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Social Networks and Labor Market Outcomes: Occupation Matters

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Social Networks and Labor Market Outcomes: Occupation Matters*

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Abstract

We study how the impact of social networks on labor market outcomes differs between blue-collar and white-collar workers. Using administrative data on more than thirteen million Brazilian workers and exploiting mass layoffs as a source of exogenous job loss, we show that social networks reduce unemployment duration and increase reemployment wages. These effects, however, vary systematically by occupation. Blue-collar workers rely more on networks to obtain employment quickly but capture smaller wage gains, while white-collar workers obtain larger wage premiums from their ties. We trace this divergence to occupational stability: networks tend to push blue-collar workers into different occupations, where they incur wage penalties, whereas white-collar workers are more likely to leverage networks to secure jobs that preserve or better reward their skills.

JEL Codes: J01, J24, J62

Keywords: Social networks, Labor Market Outcomes, Occupations, Mass-Layoff, Brazil

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1 Introduction

Social networks are widely recognized as a powerful determinant of labor market outcomes. A large body of research shows that networks facilitate job searches and expand employment opportunities (Granovetter, 1973; Rees, 1966). Theoretical models emphasize information diffusion as a key mechanism (Calvo-Armengol & Jackson, 2004), while recent empirical work demonstrates that networks reliably accelerate job finding but have more ambiguous effects on wages at reemployment, with studies documenting positive, null, and negative impacts (Bentolila, Michelacci, & Suarez, 2010; Cingano & Rosolia, 2012; Glitz, 2017; Pellizzari, 2010; Schmutte, 2015, and see Topa (2011) and Ioannides and Loury (2004) for reviews).Yet, despite broad consensus on their importance, we know much less about whether networks affect all workers in the same way. In particular, their value may depend critically on how the type of jobs that individuals perform aligns with the type of jobs that networks are able to facilitate.

The distinction is especially salient in the case of blue- versus white-collar workers. Blue-collar workers, such as waiters, mechanics, or machine operators, might rely more heavily on informal job search channels such as network-provided information (Pellizzari, 2010), benefiting more from these networks in terms of reemployment opportunities. However, because blue-collar workers often possess job-specific skills (Hanushek, Schwerdt, Woessmann, & Zhang, 2017; Howland & Peterson, 1988), 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 (Bentolila et al., 2010). Network effects for white-collar workers, such as managers, accountants, and receptionists, may differ, both because their networks might be less likely to drive them away from their original occupations after a layoff, and because occupational shifts tend to be less costly for them in terms of wage loss, thanks to the greater transferability of their skills across occupations (Howland & Peterson, 1988).

This paper investigates how the influence of former co-workers on reemployment after a displacement and subsequent job outcomes differ depending on whether displaced workers previously held blue-collar or white-collar occupations. We focus on this distinction because, as already mentioned, the existing literature has underscored the differences between blue- and white-collar workers in terms of occupational dynamics, which are likely to be particularly affected by social networks. In addition, a complementary data-driven LASSO exercise reinforces the relevance of this classification: when allowing network effects to interact with many worker characteristics, the blue-versus white-collar distinction is one of the few dimensions that consistently explains heterogeneity across the outcomes analyzed.

To examine occupational dynamics upon job loss, we analyze matched employee-employer data from Brazil, which offers a rich setting for studying labor market networks in a developing economy. A key challenge in studying social networks is their endogenous formation: individuals may self-select into networks based on unobserved characteristics that also influence labor market outcomes. Moreover, if layoffs are not random, selection into displacement could also correlate with both network characteristics and future employment prospects. Our empirical strategy addresses both concerns by focusing on workers displaced by mass layoffs (Britto, Pinotti, & Sampaio, 2022; Cingano & Rosolia, 2012). We examine the networks of displaced workers, excluding colleagues from the same layoff event, and compare individuals who were laid off together but differ in the composition of their broader network. This design allows us to construct a credible counterfactual and isolate the causal effect of networks on reemployment outcomes.

Our findings yield several insights, especially on how social networks interact with occupational choices affecting workers inequality (Calvo-Armengol & Jackson, 2004). First, we show that the share of former co-workers active in the labor market at the time of layoff, which we define as the network strength, positively impacts workers' reintegration into the labor market and their wages at the new job, extending previous findings in the literature to the context of a developing country. Second, we document novel findings on the effects of social networks on workers inequality after displacement: blue-collar workers benefit more from networks in terms of job reentry, but less in terms of wages compared to white-collar workers. Third, we shed light on the mechanisms behind those effects focusing on the occupational stability premium, finding that workers who remain in similar occupations post layoff experience a wage premium, and this effect is more pronounced for blue-collar workers. We show that networks reduce the probability of blue-collar workers returning to a similar occupation, while, if anything, they appear to slightly increase this probability for white-collar workers.

Beyond these effects, we explore the non-linear relationship between the network strength, and post-displacement outcomes. In general, we find clear evidence of diminishing marginal returns: while initial increases in network strength significantly reduce unemployment duration and raise wages at the new job, the benefits taper off as networks become stronger. This pattern is consistent with the non-monotonic relationship between networks and job matches predicted in the theoretical literature (Calvó-Armengol & Zenou, 2005) and observed empirically for job finding in other contexts (e.g. Wahba & Zenou, 2005). The dynamics, however, differ by occupation. For blue-collar workers, the diminishing marginal effect is especially pronounced for unemployment duration–the impact of the network strength on reemployment speed decreases faster than for white-collar workers–while their wage gains remain flat across the range of network strength, though consistently smaller than those of white-collar workers. In contrast, white-collar workers experience larger wage gains from networks, even though these returns decline as network strength increases. These results highlight that the value of networks depends not only on their presence but also on their intensity.

Taken together, our results underscore the dual role of networks in labor market transitions: they are crucial for reentry after displacement, particularly for blue-collar workers, but they often steer these workers into different occupations, leading to trade-offs in terms of wage gains, likely reflecting the costs of transferring skills. 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 calls for policies facilitating unemployed blue-collar 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 (Battisti, Peri, & Romiti, 2022; Cingano & Rosolia, 2012; Eliason, Hensvik, Kramarz, & Skans, 2023; Glitz, 2017; Gyetvai & Zhu, 2025). While much of this literature emphasizes similarities between workers and their networks, some studies also investigate heterogeneity in workers' characteristics. For example, Saygin, Weber, and Weynandt (2021) interact workers' attributes with those of their networks and uncover differences across dimensions such as age, nationality, and job type–although even in these results the role of shared characteristics remains central. In their context, white-collar workers are found to benefit more from networks in terms of reemployment.

Our study builds on this perspective but takes a different approach: rather than interacting workers' and network characteristics, we focus exclusively on workers' own attributes, narrowing in on the blue-/white-collar divide. By placing this distinction at the center of the analysis and examining the occupation stability premium as a potential mechanism, we provide a clearer picture of why networks generate contrasting outcomes for these two groups.

By distinguishing between blue-collar and white-collar jobs, this paper further contributes to the literature on the role of occupations in shaping labor market outcomes. Prior work shows that technological change—particularly automation—disproportionately affects routine manual workers by replacing middle-skill, routine-intensive jobs, pushing employment toward both high-skill cognitive roles and low-skill service positions (Goos, Manning, & Salomons, 2014). Workers in cognitive tasks, such as white-collar employees, are more likely to hold professional or managerial positions that offer higher wages and greater job security, while blue-collar workers, predominantly in manufacturing and agriculture, face greater risks of job loss, wage stagnation, and difficulties in transitioning to new roles (Acemoglu, 2011). Beyond these structural forces, labor market adjustments after displacement also differ. Howland and Peterson (1988) shows that blue-collar workers are more dependent on local industry-specific conditions, whereas white-collar workers can leverage more general skills to reallocate across industries. By contrast, Schwerdt, Ichino, Ruf, Winter-Ebmer, and Zweimüller (2010) report that white-collar workers experience more severe and persistent earnings and employment losses than blue-collar workers following displacement.

Our contribution is to add the role of social networks to this debate. We show that networks are especially effective in helping blue-collar workers regain employment, which may counterbalance some of the negative effects that technological change and automation have had on this group. At the same time, networks increase the likelihood that blue-collar workers switch occupations, which erodes wage gains given the substantial occupation stability premium associated with their jobs. This mechanism is consistent with Howland and Peterson (1988)'s argument that the industry specificity of blue-collar skills shapes reemployment outcomes, as our findings demonstrate that the job opportunities facilitated by networks often force these workers into roles where their prior skills are less rewarded. For white-collar workers, by contrast, networks primarily operate through improved match quality, helping them secure jobs that better reward their skills and translating into larger wage gains, even if reemployment speed is less affected. Taken together, these findings show that occupational heterogeneities in post-displacement outcomes are not only driven by technology and industry dynamics, but also by how workers rely on their networks during job search.

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 annual administrative dataset 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 comprises job records with unique identifiers for both workers and establishments, allowing for longitudinal tracking of employment histories. It includes establishment-level information such as location and industry, along with worker-level details on gender, age, education, earnings, and the dates of hiring and, when applicable, layoff.

To perform our identification strategy, we focus on workers displaced after mass-layoffs (e.g. Britto et al., 2022): 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] To capture unemployment dynamics, we rely primarily on the length of the unemployment spell, which provides a detailed view of each worker's employment trajectory after displacement. This measure, however, is right-censored, as we only observe individuals for up to five years following the layoff. As a robustness check, we also consider a binary indicator equal to one if the worker is reemployed within one year of the layoff. While less detailed, this measure is not subject to truncation and estimations based on it are reported in the appendix.

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 potential referrals as the percentage of the network which is employed at the time of the layoff (Cingano & Rosolia, 2012).

We define blue- and white-collar workers following the classification of Bernstein, Colonnelli, Malacrino, and McQuade (2022). Their study maps the Brazilian classification of occupations (*Classificacao Brasileira de Ocupacoes* – CBO) to the International Standard Classification of Occupations (ISCO-88), which groups workers into ten major occupational categories. Building on the organizational economics literature, this correspondence is commonly used to distinguish between managers, white-collar workers, and blue-collar workers. In our analysis, we follow this approach but group managers together with white-collar workers, yielding two broad categories: blue-collar and white-collar. Workers' occupations are identified using the 6-digit occupation codes from the RAIS data.

To investigate the mechanisms behind the differential impact of networks on blue- and white-collar jobs, we analyze the stability of workers' occupations across jobs using the hierarchical structure of the Brazilian CBO codes. We focus on matches at the 3- and 4-digit levels of the 6-digit codes. The 3-digit level captures whether workers remain within the same broad occupational family (e.g., cleaning and maintenance workers, CBO 514), while the 4-digit level reflects a finer similarity within narrower sub-fields—for example,

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

distinguishing public area cleaners (5142, such as waste collectors and street sweepers) from building cleaners (5143, such as janitors and window cleaners). These levels strike a balance between breadth and precision: higher levels (1-2 digits) would group overly heterogeneous jobs, while lower levels (5-6 digits) often split very similar roles into excessively narrow distinctions (e.g., Hotel Doorman and Building Doorman).

Our sample comprises roughly thirteen million workers: Table 1 describes their main characteristics.

Table 1: Descriptive statistics

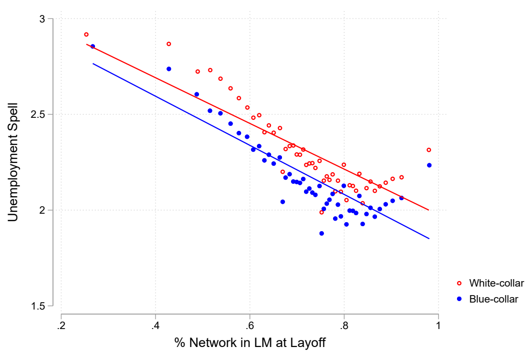
	White-collar worker	Blue-collar worker	Total
N	4,242,263 (32.12%)	8,966,886 (67.88%)	13,209,149 (100.00%)
Network Size	77.16 (63.33)	83.62 (66.14)	81.55 (65.32)
% Network in LM at Layoff	0.75 (0.13)	0.71 (0.14)	0.73 (0.14)
Unemployment Spell	2.27 (2.70)	2.19 (2.58)	2.22 (2.62)
In LM One Year After Layoff	0.72 (0.45)	0.72 (0.45)	0.72 (0.45)
Hourly wage at layoff	34.97 (52.26)	28.06 (27.98)	30.28 (37.67)
Tenure at layoff (months)	19.73 (25.39)	14.13 (19.50)	15.93 (21.72)
Hourly wage at new job	37.43 (59.50)	30.71 (34.31)	32.86 (44.09)
Same 3 digits occup. at new job	0.40 (0.49)	0.54 (0.50)	0.50 (0.50)
Same 4 digits occup. at new job	0.38 (0.48)	0.49 (0.50)	0.45 (0.50)
Black/Brown	0.38 (0.48)	0.48 (0.50)	0.45 (0.50)
Educ: College+	0.10 (0.29)	0.00 (0.05)	0.03 (0.18)
Men	0.56 (0.50)	0.89 (0.31)	0.78 (0.41)

Note: 'same 3 (4) digits occup. at new job' is a binary variable equal to one if the 3(4)-digit occupational group of the new job is the same as in the old job where the mass layoff occurred.

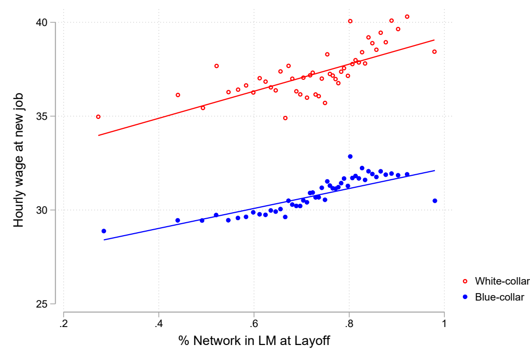
As shown in the table, blue-collar workers make up the majority of the sample (67.9%) and, on average, have larger networks at the time of layoff, slightly shorter unemployment spells, and lower wages and tenure compared to white-collar workers. They are also more likely to remain in similar occupations after displacement: 54% of blue-collar workers are reemployed within the same 3-digit group as their previous occupation (49% at the 4-digit level), compared to 40% and 38% of white-collar workers, respectively. This pattern suggests that blue-collar workers' reemployment trajectories are more concentrated within closely related occupational domains, whereas white-collar workers exhibit greater mobility across broader occupational families.

Figure 1 shows the relationship between network strength—measured as the share of previous colleagues active in the labor market at the time of layoff—and four outcomes: unemployment duration, wage in the new job, and the likelihood of finding a new job in the same 3-digit or 4-digit occupation as the previous one.

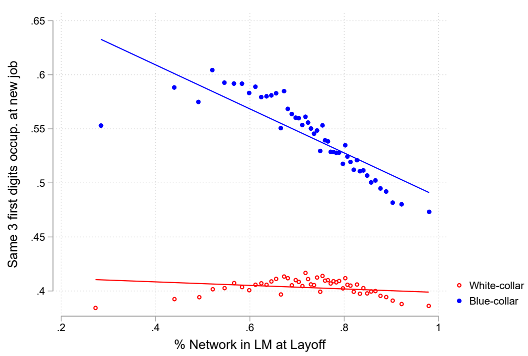
Figure 1: Workers networks and different outcomes after mass-layoff



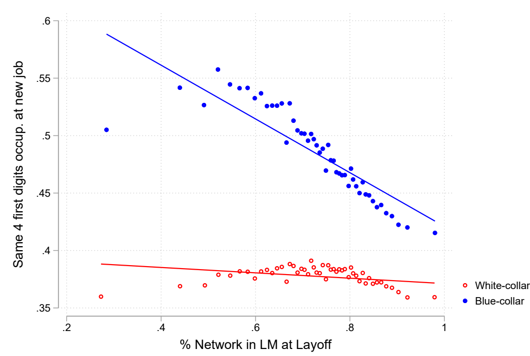
(a) Unemployment spell
(blue-collar worker slope: -1.28; white-collar worker slope: -1.19)



(b) Wage/hour at new job
(blue-collar worker slope: 5.31; white-collar worker slope: 7.2)



(c) Same 3 digits occup. at new job
(blue-collar worker slope: -0.203; white-collar worker slope: -0.016)



(d) Same 4 digits occup. at new job
(blue-collar worker slope: -0.234; white-collar worker slope: -0.023)

Note: 'same 3(4) digits occup. at new job' is a binary variable equal to one if the 3(4)-digit occupational group of the new job is the same as in the old job where the mass layoff occurred.

The figure provides descriptive evidence on the relationship between network strength and labor market outcomes. For unemployment duration, the line for blue-collar workers appears slightly steeper than that for white-collar workers, suggesting somewhat stronger gains in reemployment speed. For wages at the new job, the opposite pattern holds: the white-collar line rises a bit more sharply, indicating relatively larger wage improvements. The most striking differences, however, emerge in occupational stability: while networks reduce the likelihood that blue-collar workers remain in similar occupations, they have little effect on white-collar workers' occupational mobility.

Notably, the figures also suggest the presence of a non-linear relationship between network strength and labor market outcomes (namely unemployment spell and wages at the new job). These patterns, already described in theoretical papers such as Calvó-Armengol and Zenou (2005), underscore the importance of moving beyond simple linear specifications, since the marginal value of network ties may differ depending on overall network strength. We therefore explicitly model these non-linearities in our regression analysis.

3 Identification strategy

To correctly identify the effects of networks' strength on reemployment, we adopt a strategy inspired by previous papers on layoffs and subsequent outcomes (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.

Our model takes the following specification:

$$y_{ijst} = \beta_1 \text{Share.Network}_{it} + \beta_2 \text{Share.Network}_{it} * \text{Blue}_{it} + X_{it}\gamma + \alpha_{jst} + \varepsilon_{ijst} \tag{1}$$

Where:

- y_{ijst} is the outcome for individual i, working on job j – blue- or white-collar–, laid off from firm s at the year of mass-layoff t. We consider two main outcomes: duration of the unemployment spell, and, for workers who find a new job, hourly wage at the new job.

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

- Blue_{it} is a dummy variable that equals one if the laid-off worker was employed in a blue-collar job.

- X_{it} is a vector of individual characteristics.

- α_{jst} are job type (blue- or white-collar)-by-firm-by-year fixed effects.

The inclusion of α_{jst} to our estimation addresses challenges that examining heterogeneity between blue- and white-collar 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 – blue- or white-collar –at the time of displacement.

To empirically support our decision to focus on the blue versus white-collar distinction, Appendix B describes a LASSO procedure in which the network measure is interacted with all baseline covariates. Consistent with our conceptual motivation for examining blue- versus white-collar heterogeneity, the interaction with the blue-collar dummy emerges as one of the strongest predictors of heterogeneity. Although we treat this result as supportive rather than determinative, it reinforces the view that occupational status is a central margin along which the strength and consequences of network effects systematically vary.

The advantage of our empirical 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). In other words, we compare the impact of networks on a group of blue(white)-collar 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 job type, but rather by differences in the share of workers' networks active in the labor market at the time of layoff. A common concern in this type of estimation is the limited variation remaining after the inclusion of high-dimensional fixed effects. In our case, about 60% of the variation in the network's strength variable remains after accounting for these effects, suggesting that sufficient identifying variation is preserved.

To further strengthen our identification strategy, vector X_{it} in the model includes additional controls that could be correlated with both networks and outcomes analyzed, such as gender, age, educational level, hourly wage at the time of layoff, network size, and a proxy for severance payments. Including network size ensures that we compare individuals with the same number of former coworkers but differing levels of network strength–that is, the share of coworkers who remain active in the labor market at the time of layoff. The severance proxy, in turn, captures liquidity constraints at the moment of displacement, since workers with larger severance packages may be able to afford longer job searches before reemployment.[2]

[2] We approximate severance pay (the Brazilian FGTS system) by multiplying the worker's last observed wage by their tenure at the firm. This measure provides a close proxy because FGTS benefits are directly

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 when performing such estimations. 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.

Finally, as noted in Section 2, and consistent with theoretical predictions (Calvó-Armengol & Zenou, 2005), the descriptive evidence suggests a non-linear relationship between network strength and labor market outcomes, indicating that the marginal value of network ties may vary with overall network strength. To address this, we go beyond the baseline linear specification and explicitly account for potential non-linearities in the results section. In practice, we extend equation 1 by including quadratic terms in network strength and their interaction with the blue-collar indicator.[3]

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 unemployment duration and wages at the new job. Columns (1)-(4) report estimates for the unemployment spell, while columns (5)-(8) focus on wages. Odd-numbered columns present baseline linear effects, and even-numbered columns extend the model by incorporating quadratic terms to capture potential non-linearities and interactions with workers' occupational type (blue- vs. white-collar).

First, considering the overall impact of networks, we find that they significantly reduce

tied to accumulated contributions proportional to monthly wages and length of employment.

[3]Formally, the specification adds $(\text{Share.Network}_{it})^2$ and $(\text{Share.Network}_{it})^2 \times \text{Blue}_{it}$ as additional regressors to equation 1.

unemployment duration and increase wages at the new job.[4] In the linear specifications, a ten percentage point increase in the share of former co-workers active in the labor market at the time of displacement reduces unemployment spells by 1.3% (column (1)) and raises reemployment wages by 0.7% (column (5)).[5] These results confirm the broad consensus in the literature that networks play a central role in facilitating job finding (see Ioannides & Loury, 2004; Topa, 2011, for comprehensive reviews). At the same time, by documenting positive effects on wages, our study contributes to the ongoing debate on how networks shape reemployment earnings, where the evidence has been mixed: some studies find positive impacts (e.g. Schmutte, 2015), others report null effects (e.g. Glitz, 2017), and still others point to negative impacts (e.g. Bentolila et al., 2010).

Second, moving beyond the linear specifications reveals important new insights. When quadratic terms are introduced (columns (2) and (6)), we find clear evidence of diminishing marginal returns: the first increments of network strength have strong positive effects on both unemployment duration and wages, but the marginal value of additional network ties decreases as overall network strength grows. These results confirm the theoretical predictions of Calvó-Armengol and Zenou (2005) and add to empirical evidence of non-monotonic patterns in job finding (e.g. Wahba & Zenou, 2005). To the best of our knowledge, however, we are the first to document such non-linear effects for wages at the new job, showing that the value of networks depends not only on their presence but also on their intensity.

Third, we turn to heterogeneity by occupation type. Columns (3) and (7) present linear specifications with interaction terms. For unemployment spells, blue-collar workers benefit more strongly from networks: a ten percentage point increase in network strength reduces unemployment duration by 1.4% for blue-collar workers compared to 0.9% for white-collar workers. In contrast, the wage effects are larger for white-collar workers: the same increase

[4]Table A1 in the Appendix presents results for the likelihood of returning to the labor market one year after the mass layoff, serving as an alternative outcome measure for the unemployment spell, which is observed only for up to five years following the mass layoff. The results are largely consistent with our main estimations.

[5]The lower number of observations in the wage regressions reflects that wages can only be observed for workers who re-enter the formal labor market.

in network strength raises their reemployment wages by about 0.9%, compared to 0.7% for blue-collar workers.

Finally, the heterogeneous non-linear models in columns (4) and (8) reveal distinct patterns across outcomes and worker types. For unemployment duration, the quadratic terms show that blue-collar workers benefit strongly from networks at low levels of network strength, but these gains taper off more quickly than for white-collar workers, consistent with decreasing marginal returns in reemployment speed. In contrast, for wages at the new job, diminishing returns are negligible for blue-collar workers: their marginal wage gains remain nearly flat across the entire range of network strength. However, these gains are consistently smaller than those of white-collar workers, who capture a substantially larger wage premium from networks, even though their returns decline more sharply as network strength increases.

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 A2 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 A3 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)	(7)	(8)
	Unemployment spell (ln)				Wage at new job (ln)			
% Network in LM at Layoff	-0.126***	-0.361***	-0.091***	-0.285***	0.071***	0.092***	0.087***	0.167***
	(0.002)	(0.010)	(0.004)	(0.019)	(0.002)	(0.011)	(0.005)	(0.021)
(% Network in LM at Layoff)^2		0.182***		0.145***		-0.016**		-0.059***
		(0.007)		(0.013)		(0.008)		(0.015)
Blue-Collar worker X % Network in LM at Layoff			-0.047***	-0.092***			-0.020***	-0.092***
			(0.005)	(0.021)			(0.005)	(0.023)
Blue-Collar X (% Network in LM at Layoff)^2				0.043***				0.053***
				(0.015)				(0.017)
N	13039941	13039941	13039941	13039941	10586544	10586544	10586544	10586544
Mean dependent variable	0.410	0.410	0.410	0.410	3.280	3.280	3.280	3.280
R2	0.181	0.181	0.181	0.181	0.341	0.341	0.341	0.341

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

4.1 Mechanisms behind blue-collar heterogeneities

The intuition behind why networks help blue-collar workers find new jobs more effectively than white-collar workers rests on how skills are signaled in the labor market. White-collar workers typically have higher levels of formal education and credentials, which allow them to credibly signal their abilities through diplomas or professional certifications. This makes them less dependent on informal ties for reemployment, as firms can rely on formal recruitment channels to assess their suitability. Blue-collar workers, by contrast, often lack such formal signals. Their skills are instead attested through personal recommendations or direct referrals, making social networks especially important for accessing new job opportunities. However, networks generate a stronger wage premium for white-collar workers, which is less intuitive. A plausible explanation is that networks might help white-collar workers secure jobs where their skills are better matched to firm demands, leading to higher-quality matches that are rewarded with higher wages. For blue-collar workers, by contrast, network-mediated transitions might involve occupational shifts, which may entail wage penalties due to skill mismatches or the need for retraining, which is especially costly for blue-collar workers who usually have more specific, task-related skills that are less easily transferable.

To test this hypothesis, we begin by examining how networks affect occupational stability. Table 3 shows that networks significantly reduce the likelihood that displaced workers remain in a similar occupation, and this effect is concentrated among blue-collar workers. Overall, a ten-percentage point increase in the share of former co-workers active in the labor market decreases the probability of preserving the same 3-digit occupation by 0.94 percentage points (-1.84%, column (1)). For blue-collar workers, the reduction is much stronger: 1.26 percentage points (-2.47%), while white-collar workers actually experience a small increase of 0.14 percentage points (+0.27%) (column (2)). Results are similar at the 4-digit level: networks reduce the probability of staying in the same detailed occupation by 1.02 percentage points (-2.18%, column (3)), with the entire effect again driven by blue-collar workers (-1.34 percentage points, or -2.87%), while white-collar workers show no statistically significant change (column (4)).

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

	(1)	(2)	(3)	(4)
	Same 3 digits occup. at new job		Same 4 digits occup. at new job	
% Network in LM at Layoff	-0.094***	0.014***	-0.102***	0.003
	(0.002)	(0.003)	(0.002)	(0.003)
Blue-collar worker X % Network in LM at Layoff		-0.140***		-0.137***
		(0.004)		(0.004)
N	10588616	10588616	10588616	10588616
Mean dependent variable	0.514	0.514	0.467	0.467
R2	0.284	0.284	0.277	0.277

Note: this table presents estimations from equation 1; all estimations include controls for workers' gender, race, education, wage at the time of layoff, and type of job (white-collar or blue-collar)-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 3(4) digits occup. at new job' is a binary variable equal to one if the 3(4)-digit occupational group of the new job is the same as in the old job where the mass layoff occurred.

We then evaluate whether displaced workers experience a wage premium from occupational stability, which would explain why network-induced occupational shifts are particularly costly. Table 4 confirms the existence of such a premium. Preserving the same 3-digit occupation increases hourly wages by 5.9% overall (column (1)). The effect is more pronounced for blue-collar workers, who gain 6.6%, compared to 4.4% for white-collar workers (column (2)). At the 4-digit level, maintaining occupational stability increases wages by 4.6% overall (column (3)), with blue-collar workers again benefiting more strongly: 5.0% compared to 3.4% for white-collar workers (column (4)).

Taken together, these results suggest the contrasting wage patterns between blue- and white-collar workers can be understood through the role of occupational stability. For blue-collar workers, networks are highly effective in accelerating reemployment, but they also increase the likelihood of occupational change. Since remaining in the same occupation carries a substantial wage premium for this group, these occupational shifts erode the wage benefits of networks. As a result, the marginal impact of network strength on wages for

Table 4: Occupational stability and wages at new job

	(1)	(2)	(3)	(4)
		Wage at new job (ln)		
Same 3 digits occup. at new job	0.059***	0.044***		
	(0.001)	(0.001)		
Same 3 digits occup. at new job X Blue-collar worker		0.022***		
		(0.002)		
Same 4 digits occup. at new job			0.046***	0.034***
			(0.001)	(0.001)
Same 4 digits occup. at new job X Blue-collar worker				0.016***
				(0.002)
N	10586544	10586544	10586544	10586544
Mean dependent variable	3.280	3.280	3.280	3.280
R2	0.342	0.342	0.342	0.342

Note: this table presents OLS estimations including controls for workers' gender, race, education, wage at the time of layoff, and type of job (white-collar or blue-collar)-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 3(4) digits occup. at new job' is a binary variable equal to one if the 3(4)-digit occupational group of the new job is the same as in the old job where the mass layoff occurred.

blue-collar workers remains essentially flat, even though networks help them return to work more quickly.

For white-collar workers, in contrast, networks are less about speed and more about match quality. Their occupational stability premium is smaller, but networks appear to facilitate better alignment between worker skills and job requirements within similar occupations. This mechanism translates into higher wages at the new job. Yet, because there are limits to how much additional network strength can further improve match quality, the wage premium displays diminishing marginal returns at higher levels of network strength.

5 Conclusion

Our findings illustrate the trade-offs associated with network-driven job placements. Networks help blue-collar workers reenter the labor market more quickly, but often steer them toward new occupations, which comes at a cost given the substantial wage premium associated with occupational stability in this group. For white-collar workers, by contrast, networks are less about speed and more about quality: they help workers secure jobs that better match their skills, leading to higher wage premiums even though their impact on reemployment duration is smaller. This explains why networks, while crucial for both groups, translate into stronger wage effects for white-collar workers and primarily employment effects for blue-collar workers.

We also show that these network effects are not linear. For unemployment duration, diminishing marginal returns are more pronounced for blue-collar workers, who rely heavily on networks at low levels of strength but see these benefits taper off quickly. For wages, however, diminishing returns are negligible for blue-collar workers, whose wage gains remain consistently modest across the network distribution. White-collar workers, in contrast, capture larger wage premiums from networks, though these gains decline more steeply as network strength increases. These patterns underscore the importance of accounting for both heterogeneity and non-linearities in the study of networks and labor market outcomes.

These results carry important policy implications. In contexts where public employment services are limited and informal job search channels play a dominant role, as is often the case in developing economies, social networks represent a critical resource for displaced workers. However, our findings suggest that while networks are effective in facilitating labor market reentry, particularly for blue-collar workers, they may inadvertently reinforce occupational downgrading and wage inequality. Policymakers aiming to improve job quality, not just job access, should consider interventions that help workers maintain or upgrade their occupational status. Initiatives such as targeted reskilling programs, occupation-specific job placement services, or portable certifications recognizing prior experience could be especially beneficial for blue-collar workers, who are more vulnerable to skill mismatches during transitions.

While our study contributes novel insights, it is not without limitations. A key limitation is that we are unable to observe all dimensions of network quality or the specific mechanisms through which networks influence job outcomes –such as information flows, or moral support. These aspects are difficult to capture using administrative data alone. A promising avenue for future research would be to combine administrative records with survey data to better understand the channels through which networks operate and how they shape job search behavior and outcomes in practice.

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A Additional Tables

Table A1: Workers' network and the likelihood of returning to the labor market one year after mass-layoff

	(1)	(2)	(3)	(4)
	In LM One Year After Layoff			
% Network in LM at Layoff	0.088***	0.200***	0.061***	0.158***
	(0.001)	(0.006)	(0.002)	(0.011)
(% Network in LM at Layoff)^2		-0.087***		-0.072***
		(0.004)		(0.008)
Blue-collar worker X % Network in LM at Layoff			0.035***	0.049***
			(0.003)	(0.013)
Blue-collar worker X (% Network in LM at Layoff)^2				-0.014
				(0.009)
N	13039941	13039941	13039941	13039941
Mean dependent variable	0.723	0.723	0.723	0.723
R2	0.178	0.178	0.178	0.178

Note: this table presents estimations from equation 1; all estimations include controls for workers' gender, race, education, wage at the time of layoff, and type of job (white-collar or blue-collar)-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 layoff years 2008-2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unemployment spell (ln)				Wage at new job (ln)			
% Network in LM at Layoff	-0.151***	-0.357***	-0.110***	-0.285***	0.065***	0.096***	0.076***	0.183***
	(0.003)	(0.012)	(0.005)	(0.023)	(0.003)	(0.014)	(0.006)	(0.027)
(% Network in LM at Layoff)^2		0.160***		0.131***		-0.024**		-0.079***
		(0.009)		(0.017)		(0.011)		(0.020)
Blue-collar worker X % Network in LM at Layoff			-0.054***	-0.083***			-0.015**	-0.109***
			(0.006)	(0.026)			(0.007)	(0.031)
Blue-collar worker X (% Network in LM at Layoff)^2				0.030				0.069***
				(0.019)				(0.023)
N	8744908	8744908	8744908	8744908	6975817	6975817	6975817	6975817
Mean dependent variable	0.429	0.429	0.429	0.429	3.388	3.388	3.388	3.388
R2	0.179	0.179	0.179	0.179	0.290	0.290	0.290	0.290

Note: this table presents estimations from equation 1; all estimations include controls for workers' gender, race, education, wage at the time of layoff, and type of job (white-collar or blue-collar)-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 – Robustness dropping large networks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unemployment spell (ln)				Wage at new job (ln)			
% Network in LM at Layoff	-0.126***	-0.328***	-0.091***	-0.251***	0.071***	0.085***	0.086***	0.159***
	(0.002)	(0.009)	(0.004)	(0.019)	(0.002)	(0.011)	(0.005)	(0.021)
(% Network in LM at Layoff)^2		0.157***		0.120***		-0.011		-0.054***
		(0.007)		(0.013)		(0.008)		(0.015)
Blue-collar worker X % Network in LM at Layoff			-0.046***	-0.093***			-0.020***	-0.091***
			(0.005)	(0.021)			(0.005)	(0.023)
Blue-collar worker X (% Network in LM at Layoff)^2				0.043***				0.053***
				(0.015)				(0.017)
N	12903310	12903310	12903310	12903310	10459188	10459188	10459188	10459188
Mean dependent variable	0.412	0.412	0.412	0.412	3.278	3.278	3.278	3.278
R2	0.182	0.182	0.182	0.182	0.342	0.342	0.342	0.342

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

B Data-Driven Selection of Heterogeneity Dimensions

To assess which worker characteristics most strongly moderate the effect of social networks on re-employment outcomes, we estimate a LASSO model that includes the main network variable (residualized within the main fixed-effect structure) and all of its interactions with individual covariates. Our approach follows the high-dimensional econometric framework of Belloni, Chernozhukov, and Hansen (2014) and Farrell (2015), who use LASSO for variable selection in settings with many potential covariates and interactions.

Specifically, we allow the network variable to interact with education, tenure, previous wage, gender, age, race, network size, and the blue-collar indicator. The main network measure is excluded from penalization, while all other main effects and interaction terms are penalized. This setup lets the data select, among a rich set of potential moderators, the dimensions along which the effect of social networks varies most systematically, after absorbing high-dimensional fixed effects.[6]

Penalty Path and Stability of Interactions

Because LASSO performs variable selection by shrinking some coefficients exactly to zero, the key diagnostic is not the magnitude of a coefficient at a single penalty value, but its selection stability along the regularization path. A variable that remains nonzero across a wide range of penalty levels λ is interpreted as a robust moderator, whereas variables that only appear when the penalty becomes very small (or that disappear quickly as λ increases) have weaker empirical support.

To illustrate this, Figures A1 and A2 plot the coefficient paths for all interaction terms. The horizontal axis displays $\log(\lambda)$, which increases from left to right: the right side represents strong penalization (high λ), and the left side represents weak penalization (low λ). Interaction terms that remain active (i.e., nonzero) over a broad segment of the path are the most stable moderators. In the figures, the label $Net. * Blue - CollarWorker$ refers to the interaction between the network variable and the blue-collar indicator.

For the unemployment-duration outcome (Figure A1), the network $\times$ blue-collar interaction is among the terms that survive penalization the longest. Although some interactions—most notably network $\times$ male and network $\times$ low education — enter the model under low penalties, they shrink toward zero more quickly once the penalization increases, indicating lower stability. The blue-collar interaction, by contrast, remains nonzero across a substantially wider range of λ values.

For the wage outcome (Figure A2), the heterogeneity pattern is richer. Interactions with education and gender remain in the model longer in the path, consistent with the fact that wage determination strongly reflects returns to schooling and gender gaps. Nonetheless, the network $\times$ blue-collar interaction remains selected and nonzero over a meaningful segment of

[6] The estimation is performed with the same fixed-effect structure used in the main regressions: $id_{\text{worker}} \times year_{\text{layoff}} \times Blue - CollarWorker$ for unemployment outcomes and $id_{\text{worker}} \times year_{\text{layoff}} \times Blue - CollarWorker \times year_{\text{rejoin}}$ for wage outcomes.

the regularization path. This indicates that occupational status is also a relevant moderator for wage outcomes, even if not the predominant one in this case.

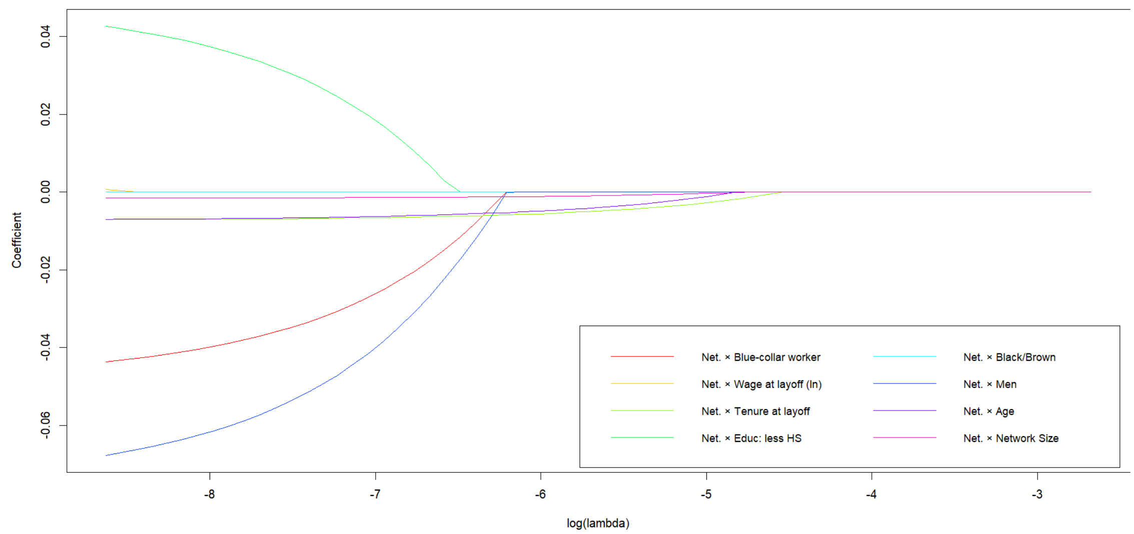

Figure A1: Coefficient Paths for Interaction Terms (Unemployment Duration)

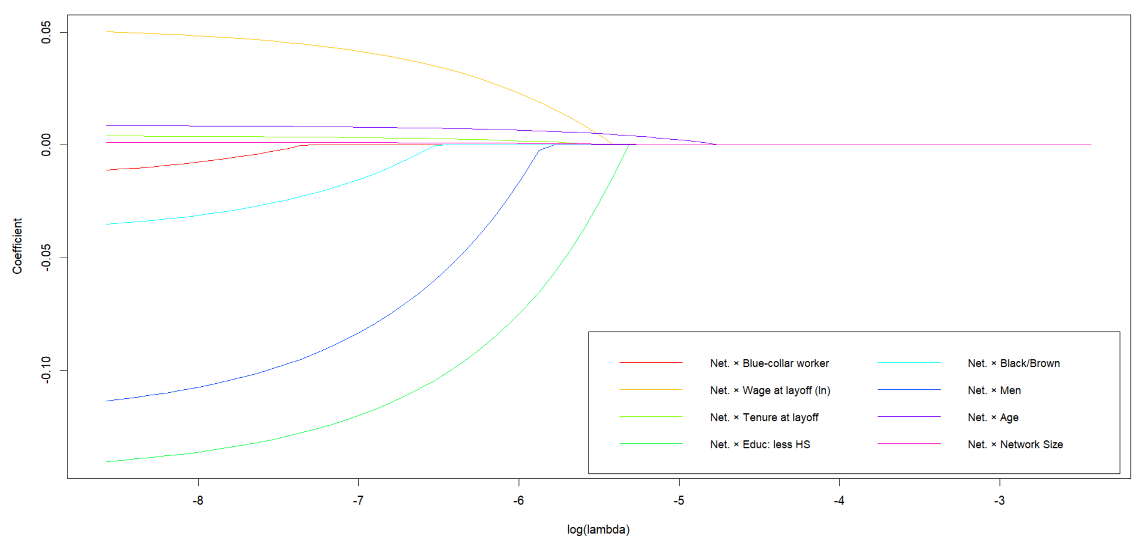

Figure A2: Coefficient Paths for Interaction Terms (Post-Unemployment Wage)

Coefficients at the Selected Penalty Level

Table A4 reports the LASSO coefficients evaluated at the least-penalizing λ used in our analysis (i.e., the smallest value of the regularization path). These coefficients should not be interpreted in a causal or magnitude sense, but simply as the set of terms that survive penalization at the chosen λ. Their role is to complement, rather than replace, the stability analysis shown in the LASSO paths.

Across both outcomes, the interaction between the network variable and the blue-collar indicator is consistently retained by the LASSO procedure and shows meaningful stability along the regularization path. This provides a data-driven justification for focusing on blue- versus white-collar heterogeneity in the main analysis, while recognizing that additional moderators play a role, especially for wage outcomes.

Table A4: LASSO Coefficients for Unemployment Duration and Post-Unemployment Wage

	Unempl. Spell	**Log Wage in New Job**
(Intercept)	0.409	3.281
% Network in LM at Layoff (residualized)	-0.175	0.111
Blue-collar Worker (residualized)	-0.016	-0.092
Hourly Wage at Layoff (residualized)	-0.031	0.129
Tenure at Layoff (months, residualized)	0.001	0.001
Low Education (residualized)	0.023	-0.087
Black/Brown (residualized)	-0.018	-0.027
Male (residualized)	-0.105	0.122
Age (residualized)	0.008	0.004
Network Size (residualized)	-0.001	0.000
% Network in LM × Blue-collar Worker	-0.044	-0.011
% Network in LM × Hourly Wage at Layoff	0.001	0.050
% Network in LM × Tenure at Layoff (months)	-0.007	0.004
% Network in LM × Low Education	0.043	-0.140
% Network in LM × Black/Brown	0.000	-0.035
% Network in LM × Male	-0.068	-0.114
% Network in LM × Age	-0.007	0.009
% Network in LM × Network Size	-0.002	0.001

Note: This table reports LASSO coefficients at the least penalized value of λ along the regularization path. Coefficients equal to zero (not shown) indicate that the corresponding variables were shrunk to zero by the LASSO penalization. These results complement the stability analysis shown in Figures A1 and A2, which illustrate how each coefficient evolves across different levels of penalization.