Social Networks and Labor Market Outcomes: Occupation Matters

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Abstract

We study how the influence of social networks on individual labor market outcomes varies across occupations, specifically between manual and cognitive jobs. Using data from over fourteen million Brazilian workers and exploiting exogenous job termination due to mass layoffs, we confirm that social networks reduce unemployment duration and increase wages in the new job, but show that these effects are heterogeneous depending on workers' occupations at the time of displacement. Manual workers benefit more from networks in terms of job reentry but less in terms of wages compared to workers performing cognitive tasks. We argue that these different patterns are due to the fact that networks reduce the likelihood that manual workers find new jobs in the same occupation, given that occupational change is associated with reductions in wages.

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1 Introduction

The role of social networks in shaping labor market outcomes is well-established in the literature. Early studies present conceptual frameworks highlighting how networks positively impact job searches and employment opportunities (Granovetter, 1973; Rees, 1966), with theoretical models emphasizing information diffusion as a key mechanism driving these effects (Calvo-Armengol & Jackson, 2004). Building on these foundations, recent empirical work demonstrates how social networks facilitate job searches and enhance wages at new jobs (Cingano & Rosolia, 2012; Glitz, 2017; Schmutte, 2015, and see Topa (2011) and Ioannides and Loury (2004) for comprehensive literature reviews). Despite these advances, important questions remain about the variability of network efficacy across job types and skill requirements. Specifically, it is unclear how networks influence reemployment outcomes and wages depending on the transferability of skills between occupations.

This paper investigates how the influence of former co-workers on reemployment after a displacement and subsequent job outcomes differs depending on whether displaced workers previously held manual or cognitive occupations. Manual workers, who rely more heavily on informal job search channels such as network-provided information, may benefit more from these networks in terms of reemployment opportunities. However, because manual workers often possess job-specific skills, the opportunities facilitated by networks may lead to occupational shifts that involve skill loss and retraining costs, potentially limiting the quality of their job matches and earnings in the new role.

To examine these dynamics, we analyze matched employee-employer data from Brazil, which offers a rich setting for studying labor market networks in a developing economy. Our empirical strategy addresses a key challenge in studying social networks: their endogenous formation. For instance, individuals might self-select into networks based on shared unobserved characteristics that correlate with labor market outcomes. To address this issue, we focus on workers displaced by mass layoffs (Britto, Pinotti, & Sampaio, 2022; Cingano & Rosolia, 2012) and focus on the network of displaced workers, excluding the colleagues displaced by the same mass layoff. By comparing displaced workers from the same layoff event with differing network characteristics, we construct a counterfactual that isolates the causal effect of networks on reemployment outcomes.

Our findings yield several insights. First, we replicate prior evidence that networks help workers reintegrate into the labor market and positively impact their wages at the new job, extending this result to the context of a developing country. Second, we document an important heterogeneity in network effects depending on workers' occupations at the time of displacement: manual workers benefit more from networks in terms of job reentry but less in terms of wages compared to workers performing cognitive tasks. Third, we explain such a pattern by exploring the occupational stability premium, finding that workers who remain in the same occupation post-layoff experience a wage premium, and this effect is more pronounced for manual workers. Finally, we show that networks reduce the likelihood of returning to the same occupation, especially for manual workers. At the same time, they promote job-type stability for cognitive workers.

Taken together, our results highlight the dual role of networks in labor market transitions: they are crucial for reentry after displacement, particularly for manual workers, but they often steer these workers into different occupations, leading to trade-offs in terms of wage gains and skill transfer costs. By shedding light on these dynamics, our study contributes to the broader understanding of social networks and labor market inequality, particularly in the context of emerging economies, and supports the design of policies facilitating unemployed manual workers' job search in similar occupations.

This paper builds on the literature concerning workers' networks, particularly studies investigating how social connections influence job outcomes based on the characteristics of both workers and their networks. Previous research has demonstrated that workers with similar attributes–such as locality, technological expertise, ethnicity, and job type–tend to exert a stronger influence on the job reintegration of displaced colleagues (Cingano & Rosolia, 2012; Eliason, Hensvik, Kramarz, & Skans, 2023; Glitz, 2017; Gyetvai & Zhu, 2025).

In contrast, our study emphasizes heterogeneity by focusing on the displaced workers' own characteristics. While factors like age and nationality have been examined (e.g. Saygin, Weber, & Weynandt, 2021), this is, to the best of our knowledge, the first paper to systematically explore occupational differences–specifically, the contrast between manual and cognitive jobs–among displaced workers.

By distinguishing between manual and cognitive jobs, this paper further contributes to the literature on the role of occupations in shaping job outcomes. For instance, technological change–particularly automation–disproportionately affects routine manual workers by replacing middle-skill, routine-intensive jobs. This technological shift leads to an employment reallocation toward both high-skill cognitive roles and low-skill service positions (Goos, Manning, & Salomons, 2014). Workers engaged in cognitive tasks are more likely to hold professional or managerial positions, which typically offer higher wages and greater job security. In contrast, manual workers, predominantly found in manufacturing and agriculture, face higher risks of job loss, wage stagnation, and difficulties in transitioning to new roles (Acemoglu, 2011). Our contribution lies in demonstrating that while networks have a larger effect on facilitating job re-entry for manual workers, they may also exacerbate wage inequality by exerting a stronger influence on the wages of workers performing cognitive roles.

Finally, by leveraging large-scale administrative data on Brazilian workers, our study enriches the literature on labor market dynamics in developing economies (Britto et al., 2022; Dix-Carneiro & Kovak, 2017). Unlike previous studies focused primarily on North American and European labor markets, our analysis examines network effects within an emerging market characterized by unique institutional settings, where unemployment insurance and job loss can have broader socio-economic consequences (Britto et al., 2022). This perspective complements existing research on the influence of networks in regional and occupational labor mobility (Dustmann, Glitz, Schönberg, & Brücker, 2016).

The remainder of the paper is structured as follows. Section 2 describes the data and provides descriptive statistics. Sections 3 and 4 present our empirical strategy and results, respectively. Section 5 concludes.

2 Data

As our main data source, we rely on the *Relação Anual de Informações Sociais* (RAIS), from the Brazilian Ministry of Labor (Ministerio do Trabalho). This dataset is an annual administrative compilation that provides a comprehensive census of the formal labor market in Brazil (De Negri, Castro, Souza, & Arbache, 2001; Dix-Carneiro & Kovak, 2017). Accurate data in RAIS are essential for workers to receive various government benefits, and firms face penalties for non-compliance, which incentivizes the reporting of precise information. RAIS covers nearly all formally employed individuals, meaning those holding a signed work card, that grants them access to legal employment benefits.

The dataset consists of job records, featuring unique worker and establishment identifiers that enable longitudinal tracking of both entities. It provides information on the establishment's location and industry, as well as worker-specific details, including gender, age, education, and earnings.

In order to perform our identification strategy, we focus on workers displaced after mass-layoffs (Britto et al., 2022; Cingano & Rosolia, 2012): as we explain in Section 3, this addresses the bias coming from unobservable characteristics of displaced workers. We consider a worker to be part of a mass-layoff when she is let go together with at least 33% of a firm's workers. We look at the layoffs happening between 2008 and 2015 and we follow workers until 2020 to check whether they find a new job.[1] For each worker exposed to a layoff at year t, we consider part of her network all her colleagues from $t-1$ up to $t-5$. We measure the strength of her network in terms of referrals as the percentage of the network which is employed at the time of the layoff (Cingano & Rosolia, 2012).

We define manual workers following the classification of Adamczyk, Ehrl, and Monasterio

[1] We perform robustness checks excluding the years near the 2008 crisis.

(2024). This study classifies skills requirements by occupation, offering four ad-hoc categories referred to the Brazilian economy, that we refer to as job type: non-routine cognitive, routine cognitive, routine manual, and non-routine manual. Thus, we follow this classification and categorize a worker as manual in the case that she is employed in an occupation involving mainly routine or non-routine manual tasks. We instead define workers' occupations based on the 6-digit occupation code from the RAIS data.

Our sample comprises almost fourteen million workers: Table 1 describes their main characteristics.

Table 1: Descriptive statistics

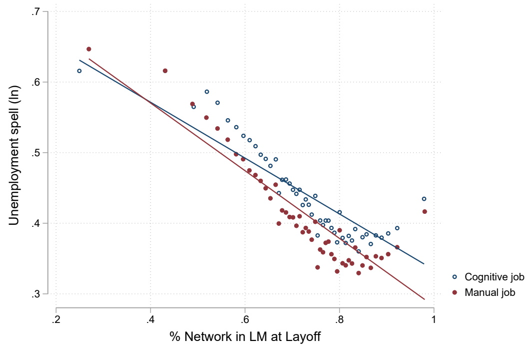
	Cognitive Job	Manual Job	Total
N	3,961,026 (28.79%)	9,796,345 (71.21%)	13,757,371 (100.00%)
Network Size	76.03 (62.24)	83.34 (66.04)	81.24 (65.05)
% Network in LM at Layoff	0.76 (0.12)	0.72 (0.14)	0.73 (0.14)
Unemployment Spell	2.28 (2.70)	2.23 (2.63)	2.25 (2.65)
In LM One Year After Layoff	0.71 (0.45)	0.72 (0.45)	0.72 (0.45)
Wage at layoff (ln)	3.20 (0.95)	3.11 (0.89)	3.13 (0.91)
Wage at new job (ln)	3.35 (0.79)	3.25 (0.74)	3.28 (0.75)
Same occupation at new job	0.27 (0.44)	0.39 (0.49)	0.36 (0.48)
Same job type at new job	0.58 (0.49)	0.71 (0.45)	0.67 (0.47)
Black/Brown	0.36 (0.48)	0.47 (0.50)	0.44 (0.50)
Educ: College+	0.11 (0.32)	0.00 (0.07)	0.04 (0.19)
Men	0.52 (0.50)	0.87 (0.33)	0.77 (0.42)

Note: 'same occupation' is a binary variable equal to one if the 6-digit occupation at the new job is the same as in the old job where mass-layoff occurred; 'same job type' is a binary variable indicating if the job type (non-routine cognitive, routine cognitive, non-routine manual, or routine manual) of the new job is the same as in the old job where mass-layoff occurred.

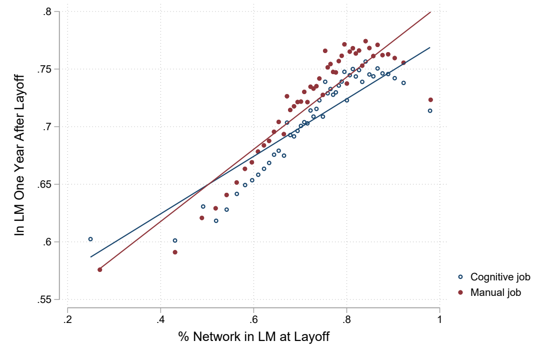
As we can see from the table, manual and cognitive workers are comparable in terms of network size and unemployment spell. However, manual workers are more likely to find a new job in the same occupation, and with a similar job type with respect to workers performing cognitive tasks, signaling a difficulty in transferring their skills elsewhere.

In Figure 1, we can observe the relationship between network strength (measured as the percentage of previous colleagues active in the labor market at layoff time) and five different outcomes: unemployment spell, probability of reinsertion in the labour market within a year, probability of finding a new job in the same occupation and with the same job type as the previous one, and the wage of the new job. Each outcome is observed for both manual and cognitive workers.

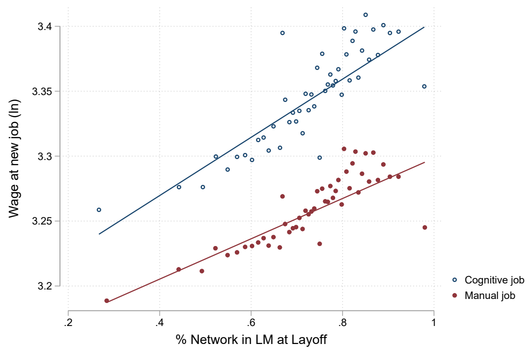
Figure 1: Workers networks and different outcomes after mass-layoff



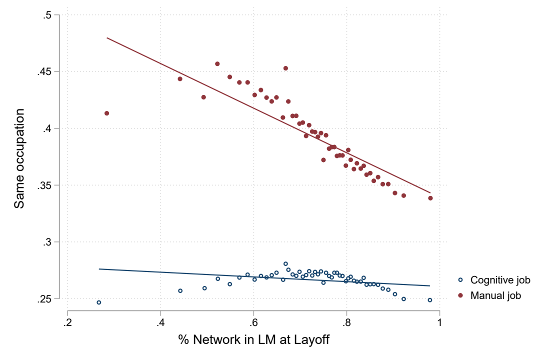
(a) Unemployment spell



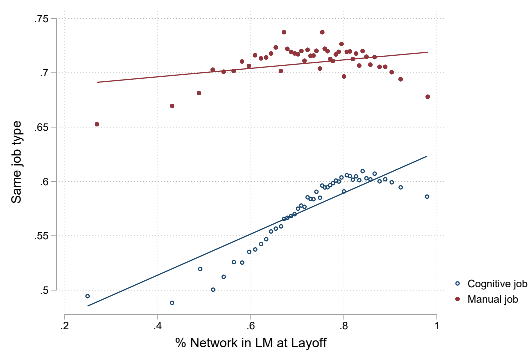
(b) In LM one year after layoff



(c) Wage/hour at new job



(d) Same occupation in new job



(e) Same job type in new job

Note: 'same occupation' is a binary variable equal to one if the 6-digit occupation at the new job is the same as in the old job where mass-layoff occurred; 'same job type' is a binary variable indicating if the job type (non-routine cognitive, routine cognitive, non-routine manual, or routine manual) of the new job is the same as in the old job where mass-layoff occurred.

We can observe from the figure how the association between the share of former co-workers active in the labor market at the time of layoff and re-employment (sub-figures (a) and (b)) is positive and similar for both manual and cognitive workers, although slightly stronger for manual workers. When it comes to wages at the new job (sub-figure (c)), however, the pattern is notably different. While cognitive workers, on average, attain higher wages upon re-entering the labor market compared to manual workers, they also benefit more from their networks: the positive association between networks and wages is significantly stronger for cognitive workers.

To better understand the role of occupational dynamics as a potential channel through which networks influence wages, we turn to sub-figures (d) and (e). Sub-figure (d) highlights that manual workers are more likely to retain their previous occupation when re-entering the labor market compared to cognitive workers, reflecting the higher costs associated with transferring job-specific skills into a new occupation. However, a larger share of former active co-workers are linked to a decreased likelihood of staying in their prior occupation for manual workers, a shift that might come at the cost of lower wages. If workers change occupations but maintain the same job type, the transition costs may be mitigated. However, networks appear less effective in supporting manual workers retaining their job type after displacement. Sub-figure (e) shows that while networks help cognitive workers maintain their job type, even if switching occupations, they are notably less successful in achieving the same outcome for manual workers.

Overall, these figures reveal a clear distinction in how networks affect reemployment outcomes across job types, playing a mixed role for manual workers: they improve the likelihood of reemployment but also push workers toward occupational shifts, often at the expense of wages. In contrast, networks not only help cognitive workers secure higher wages but also facilitate job-type stability, minimizing transition costs. In the next section, we formally test these patterns to establish a causal relationship.

3 Identification strategy

To correctly identify the effects of networks' strength on reemployment, we adopt a strategy inspired by previous papers on layoffs and reemployment (see for instance Britto et al., 2022; Cingano & Rosolia, 2012). When looking at unemployed workers, one of the major sources of concern is that they might have specific characteristics that make them different from those employed, creating a selection bias in our sample. These characteristics could be correlated with networks and reemployment. For instance, less productive individuals might both have worse networks and get fired more easily, or a worker could get fired with part of her network. Moreover, workers might be exposed to unobserved factors that are common to their networks, for instance, the same skill-specific market shocks. All of these factors could potentially generate a bias in our estimation of the effect of networks on reemployment. Therefore, we look at workers displaced after mass layoffs, defined as events in which an individual is displaced together with at least 33% of the firm's workers. Mass layoffs could be considered semi-exogenous events in which a worker is displaced together with other workers, creating the conditions for a more convincing comparison between individuals with different network sizes/strengths who start searching for a new job at the same time.

Beyond this identification strategy, our empirical model controls for other potential confounders. Our model takes the following specification:

$$y_{ijst} = \beta_1 \text{Share.Network}_{it} + \beta_2 \text{Share.Network}_{it} * \text{Manual}_{it} + X_i\gamma + \alpha_{jst} + \varepsilon_{ijst} \qquad (1)$$

Where:

- y_{ismt} is the outcome for individual i, performing task j – manual or cognitive–, laid off from firm s at the year of mass-layoff t. We consider five outcomes: duration of the unemployment spell, the likelihood that the worker is in the labor market one year after the layoff, and, for workers who find a new job, hourly wage and likelihood of finding a job in the same occupation or job type.

- Share.Network$_{it}$ is the share of previous colleagues of individual i who were working at t (time of mass-layoff).

- Manual$_{it}$ is a dummy variable that equals one if the laid-off worker was employed in a manual job.

- X_i is a vector of individual characteristics such as gender, race, education, and wage at the time of layoff.

- α_{jst} are task-by-firm-by-year fixed effects.

The inclusion of α_{jst} to our estimation, namely task type (manual vs. cognitive)-by-firm-by-year fixed effects addresses challenges that examining heterogeneity between manual and cognitive workers could present, in addition to the endogeneity of job loss discussed earlier. As Table 1 suggests, these two groups may represent inherently different sets of workers. The inclusion of α_{jst} ensures that comparisons are made within the same firm and mass-layoff event and within workers employed in similar occupations – manual or cognitive –at the time of displacement.[2] The advantage of this approach is that we compare individual outcomes by taking into account all common shocks of co-displaced workers, for instance, those linked to the specific sector of activity, location, or business cycle conditions (Cingano & Rosolia, 2012). For example, we compare the impact of networks on a group of manual (cognitive) workers who were all displaced from the same firm in the same year, ensuring that any observed differences are not driven by variations across workers, firms or task type, but rather by differences in the share of workers' networks active in the labor market at the time of layoff.

Nevertheless, even with this strategy and the inclusion of fixed effects, additional unobserved individual factors could still be correlated with both networks and our outcomes: to address this concern, the model features additional controls, such as gender, age, educational level, and hourly wage at the time of layoff in our estimations.

[2] This leads our network variable to exclude in its computation the colleagues of the last firm before displacement.

Analyzing outcomes at the new job after workers re-enter the labor market following a mass layoff poses further challenges due to the endogenous nature of job reallocation. Specifically, whether and when workers find a new job after a layoff depends on unobserved factors. To mitigate this issue, we include the year of re-insertion into the labor market in our fixed-effects interaction. This approach allows us to compare the new job outcomes of workers employed in the same firm and in similar occupations at the time of displacement who started new jobs within the same year.

4 Results

We present our main results in Table 2, which reports estimates of how the share of former co-workers who are active in the labor market at the time of displacement affects various labor market outcomes. Columns (1) and (2) show estimates for the unemployment spell; columns (3) and (4) report estimates for the likelihood of re-entering the labor market one year after the layoff; and columns (5) and (6) present estimates for the hourly wage at the new job. Odd-numbered columns provide estimates of the general impact of networks, while even-numbered columns focus on the heterogeneous effects based on workers' occupation at the time of layoff – manual or cognitive.

First, considering the overall impact of networks, we find that they reduce the unemployment spell, increase the likelihood of finding a new job within one year of displacement, and – among those who eventually re-enter the labor market – networks also enhance job fit, as measured by hourly wage. Specifically, a ten percent increase in the share of former co-workers active in the labor market at the time of displacement reduces the unemployment spell by 1.4% (column (1)), increases the likelihood of finding a job within one year by 0.94 percentage points (or 1.31%) (column (3)), and raises hourly wages by 0.67% for those who are re-employed (column (5)).

Second, we observe significant heterogeneity between workers performing manual or cognitive tasks at the time of layoff, with the former benefiting more from networks in terms of labor market re-entry, but less in terms of wages at the new job. A ten percentage point increase in the share of former co-workers active in the labor market reduces the unemployment spell by 1.06% for cognitive workers, while the impact is a reduction of 1.48% for manual workers (see column (2)). Similarly, a ten percentage point increase in the share of former co-workers active in the labor market increases the likelihood of re-entering the labor market within one year by 0.93% for cognitive workers, while this likelihood increases by 1.41% for manual workers (column (4)). Finally, a ten percentage point increase in the share of former co-workers active in the labor market raises hourly wages by 0.82% for cognitive workers, but only by 0.63% for manual workers.

We present two robustness checks in the Appendix. First, since our data includes mass-layoff events that occurred during the 2008 financial crisis, we test whether our results are driven by labor market dynamics specific to those years. Table A1 reports estimations that exclude the years 2008 to 2010. Second, although the average network size in our data is relatively small, there are some extremely large networks in the upper tail of the distribution (reaching up to approximately 10,000 workers). To ensure that our results are not driven by these outliers, Table A2 presents estimations excluding networks larger than the 99th percentile of the size distribution. In both cases, the results remain remarkably consistent with our main findings.

Table 2: Workers' network and labor market outcomes after mass-layoff

	(1)	(2)	(3)	(4)	(5)	(6)
	Unemployment spell (ln)		In LM One Year After Layoff		Wage/hour (ln)	
% Network in LM at Layoff	-0.139***	-0.106***	0.094***	0.067***	0.067***	0.082***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.005)
Manual Job X % Network in LM at Layoff		-0.042***		0.034***		-0.019***
		(0.005)		(0.003)		(0.005)
N	13591282	13591282	13591282	13591282	10979115	10979115
Mean dependent variable	0.420	0.420	0.717	0.717	3.281	3.281
R2	0.173	0.173	0.170	0.170	0.334	0.334

Note: this table presents estimations from equation 3; all estimations include controls for workers' gender, race, education, wage at the time of layoff, and task(manual or cognitive)-by-firm-by-year fixed effects; standard errors clustered at the firm-by-year level shown in parenthesis; significance levels are indicated by $* < .1$, ** < .05, *** < .01.

The intuition behind why networks help manual workers find new jobs more effectively than cognitive workers is clear. Manual occupations often require job-specific skills and knowledge that are less transferable across employers, making personal connections essential for accessing opportunities. In contrast, cognitive occupations tend to rely on skills that are more effectively signaled through formal recruitment channels. However, the reason behind the stronger wage premium associated with networks for cognitive workers compared to manual workers is less apparent. We hypothesize that this difference arises because networks enhance the alignment between worker skills and job requirements for cognitive workers, leading to higher-quality job matches that are rewarded with better wages. For manual workers, if network-provided opportunities involve occupational shifts, they may face wage penalties due to skill loss and the need for retraining.[3]

To test this hypothesis, we first examine how networks influence occupational and job type stability. Table 3 shows that networks decrease the likelihood of displaced workers preserving their previous occupation, particularly for manual workers. Specifically, a ten-percentage-point increase in the share of former co-workers active in the labor market decreases the likelihood of preserving the same occupation by 0.93 percentage points (-2.51%) overall (column (1)). This effect is concentrated among manual workers, who experience a 1.14 percentage point (-3.08%) decrease, compared to only a 0.07 percentage point (-0.19%) decrease for cognitive workers (column (2)).

When looking at job type (non-routine cognitive, routine cognitive, non-routine manual, or routine manual), networks decrease, in general, the likelihood of preserving the same job type by 0.54 percentage points (-0.67%) (column (3)). However, the results reveal a divergence when comparing manual and cognitive workers: networks positively impact the likelihood that cognitive workers maintain their job type, increasing it by 0.65 percentage points (0.83%), but negatively affect manual workers, decreasing it by 0.81 percentage points (-1.04%) (column (4)). These findings highlight that manual workers are not only more likely

[3] This is especially true for manual workers performing routine tasks. We show in Table A3 in the Appendix that our results are similar if we consider routine jobs instead of manual ones.

to change occupations but also less likely to remain in the same job type when reemployed through networks, which may contribute to the wage penalties that they face.

Table 3: Workers' network and occupational stability at new job

	(1)	(2)	(3)	(4)
	Same occupation		Same job type	
% Network in LM at Layoff	-0.093***	-0.007***	-0.052***	0.065***
	(0.002)	(0.003)	(0.001)	(0.003)
Manual Job X % Network in LM at Layoff		-0.107***		-0.146***
		(0.003)		(0.003)
N	10981362	10981362	10981362	10981362
Mean dependent variable	0.370	0.370	0.778	0.778
R2	0.255	0.255	0.270	0.270

Note: this table presents estimations from equation 3; all estimations include controls for workers' gender, race, education, wage at the time of layoff, and task(manual or cognitive)-by-firm-by-year fixed effects; standard errors clustered at the firm-by-year level shown in parenthesis; significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$; 'same occupation' is a binary variable equal to one if the 6-digit occupation at the new job is the same as in the old job where mass-layoff occurred; 'same job type' is a binary variable indicating if the job type (non-routine cognitive, routine cognitive, non-routine manual, or routine manual) of the new job is the same as in the old job where mass-layoff occurred.

Second, we evaluate whether displaced workers experience an occupational or job type stability premium in wages, which would explain why occupational and job type changes driven by networks are costly. Table 4 confirms the existence of such a premium. Preserving the same occupation increases hourly wages at the new job by 2.4% overall (column (1)), while preserving the same job type leads to an even higher increase of 5.0% (column (3)). This premium is more pronounced for manual workers: maintaining the same occupation raises their hourly wages by 2.6%, compared to 1.9% for cognitive workers (column (2)). The effect is even larger for job type stability, with manual workers experiencing a 6.5% increase in wages, compared to a 2.0% increase for cognitive workers.

Table 4: Occupational stability and wages at new job

	(1)	(2)	(3)	(4)
	Wage/hour (ln)			
Same occupation	0.024***	0.019***		
	(0.001)	(0.001)		
Same occupation X Manual Job		0.007***		
		(0.002)		
Same job type			0.050***	0.020***
			(0.001)	(0.001)
Same job type X Manual Job				0.045***
				(0.001)
N	10979115	10979115	10979115	10979115
Mean dependent variable	3.281	3.281	3.281	3.281
R2	0.334	0.334	0.334	0.334

Note: this table presents OLS estimations including controls for workers' gender, race, education, wage at the time of layoff, and task(manual or cognitive)-by-firm-by-year fixed effects; standard errors clustered at the firm-by-year level shown in parenthesis; significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$; 'same occupation' is a binary variable equal to one if the 6-digit occupation at the new job is the same as in the old job where mass-layoff occurred; 'same job type' is a binary variable indicating if the job type (non-routine cognitive, routine cognitive, non-routine manual, or routine manual) of the new job is the same as in the old job where mass-layoff occurred.

5 Conclusion

Our findings illustrate the trade-offs associated with network-driven job placements. Networks help manual workers reenter the labor market but often steer them toward new occupations or job types, resulting in wage penalties due to skill transfer costs and retraining requirements. For cognitive workers, networks are more effective in ensuring job type stability, leading to better job matches and higher wage premiums. This explains why networks, while crucial for reemployment, have a lower impact on wages for manual workers compared to cognitive workers.

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A Appendix

Table A1: Workers' network and labor market outcomes after mass-layoff – Robustness dropping layoff years 2008-2010

	(1)	(2)	(3)	(4)	(5)	(6)
	Unemployment spell (ln)		In LM One Year After Layoff		Wage/hour (ln)	
% Network in LM at Layoff	-0.162***	-0.118***	0.106***	0.075***	0.061***	0.077***
	(0.003)	(0.005)	(0.002)	(0.003)	(0.003)	(0.006)
Manual Job X % Network in LM at Layoff		-0.056***		0.039***		-0.019***
		(0.006)		(0.004)		(0.007)
N	9106900	9106900	9106900	9106900	7226441	7226441
Mean dependent variable	0.438	0.438	0.702	0.702	3.391	3.391
R2	0.170	0.170	0.168	0.168	0.282	0.282

Note: this table presents OLS estimations including controls for workers' gender, race, education, wage at the time of layoff, and task(manual or cognitive)-by-firm-by-year fixed effects; standard errors clustered at the firm-by-year level shown in parenthesis; significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table A2: Workers' network and labor market outcomes after mass-layoff – Robustness dropping large networks

	(1)	(2)	(3)	(4)	(5)	(6)
	Unemployment spell (ln)		In LM One Year After Layoff		Wage/hour (ln)	
% Network in LM at Layoff	-0.139***	-0.106***	0.094***	0.067***	0.066***	0.081***
	(0.002)	(0.004)	(0.001)	(0.002)	(0.002)	(0.005)
Manual Job X % Network in LM at Layoff		-0.041***		0.033***		-0.019***
		(0.005)		(0.003)		(0.005)
N	13452510	13452510	13452510	13452510	10849860	10849860
Mean dependent variable	0.422	0.422	0.715	0.715	3.279	3.279
R2	0.173	0.173	0.170	0.170	0.334	0.334

Note: this table presents OLS estimations including controls for workers' gender, race, education, wage at the time of layoff, and task(manual or cognitive)-by-firm-by-year fixed effects; standard errors clustered at the firm-by-year level shown in parenthesis; significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table A3: Workers' network and labor market outcomes after mass-layoff

	(1)	(2)	(3)	(4)	(5)	(6)
	Unemployment spell (ln)		In LM One Year After Layoff		Wage/hour (ln)	
% Network in LM at Layoff	-0.141***	-0.120***	0.095***	0.074***	0.081***	0.155***
	(0.002)	(0.005)	(0.001)	(0.003)	(0.002)	(0.006)
Routine Job X % Network in LM at Layoff		-0.024***		0.025***		-0.085***
		(0.006)		(0.003)		(0.006)
N	13584233	13584233	13584233	13584233	11005367	11005367
Mean dependent variable	0.420	0.420	0.717	0.717	3.279	3.279
R2	0.169	0.169	0.166	0.166	0.329	0.329

Note: this table presents OLS estimations including controls for workers' gender, race, education, wage at the time of layoff, and task(routine or non-routine)-by-firm-by-year fixed effects; standard errors clustered at the firm-by-year level shown in parenthesis; significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.