, although more likely to be hired by a connected firm, do not benefit as much from a link to a former coworker as do white-collar workers. The opposite holds for workers with Austrian nationality. Comparing hiring probabilities across age groups, we confirm that direct links to connected firms are more important for older workers. Survey evidence typically finds that informal job-search methods are most widely used by individuals of low socioeconomic status (Topa 2011), such as blue-collar workers or migrants. By contrast, our results imply that the productivity of work-related networks is highest for natives, the more highly qualified, and older workers. The results in panel A2 referring to a regression with multiple covariates are consistent with those in panel A1.

Table 10, panels B1 and B2, investigate how strongly the link effects are related to characteristics of the connected firm. We estimate similar specifications as in Equation (5). But the characteristics of the connected firm do

Table 10. Probability of Finding a New Job in a Connected Firm, Heterogeneity Analysis

	Female	*Blue collar*	*Austrian*	*Age < 29*	*Age 29 to 35*	*Age 36 to 43*	*Age > 43*
Panel A1							
coefficient β^0	0.066	0.090	0.023	0.076	0.078	0.059	0.057
	(0.004)	(0.004)	(0.011)	(0.005)	(0.005)	(0.004)	(0.004)
Main effect	–0.005	0.022	–0.050	0.010	0.040	–0.013	–0.029
	(0.011)	(0.010)	(0.014)	(0.011)	(0.011)	(0.012)	(0.017)
Link interaction	0.002	–0.040	0.049	–0.030	–0.045	0.035	0.040
	(0.008)	(0.007)	(0.013)	(0.011)	(0.012)	(0.012)	(0.017)
Panel A2							
Main effect	0.002	0.021	–0.036		0.020	–0.022	–0.029
	(0.012)	(0.011)	(0.015)		(0.011)	(0.011)	(0.018)
Link interaction	–0.009	–0.044	0.032		–0.009	0.055	0.057
	(0.008)	(0.008)	(0.014)		(0.011)	(0.012)	(0.018)

	Closing and connected firms		*Connected firms*				
	Same industry	*Same region*	*High wage*	*Hiring*	*Size < 15*	*Size 15 to 90*	*Size ≥ 90*
Panel B1							
coefficient β^0	0.049	0.044	0.062	0.055	0.067	0.064	0.071
	(0.002)	(0.002)	(0.003)	0.003	(0.003)	(0.003)	(0.003)
Link interaction	0.101	0.050	0.010	0.026	0.002	0.009	–0.011
	(0.010)	(0.006)	(0.005)	0.006	(0.006)	(0.006)	(0.006)
Panel B2							
Link interaction	0.101	0.054	0.014	0.027	0.015	0.009	
	(0.010)	(0.006)	(0.006)	0.006	(0.007)	(0.007)	

Notes: Estimations for the probability of finding a new job in a connected firm from linear probability models. Observations are pairs of closing and connected firms. For the definition of the dependent variable, see Equation (6). Panels A1 and B1 present estimation results from separate regressions in which one covariate is introduced in the model at a time. Column heads denote the covariates. Panels A2 and B2 present estimation results from single regressions entering all worker characteristics or employer characteristics simultaneously. Coefficients show the main effects for covariates and the interaction between covariate and link indicator in panels A1 and A2 and they show the interaction between covariate and link indicator in panels B1 and B2. Estimations are weighted by the number of links between closing and connected firms. Standard errors are in parentheses and clustered at the closing-firm level. Coefficients and standard errors are multiplied by 100. The number of observations is 5,711,461.

not vary at the displaced worker level, thus the coefficient δ is 0 by construction. The coefficient β^x tells us if a direct link to a former coworker in a connected firm of a certain type is more effective. Panel B1 reports results from separate regressions, and panel B2 shows results from introducing all covariates simultaneously. We find that direct links to connected firms in the same industry and the same region as the closing firm are more valuable in generating jobs than are direct links to the average connected firm. This outcome means that sectoral as well as regional distance matter. The result on high-wage connected firms confirms the job-seeker analysis, namely, that direct links to high-wage firms increase the probability of being hired. We find little indication of heterogeneity by the size of the connected firm. The coefficient in the smallest firm-size group is positive and marginally significant in the joint specification in panel B2, meaning that the smallest firms are more likely to hire connected workers. Assuming that larger firms overall hire more workers, our result is in line with Eliason et al. (2017), who reported that in Sweden the share of connected hires in total hires is relatively lower in larger firms.

Conclusion

In this article we have investigated the effects of work-related social networks on the job-search outcomes of displaced workers. We implemented our definition of former-coworker networks in large-scale register data from the universe of Austrian social security registers, which provides us with very detailed network characteristics for a large sample of workers displaced from closing firms. An advantage of our setup is that we can study network effects from both the job seeker's perspective and the hiring firm's perspective. This approach allows us to gain some insights on the mechanisms through which social networks affect labor market outcomes.

Specifically, we identified three potential mechanisms in the Theoretical Background section. Our empirical evidence could be driven by the preference mechanism if displaced workers' preferences are influenced by their successful contacts and they try harder to find good jobs as well. The finding that contacts matter specifically early in the unemployment spell could be interpreted as reflecting the negative stigma of unemployment in a high-profile network. However, this mechanism is silent about how job offers are generated. We find that the type of firm in which contacts are employed matters more than just the fact that contacts are employed, which suggests that information transmission is an important component of the network effects. Job-related information may be of a more general nature if social contacts relate their experiences about good firms or favorable wage offers. But job-related information can also come through referrals. Our evidence is compatible with both types of information. We document that referrals are an important mechanism in the firm-side analysis. Generally, we find that information through social contacts generates valuable job offers, which are preferable to the outside option of remaining unemployed.

With respect to the heterogeneity of network effects, we find that work-related social contacts are most productive for more highly qualified or older individuals and natives; these groups might be more experienced in exploiting work-related contacts. Alternatively, job referrals might be a stronger signal to the employer, particularly for older workers. The heterogeneity analysis allows us to directly compare predictions from the job-seeker analysis with the firm-side analysis. In particular, we find that coworkers employed in expanding firms or in high-wage firms reduce search durations. This outcome is confirmed by the finding that hires are more likely if the link is with a former coworker who is employed in expanding firms or in high-wage firms.

A large literature documents that job displacements lead to large and persistent earnings losses for affected workers, which are particularly severe during recessions (Davis and von Wachter 2011). Our results show that individuals with good connections are protected from adverse effects, to a certain extent, especially if they manage to join one of their former coworkers in a high-wage firm.[18] Policy implications from this result are to encourage displaced workers to contact their social networks and to concentrate counselling and placement efforts on individuals with poor social connections, who may be disadvantaged by employers who favor referred applicants (DiTomaso 2013).

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[18]In a recent study using US data, Hellerstein et al. (2016) showed that residential networks also help displaced workers find jobs. Similar to our approach, they focused on network measures related to hiring rates in the residential networks of displaced workers where they also captured the labor demand in local labor markets. They studied the impact of these network measures on the re-employment of workers displaced by mass layoffs before, during, and after the Great Recession in the United States and found that the impact of networks was lower during the Great Recession compared to prior and subsequent years. They argued that the lower impact is associated with lower hiring rates in the networks during the Recession, which is consistent with the weak labor demand conditions during the Recession.

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