Coworker Networks and the Role of Occupations in Job Finding

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Abstract

Which former coworkers help displaced workers find jobs? We answer this question by studying occupational similarity in job finding networks. Using matched employer-employee data from Hungary, this paper relates the unemployment duration of displaced workers to the employment rate of their former coworker networks. We find that while coworkers from all occupations are helpful in job finding, there is significant heterogeneity in effects by occupation skill-level. For workers in low-skill jobs, coworkers in the same narrow occupation as the displaced worker are the most useful network contacts. For workers in high-skill jobs, coworkers from different occupations help the most.

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A well-established body of research finds that social networks play an important role in helping people find jobs (Ioannides and Datcher Loury, 2004; Topa, 2011). Furthermore, network links in various social contexts have been shown to be helpful in the job search process, including family members, residential neighbors, people from a shared ethnic background, roommates, classmates, and former coworkers.[1] However, little is known regarding which links within a given social network are most valuable for job seekers. Presumably, some neighbors, co-ethnic contacts, or coworkers possess more relevant information about the job seeker or available opportunities than others.

This paper explores which links in a social network are relevant in job finding for unemployed individuals, focusing on networks formed by individuals' former coworkers. Specifically, we examine the role of former coworkers by occupational similarity in helping the unemployed find jobs. Coworkers working in a similar occupation as an unemployed individual may be more relevant in job finding than coworkers in unrelated fields. To assess the role of occupation-specific coworker networks, we use administrative matched employer-employee data from Hungary, which track workers' occupations over time. Using these data, we construct coworker networks and measure their occupational similarity to unemployed job seekers.

We first establish that having a stronger coworker network, defined as a worker's former coworkers having a higher employment rate, reduces unemployment duration. A 10 percentage point increase in the employment rate of an unemployed worker's coworker network decreases unemployment duration by 4.0 percent. Next, we examine whether this effect is driven by former coworkers who worked in similar occupations to the job seeker, compared to those who worked in different occupations. A priori, the expected direction of these effects is ambiguous. On one hand, coworkers who worked in a different occupation than the job seeker may be more valuable in job finding if they are less likely to have redundant information or

[1]Family members: Kramarz and Skans (2014). Residential neighbors: Bayer, Ross, and Topa (2008); Hellerstein, Kutzbach, and Neumark (2019). Same ethnic background: Munshi (2003); Dustmann, Glitz, Schönberg, and Brücker (2016). Roommates: Sacerdote (2001). Classmates: Kramarz and Thesmar (2013); Zimmerman (2019); Zhu (2022).

connections (Granovetter, 1973; Zenou, 2015). On the other hand, coworkers who worked in the same occupation as the job seeker may be more valuable if they are more knowledgeable about the worker's skills or other attributes that are valued on the job market, or if have stronger ties with the workers (Gee, Jones, and Burke, 2017; Eliason, Hensvik, Kramarz, and Skans, 2022). Assessing the role of coworker network strength by occupational similarity brings us closer to understanding the mechanisms through which workers use networks to find jobs.

One key challenge in measuring network effects is that individuals do not choose friends and acquaintances randomly. In the context of this study, unobserved characteristics that lead individuals to be in the same coworker network may affect both network employment rate and an individual's own unemployment duration. To measure the causal effect of the worker's network employment rate, following the approach of Cingano and Rosolia (2012), we first restrict our analysis to comparisons of unemployed individuals who were displaced by the same firm closure. This restriction provides an exogenous source of job separation, addressing the concern that separation decisions are correlated with network strength. Since workers likely sort into firms along unobservable characteristics, this approach also eliminates time-invariant unobserved traits across networks. Thus, identification comes from variation in the sets of individuals that co-displaced workers worked with in the five-year window prior to displacement, both from the firm of displacement and from previous workplaces. Co-displaced workers are not included in each others' networks. Next, we rule out heterogeneous effects among workers at closing firms that may affect both former coworker network characteristics and unemployment duration. We control for a number of pre-displacement labor market outcomes, such as wages, wage growth, employment history, industries and occupations during a period of time leading to eventual displacement. These controls ensure that identification of network effects comes from comparing two very similar workers who are displaced from the same firm at the same time, exploiting variation in the employment rate of the different sets of coworkers the two workers worked with in the years leading up to displacement.

Results indicate that in aggregate, only coworkers from the same narrow occupation are helpful for job finding. A 10 percentage point increase in the network employment rate of former coworkers from a different occupation (defined as coworkers who did not work in the same four-digit occupation as the displaced worker) reduces unemployment duration by 2.6 percent. For coworkers from the same four-digit occupation, the effect is 1.8 percentage points higher in magnitude. Further analyses show that the network employment rate of same-occupation coworkers in job-finding are driven exclusively by workers in occupations that require no more than a primary level of education. For workers in occupations requiring at least a high school level of education, network employment rate of same-occupation workers has no effect on unemployment duration. However, for workers in these occupations, an increase in the employment rate of former coworkers from different occupations does significantly reduce unemployment duration for these displaced workers. The precise mechanism through which these heterogeneous effects operate are outside the scope of this paper. One potential explanation is that workers in high-skilled jobs may be qualified for a wider set of jobs than low-skilled counterparts, consistent with research indicating there are heterogeneous displacement costs in the transfer of workers' skills across sectors (Yi, Mueller, and Stegmaier, 2017). Another possibility is that high-skilled workers may have more information about job openings in their field at baseline.

This paper relates to economic research in both labor market networks and the role of occupations in job search. It contributes to studies looking at the role of coworker networks in job finding. Multiple prior studies have established that prior coworkers aid workers in the job finding process (Cingano and Rosolia, 2012; Hensvik and Skans, 2016; Glitz, 2017). This paper adds to studies aiming to expand our understanding of *which* coworker links are useful. Saygin et al. (2021) also look at differences in networking between blue-collar and white-collar workers, finding that former coworker networks are much stronger for white-collar workers. Glitz (2017) also looks at heterogeneity by network sector, finding that former coworkers who work in a different industry than the one in which a displaced worker was last employed are more effective in helping a displaced worker out than former coworkers working in the same industry. Eliason et al. (2022) focus on assessing the match between high-/low-wage workers to high-/low-wage firms, finding that social networks facilitate the pipeline of high-wage workers to high-wage establishments through their high-wage network connections.

We contribute to this literature in exploring the role of occupational similarity in job networks. Occupation plays an important policy role in the job search process, and studies have shown that there is significant occupational mismatch in terms supply of job seekers and demand for jobs across jobs (Şahin, Song, Topa, and Violante, 2014; Patterson, Şahin, Topa, and Violante, 2016). A well-established literature indicates this is a significant challenge to overcome, given information frictions across occupations and that learning information about occupations is an important part of the job search process (Miller, 1984; Neal, 1999; Gibbons and Waldman, 1999; Gibbons, Katz, Lemieux, and Parent, 2005; Papageorgiou, 2014; Groes, Kircher, and Manovskii, 2015). Public policy echoes these sentiments, as evidenced by the fact that most OECD countries require individuals to accept jobs beyond their occupation of previous employment as a condition of receiving benefits (Venn, 2012). Additionally, Belot, Kircher, and Muller (2018) show that broadening the set of occupations over which job seekers search increases interviews workers receive. We contribute to this literature by analyzing the role of occupation-specific coworker networks and uncovering significant differences in results across occupations by skill level requirement. Furthermore, our findings help to reconcile and shed light on some seemingly contradictory existing findings. In their study of workers in two Italian provinces, Cingano and Rosolia (2012) find that workers with the same broad skill level (blue vs. white collar) as a displaced worker are more useful in job finding. In contrast, studying a universal administrative data set of German workers, Glitz (2017) finds that coworkers with a different education level are significantly more helpful in reducing unemployment for workers.

Notably, we find that for workers in high-skill occupations, coworkers from different occupations are the ones who instrumental in finding jobs, while the opposite is true for workers in low-skill occupations. These findings reflect potential differences in what kind information is valuable towards workers and/or employers in different jobs. Higher-skilled workers may benefit coworkers from different occupations since they have skills that may be transferable to other occupations, while this is less true for low-skilled workers. This distinction has important implications for how we think of the efficacy of social networks. As an example, an individual who works in an information technology (IT) position at a hospital, where most of her coworkers are not in IT, will likely have a different network strength than an IT worker at an IT firm with most coworkers in IT, even if both have the same number of coworkers. Furthermore, this distinction may depend on whether a worker is an IT worker (high-skilled job) versus if they are a food service worker (low-skilled job).

Moving forward, Section 1 introduces a conceptual framework for quantifying the impact of coworker networks on job finding. Section 2 discusses the empirical strategy to identify the effect of the network strength by occupational similarity on a displaced worker's unemployment duration. Section 3 introduces the data and shows relevant descriptive statistics. Section 4 presents the main results of the analysis. Finally, Section 5 discusses the implications of our findings.

1 Conceptual Framework

We start by laying out a conceptual framework for our paper. In this economy, firms can hire workers through two channels: (i) an open labor market, or (ii) the networks of their incumbent employees. Our paper focuses on this second channel. We remain agnostic as to the exact mechanisms through which information transmission through networks occur.[2]

Suppose there is an unemployed individual. This individual can meet hiring firms ei-

[2]For example, it may be that firms explicitly ask their incumbent employees for a referral. Alternatively, it may be that the employee notifies their contact about the job opening.

ther (i) on the open market, or (ii) through her former coworkers if the coworkers' current employers are hiring. Individuals come across firms with some contact rate, $\tilde{\lambda}$. We assume that, upon meeting on the open market, the unemployed individual is instantly hired. The individual encounters firms with a contact rate that we allow to vary by the individual's skill level, $s \in \{\ell, h\}$. The more interesting channel for our purposes is hiring through networks: we assume that the unemployed individual meets firms through her former coworkers at the contact rate $\nu_s(E_\ell, E_h)$, where E_ℓ and E_h stand for her number of former low-skilled and high-skill coworkers, respectively, that are currently employed. Putting the two channels together, the hazard of exiting unemployment for an unemployed individual of skill level s is:

Suppose there is an unemployed individual of skill level $s \in \{\ell, h\}$. This individual can meet hiring firms either (i) on the open market, or (ii) through her former coworkers if the coworkers' current employers are hiring. On the open market, the contact rate is $\tilde{\lambda}_s$. We assume that, upon meeting, the unemployed individual is instantly hired. The more interesting channel for our purposes is hiring through networks: we assume that the unemployed individual meets firms through her former coworkers at the contact rate $\nu_s(E_\ell, E_h)$, where E_ℓ and E_h stand for her number of former low-skilled and high-skill coworkers, respectively, that are currently employed. Putting the two channels together, the hazard of exiting unemployment for an unemployed individual of skill level s is:

$$\lambda_s = \tilde{\lambda}_s + \nu_s(E_\ell, E_h). \tag{1.1}$$

Note that the network contact rate depends on the number of both low and high-skilled former coworkers that are currently employed, regardless of the unemployed individuals' own skill level. In other words, we allow for the possibility that every network contact may be useful in job finding, regardless of their occupational similarity to the unemployed individual, and that the size of these effects may differ.

Our goal is to identify the impact of the strength of skill-specific coworker networks on unemployment duration. However, relating the number of former coworkers who are currently employed to unemployment duration would conflate strength and size effects: more employed network contacts imply both a stronger and a larger network. We separate them by splitting the impact of the number of employed skill-s network contacts to the impact of the skill-s network employment rate ER_s and the size of the overall skill-s network N_s. Note that, by definition, the skill-s network employment rate is $ER_s = E_s/N_s$. Therefore,

$$\log(E_s) = \log(ER_s) + \log(N_s). \tag{1.2}$$

We use the network employment rate to capture strength effects, and the size of the whole skill-s network to control for size effects. This framework yields three margins that we subsequently test empirically:

1. $\partial\nu_\ell/\partial ER_\ell \overset{?}{>} 0$ and $\partial\nu_h/\partial ER_h \overset{?}{>} 0$: Do having stronger same-skill networks allow unemployed individuals to exit unemployment faster?

2. $\partial\nu_\ell/\partial ER_\ell \overset{?}{>} \partial\nu_\ell/\partial ER_h$ and $\partial\nu_h/\partial ER_h \overset{?}{>} \partial\nu_h/\partial ER_\ell$: Do unemployed individuals exit unemployment faster through same-skill than different-skill networks?

3. $\partial\nu_h/\partial ER_\ell \overset{?}{>} \partial\nu_\ell/\partial ER_h$: Do high-skilled unemployed individuals exit unemployment through low-skill networks faster than low-skilled unemployed through high-skill networks?

We present empirical evidence answering "Yes" to all of these questions in the upcoming sections.

To aid interpretation, we implement these tests on same vs. different-skill networks. That is, we switch from the low vs. high-skilled classification to skill similarity. For example, the same-skill network of a low-skilled job seeker is formed by her former low-skilled coworkers.

This paradigm bears two advantages over the low vs. high-skilled classification. First, we can use a granular measure of skill similarity, rather than only low vs. high-skilled networks. We proxy skills by occupations in later sections, and we leverage the nested structure of the occupational classification to test the sensitivity of our results to the granularity of skills. Second, we are able to strengthen our estimates by simultaneously using low and high-skilled networks, and parsing them at will.

2 Empirical Strategy

Our empirical strategy measures the impact of coworker network strength on unemployment duration. Specifically, we relate the time a displaced worker spent in unemployment to the employment rate among her former coworkers, splitting these individuals into those who worked in the same occupation versus a different occupation from the displaced worker. We estimate the following regression:

$$u_{ij} = \alpha + \gamma_1 ER_i^{\text{same}} + \gamma_2 ER_i^{\text{diff}} + \theta_1 \log(N_i^{\text{same}}) + \theta_2 \log(N_i^{\text{diff}}) + X_i\beta + \lambda_j + \varepsilon_{ij} \tag{2.1}$$

where u_{ij} measures the log unemployment duration of worker i displaced from firm j.[3] ER^{same} captures the employment rate of former coworkers from the same occupation, while ER^{diff} captures the employment rate of former coworkers who worked in a different occupation. Former coworkers are defined as the set of all individuals who were contemporaneously employed at the same firm as an individual in the five year window prior to displacement. They include both coworkers from the displacing firm, as well as coworkers the individual may have worked with in previous places of employment. Workers who were co-displaced with the worker are not included in the prior co-worker networks used to calculate ER^{same} and ER^{diff}.

[3]We focus on unemployment duration as our main outcome of interest because it captures the extensive margin of job search. Other, intensive labor market outcomes of interest, such as wages and occupation in a new job, are conditional on a worker finding a job after displacement.

We calculate the network employment rates ER^{same} and ER^{diff} at the time of displacement. This timing addresses the concern that our results might be driven by labor demand shocks for particular occupations. Furthermore, to ensure that the results are not driven by the size of these networks, Equation 2.1 controls for the number of former coworkers from same and different occupations, N^{same} and N^{diff}, respectively.

A key concern in the identification network employment rate effects is that networks may be endogenous. In other words, unobserved factors that affect an displaced invididual's unemployment duration following a firm closure may also affect the contemporaneous employment rate of their former coworker network. We take several measures to address this concern. As a starting point, to overcome the concern that network strength may be endogenous with searching for a new job, we focus on individuals who become unemployed due to firm closures, a standard practice in the literature (Cingano and Rosolia, 2012; Saygin et al., 2021; Eliason et al., 2022). We restrict our analysis to workers co-displaced by the same firm using a closing firm fixed effect, λ_j. To the extent that workers sort along unobserved characteristics that are correlated with network composition over time, comparing co-displaced workers will control for these unobserved characteristics. Furthermore, the closing firm fixed effects absorb any location-, sector-, or time-specific shocks that may affect unemployment duration.

Even with the inclusion of closing firm fixed effects, a given pair of co-displaced workers might differ in ways that affect both unemployment duration and the characteristics of their networks. Another concern is that a displaced worker and their former coworkers may have accumulated specific human capital while working together that subsequently affect labor market outcomes of both the former coworkers and the displaced individual. To address these concerns, we control for a rich set of pre-displacement employment history characteristics, captured in the vector X_i.

The vector X_i includes three categories of individual controls: demographic characteristics, pre-displacement earnings and employment information, and pre-displacement job characteristics. Demographic controls include gender and age. Pre-displacement earnings and employment include information on earnings at time of displacement, wage growth in years leading up to displacement, tenure at the closing firm, and the amount of time an individual spent unemployed in years prior to displacement. These controls address the concern that co-displaced workers sort into firms prior to displacement in ways that will affect both their network composition and unemployment duration. Additionally, we control for pre-displacement job characteristics, which include the number and average size of pre-displacement employers, the primary pre-displacement industry of employment, and occupation at time of displacement. These variables control for the possibility that compensating differentials may affect worker sorting in ways that are not captured by earnings and unemployment. This is especially important since we are looking at occupation-specific networks. Furthermore, the inclusion of pre-displacement sector and occupation fixed effects ensures that we are capturing differences in same- vs. different-occupation coworkers within occupations and sectors, rather than across these domains. For example, this controls for the possibility that a labor demand shock for a particular occupations raises not only the employment rate among peers in the same occupation, but also reduce the unemployment duration for the worker herself.

The goal of our empirical strategy is to isolate the effects of individual-specific networks from other factors affecting unemployment duration. We include closing firm fixed effects and detailed controls for individuals' employment histories to control for any unobservable characteristics that may be correlated with both unemployment duration and network characteristics. The key identifying assumption for a causal interpretation of Equation 2.1 is that with the inclusion of these fixed effects and controls, the network employment rate of same- and different-occupation coworkers is not correlated with other unobserved factors that affect a displaced worker's unemployment duration. The coefficients of interest, γ_1 and γ_2, measure the effect of the employment rate at time t of network contacts who worked in the same vs. a different occupation as i on i's unemployment duration.

We conclude this section by addressing two issues related to our empirical strategy: (i) regression vs. duration analysis, and (ii) the lack of spurious correlation between our network variables. Regarding the first point, our regression framework coincides with an accelerated failure time (AFT) model with lognormally distributed durations (see, e.g., Lancaster, 1990). The interpretation of the resulting coefficients is slightly different in the two frameworks, but ultimately similar.[4] However, the AFT model requires the additional assumption about the distribution of failure times. For these reasons, we choose to interpret our empirical results in a regression framework.

Regarding the second point, the peer effects literature (e.g. Angrist, 2014; Caeyers and Fafchamps, 2020) has documented potentially large exclusion biases. Intuitively, regressing some outcome variable on the leave-one-out average of the same outcome in one's network mechanically leads to a downward bias. Fortunately, networks in our data are large—the median network size is 257 contacts (see Table 3.1). Therefore, even if our measures were subject to exclusion bias, the impact of one's outcome on the leave-one-out mean would likely be negligible. Furthermore, since workers have heterogeneous past employment histories, coworker networks differ between co-displaced workers, further mitigating the scope for exclusion bias.

3 Data

This paper uses matched employer-employee data from Hungarian administrative records. The data span the years 2003–2011 and cover a 50 percent de facto random sample[5] of the population, which translates to approximately 4.6 million individuals linked across 900

[4]As an example, consider a coefficient estimate $\hat{\gamma}_1 = -0.4$. In a regression framework, this estimate is interpreted as a 4 percent decrease in the unemployment duration for workers with a 10 percentage point higher same-occupation network employment rate. In an AFT framework, the interpretation is that workers with a 10 percentage point higher same-occupation network employment rate exit unemployment $\exp(-0.4 \times 0.1) = 1.041$ times faster.

[5]Every Hungarian citizen born on Jan 1, 1927 and every second day thereafter are observed. DellaVigna, Lindner, Reizer, and Schmieder (2017) termed this sampling scheme as “de facto random.”

thousand firms.[6]

This study focuses on workers displaced in 2008, with displaced workers defined as workers who lose their jobs through a firm closure. We focus our analysis on displacement in 2008 in order to observe five years of employment histories before displacement and three years after. We include workers who were displaced from firms that do not get acquired by or merge with another firm, and had at least 10 employees at time of closure. A worker is not included in the displaced sample if, following displacement, more than half of the employees moved to the same new firm: these mass movements likely reflect some other mechanism than finding a new job through network contacts.[7]

3.1 Occupation Classifications

One key feature of our data is that they contain detailed information on worker occupations. These codes are defined by the Hungarian Standard Classification of Occupations (HSCO) and operate on a four-digit system.[8] The first digit breaks down occupations into major groups. The second digit specifies a more detailed occupational group, the third digit specifies occupational sub-group, and the fourth digit specifies the occupation itself. There are 485 unique occupation codes defined by this system. To give an idea of the level of detail provided, occupation code 251 denotes the occupational subgroup "Finance and Accounting Professionals". Occupations within this include 2511–Financial Analyst and 2513–Accountant. Appendix Figure A.1 provides a visual guide of how occupations are nested and broken down by digits using the classification of "blacksmith" as an example.

A unique feature of the occupation classification system is that major groups (i.e. one-digit occupation classifications) are categorized by skill requirement. Major occupational

[6] Note that this sampling scheme does not bias our results. (1) The network employment rate is observed without error. (2) The true network size is double of the observed one, thus controlling for the log of the observed network size makes no quantitative difference.

[7] The analysis in this paper presents results using the full sample of displaced workers. We have also run specifications restricting the sample to workers at closing firms with 500 or fewer employees (following Hensvik and Skans, 2016) and find similar results.

[8] The HSCO follows the basic structure of the International Standard Classification of Occupations and is also similar to the Standard Occupational Classification system by the US Bureau of Labor Statistics.

group 9 includes jobs that typically consist of simple and routine manual tasks, which generally require no formal training. Major groups 8, 7, 6, 5 and 4 require more specialized skills that are typically acquired in primary levels of education and possibly some vocational education, such as operating machinery, maintenance/repair of electrical and mechanical equipment, and management of information. Finally, major groups 3, 2, and 1 involve more complex tasks that require specialized knowledge and skills that are typically obtained through secondary school and/or higher educational institutions. Almost two-thirds of workers come from occupations that require a primary level of education, with remaining workers split fairly evenly between occupations requiring no formal education and occupations requiring at least a high school level of education. Appendix Table A.1 shows a detailed the distribution of displaced workers in our sample across major occupational groups. Appendix Table A.2 displays more information on specific four-digit occupations in the data.

3.2 Summary Statistics

This paper considers a five-year pre-displacement window for network formation and a three-year post-displacement window to measure reemployment outcomes. To that end, we focus on workers who were displaced from closing firms in 2008 in order to be able to observe full pre-displacement and post-displacement networks in the data.[9]

We calculate the unemployment duration of displaced workers as months after displacement without employment records. We relate these durations to the share of their former coworkers who are employed at the time of displacement, and to the size of these networks of former coworkers, measured as the number of their previous coworkers at all the firms they worked at in the preceding five years.

Table 3.1 displays summary statistics for displaced workers in the sample. Approximately 38 percent of displaced workers are female, and the average age of the sample is 37. The

[9]We are able to observe a worker for up three years after displacement. In the data, 89 percent of workers find jobs within this time frame. We top-code unemployment duration for the maximum observed duration for workers who do not find a job in the sample time window.

mean monthly wage for workers in the five years prior to displacement is equivalent to about \$532.[10] Furthermore, workers experience approximately a 1.3 percent nominal wage growth during this period. The median number of employees at the firms individuals worked in during the period prior to displacement is 68. (Few people work at firms with a large number of employees, thus the mean headcount is driven by outliers.) Finally, the average duration of the jobs individuals held in the five-year period prior to displacement was 18 months, with a median of 10 months.

Table 3.1 also shows summary statistics for displaced workers in the period after displacement. On average, it takes a displaced worker about 10 months to find a new job during this period. The average employment rate of a given displaced worker's former coworkers (not including co-displaced coworkers) is 77 percent. We define former coworkers as individuals who appeared in the same firm as the worker in at least one (monthly) observation period prior to displacement. The mean employment rate of former coworkers who worked in the same occupation as the displaced worker, defined as individuals who worked in the same four-digit occupation, is slightly lower, at 72.2 percent. Finally, a worker has a median network size of 257 (mean 2,265). Restricting this sample to network members who work in the same occupation, median network size is 75 (mean 571).[11]

Table 3.1 also shows descriptive statistics for displaced workers broken down by education level.[12] Workers displaced from occupations that require higher levels of education had higher pre-displacement wages, worked at smaller firms, and had longer tenure at their firms on average. More highly educated workers also have smaller overall networks and smaller same-occupation networks than less educated workers, stemming from the fact that they tended to work at smaller firms and stay at the same firm for longer in the years prior to displacement. More educated workers also have shorter unemployment duration after

[10] Values are denoted by real 2010 US dollars.

[11] A few networks in the data are huge, as evidenced by the large mean of the network size variables. We provide robustness tests in Appendix B, indicating that our results are not driven by these huge networks.

[12] We do not observe the education level of a given worker in the data. Instead, education refers to the education level requirement of the job the worker was displaced from.

Table 3.1: Summary Statistics

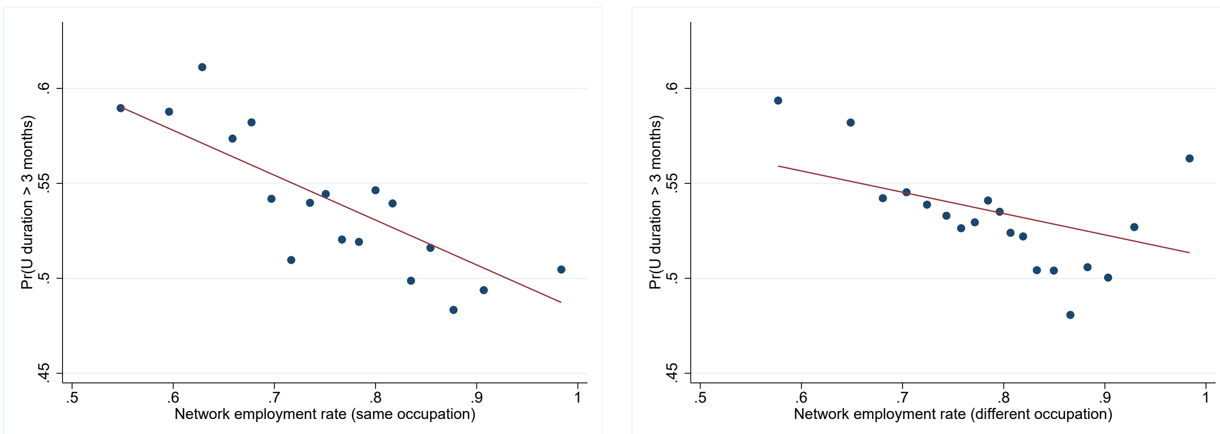
Variable	Total: Percentiles 25th	50th	75th	Mean (S.D.)	By Education: None	Primary	HS+
					Means† and Medians×		
Female (%)	–	–	–	37.6 (0.5)	46.8†	33.6†	45.3†
Age	27	35	48	37.3 (12.2)	39.3†	37.0†	37.1†
Pre-displacement							
Wage (USD, 2010)	308	397	567	532.2 (761.3)	314.3†	465.9†	1,079.3†
Wage growth (%)	0.1	1.0	2.1	1.3 (5.3)	1.0†	1.2†	1.3†
Firm size (headcount)	25	68	258	782.9 (2,567.6)	72.1×	68.3×	53.0×
Tenure (months)	4	10	26	18.2 (18.7)	12.5†	18.2†	25.6†
Post-displacement							
Unemployment duration (months)	0	4	12	10.0 (13.1)	10.7†	8.9†	8.4†
Network employment rate (%)	70.1	77.9	84.0	77.0 (10.8)	73.9†	76.9†	80.3†
Same occupation (%)	65.0	75.4	85.4	72.2 (22.0)	69.0†	73.6†	70.4†
Network size	62	257	1,600	2,265.3 (4,917.2)	285×	272×	146×
Same occupation	13	75	465	570.8 (12,489.0)	108×	94×	11×

†: mean. ×: median. Sample consists of workers displaced in 2008. Pre-displacement window is five years prior to displacement. Post-displacement window is three years after displacement.

displacement, and their overall network of former coworkers tend to have higher employment rates at all. The employment rate of same-occupation prior coworkers does not increase monotonically with education, though—workers in jobs requiring no formal education have a 69 percent employment rate among their same-occupation former coworkers, while workers in jobs requiring a primary level of education have a 74 percent same-occupation network employment rate, and workers in jobs requiring a high school level education or higher have a 70 percent same-occupation employment rate.

Next, Figure 3.1 looks descriptively at the correlation between former coworker network employment rate and unemployment duration for a displaced worker. Network employment rate denotes the share of workers out of all of the workers in from the same occupation who are employed. The figure plots the correlation between network employment rate and the propensity of being unemployed for longer than three months[13] after displacement for same-occupation and different-occupation coworkers networks. We classify a former coworker as same-occupation if they worked in the same four-digit occupation as the displaced worker. The figure shows a negative correlation between network employment rate and unemployment duration for both same-occupation and different-occupation coworkers with a slightly steeper slope for the employment rate of same-occupation coworkers.

Figure 3.1: Network Employment Rate and Unemployment Duration



While Figure 3.1 is suggestive of network employment rates playing a role in reducing unemployment duration, the relationships should not be interpreted causally. This graph does not include firm fixed effects, controls for pre-displacement labor market trends, network size, or any other controls for unobserved factors that may be driving both unemployment duration and network employment rate. Additionally, it does not disentangle the correlation between same-occupation network employment rate and different-occupation network employment rate, which prevents us from making a meaningful causal comparison of the two. The next section addresses these identification challenges by using the empirical approach from Section 2 to analyze the effects of network employment rate on a displaced worker's

[13] The 3 month threshold signifies finding a job in the first tier of the UI benefit scheme. At the time, the Hungarian UI system paid a high level of benefits in the first 90 days of unemployment, then cut benefits substantially afterwards (see e.g. DellaVigna, Lindner, Reizer, and Schmieder, 2017). Appendix Figure A.2 displays the same patterns using alternative thresholds.

unemployment duration.

4 Results

Table 4.1 shows analysis results of the role of network contacts by occupational similarity on unemployment duration of displaced workers. First, column (1) looks at aggregate effects the role of former coworkers from all occupations. We analyze whether an increase in the overall network employment rate of former coworkers affects a displaced worker's unemployment duration. The specification includes closing firm fixed effects, as well as a rich set of pre-displacement firm and worker characteristics in the five-year period prior to displacement. We find that an increase in the network employment rate by 10 percentage points decreases a displaced worker's unemployment duration by 4 percent, or 12 days,[14] indicating former coworkers play a significant role in the job search process. Next, we look at the role of occupational similarity between coworkers in the networking process.

Column (2) adds a separate control for the network employment rate of former coworkers who worked in the same four-digit occupation as the displaced worker, as well as an interaction of this variable with log network size. Results indicate that a significant portion of the benefit of network contacts comes from contacts who worked in the same four-digit occupation—a 10 percentage point increase in the network employment rate of former coworkers who did not work in the same exact four-digit occupation as a displaced worker decreases unemployment duration by 2.6 percent, or 8 days. However, a 10 percentage point increase in the network employment rate of former coworkers from the same four-digit occupation decreases employment rate by an additional 1.8 percentage points, for a total of 4.5 percent (14 days).

Table 4.1 separates coworkers into two categories: those who worked in the same four-digit occupation category as a displaced worker and those who did not, which is a fairly stringent

[14]The average unemployment duration for displaced workers is 10 months, as shown in Table 3.1.

Table 4.1: Same- vs. Different-Occupation Network Employment Rates on Unemployment Duration

	(1)	(2)
Network Employment Rate	-0.398^{***}	-0.263^{*}
	(0.097)	(0.116)
Network Employment Rate, Same Occ.		-0.184^{*}
		(0.072)
Log Network Size	-0.015^{*}	-0.017^{*}
	(0.007)	(0.007)
Log Network Size×Share Same Occ.		-0.004
		(0.006)
Wage at Displacement	-0.286^{***}	-0.286^{***}
	(0.021)	(0.021)
Predisplacement Wage Growth	-0.732^{***}	-0.735^{***}
	(0.182)	(0.182)
Predisplacement Unemployment	0.721^{***}	0.716^{***}
	(0.041)	(0.041)
Predisplacement Firm Size	0.011	0.013
	(0.009)	(0.009)
Num. Predisplacement Employers		
1	-0.236^{***}	-0.239^{***}
	(0.041)	(0.042)
2	0.003	0.006
	(0.039)	(0.039)
3	-0.052	-0.051
	(0.040)	(0.040)
N	$22,248$	$22,248$
Closing firm FE	Y	Y
Predisplacement occ. FE	Y	Y
Predisplacement sector FE	Y	Y
R^2	0.303	0.303
Within-Firm R^2	0.071	0.071

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Outcome variable is log unemployment duration, measured in months. All regressions include controls for gender, a quadratic in age, and tenure at closing firm. Pre-displacement variables are computed in a five year window prior to displacement. Same-occupation coworkers are defined as coworkers who worked in the same four-digit occupation as the displaced worker. All other coworkers are defined as different-occupation.

definition of same-occupation coworkers.[15] Next, we provide a more in-depth assessment of the threshold of occupational similarity for which coworkers are helpful in job finding.

Table 4.2 breaks down coworker networks by those that share one-, two-, three-, and four-digit occupations with the displaced worker. Occupational similarity categories are *not* nested. In other words, same three-digit occupation coworkers here denote coworkers that share the same three-digit occupation code but not the same four-digit occupation code. As before, this specification includes closing firm fixed effects, as well as a rich set of pre-displacement firm and worker characteristics. Results indicate the effect of coworkers helping displaced workers find jobs is predominantly driven by coworkers from the same narrowly-defined four-digit occupation as the coworker. A 10 percentage point increase in the network employment rate of coworkers from the same four-digit occupation codes decreases unemployment duration by 2.5 percent, or 8 days. An increase in network employment rate of coworkers from the same three-digit occupation though has no significant effect on a worker's unemployment duration. Similarly, network employment rate of coworkers from the same two-digit, one-digit, and different occupations have no bearing on a displaced worker's unemployment duration. The magnitudes of estimates on same one-, two-, and three-digit occupation coworkers is small in magnitude compared to same four-digit occupation coworkers as well. Interestingly, while the employment rate of former coworkers who were in a completely different occupation from the displaced worker (i.e. worked in a different one-digit major occupation group) were not statistically significant, the magnitude of the estimated effect is sizable.

Overall, results from our analysis show that occupational similarity plays an important role when it comes to coworker networks. In fact, only former coworkers who worked in the same narrowly defined occupation as a displaced worker matter in reducing a worker's

[15]For example, "Sales Professionals" and "Advertising/Marketing Professionals" fall under different four-digit occupation categories, although they are in the same three-digit occupation "Sales and Marketing Occupations." Similarly, an "Electrical Power Current Engineering Technician" falls under a different four-digit occupation from an "Electronics Light Current Engineering Technician," although both fall under the same three-digit occupation "Electrical Engineering Technicians."

Table 4.2: Network Employment Rate on Unemployment Duration: Detailed Occupational Similarity Breakdown

	(1)
Network Employment Rate, Same 4-digit Occ.	-0.249^{***}
	(0.063)
Network Employment Rate, Same 3-digit Occ.	-0.036
	(0.026)
Network Employment Rate, Same 2-digit Occ.	-0.011
	(0.026)
Network Employment Rate, Same 1-digit Occ.	0.008
	(0.027)
Network Employment Rate, Different Occ.	-0.115
	(0.069)
N	$22,248$
Predisplacement worker characteristics	Y
Predisplacement firm characteristics	Y
Closing firm FE	Y
Prediscplacement occ. FE	Y
Prediscplacement sector FE	Y
Network size controls	Y
R^2	0.303
Within R^2	0.072

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Outcome variable is log unemployment duration, measured in months. All regressions include controls for gender, a quadratic in age, and tenure at closing firm, as well as controls for pre-displacement worker and firm characteristics. Pre-displacement variables are computed in a five year window prior to displacement. Network size controls include controls for work size interacted with occupational similarity.

Table 4.3: Network Employment Rate on Unemployment Duration by Occupation Education Requirements

	No Formal (1)	Primary (2)	High School+ (3)
Network Employment Rate, Same 4-digit Occ.	-0.366^{*}	-0.290^{***}	0.022
	(0.164)	(0.084)	(0.159)
Network Employment Rate, Same 3-digit Occ.	0.082	-0.056	0.011
	(0.068)	(0.033)	(0.083)
Network Employment Rate, Same 2-digit Occ.	-0.004	-0.006	0.002
	(0.068)	(0.034)	(0.083)
Network Employment Rate, Same 1-digit Occ.	-0.020	0.044	0.075
	(0.067)	(0.036)	(0.088)
Network Employment Rate, Different Occ.	-0.076	-0.106	-0.801^{**}
	(0.146)	(0.088)	(0.298)
Observations	3,697	14,373	3,387
Predisplacement worker characteristics	*Y*	*Y*	*Y*
Predisplacement firm characteristics	*Y*	*Y*	*Y*
Closing firm FE	*Y*	*Y*	*Y*
Prediscplacement occ. FE	*Y*	*Y*	*Y*
Prediscplacement sector FE	*Y*	*Y*	*Y*
Network size controls	*Y*	*Y*	*Y*
R^2	0.337	0.308	0.435
Within R^2	0.067	0.073	0.101
Joint F-test	1.564	4.206	0.204
p-value	0.181	0.002	0.936

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Outcome variable is log unemployment duration, measured in months. All regressions include controls for gender, a quadratic in age, and tenure at closing firm. Pre-displacement variables are computed in a five year window prior to displacement. Same 4-digit occupation coworkers are defined as coworkers who worked in the same four-digit occupation as the displaced worker, but not the same three-digit occupation, and the same pattern is used to define same 3-digit and 2-digit coworkers. Network size controls include controls for work size interacted with occupational similarity.

unemployment duration. Next, Table 4.3 looks at how these results vary across different levels of education. Column (1) looks at workers displaced from occupations that require no formal education, column (2) looks at workers in occupations that require an primary education level of knowledge, and column (3) looks at workers in occupations that require high school level knowledge and above. Appendix Table A.3 provides information on cell counts for different categories of coworkers across worker occupation education requirements.

Results indicate which coworkers are important to a displaced worker in the job finding process varies across the type of job workers are seeking, in terms of education requirements. For workers in jobs requiring no formal education, the role of former coworkers in reducing unemployment duration is driven by coworkers who worked in the same four-digit occupation as the displaced worker—a 10 percentage point increase in the network employment rate of coworkers from the same four-digit occupation codes decreases unemployment duration by 3.7 percent. The employment rate of former coworkers in the same three-digit, two-digit, one-digit, or different occupations do not affect unemployment duration of the displaced worker. Similarly, for workers in jobs requiring only a primary level of education, a 10 percentage point increase in the network employment rate of coworkers from the same four-digit occupation codes decreases unemployment duration by 2.9 percent, with no significant effect on the employment rate of other former coworkers.

Results are different for workers who are displaced from jobs requiring at least a high school education. For these workers, the employment rate of former coworkers who worked in the same major occupation group (i.e. shared a one-digit occupation or more) have no effect on unemployment duration. However, former coworkers who worked in a completely different occupational field do help in the job search process. A 10 percentage point increase in the employment rate of former coworkers who worked in a different major occupational group decreases unemployment duration for workers in skilled jobs by 8.0 percent.

These findings suggest that the usefulness of different types of network contacts, in terms of similarity, varies across different types of occupations. Workers in jobs across the education spectrum likely face different job market landscapes in terms of the number and types of options they have and the kinds of information about workers that their potential employers value.[16] One possible interpretation of results in Table 4.3 is that a significant barrier for workers finding jobs that require lower levels of education is knowledge regarding job opportunities, and same-occupation coworkers are useful in providing this information. However, for higher-skilled jobs, it may be that employers focus more on things like credentials and

[16] A look at descriptive outcomes in Appendix Table A.4 reveals that individuals displaced from occupations that require more education have lower unemployment durations. Additionally, workers displaced from occupations that require at least a high school level of occupation are less likely to switch occupations immediately after displacement, compared to those working in jobs requiring a primary level education or no formal education.

work experience, so having network contacts in the same occupation is not as helpful. But for them, different-occupation coworkers may be helpful if higher-skilled workers are able to perform a wide variety of occupations and these coworkers are able to notify them of jobs that would not otherwise be on their radar. Conversely, for lower-skilled workers, different-occupation coworkers may be less useful if they are not qualified for these other occupations. There are a number of possible information channels underlying these results, and more research is required to pin down these mechanisms.

5 Conclusion

This paper expands our understanding of the role of coworker social networks in the job finding process. Specifically, we relate the strength of coworker networks by occupational similarity to the unemployment duration of displaced workers. Our results indicate that only those coworkers help displaced workers find jobs who worked in the same, narrowly-defined occupation as the displaced worker. Further analyses reveal that this effect is driven exclusively by coworkers in occupations that require low levels of education. For workers in occupations requiring at least a high school level of education, same-occupation coworkers have no effect but former coworkers in different broad occupations do. These findings suggest that different coworkers matter for different types of jobs, which likely reflect the differences in how and what kind of information transmission is important for different jobs.

Much of the prior research has demonstrated that social networks in a variety of social categories—such as family members, neighbors, ethnic contacts, roommates, classmates—are useful for job finding. This study, focusing on coworker networks, provides new insights indicating that not all contacts are created equal in this context, which has implications for workplace composition in the face of networking. As an example, a high school nurse may have vastly different networking prospects than a nurse who works as one of many nurses as a hospital. Similarly, a mechanic working at an auto shop full of mechanics may face a different network than one of the handful of mechanics at a car dealership. In future work, we plan to analyze further the information content of social networks in the job search process. Specifically, we intend to probe deeper into what kind of information about workers or firms, and what aspects of relationship dynamics, are important for workers in various jobs.

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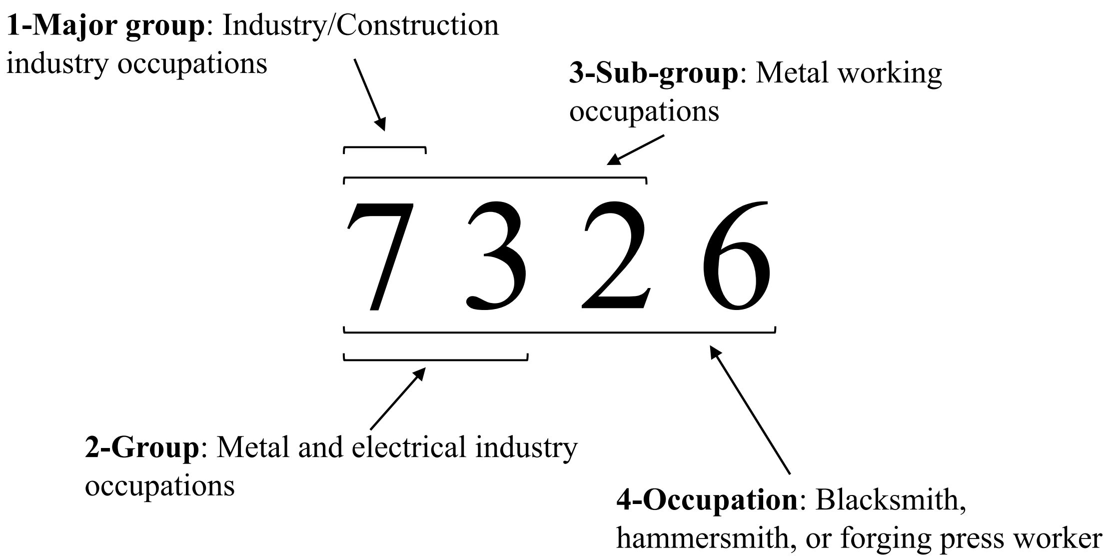
Appendices

A Additional Data Summaries

Appendix Figure A.1: Occupation Classification Example: Blacksmith



Appendix Figure A.1 provides an example of how occupations are nested and broken down by digits for the classification of "blacksmith."

Appendix Table A.1: Occupational Distribution of Displaced Workers

Occupation Group	Education Level	Count	Percent
1–Managers	High School+	915	4.09
2–Professionals	High School+	839	3.75
3–Technicians and Associate Professionals	High School+	2,059	9.20
4–Office and Management	Primary	1,243	5.55
5–Commercial and Services	Primary	3,756	16.78
6–Agricultural and Forestry	Primary	117	0.52
7–Industry and Construction	Primary	5,563	24.85
8–Machine Operators, Assembly Workers, Drivers	Primary	3,954	17.66
9–Elementary Occupations	None	3,939	17.60

Appendix Table A.1 displays the distribution of displaced workers in our sample across major occupational groups.

Appendix Table A.2: Most Prevalent Occupations

	Four-digit Occupations	Num.	Freq.	Cum. Freq.
9190	Labourers and helpers n.e.c. (e.g. odd-job persons)	1,609	7.19	7.19
5112	Shop assistants	1,131	5.05	12.24
5366	Security guards	1,127	5.03	17.27
8356	Heavy-truck and lorry drivers	1,090	4.87	22.14
8193	Production-line assemblers	1,023	4.57	26.71
7421	Locksmiths	641	2.86	29.58
9111	House, flat and office cleaners	592	2.64	32.22
7211	Meat, fish and poultry processing workers	535	2.39	34.61
4199	Office clerks n.e.c.	515	2.30	36.91
5123	Waiters, restaurant salespersons	458	2.05	38.96
9150	Elementary services occupations	413	1.84	40.80
7425	Welders, flame cutters	398	1.78	42.58
8199	Processing machine operators, production-line workers n.e.c.	387	1.73	44.31
7530	Stock clerks, warehousemen	366	1.63	45.94
9131	Manual materials handlers, hand packers	360	1.61	47.55
9119	Cleaners and related elementary occupations n.e.c.	358	1.60	49.15
7641	Road construction and paving workers, road maintenance workers	349	1.56	50.71
8136	Plastic processing machine operators	259	1.16	51.87
4193	Office administrators, clerical writers	250	1.12	52.98
7611	Bricklayers, masons	243	1.09	54.07
5114	Occupations in making up consignment of goods	226	1.01	55.08

Appendix Table A.2 displays the most common four-digit occupations for displaced workers in the sample. The most common occupations in our sample of displaced workers are laborers and helpers, shop assistants, and security guards.

Appendix Table A.3: Coworkers-by-Occupation Counts Across Education Levels

	By Education		
Variable	**None**	**Primary**	**HS+**
	Means† and Medians$^{\times}$		
Network size, same 4-digit occ.	640.7†	628.9†	195.6†
	108$^{\times}$	94$^{\times}$	11$^{\times}$
Network size, same 3-digit occ.	73.7†	104.6†	39.3†
	0$^{\times}$	2$^{\times}$	1$^{\times}$
Network size, same 2-digit occ.	150.6†	204.8†	74.2†
	3$^{\times}$	1$^{\times}$	2$^{\times}$
Network size, same 1-digit occ.	49.9†	90.4†	97.2†
	0$^{\times}$	3$^{\times}$	3$^{\times}$

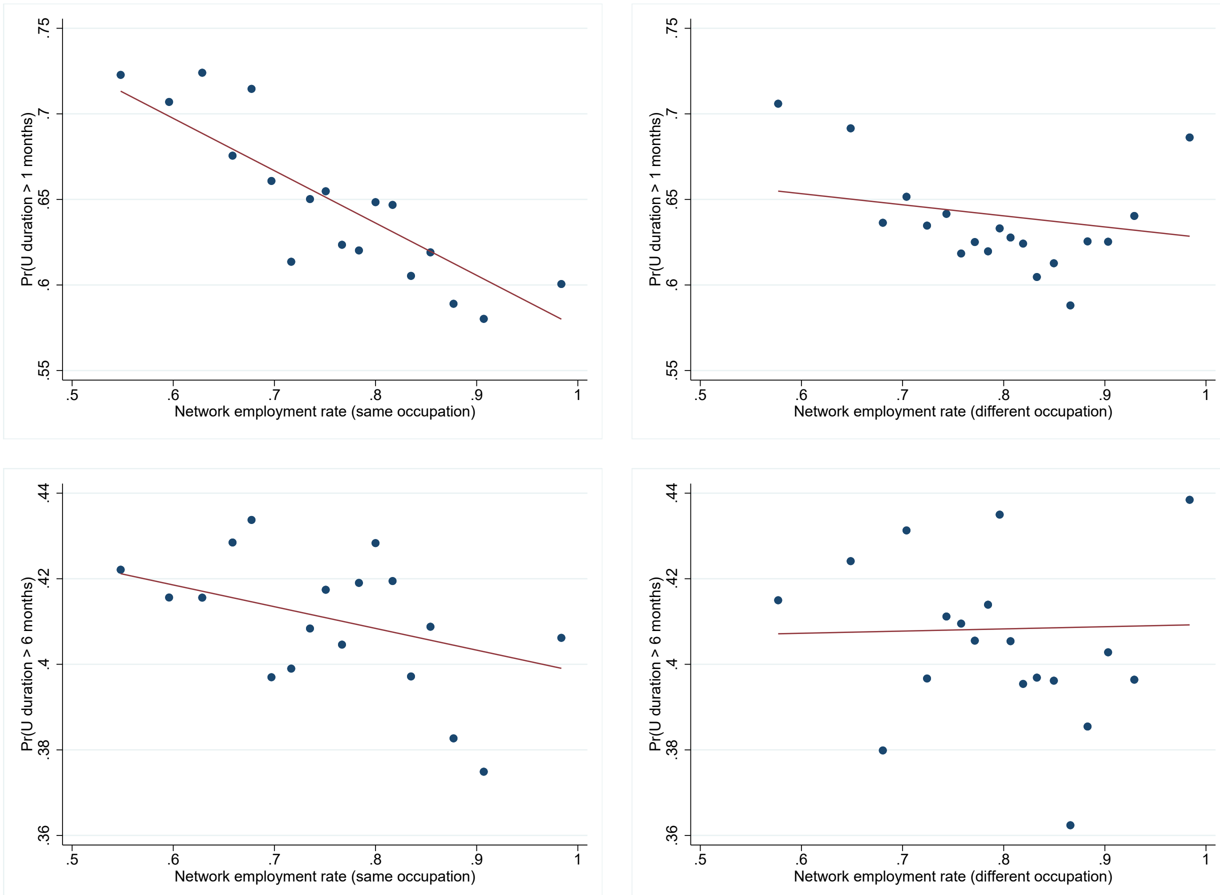
Appendix Table A.3 displays the mean and median number of former coworkers in each nested occupational group by educational level.

Appendix Table A.4: Post-Displacement Outcomes across Occupational Education Levels

	No Formal	Primary	High School+
Unemployment Duration (months)	5.17	4.67	3.79
Switch Occupations	0.40	0.46	0.30

Appendix Table A.4 shows summary statistics of post-displacement outcomes by the level of educational requirements of occupations. The first row looks at average unemployment duration of displaced workers, measured in months. The second row measures the propensity for the worker's first job after displacement to be in a different occupation than the job they had at time of displacement.

Appendix Figure A.2: Network Employment Rate and Unemployment Duration–Alternative Thresholds



Appendix Figure A.2 provides alternative thresholds for Figure 3.1. The same pattern emerges: the correlation between stronger same-occupation networks and longer unemployment duration is stronger than that for different-occupation networks, for using either 1, 3, or 6 months as a threshold for defining long unemployment.

B Robustness to Excluding Large Networks

The following tables replicate our main results in Tables 4.1, 4.2, and 4.3 on a subsample that excludes large networks. We define large networks as those above the 99th percentile of the network size distribution, i.e., 27,265 coworkers in the five years leading up to displacement. (The mean size of same 4-digit occupation networks for these observations is 4,585.4 and the median is 2,895.) Our results are robust to this exclusion.

Appendix Table B.1: Same- vs. Different-Occupation Network Employment Rates on Unemployment Duration–Excluding Large Networks

	(1)	(2)
Network Employment Rate	-0.396^{***}	-0.269^{*}
	(0.098)	(0.116)
Network Employment Rate, Same Occ.		-0.176^{*}
		(0.072)
Log Network Size	-0.014^{*}	-0.017^{*}
	(0.007)	(0.007)
Log Network Size × Share Same Occ.		-0.004
		(0.006)
Wage at Displacement	-0.286^{***}	-0.285^{***}
	(0.021)	(0.021)
Predisplacement Wage Growth	-0.723^{***}	-0.725^{***}
	(0.182)	(0.182)
Predisplacement Unemployment	0.717^{***}	0.713^{***}
	(0.041)	(0.041)
Predisplacement Firm Size	0.011	0.012
	(0.010)	(0.010)
Num. of Predisplacement Employers		
1	-0.246^{***}	-0.249^{***}
	(0.042)	(0.042)
2	0.003	0.006
	(0.040)	(0.040)
3	-0.055	-0.054
	(0.040)	(0.040)
N	$22,017$	$22,017$
Closing firm FE	Y	Y
Predisplacement occ. FE	Y	Y
Predisplacement sector FE	Y	Y
R^2	0.302	0.303
Within R^2	0.071	0.071

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Outcome variable is log unemployment duration, measured in months. All regressions include controls for gender, a quadratic in age, and tenure at closing firm. Pre-displacement variables are computed in a five year window prior to displacement. Same-occupation coworkers are defined as coworkers who worked in the same four-digit occupation as the displaced worker. All other coworkers are defined as different-occupation.

Appendix Table B.2: Network Employment Rate on Unemployment Duration: Detailed Occupational Similarity Breakdown–Excluding Large Networks

	(1)
Network Employment Rate, Same 4-digit Occ.	-0.242^{***}
	(0.063)
Network Employment Rate, Same 3-digit Occ.	-0.036
	(0.026)
Network Employment Rate, Same 2-digit Occ.	-0.012
	(0.027)
Network Employment Rate, Same 1-digit Occ.	0.008
	(0.027)
Network Employment Rate, Different Occ.	-0.115
	(0.069)
Observations	22,017
Predisplacement worker characteristics	Y
Predisplacement firm characteristics	Y
Closing firm FE	Y
Prediscplacement occ. FE	Y
Prediscplacement sector FE	Y
R^2	0.303
Within R^2	0.071

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Outcome variable is log unemployment duration, measured in months. All regressions include controls for gender, a quadratic in age, and tenure at closing firm, as well as controls for pre-displacement worker and firm characteristics. Pre-displacement variables are computed in a five year window prior to displacement.

Appendix Table B.3: Network Employment Rate on Unemployment Duration by Occupation Education Requirements–Excluding Large Networks

	(1)	(2)	(3)
Network Employment Rate, Same 4-digit Occ.	-0.351^{*}	-0.283^{***}	0.028
	(0.166)	(0.085)	(0.159)
Network Employment Rate, Same 3-digit Occ.	0.081	-0.056	0.005
	(0.068)	(0.033)	(0.083)
Network Employment Rate, Same 2-digit Occ.	-0.014	-0.003	0.005
	(0.069)	(0.034)	(0.084)
Network Employment Rate, Same 1-digit Occ.	-0.014	0.045	0.070
	(0.068)	(0.036)	(0.088)
Network Employment Rate, Different Occ.	-0.074	-0.111	-0.840^{**}
	(0.146)	(0.088)	(0.300)
Observations	3,637	14,220	3,368
Predisplacement worker characteristics	Y	Y	Y
Predisplacement firm characteristics	Y	Y	Y
Closing firm FE	Y	Y	Y
Prediscplacement occ. FE	Y	Y	Y
Prediscplacement sector FE	Y	Y	Y
R^2	0.335	0.308	0.436
Within R^2	0.068	0.073	0.099
Joint F-test	1.425	3.992	0.174
p-value	0.223	0.003	0.952

Robust standard errors in parentheses. *** p<0.001, ** p<0.01, * p<0.05. Outcome variable is log unemployment duration, measured in months. All regressions include controls for gender, a quadratic in age, and tenure at closing firm. Pre-displacement variables are computed in a five year window prior to displacement. Same 4-digit occupation coworkers are defined as coworkers who worked in the same four-digit occupation as the displaced worker, but not the same three-digit occupation, and the same pattern is used to define same 3-digit and 2-digit coworkers.