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 administrative matched employer-employee data from Hungary, this paper relates the unemployment duration of displaced workers to the employment rate in the networks of their former coworkers in various occupations. We find that coworkers of all occupational backgrounds are helpful in the job finding process, but coworkers who worked in the same narrow occupation as the displaced worker are significantly more useful. Additionally, effects vary substantially along skill levels: for displaced workers in occupations that require little to no education, coworkers in the same narrow occupation matter; for those in occupations requiring more education, coworkers in different occupations reduce unemployment.

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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 information about the job seeker or available opportunities than others.

This paper explores which links within a social network are relevant in job finding for displaced workers, focusing on networks formed by their former coworkers. Specifically, we examine the role of former coworkers by occupational similarity in helping displaced workers find jobs. Coworkers working in a similar occupation as the displaced worker may be more relevant in job finding than coworkers in unrelated fields. A key empirical challenge in this setting is that data on occupation-specific coworker networks are rarely available. We overcome this challenge by exploiting administrative matched employer-employee data from Hungary, which tracks workers' occupations over time. Using these data, we construct coworker networks and measure their occupational similarity to displaced workers.

We first establish that having a stronger coworker network, defined as a worker's former coworkers having a higher employment rate, reduces the unemployment duration of a displaced worker. Next, we examine whether this effect is driven by former coworkers who worked in similar occupations to the worker, 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 displaced worker may be more

[1]Family members: Kramarz and Skans (2014). Residential neighbors: Bayer, Ross, and Topa (2008); Hellerstein, Kutzbach, and Neumark (2015). Same ethnic background: Munshi (2003); Dustmann, Glitz, Schönberg, and Brücker (2016). Roommates: Sacerdote (2001). Classmates: Kramarz and Thesmar (2013); Zhu (2019); Zimmerman (2019).

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 displaced worker may be more valuable if they are more knowledgeable about the worker's skills or other attributes that are valued on the job market. 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 such network effects is that individuals do not choose their friends and acquaintances randomly. In the context of our study, unobserved characteristics that lead individuals to be in the same network may drive both network employment rate and an individual's own unemployment duration. To measure the causal effect of the network employment rate, we first restrict our analysis to comparisons of workers 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 unobservables, this treatise also eliminates time-invariant unobserved traits across networks. Next, we rule out heterogeneous effects within workers at closing firms that may affect both former coworker network characteristics and unemployment duration. To that end, 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 workers who are displaced from the same firm at the same time and 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 the a different occupation (defined as coworkers who did not work in the same four-digit occupation as the displaced worker) reduces unemployment duration by 2.5 percent. For coworkers from the same four-digit occupation, the effect is 2 percentage points higher in magnitude. This effect is driven entirely by coworkers who worked in the same four-digit occupation as the displaced worker, and the network employment rate of all other coworkers does not have a significant effect on unemployment duration. Further analyses reveal that the effects are driven exclusively by workers in occupations that require up to primary levels 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, an increase in the employment rate of former coworkers from different occupations does significantly reduce unemployment duration for these displaced workers.

This paper contributes to two main strands of economic research on networks. First, 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). Adding to these studies, this paper is the first to examine *which* coworker links are useful by occupational similarity. Notably, we find significant differences in results across the jobs by skill level requirement, which may be reflective of underlying differences in what information is valuable towards workers and/or employers in different jobs. This distinction has important implications for how we think of the utility of social networks. As an example, an individual who works in an 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). Through this key channel, an individual's contemporary job may affect her future career trajectory.

Second, this paper contributes to the literature on the role of "strong and weak ties" in networking, where tie strength is a measure of how close two individuals are. Granovetter (1973) first proposed his seminal theory emphasizing weak ties to be relatively more important than strong ties, since strong ties likely possess redundant information while weak ties are more likely to possess novel information. Gee, Jones, and Burke (2017) test this theory on Facebook data, measuring tie strength as a function of how often two individuals have interactions on the platform. Their findings refute Granovetter's (1973) theory—the authors find that, for a given tie, a strong tie is more helpful than a weak tie in job finding. One potential resolution for this discrepancy may be that only certain types of strong ties have redundant information. Namely, Facebook captures a wide array of interpersonal ties, many of which may not carry significant information along dimensions related to job search. Former coworkers, on the other hand, are an especially relevant set of contacts for job finding since they likely possess a great deal of relevant information on an individual in a professional setting. The fact that this study also finds that stronger ties, as proxied by former coworkers in the same occupation, are more useful in job finding than weak ties further refutes the hypothesis of Granovetter (1973) that strong ties are redundant sources of information.

Moving forward, 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.

2 Empirical Strategy

Our empirical strategy measures the relationship between unemployment duration and network strength. 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:

$$u_{ijt} = \alpha + \gamma_1 ER_{it}^{\text{same}} + \gamma_2 ER_{it}^{\text{diff}} + \theta_1 \log(N_{it}^{\text{same}}) + \theta_2 \log(N_{it}^{\text{diff}}) + X_{it}\beta + \lambda_{jt} + \varepsilon_{ijt} \quad (2.1)$$

where u_{ijt} measures the log unemployment duration of worker i displaced from firm j at time t. ER_{it}^{same} captures the employment rate of former coworkers from the same occupation at time t, while ER_{it}^{diff} captures the employment rate of former coworkers who worked in a different occupation. 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.

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. We restrict our analysis to workers co-displaced by the same firm using a closing firm fixed effect, λ_{jt}. 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 have different unobservable characteristics that affect both their respective unemployment durations 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_{it}.

The vector X_{it} 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. Addressing the concern that co-displaced workers sort into firms prior to displacement in ways that will affect both their network composition and unemployment duration, we aim to capture this in their earnings and unemployment duration during this period. 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. 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.

The goal of the 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.

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[2] of the population, which translates to approximately 4.6 million individuals linked across 900 thousand firms.

[2]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."

This study zooms in on workers displaced in 2008 in order to isolate the effect of referrals using exogenous job separations. Displaced workers are 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.

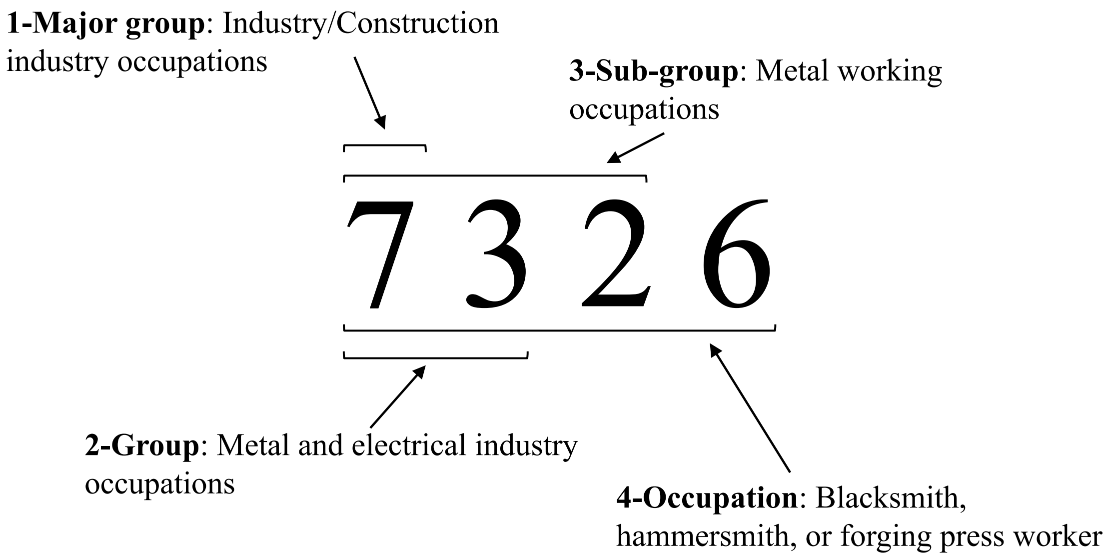
During the displacement period of this sample, the Hungarian unemployment insurance system had a two-tier setup. Broadly, in the first tier, the unemployed were eligible for benefits with a 60 percent replacement rate for 91 days. In the second tier, they were eligible for benefits of 60 percent of the minimum wage for another 179 days. After that, they could collect general social security benefits which anyone is eligible for, although those amounts were fairly small. In sum, the unemployment insurance scheme gave displaced workers a monetary incentive to exit unemployment soon after claiming benefits.

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 and operate on a four-digit system. 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.[3] Figure 3.2 shows an example of how occupations are nested and broken down by digits using the classification of "blacksmith".

[3]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.

Figure 3.1: Occupation Classification Example: Blacksmith



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 consists of 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. Table 3.1 shows the distribution of displaced workers in our sample across major occupational groups. 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.

The most common four-digit occupations in our sample of displaced workers are laborers and helpers, shop assistants, and security guards. Table 1 in the Appendix contains more information on four-digit occupations in the data.

Table 3.1: 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

3.2 Summary Statistics

Following Cingano and Rosolia (2012), 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. This year coincides with the global financial crisis which hit Hungary particularly severely and likely contributes to the number of displacements observed in the data.

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 3.2 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 mean monthly wage for workers in the five years prior to displacement is equivalent to about \$532.[4] 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

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

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 3.2 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.[5] The average employment rate of a given displaced worker's former coworkers (not including co-displaced coworkers) is 77 percent. 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).

Table 3.2 also shows descriptive statistics for displaced workers broken down by education level.[6] 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 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

[5] 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.

[6] 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 3.2: Summary Statistics

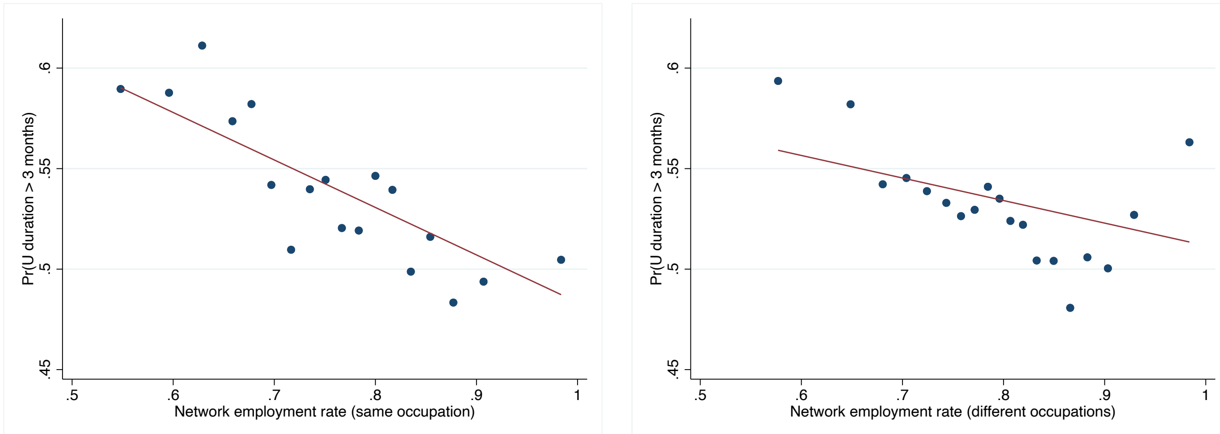
	Total				By Education		
Variable	Percentiles			Mean	**None**	**Primary**	**HS+**
	25th	50th	75th	(S.D.)	Means† and Medians$^{\times}$		
Female (%)	–	–	–	37.6	46.8†	33.6†	45.3†
				(–)			
Age	27	35	48	37.3	39.3†	37.0†	37.1†
				(12.2)			
Pre-displacement							
Wage (USD, 2010)	308	397	567	532.2	314.3†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

†: mean. $^{\times}$: 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.

employment rate, and workers in jobs requiring a high school level education or higher have a 70 percent same-occupation employment rate.

Next, Figure 3.2 looks descriptively at the correlation between former coworker network employment rate and unemployment duration for a displaced worker. The figure plots the correlation between network employment rate and the propensity of being unemployed for greater than three months after a displacement 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 3.2: Network Employment Rate and Unemployment Duration



While Figure 3.2 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 discussed earlier to analyze the effects of network employment rate on a displaced worker's unemployment duration.

4 Results

Table 4.1 shows analysis results of the role of network contacts by occupational similarity on 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. We find that an increase in the network employment rate by 10 percentage points decreases a displaced worker's unemployment duration by 4 percent, indicating former coworkers do 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. 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.

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 definition of same-occupation coworkers.[7] 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 displace 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

[7] 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 4.1: 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)
Pre-Displacement Wage Growth	-0.732^{***}	-0.735^{***}
	(0.182)	(0.182)
Pre-Displacement Unemployment	0.721^{***}	0.716^{***}
	(0.041)	(0.041)
Pre-Displacement Firm Size	0.011	0.013
	(0.009)	(0.009)
Number of Pre-Displacement Firms		
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 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.

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
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.

workers find jobs is dominantly 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. An increase in network employment rate of coworkers from the same three-digit occupation though has no 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. 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.

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

	(1)	(2)	(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)
N	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
R^2	0.337	0.308	0.435
Within R^2	0.067	0.073	0.101

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.

Overall, the 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 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.

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 percent.

These findings suggest that the usefulness of different types of network contacts, in terms of similarity, varies across different types of occupations. We rationalize these findings by remarking that 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.[8] 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 work experience, so having network con-

[8]A look at descriptive outcomes in Table 2 in the Appendix 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.

tacts 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 labor market landscapes that workers in various education levels face.

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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Appendix

Table 1 displays the most common four-digit occupations for displaced workers in the sample:

Table 1: 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

Descriptive Outcomes by Occupation Type

Table 2 shows summary statistics of post-displacement outcomes by occupation education level type. 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.

Table 2: Post-Displacement Outcomes across Occupation Types

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