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 within their former coworker networks. We find that only coworkers from the same narrow occupation are helpful in job finding, while those from different occupations are not. This effect lasts for a few months after displacement and is primarily driven by former coworkers in occupations requiring at most a primary level of education.

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1 Introduction

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. 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 unemployed individuals' former coworker networks and observe the occupational similarity of these network members to the job-seeking individuals. We then measure the impact of stronger occupational network employment rates on shortening unemployment duration. We find that only network contacts who used to work in the same, narrowly defined occupation as the unemployed job seeker are helpful in job finding.

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 own unemployment duration. We overcome this challenge in three steps. First,

[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).

following prior work, we restrict our analysis to comparisons of unemployed individuals who were displaced by the same firm closure—an exogenous source of job separation—to address the concern that separation decisions are correlated with network strength. Second, we control for a host of pre-displacement labor market outcomes, addressing heterogeneous characteristics among workers at closing firms that may affect both network characteristics and unemployment duration. Third, we include controls for the average worker and match quality in displaced workers' networks to further control for unobserved shared characteristics between a displaced worker and her network contacts that may be correlated with unemployment duration. These steps ultimately ensure that identification of network effects comes from comparing two very similar unemployed individuals who are displaced from the same firm at the same time, exploiting variation in the network composition of the two different sets of former coworkers.

We start by analyzing whether a stronger coworker network—defined as a higher employment rate among former coworkers—reduces unemployment duration and whether this effect is stronger for former coworkers in similar occupations to the unemployed job seeker compared to those in different occupations. A priori, the expected direction of these effects is ambiguous. On the 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 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 they have stronger ties with the the displaced worker (Gee, Jones, and Burke, 2017; Eliason, Hensvik, Kramarz, and Skans, 2023). Analyzing the strength of coworker networks by occupational similarity helps us better understand how workers leverage their networks in the job search process.

Consistent with prior studies, we find that a higher network employment rate of former coworkers is helpful in job finding for displaced workers. A 10 percentage point increase in the network employment rate of former coworkers reduces unemployment duration by 2.6 percent. Furthermore, results indicate that on average, only coworkers from the same occupation are helpful for job finding: a 10 percentage point increase in their network employment rate decreases unemployment duration by 3.0 percent, while the effect of former coworkers in different occupations is statistically indistinguishable from zero. We also show that the effect of former coworkers is present only for narrowly defined (i.e., four-digit) occupations. These results emphasize that network quality, as captured by the employment rate of former coworkers, matters for job finding rather than the number of former coworkers.

Next we zoom in on the heterogeneity of our results. We show that the effect of same-occupation former coworkers fades quickly after displacement. Former coworkers in the same narrow occupation are helpful in the first four months of unemployment, and their impact vanishes over longer time horizons. At the same time, former coworkers in different occupations do not affect the probability of job finding. Further analyses reveal that the effect of network employment rate of same-occupation coworkers on job finding are driven exclusively by workers in occupations that require no more than primary levels of education. However, for workers in occupations requiring at least a high school education, larger networks are helpful in job finding—i.e., only for this high-skilled group the quantity, rather than the quality of network contacts seem to matter.

This paper relates to research on both labor market networks and the role of occupations in job search, specifically contributing 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; Garcia-Louzao and Silva, 2024). This paper adds to studies aiming to expand our understanding of *which* coworker links are useful. Saygin, Weber, and Weynandt (2021) 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, Hensvik, Kramarz, and Skans (2023) 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 by exploring the role of occupational similarity in job networks. Occupation plays an important role in the job search process, and studies have shown that there is significant occupational mismatch in terms of 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 the number of 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.

Moving forward, Section 2 introduces a conceptual framework for quantifying the impact of coworker networks on job finding. Section 3 discusses the empirical strategy used to identify the effect of the network strength by occupational similarity on a displaced worker's unemployment duration. Section 4 introduces our data and shows relevant descriptive statistics. Section 5 presents the main results of the analysis. Finally, Section 6 discusses the implications of our findings.

2 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 the latter channel. We remain agnostic as to the exact mechanisms through which information transmission through networks occur.[2]

Suppose a displaced worker is looking for a job. She can meet hiring firms either (i) on the open market, or (ii) through her former coworkers if the coworkers' current employers are hiring. Once she meets a firm through either channel, she is hired immediately. Her skill level s affects the rate at which she encounters firms on the open market, $\tilde{\lambda}_s$. This contact rate is not the focus of our analysis. The channel we focus on is hiring through networks: we assume that the displaced worker meets firms through her former coworkers at the contact rate $\nu_s(E_s, E_{s'})$, where E_s and $E_{s'}$ stand for her number of same and different-skilled former coworkers, respectively, that are currently employed. Putting the two channels together, the hazard rate of exiting unemployment for a displaced worker of skill level s is:

$$\lambda_s = \tilde{\lambda}_s + \nu_s(E_s, E_{s'}). \tag{2.1}$$

We offer some remarks. First, the network contact rate depends on the number of both same-skilled and different-skilled former coworkers that are currently employed. This means

[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.

that every network contact may contribute to job finding, regardless of their occupational similarity to the displaced worker, and the impact of these contacts may vary. Second, network size does not affect the open market contact rate: displaced workers of skill s can always meet firms on the open market at the same rate, regardless of how many former coworkers they have.

Our goal is to assess the effect of skill-specific coworker networks on unemployment duration. However, relating the number of former coworkers that are currently employed to unemployment duration would conflate strength and size effects: more employed network contacts imply both a stronger network and a larger one. To distinguish between these effects, we separate the impact of the number of employed skill-s network contacts into the effects of the skill-s network employment rate ER_s and the overall size of the skill-s network N_s. Note that, by definition, the skill-s network employment rate is $ER_s = E_s/N_s$. We use the network employment rate ER_s to capture strength effects and the network size N_s to control for size effects.

This framework yields the following testable margins:

1. $\partial\nu_s/\partial ER_s \overset{?}{>} 0$: Does having stronger same-skill networks allow displaced workers to exit unemployment faster?

2. $\partial\nu_s/\partial ER_s \overset{?}{>} \partial\nu_s/\partial ER_{s'}$: Do displaced workers exit unemployment faster through same than different-skill networks?

3. $\partial\nu_s/\partial N_s \overset{?}{>} \partial\nu_s/\partial N_{s'} \overset{?}{>} 0$: Do displaced workers with larger networks exit unemployment faster? If so, does the size of same- or different-skill network matter more?

We empirically test these hypotheses in the upcoming sections. In our empirical tests, we proxy skills by occupations. All occupations are indexed by the level of education required to perform tasks needed for the job. We use data on hundreds of unique occupations and leverage the nested structure of the occupational classification to test the sensitivity of our results to the granularity of skills.

3 Empirical Strategy

Our empirical strategy measures the impact of coworker network strength on unemployment duration. Specifically, we relate the time a displaced worker spends in unemployment to the employment rate among her former coworkers. We categorize these coworkers based on whether they worked in the same occupation as the displaced worker while they were coworkers or in a different one. We estimate the following regression:

$$u_{ij} = \alpha + \gamma_1 ER_i^{\text{same}} + \gamma_2 ER_i^{\text{diff}} + \theta_1 \log(N_i^{\text{same}}) + \theta_2 \log(N_i^{\text{diff}}) + X_i\beta + \lambda_j + \varepsilon_{ij} \tag{3.1}$$

where u_{ij} represents the log unemployment duration of worker i displaced from firm j.[3] ER_i^{same} captures the employment rate of former coworkers from the same occupation, while ER_i^{diff} captures the employment rate of former coworkers who worked in a different occupation. Former coworkers are defined as the set of 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. However, workers who were co-displaced with the individual are excluded from the networks used to calculate ER_i^{same} and ER_i^{diff}.

We calculate the network employment rates ER_i^{same} and ER_i^{diff} at the time of displacement. This timing addresses the concern that our results might be driven by labor demand shocks affecting specific occupations. Furthermore, to ensure that the results are not driven by the size of these networks, Equation 3.1 controls for the number of former coworkers from same and different occupations, N_i^{same} and N_i^{diff}, respectively.

A key identification concern is the potential endogeneity of networks. Unobserved factors that affect a displaced individual's unemployment duration following a firm closure might

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

also influence the contemporaneous employment rate of their former coworker network. We take several measures to address this concern. As a starting point, to mitigate concerns about network strength being endogenous to job search efforts, we focus on individuals who become unemployed due to firm closures, a common approach in the literature (Cingano and Rosolia, 2012; Saygin, Weber, and Weynandt, 2021; Eliason, Hensvik, Kramarz, and Skans, 2023). 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 controls for these unobserved characteristics. Furthermore, 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. Additionally, displaced workers and their former coworkers may have developed specific human capital while working together, which could subsequently influence the labor market outcomes of both groups. 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 four categories of individual controls: demographic characteristics, pre-displacement earnings and employment information, pre-displacement job characteristics, and network controls. 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 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.[4] For example, this controls for the possibility that a labor demand shock in a particular occupation raises not only the employment rate among peers in the same occupation, but also reduce the unemployment duration for the worker herself.

Even with the inclusion of these controls, concerns may remain that displaced workers share unobservable similarities with their network contacts beyond what is accounted for by their pre-displacement characteristics.[5] These underlying similarities present an identification problem if they also affect unemployment duration after displacement. We dispel this concern by adding a fourth set of controls: the average worker and match quality among displaced workers' network contacts. We calculate worker and match quality for all workers in an auxiliary two-way fixed effects regression from Abowd, Kramarz, and Margolis (1999, i.e., AKM estimator) and calculate the mean of these two sets of fixed effects within the network contacts of each displaced worker. These controls ensure that shared unobserved traits of displaced workers and their network contacts do not bias our results.

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 3.1 is that, with the inclusion of these fixed effects and controls, the network employment rate

[4]Note that the pre-displacement occupation fixed effects pick up the skill-specific contact rate $\tilde{\lambda}_s$ in our theoretical framework. As we do not focus on hiring through this channel, we omit these estimates from our reported results.

[5]Indeed, Boza and Ilyés (2020) find that former coworkers may influence the employer and match quality of the firms individuals sort into, although they do not focus on the role of former coworkers after mass displacements.

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 versus 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 empirical implementation of these two frameworks is identical, and the interpretation is slightly different but ultimately similar.[6] 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, 2023) 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 314 contacts (see Table 4.1). 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.

[6] As an example, consider a coefficient estimate $\hat{\gamma}_1 = -0.3$. In a regression framework, this estimate is interpreted as a 3 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 at a $\exp(-(-0.3 \times 0.1)) = 1.030$ times faster rate than the baseline.

4 Data

This paper uses matched employer-employee data from Hungarian administrative records.[7] The data span the years 2003–2011 and cover a 50 percent de facto random sample of the population at a monthly frequency—this translates to approximately 4.6 million individuals linked across 900 thousand firms over 108 months.[8]

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, consistent with the literature (e.g., Cingano and Rosolia, 2012).[9] We expand our displacement window to 2008–2010 in a few additional analyses for robustness checks, restricting our post-displacement window to one year. 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. We require workers to have held only one full-time job and earned a positive wage at the time of displacement. Furthermore, a worker is dropped from 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.[10] Overall, our sample covers 27,699 displaced workers in 1,728 displacing firms (59,688 workers and 4,343 firms when extending the displacement window to 2008–2010).

[7]The raw administrative data are provided by various government offices. The HUN-REN CERS Databank collected, cleaned, cross-checked, and harmonized the raw data to assemble the final dataset called "Admin2," which is made available to researchers.

[8]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." Note that this sampling scheme does not bias our results as the network employment rate is observed without error. Furthermore, the true network size is double of the observed one, thus controlling for the log of the observed network size makes no quantitative difference.

[9]We observe the year of firm closure and the month of an individual separating from a particular firm in the data. We define pre- and post-displacement windows in a rolling fashion, i.e., 60 months preceding and 36 months following the month of separation from a firm that closed in 2008.

[10]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.

The high frequency of our data yields several advantages. First, we observe all job spells, not only those that are ongoing in a particular month of the year as is the case in many other linked employer-employee datasets; specifically, we observe short spells, which yields a shorter mean and median tenure than seen in other papers. Second, relatedly, we see every movement across firms and in and out of non-employment for any spells lasting at least one month. Consequently, the coworker networks we construct are much larger than in prior studies because we observe many more transitions in the network formation period. Third, this larger data size yields higher statistical power, which allows us to add many more fixed effects and controls than previously possible, resulting in tighter comparisons of displaced workers.

4.1 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.[11] 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 521 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 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

[11]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.

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 the 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 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.

4.2 Summary Statistics

This paper considers a five-year pre-displacement window for network formation and a post-displacement window of three years to measure re-employment outcomes. In our main specification, the outcome of interest is unemployment duration. We calculate the unemployment duration of displaced workers as months after displacement without employment records. In these estimations, we focus on workers who were displaced from closing firms in 2008 to capture full pre- and post-displacement networks in the data. As a robustness exercise, we also use the probability of finding a job within 12 months as our outcome, and we examine workers displaced between 2008–2010 in these analyses.[12]

Table 4.1 displays summary statistics for displaced workers in the sample. 40 percent of displaced workers are female, and the average age in the sample is 38. The mean monthly wage for workers in the five years prior to displacement is about \$530.[13] Furthermore, the median nominal wage growth is 1.0 percent per month or 12.0 percent per annum—combined with a 5.4 percent average yearly inflation between 2003–2008, this translates to

[12]The data begin in 2003 and go until 2011. For workers who remain unemployed within the sample period, we top-code the unemployment duration to the maximum observed duration.
[13]Values are denoted in 2010 U.S. dollars.

an annual real wage growth rate of 6.6 percent. The median number of employees at the firms individuals worked in during the period prior to displacement is 73. (Few people work at firms with a large number of employees; thus, the mean headcount is driven by outliers.) Finally, the average job tenure in the five-year period before displacement is 18 months, with a median tenure of 10 months.

Table 4.1 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, and 76 percent of them find a job within one year.[14] The average employment rate of a given displaced worker's former coworkers (not including co-displaced coworkers) is 74 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 69 percent. Finally, a worker has a median network size of 314 (mean 3,448). Restricting this sample to network members who work in the same occupation, the median network size is 104 (mean 1,098).[15]

Table 4.1 also shows descriptive statistics for displaced workers broken down by the education requirement of the job. Workers displaced from occupations that require higher levels of education have higher pre-displacement wages, worked at smaller firms, and had longer tenure at their firms on average. Workers in jobs with higher education requirements also have smaller overall networks and smaller same-occupation networks than counterparts in jobs with lower education requirements, 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. Workers

[14] Note that the 75th percentile of unemployment durations is 13 months, while the 12-month job finding probability is 75.9 percent. These numbers do not align because they are calculated in different subsamples: unemployment duration is calculated among those workers who were displaced in 2008 while job finding probabilities are calculated among those displaced in 2008–10.

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

Table 4.1: Summary Statistics

Variable	Total					By Education		
	Percentiles			Mean	(S.D.)	None	Primary	HS+
	25th	50th	75th			Means† and medians$^{\times}$		
Female (%)	–	–	–	40.1	–	44.1†	36.7†	50.2†
Age (years)	28	36	48	37.9	(12.2)	39.4†	38.2†	39.1†
Pre-displacement								
Wage (USD, 2010)	301	398	559	529.8	(779.1)	344.5†	470.4†	997.8†
Wage growth (%)	0.1	1.0	2.0	1.2	(5.3)	1.3†	1.1†	1.2†
Firm size (headcount, num.)	25	73	275	1,491	(5,626)	79$^{\times}$	76$^{\times}$	65$^{\times}$
Tenure (months)	4	10	26	17.9	(18.8)	13.6†	18.2†	24.7†
Post-displacement								
Unemployment duration (months)	0	4	13	10.0	(13.0)	11.4†	10.0†	9.0†
1-month job finding probability (%)	–	–	–	38.2	–	30.5†	37.8†	46.8†
6-month job finding probability (%)	–	–	–	60.8	–	56.0†	61.0†	62.5†
12-month job finding probability (%)	–	–	–	75.9	–	72.9†	76.0†	76.0†
Network employment rate (%)	66.7	74.6	81.7	74.0	(11.8)	72.4†	73.6†	77.2†
Same occupation (%)	61.2	71.2	80.8	69.2	(19.8)	65.6†	69.9†	69.5†
Network size (num.)	69	314	2,652	3,448.4	(7,431.4)	361$^{\times}$	290$^{\times}$	190$^{\times}$
Same occupation (num.)	17	104	745	1,098.2	(2,729.6)	163$^{\times}$	102$^{\times}$	21$^{\times}$

Notes: † denotes means, $^{\times}$ denotes medians. Sample consists of workers displaced in 2008–10, except unemployment duration which is only for 2008. Pre-displacement window is five years prior to displacement. Post-displacement window is up to three years after displacement. Unemployment durations are right-censored at the end of 2011. *Source:* HUN-REN CERS, authors' own calculations.

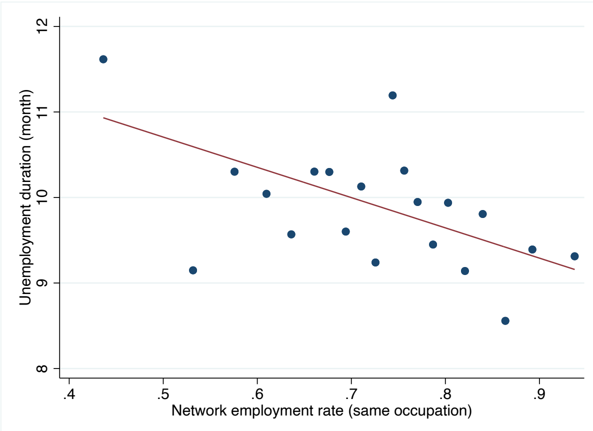
in higher education jobs also have shorter unemployment duration after displacement, and their overall network of former coworkers tend to have higher employment rates at all. At the same time, the employment rate of same-occupation former coworkers is flatter across education levels.

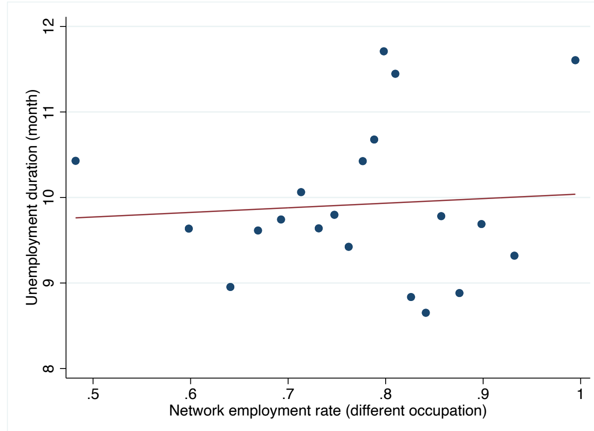
Next, Figure 4.1 provides a descriptive analysis of the correlation between former coworker network employment rate and unemployment duration for a displaced worker.[16] The figure illustrates a negative correlation between network employment rate and unemployment duration for same-occupation coworkers, whereas the correlation is negligible or slightly positive for the employment rate of different-occupation coworkers.

While Figure 4.1 suggests that unemployment duration varies with the network employment rate, the relationship should not be interpreted causally. This graph does not include firm fixed effects, controls for pre-displacement labor market trends, network size, or any

[16] Appendix Figure A.2 displays similar patterns using the probability of finding a job within 1, 3, or 6 months for a longer sample.

Figure 4.1: Network Employment Rate and Unemployment Duration





Notes: Binscatter plot of unemployment duration on network employment rates. Sample consists of workers displaced in 2008. Unemployment durations are right-censored at the end of 2011. *Source:* HUN-REN CERS, authors' own calculations.

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 outlined in Section 3 to analyze the effects of network employment rate on the unemployment duration of displaced workers.

5 Results

Table 5.1 presents our main results analyzing the effect of network strength by occupational similarity on unemployment duration of displaced workers. Column (1) examines the overall effect of former coworkers from all occupations: we assess 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 a 10 percentage point increase in the network employment rate decreases a displaced worker's unemployment duration by 2.6 percent, or 8 days, indicating former coworkers play a significant role in the job search process.[17]

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 analog of this variable for log network size. Results indicate that the benefit of network contacts comes solely from coworkers who worked in the same four-digit occupation. When looking at the impact of the network employment rate of all former coworkers, our estimate is not statistically significant. However, a 10 percentage point increase in the network employment rate of former coworkers from the same four-digit occupation decreases unemployment duration by an additional 1.8 percentage points relative to the (statistically insignificant) baseline of 1.2 percent, for a total effect of 3.0 percent (9 days).

Next, instead of using a binary definition of same- and different-occupation coworkers, we provide a more in-depth assessment of the threshold of occupational similarity for which coworkers are helpful in job finding. Specifically, Table 5.2 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. That is, 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 controls for the size of same- and different-occupation networks (omitted for brevity), 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 four-digit occupation as the coworker—the narrowest definition of occupations available to us. A 10 percentage point increase in the network employment rate of coworkers from the same four-digit occupation codes decreases unemployment duration by 2.0 percent (6 days). An increase in network employment rate of coworkers from the same three-digit

[17] The average unemployment duration for displaced workers is 10.0 months, as shown in Table 4.1.

Table 5.1: Same- vs. Different-Occupation Network Employment Rates on Unemployment Duration

	(1)	(2)
Network employment rate	-0.261^{***}	-0.117
	(0.096)	(0.113)
Network employment rate, same occ.		-0.180^{**}
		(0.075)
Log network size	-0.008	-0.006
	(0.007)	(0.012)
Log network size, same occ.		-0.005
		(0.011)
AKM worker FE in network	0.027	0.019
	(0.066)	(0.066)
AKM match FE in network	0.165	0.192
	(0.169)	(0.172)
Wage at displacement	-0.291^{***}	-0.291^{***}
	(0.037)	(0.037)
Pre-displacement wage growth	-0.722^{***}	-0.728^{***}
	(0.199)	(0.198)
Pre-displacement unemployment	0.896^{***}	0.890^{***}
	(0.049)	(0.049)
Pre-displacement firm size	0.016^{*}	0.017^{**}
	(0.008)	(0.008)
Num. pre-displacement employers – 1	-0.236^{***}	-0.238^{***}
	(0.067)	(0.067)
Num. pre-displacement employers – 2	-0.020	-0.019
	(0.041)	(0.041)
Num. pre-displacement employers – 3	-0.053	-0.054
	(0.039)	(0.039)
Observations	23,219	23,219
Closing firm FE	*Y*	*Y*
Pre-displacement occ. FE	*Y*	*Y*
Pre-displacement sector FE	*Y*	*Y*
R^2	0.296	0.296
Within R^2	0.069	0.069

Notes: Cluster-robust standard errors at the closing firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Sample consists of workers displaced in 2008, and unemployment durations are right-censored at the end of 2011. 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 4-digit occupation as the displaced worker. All other coworkers are defined as different-occupation. *Source:* HUN-REN CERS, authors' own calculations.

Table 5.2: Network Employment Rate on Unemployment Duration: Detailed Occupational Similarity Breakdown

Network employment rate, same 4-digit occ.	-0.204^{***}
	(0.066)
Network employment rate, same 3-digit occ.	-0.039
	(0.026)
Network employment rate, same 2-digit occ.	0.003
	(0.027)
Network employment rate, same 1-digit occ.	0.022
	(0.029)
Network employment rate, other occ.	-0.055
	(0.073)
Log network size	-0.011
	(0.008)
Observations	23,219
Occ. network composition	*Y*
Network AKM FEs	*Y*
Pre-displacement worker characteristics	*Y*
Pre-displacement firm characteristics	*Y*
Closing firm FE	*Y*
Pre-displacement occ. FE	*Y*
Pre-displacement sector FE	*Y*
R^2	0.296
Within R^2	0.069

Notes: Cluster-robust standard errors at the closing firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Sample consists of workers displaced in 2008, and unemployment durations are right-censored at the end of 2011. Outcome variable is log unemployment duration, measured in months. Occ. networks are mutually exclusive (i.e., former coworkers in same x-digit networks are not part of same $(x+1)$-digit network. Occ. network composition: share of network contacts in each mutually exclusive occ. category. Network AKM FEs: average AKM worker and match FE in network. 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. *Source:* HUN-REN CERS, authors' own calculations.

occupation, though, has no significant effect on a worker's unemployment duration. Similarly, the network employment rate of coworkers from the same two-digit, one-digit, and different occupations has no bearing on a displaced worker's unemployment duration. The magnitudes of estimates on same one-, two-, and three-digit occupation coworkers are small in comparison to same four-digit occupation coworkers as well.

5.1 Heterogeneity

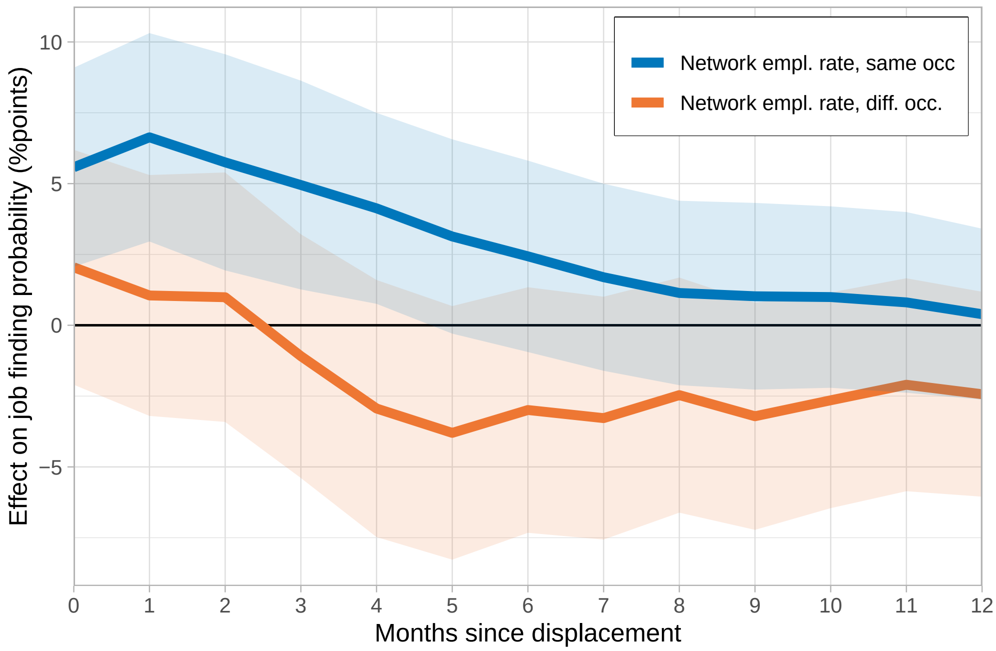
Our main analyses reveal that occupational similarity plays an important role in job finding through coworker networks. In fact, only former coworkers who worked in the same narrowly defined occupation as a displaced worker matter in reducing a worker's unemployment duration. We now explore whether these effects are universally present through time spent in unemployment, and whether they hold for job seekers at all skill levels.

We first look at the heterogeneity of our results along unemployment duration. To do so, we estimate a series of regressions modifying Equation 3.1, where (i) we replace the outcome variable by the probability that the unemployed individual found a job within t months of displacement, and (ii) we vary t. This analysis extends that of Glitz (2017) who looks at the probability of finding a job within 12 months: given the granularity of our data we are able to look at finer, monthly durations, ranging from 0 to 12 months. This approach has the added benefit that we can use a larger sample: since we only need to observe outcomes in a 12-month post-displacement window, we can include individuals who were displaced by a firm closure up to 2010.

Figure 5.1 displays the estimated coefficients on same- and different-occupation network employment rates in these separate regressions, with the time window for job finding being displayed on the horizontal axis. Results reveal that same-occupation network contacts matter in the beginning of the unemployment spell, up to four months, although these effects quickly fade and we do not detect a statistically significant effect at longer durations. In contrast, network contacts in different occupations do not have a statistically significant impact on job finding at any duration.

We next turn to exploring the heterogeneity of our main results across skill levels in Table 5.3. Results are estimated in one single regression that interacts network employment rate by occupational similarity with the education requirements of the job. Results are displayed across columns by job requirements for ease of interpretation. The first column looks at

Figure 5.1: Time-Varying Impact of Network Employment Rate on Job Finding Probability



Notes: Sample consists of workers displaced between 2008–2010. Solid lines represent regression coefficients on same and different four-digit occupation network employment rates in regressions where the outcome is job finding probability within t months, t on the horizontal axis. Shaded areas represent 95% confidence bounds using cluster-robust standard errors at the closing firm level. *Source:* HUN-REN CERS, authors' own calculations.

workers displaced from occupations that require no formal education, the second column looks at workers in occupations that require a primary education level of knowledge, and the third column 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 occupation education requirements.

Results reveal significant heterogeneity in the role of coworkers by occupational similarity across job categories. For workers in jobs requiring no formal education, the reduction in 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 2.8 percent. The employment rate of former coworkers in the same three-digit,

Table 5.3: Network Employment Rate on Unemployment Duration by Occupation Education Requirements

	No formal	Primary	High school+
Network employment rate, same 4-digit occ.	-0.280^{**}	-0.212^{***}	-0.059
	(0.124)	(0.075)	(0.119)
Network employment rate, same 3-digit occ.	-0.053	-0.032	-0.062
	(0.057)	(0.032)	(0.064)
Network employment rate, same 2-digit occ.	-0.096	0.031	-0.046
	(0.061)	(0.032)	(0.064)
Network employment rate, same 1-digit occ.	-0.023	0.022	0.107
	(0.062)	(0.034)	(0.067)
Network employment rate, other occ.	0.125	-0.089	-0.198
	(0.130)	(0.082)	(0.148)
Log network size	-0.009	-0.015	-0.035^{**}
	(0.015)	(0.009)	(0.015)
Observations		21,692	
Occ. network composition		Y	
Network AKM FEs		Y	
Pre-displacement worker characteristics		Y	
Pre-displacement firm characteristics		Y	
Closing firm FE		Y	
Pre-displacement occ. FE		Y	
Pre-displacement sector FE		Y	
R^2		0.307	
Within R^2		0.075	
Joint F-test		24.01	
p-value		0.000	

Notes: Cluster-robust standard errors at the closing firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Sample consists of workers displaced in 2008, and unemployment durations are right-censored at the end of 2011. Outcome variable is log unemployment duration, measured in months. Occ. networks are mutually exclusive (i.e., former coworkers in same x-digit networks are not part of same $(x+1)$-digit network. Occ. network composition: share of network contacts in each mutually exclusive occ. category. Network AKM FEs: average AKM worker and match FE in network. 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. *Source:* HUN-REN CERS, authors' own calculations.

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 2.1 percent, with no significant effect on the employment rate of other former coworkers. However, results look very different for workers who are displaced from jobs requiring at least a high school education. For these workers, there is no notable effect of the employment rate of former coworkers on unemployment duration, regardless of their occupational similarity level. At the same time, the size of networks matters for this group: a 10 percent larger network decreases unemployment duration by 0.35 percent or 1 day. The effect is economically small but statistically significant—however, we note that the effects of network size on unemployment duration for the two lower-skilled groups are precisely estimated zeros.

5.2 Interpreting Our Results

Theoretical work has assessed the presence of network effects in job finding through two mechanisms, demand-side and supply-side channels. Supply-side mechanisms focus on transmission of information about job opportunities between workers and their contacts (Calvo-Armengól and Jackson, 2004). Demand-side mechanisms focus on the role of employers receiving information about potential hires (Montgomery, 1991; Simon and Warner, 1992; Dustmann, Glitz, Schönberg, and Brücker, 2016). We emphasize that we are not able to isolate supply and demand forces in this setting, and that the network effects we find are compatible with transmission of information among workers, as well as job referrals from workers to employers (Saygin, Weber, and Weynandt, 2021).

Specifically, results could reflect a demand-side story if a significant barrier for workers seeking lower-skilled jobs is knowledge regarding job opportunities, and same-occupation coworkers are useful in providing this information. For higher-skilled jobs, it may be that the match between workers and firms are more important (e.g., employers focus more on factors like credentials and work experience); thus, having network contacts in the same occupation is not necessarily helpful. But for these workers, larger networks may be helpful in increasing the contact rate with vacancies, and their former coworkers are able to notify them of jobs that would not otherwise be on their radar. Alternatively, results could reflect a supply-side story if low-skilled workers benefit from people in their own occupation because contacts in more skilled occupations are unwilling to recommend them to their current employer. The same may not hold for high-skilled workers if workers in other occupations are willing to recommend them because they are expected to be of good quality. More research is required to pin down these mechanisms.

5.3 Robustness

One potential concern with looking at the effects of network employment rate on job finding is that the outcome for some observations will be right-censored in our data. Namely, we only observe employment outcomes for individuals through the end of 2011. We aim to minimize this issue by restricting the sample to individuals displaced in 2008 when looking at the outcome of unemployment duration so that we can track employment outcomes for all individuals for at least 36 months. 11.8 percent of our observations are right-censored, in line with the descriptive statistics in Table 4.1 showing that the average unemployment duration is 10 months with the 75th percentile being 13 months. As a result, we consider right censoring a negligible issue in our setting. Nonetheless, as a robustness check, we use the probability that a displaced worker finds a job within one month of displacement as an alternative outcome. We choose one month as our time frame of interest since Figure 5.1 suggests that the role of coworker networks matters the most immediately following displacement. Results are also robust to longer job finding time frames. Additionally, choosing a displacement window of one month as the outcome allows us to maximize our sample and look at the effects of network employment rates for workers displaced between 2008–2011, since we only need to be able to follow workers for one month post-displacement.

Appendix Table A.5 replicates the results in Table 5.1 using the probability of finding a job within one month after displacement instead of unemployment duration as the outcome of interest. We find qualitatively very similar results to those of the main specification. Namely, a higher network employment rate increases the probability that displaced individuals find a job within one month of displacement. Furthermore, these results are driven by the network employment rate of former coworkers who worked in the same four-digit occupation as the displaced worker. Specifically, the network employment rate of coworkers from a different occupation does not affect job finding for displaced workers. However, a 10 percentage point increase in the network employment rate of coworkers from the same four-digit occupation code increases the probability of finding a job within a month by 5.9 percentage points relative to the effect of those from a different occupation.

Additionally, we check for the robustness of our results to the exclusion of individuals who have extremely large former coworker networks. Table 4.1 indicates that the median number of former coworkers in a displaced worker's network is 314. However, the mean value is 3,448, indicating the distribution of network size is right-skewed. To ensure that results are not being driven by these large networks, Appendix B re-estimates our main results in a subsample excluding large networks, defined as those above the 99th percentile of the network size distribution. Reassuringly, the results are robust to the exclusion of these observations.[18]

6 Conclusion

This paper expands our understanding of the role of coworker 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 who worked in the same, narrowly-defined occupation help displaced workers

[18] We have also performed the analyses in Appendix B using alternative network size cutoffs at the 90th, 95th, 99th, and 99.9th percentiles. Our results are robust to the choice of cutoff.

find jobs. Further analyses reveal that this effect is present for only a few months after displacement and is driven exclusively by coworkers in occupations that require low levels of education. Our results suggest that different coworkers matter for different types of jobs, which likely reflect the differences in how and what kind of information is being transmitted through coworker networks for job finding.

Much of the prior research has demonstrated that 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, which has implications for workplace composition in the face of networking. It would be illustrative for future work to further analyze the information content of social networks in the job search process. Specifically, it would be informative to know 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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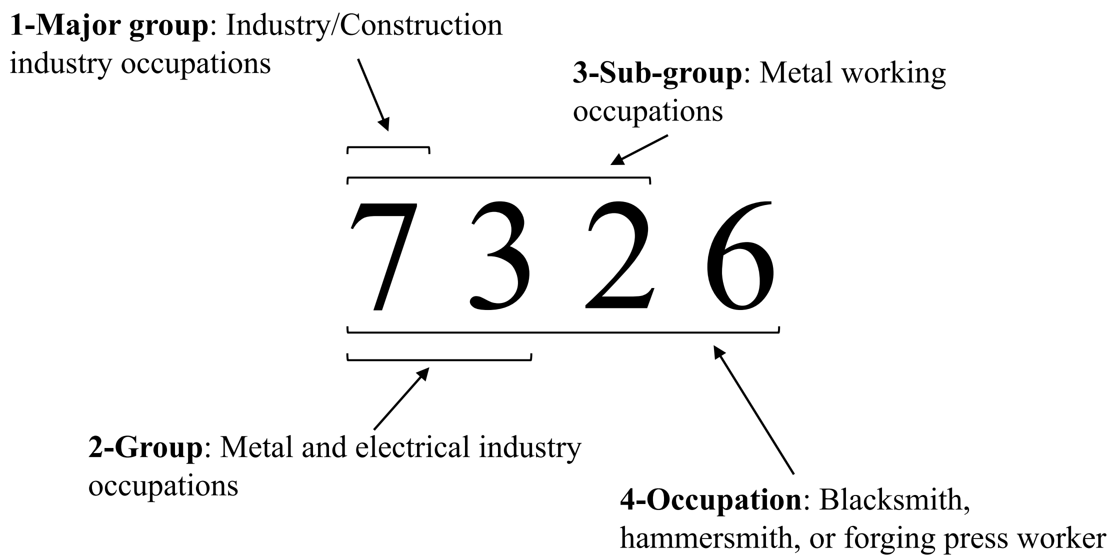
Appendices

A Additional Data Summaries

Appendix Figure A.1: Occupation Classification Example: Blacksmith



Source: authors' own illustration.

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+	2,080	3.78
2–Professionals	High School+	2,250	4.09
3–Technicians and Associate Professionals	High School+	5,561	10.11
4–Office and Management	Primary	2,675	4.86
5–Commercial and Services	Primary	9,691	17.62
6–Agricultural and Forestry	Primary	618	1.12
7–Industry and Construction	Primary	13,180	23.96
8–Machine Operators, Assembly Workers, Drivers	Primary	8,760	15.93
9–Elementary Occupations	None	10,184	18.52

Source: HUN-REN CERS, authors' own calculations.

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)	4,307	8.78	8.78
5366	Security guards	2,950	6.02	14.80
5112	Shop assistants	2,395	4.88	19.69
8356	Heavy-truck and lorry drivers	2,025	4.13	23.82
8193	Production-line assemblers	1,767	3.60	27.42
9111	House, flat and office cleaners	1,520	3.10	30.52
7421	Locksmiths	1,182	2.41	32.93
7211	Meat, fish and poultry processing workers	1,068	2.18	35.11
9119	Cleaners and related elementary occupations n.e.c.	1,019	2.08	37.19
7530	Stock clerks, warehousemen	759	1.55	38.74
5123	Waiters, restaurant salespersons	755	1.54	40.28
4199	Office clerks n.e.c.	741	1.51	41.79
5231	Mail carriers	697	1.42	43.21
7425	Welders, flame cutters	676	1.38	44.59
9131	Manual materials handlers, hand packers	671	1.37	45.96
8199	Processing machine operators, production-line workers n.e.c.	554	1.13	47.09
7611	Bricklayers, masons	540	1.10	48.19
9150	Elementary services occupations	540	1.10	49.29
8129	Light industry machine operators and production-line workers n.e.c.	533	1.09	50.38
4193	Office administrators, clerical writers	504	1.03	51.41

Source: HUN-REN CERS, authors' own calculations.

Appendix Table A.2 displays the 20 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, security guards, and shop assistants.

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

Variable	By Education None	Primary	HS+
	Means† and Medians$^{\times}$		
Network size, same 4-digit occ.	1,172.3†	912.5†	731.0†
	163$^{\times}$	102$^{\times}$	21$^{\times}$
Network size, same 3-digit occ.	85.0†	149.1†	60.2†
	0$^{\times}$	2$^{\times}$	1$^{\times}$
Network size, same 2-digit occ.	440.8†	201.8†	355.5†
	5$^{\times}$	1$^{\times}$	3$^{\times}$
Network size, same 1-digit occ.	45.2†	87.5†	187.2†
	0$^{\times}$	3$^{\times}$	5$^{\times}$
Network size, different 1-digit occ.	2,670.6†	1,906.8†	2,895.1†
	118$^{\times}$	109$^{\times}$	127$^{\times}$

Source: HUN-REN CERS, authors' own calculations.

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

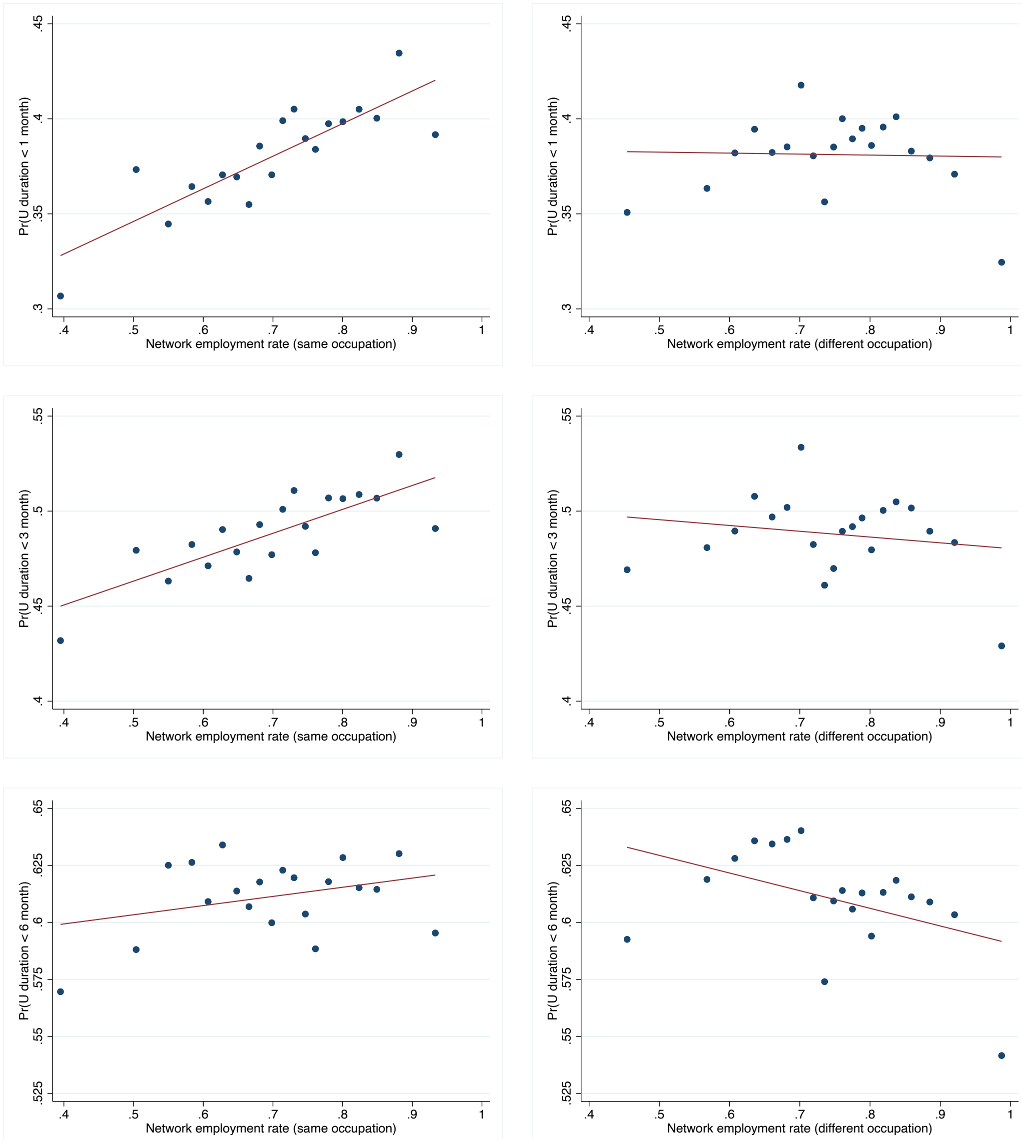
Appendix Table A.4: Post-Displacement Outcomes across Occupational Education Levels

	No Formal	Primary	High School+
Unemployment Duration (months)	11.38	9.99	9.04
Staying in Occupation (percent)	46.3	48.8	35.1

Source: HUN-REN CERS, authors' own calculations.

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 the same occupation than the job they had at the time of displacement.

Appendix Figure A.2: Network Employment Rate and Job Finding Probability



Notes: Sample consists of workers displaced between 2008–2011. *Source:* HUN-REN CERS, authors' own calculations.

Appendix Figure A.2 provides an alternative to Figure 4.1: it shows the relationship between the network employment rate and the probability of finding a job within 1, 3, and 6 months. The same pattern emerges: there is a positive correlation between stronger same-occupation networks and the job finding probability for all time horizons, while the correlation is zero or slightly negative for stronger different-occupation networks.

Appendix Table A.5: Effect of Network Employment Rate on Finding a Job within One Month of Displacement

	(1)	(2)
Network employment rate	0.077***	0.029
	(0.028)	(0.031)
Network employment rate, same occ.		0.059***
		(0.021)
Log network size	0.000	−0.000
	(0.002)	(0.003)
Log network size, same occ.		0.001
		(0.003)
AKM worker FE in network	−0.001	0.002
	(0.018)	(0.018)
AKM match FE in network	0.039	0.033
	(0.048)	(0.048)
Wage at displacement	0.077***	0.077***
	(0.007)	(0.007)
Pre-displacement wage growth	0.166***	0.167***
	(0.041)	(0.041)
Pre-displacement unemployment	−0.273***	−0.270***
	(0.013)	(0.013)
Pre-displacement firm size	−0.009***	−0.009***
	(0.003)	(0.003)
Num. pre-displacement employers – 1	0.036*	0.036**
	(0.018)	(0.018)
Num. pre-displacement employers – 2	−0.006	−0.006
	(0.011)	(0.011)
Num. pre-displacement employers – 3	−0.010	−0.010
	(0.011)	(0.011)
Observations	48,678	48,678
Closing firm FE	Y	Y
Pre-displacement occ. FE	Y	Y
Pre-displacement sector FE	Y	Y
R^2	0.293	0.293
Within R^2	0.032	0.032

Notes: Cluster-robust standard errors at the closing firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Sample consists of workers displaced in 2008, and unemployment durations are right-censored at the end of 2011. 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 4-digit occupation as the displaced worker. All other coworkers are defined as different-occupation. *Source:* HUN-REN CERS, authors' own calculations.

B Robustness to Excluding Large Networks

The following tables replicate our main results in Tables 5.1, 5.2, and 5.3 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	-0.257^{***}	-0.115
	(0.096)	(0.113)
Network employment rate, same occ.		-0.179^{**}
		(0.076)
Log network size	-0.007	-0.005
	(0.007)	(0.012)
Log network size, same occ.		-0.006
		(0.011)
AKM worker FE in network	0.021	0.013
	(0.065)	(0.065)
AKM match FE in network	0.166	0.193
	(0.170)	(0.173)
Wage at displacement	-0.290^{***}	-0.291^{***}
	(0.037)	(0.037)
Pre-displacement wage growth	-0.717^{***}	-0.723^{***}
	(0.198)	(0.198)
Pre-displacement unemployment	0.897^{***}	0.891^{***}
	(0.049)	(0.049)
Pre-displacement firm size	0.015^{*}	0.017^{*}
	(0.009)	(0.009)
Num. pre-displacement employers – 1	-0.236^{***}	-0.238^{***}
	(0.067)	(0.066)
Num. pre-displacement employers – 2	-0.019	-0.019
	(0.042)	(0.042)
Num. pre-displacement employers – 3	-0.054	-0.055
	(0.039)	(0.039)
Observations	23,141	23,141
Closing firm FE	Y	Y
Pre-displacement occ. FE	Y	Y
Pre-displacement sector FE	Y	Y
R^2	0.296	0.296
Within R^2	0.069	0.069

Notes: Cluster-robust standard errors at the closing firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Sample consists of workers displaced in 2008, and unemployment durations are right-censored at the end of 2011. 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 4-digit occupation as the displaced worker. All other coworkers are defined as different-occupation. *Source:* HUN-REN CERS, authors' own calculations.

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

Network employment rate, same 4-digit occ.	-0.202^{***}
	(0.067)
Network employment rate, same 3-digit occ.	-0.039
	(0.026)
Network employment rate, same 2-digit occ.	0.003
	(0.027)
Network employment rate, same 1-digit occ.	0.023
	(0.029)
Network employment rate, other occ.	-0.054
	(0.073)
Log network size	-0.010
	(0.008)
Observations	$23,141$
Network AKM FEs	Y
Pre-displacement worker characteristics	Y
Pre-displacement firm characteristics	Y
Closing firm FE	Y
Pre-displacement occ. FE	Y
Pre-displacement sector FE	Y
R^2	0.296
Within R^2	0.069

Notes: Cluster-robust standard errors at the closing firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Sample consists of workers displaced in 2008, and unemployment durations are right-censored at the end of 2011. Outcome variable is log unemployment duration, measured in months. Occ. networks are mutually exclusive (i.e., former coworkers in same x-digit networks are not part of same $(x+1)$-digit network. Occ. network composition: share of network contacts in each mutually exclusive occ. category. Network AKM FEs: average AKM worker and match FE in network. 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. *Source:* HUN-REN CERS, authors' own calculations.

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

	No formal	Primary	High school+
Network employment rate, same 4-digit occ.	-0.271^{**}	-0.211^{***}	-0.060
	(0.124)	(0.075)	(0.119)
Network employment rate, same 3-digit occ.	-0.052	-0.032	-0.063
	(0.057)	(0.032)	(0.064)
Network employment rate, same 2-digit occ.	-0.093	0.030	-0.046
	(0.062)	(0.032)	(0.064)
Network employment rate, same 1-digit occ.	-0.019	0.022	0.107
	(0.063)	(0.034)	(0.067)
Network employment rate, other occ.	0.120	-0.082	-0.190
	(0.130)	(0.082)	(0.148)
Log network size	-0.007	-0.014	-0.034^{**}
	(0.015)	(0.009)	(0.015)
Observations		21,623	
Occ. network composition		Y	
Network AKM FEs		Y	
Pre-displacement worker characteristics		Y	
Pre-displacement firm characteristics		Y	
Closing firm FE		Y	
Pre-displacement occ. FE		Y	
Pre-displacement sector FE		Y	
R^2		0.307	
Within R^2		0.075	
Joint F-test		23.89	
p-value		0.000	

Notes: Cluster-robust standard errors at the closing firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.10. Sample consists of workers displaced in 2008, and unemployment durations are right-censored at the end of 2011. Outcome variable is log unemployment duration, measured in months. Occ. networks are mutually exclusive (i.e., former coworkers in same x-digit networks are not part of same $(x + 1)$-digit network. Occ. network composition: share of network contacts in each mutually exclusive occ. category. Network AKM FEs: average AKM worker and match FE in network. 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. *Source:* HUN-REN CERS, authors' own calculations.