Strong Ties and Stable Jobs: Occupational Embeddedness in the Labor Market

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ABSTRACT

This paper develops a network-based explanation for persistent variation in job precarity across occupations and individuals. It introduces the concept of occupational embeddedness, defined as the degree of overlap between workers' professional and personal social ties. Drawing on insights from social network analysis and field theory, the paper argues that tightly knit occupational communities reduce members' exposure to economic shocks by facilitating information flow and fostering strong work-centered identities. Using data from the General Social Survey's special module on social networks, I find that occupational embeddedness varies systematically across occupational groups and is strongly associated with lower perceived job loss risk and higher job security. It appears that "upper-class" occupational groups confer benefits to their members not only through direct income, industry, or education effects, but also by fostering collective work-centered identities.

Keywords: Occupational embeddedness; job precarity; social network analysis; field theory

Word Count: 4495

1 Introduction

Why does unemployment risk vary across individuals and occupational groups? As globalization, demographic shifts, and technological change have dramatically reshaped the occupational landscape over the past few decades (Oesch 2013), precarious work has become a focal point among stratification scholars, economists, and political scientists alike (Kalleberg 2009; Wood et al. 2019; Caldarola et al. 2024; Griesbach 2025). However, while those located in low-skilled, blue-collar sectors have historically faced greater precarity during economic recessions, the mechanisms behind this stylized fact are somewhat opaque. Workers that are the most socially and economically necessary are often crowded in precarious sectors, while highly educated and technically abstract occupations are relatively immune to business cycle effects. Numerous explanations—ranging from demand volatility to skill specificity to sociodemographic discrimination—have attempted to solve this puzzle. However, the dominant analytical framework underlying these extant theories is overwhelmingly structural, leaving little conceptual space for actors to shape outcomes related to their most critical income-generating asset: their labor.

[†]Data and replicable code can be found here: https://github.com/lydiagcamp/occupational_embeddedness.

While this paper does not negate the role of macroeconomic shifts or demographic discrimination, I argue that socially skilled actors are more agentic than often assumed when it comes to protecting their labor market advantage. In this sense, the relative placidity of certain "non-essential" occupational groups throughout crises can be understood as the result of the strategic, endogenous practices enacted by some occupational groups to strengthen their internal networks. The core objective of this paper, then, is to explain the persistent variation in precarity by connecting micro-level (individual) strategies to macro-level (occupational) outcomes, primarily through the mechanism of social networks. Although the study of networks in labor markets has a long history (Granovetter 1973, 1974, 1985), this literature has primarily focused on job search processes, *i.e.* "getting a job" (Mehreen et al. 2019; Rajkumar et al. 2022; Kim 2023). Similarly, a few studies in the management literature have evaluated the relationship between workplace friendship and job performance and life satisfaction (Hurlbert 1991; Methot et al. 2016; Barroso 2022). However, this is the first paper to systematically document how the overlap between professional and personal ties is stratified across occupational groups and social classes, as well as to examine how this overlap relates to job precarity more broadly.

After reviewing existing explanations of divergent labor market trajectories in Section 2, I develop my theoretical framework in Section 3. I innovatively borrow the term "occupational embeddedness"—which I define as occupational network homogeneity—from management scholarship and introduce it into the sociological literature. I argue that denser within-occupation ties facilitate the flow of occupation-specific information, thereby minimizing information friction, reducing uncertainty, and allocating actors more efficiently to positions in the labor market. On a more sociological note, I also suggest that occupational network homogeneity promotes a more coherent occupational identity that protects actors within its "in-group." Then, I present descriptive statistics and exploratory regression models in Section 4 using the *General Social Survey* social networks module. The results indicate that the overlap between professional contacts and close friends varies widely across occupations and has significant predictive power in terms of job precarity. Weak ties may help you get a job, but strong ties seem to help you keep it. Section 5 then outlines potential strategies for future identification *vis-à-vis* LinkedIn data, and Section 6 concludes.

2 Occupational Differences in Job Precarity

In light of its day-to-day salience, along with the relative ease of differentiating individuals along this axis, I take the occupation as the primary unit of analysis. Occupations, comprising a set of jobs with similar tasks, are typically aggregated to the one- through four-digit level of ISCO categorizations and convey information about task specificity with varying levels of detail (ILO 2025). Although these classificatory schemas are inevitably subject to ambiguity and coder interpretation (Martin-Caughey 2021), they usefully differentiate between patterns of work logics (Oesch 2006), helping researchers understand what people generally do when they clock in to work. Occupations tend to cluster along various axes, with one prominent example being the rate of unemployment. As depicted in Table 1, both the "natural rate" and relative increase in unemployment from 2007 to 2010 (interpreted as the effect of the 2008 financial crisis) vary widely among occupational groups, as categorized by the U.S. Bureau of Labor Statistics.

Table 1: **Change in Unemployment Rates by Occupation (2007–2010)**

Occupational Group	**Rate (2007)**	**Rate (2010)**	**Change (%)**
Architecture and engineering occupations	1.6	6.2	287.5
Installation, maintenance, and repair occupations	3.4	9.3	173.5
Management, business, and financial operations occupations	1.9	5.1	168.4
Management occupations	1.8	4.8	166.7
Construction and extraction occupations	7.6	20.1	164.5
Natural resources, construction, and maintenance occupations	6.3	16.1	155.6
Computer and mathematical occupations	2.1	5.2	147.6
Business and financial operations occupations	2.4	5.6	133.3
Life, physical, and social science occupations	2.0	4.6	130.0
Production occupations	5.7	13.1	129.8
Management, professional, and related occupations	2.1	4.7	123.8
Office and administrative support occupations	4.0	8.7	117.5
Professional and related occupations	2.1	4.5	114.3
Sales and office occupations	4.3	9.0	109.3
Transportation and material moving occupations	6.0	12.4	106.7
Arts, design, entertainment, sports, and media occupations	4.4	8.9	102.3
Community and social services occupations	2.3	4.6	100.0
Sales and related occupations	4.8	9.4	95.8
Farming, fishing, and forestry occupations	8.5	16.3	91.8
Building and grounds cleaning and maintenance occupations	6.7	12.8	91.0
Education, training, and library occupations	2.3	4.2	82.6
Personal care and service occupations	4.8	8.7	81.2
Service occupations	5.9	10.3	74.6
Healthcare support occupations	4.5	7.6	68.9
Food preparation and serving related occupations	7.5	12.4	65.3
Protective service occupations	3.7	5.9	59.5
Legal occupations	2.3	2.7	17.4

Note: Percentage change is calculated as the relative increase in the unemployment rate between 2007 and 2010 in the United States. Data are drawn from multiple waves of the Current Population Survey (CPS) conducted by the Bureau of Labor Statistics (BLS).

This divergence has been attributed to a range of factors, with many economic theories concluding that cyclical unemployment most strongly affects those in low-skilled and blue-collar occupations (Candelon et al. 2009). However, the concrete mechanisms behind this assumption are not particularly straightforward. Some scholars point to demographic differences in the general makeup of occupational groups (Clark and Summers 1981; Vedder and Gallaway 1992; Tolvi 2003),[1] while others highlight differentials in skill specificity (Teulings and Koopmanschap 1989; Fabiani et al. 2001; Tåhlin 2007; Oesch 2006; Oesch and Rennwald 2010). While useful, however, skill-based theories treat individuals as passive holders of skills, meaning that these frameworks cannot explain why occupations requiring similar technical competencies exhibit divergent outcomes. A similar critique applies to arguments emphasizing exogenous shifts in labor demand or automation potential (Autor et al. 2006; Frey and Osborne 2017), since substantial institutional and political resistance often constrains the development of technologies that would displace upper-class work.

Another popular explanation of variation in job precarity is rooted in the long tradition of class theory. Ever since the development of the Weberian "Erikson-Goldthorpe-Portocarero" (EGP) schema (Erikson and Goldthorpe 1992), class has been functionally interchangeable with occupational groupings, and Kim Weeden and David Grusky's (2001; 2005) "micro-class" agenda completes this process by quite literally equating the two. Within these broader theories of social class, occupational groups are more or less remunerated and perceived as socially valuable based on objective differentiation not only in skill specificity but also in monitoring capacity. Within this framework, labor market precarity is predicted to be correlated with jobs in which employees can be easily monitored and quickly fired and hired.

However, this approach provides parsimony at the expense of obscuring the concrete mechanisms underlying occupational patterns in precarity. I therefore conceptually distinguish between occupations and occupation-based class schemas for two main reasons. First, the demarcation is useful if one wants to better isolate the effect of the occupation, which is necessary to circumvent the internal heterogeneity accompanying studies of social class. While people often misrepresent their location within class and income distributions (Fernández-Albertos and Kuo 2018), occupations are widely recognizable social divides with observable closure processes that correspond to relatively uncontroversial professional identities.[2] I therefore aim to disaggregate class and align my argument with the categorization schemas most commonly used by individuals in day-to-day terminology. Second, rather than taking an individual's labor contract as exogenously determined, I assume that occupational groupings themselves are the historical result of socially skilled actors creating barriers to entry to maximize rent-seeking behavior. While social classes function in similar ways, closure and job-related decisions have historically been more formalized at the occupational level. Since the medieval period, occupational groups have banded together to prevent the dilution of the rents extracted by insiders. The extensive literature on the political economy of medieval guilds (Epstein 1998; Ogilvie 2014), which are often considered as proto-occupational groups, suggests that members of these monopsonistic institutions designed barriers to entry as a hedge against labor market uncertainty. This logic is still observable a millennium later, with

[1] Minorities are more likely to be laid off during retrenchment periods (Couch et al. 2016), a pattern colloquially referred to as "last hired, first fired."

[2] This argument is similar to that of Weeden and Grusky (Weeden and Grusky 2001, 2005), yet I suggest that, in contrast to the "micro-class" approach, equating occupations to social classes is largely superfluous and perhaps even complicates analyses of the occupational structure (Birkelund 2002).

occupational licensing and accreditation shielding incumbents from competition with new entrants (*e.g.* minorities, women, immigrants, and the inexperienced). Precarity is not unique to the gig economy, and understanding its origins requires moving beyond purely structural explanations to consider how actors themselves navigate uncertainty in the labor market.

3 Theoretical Framework

3.1 Multiplex Networks and Occupational Embeddedness

I therefore suggest that a key mechanism through which occupational groups confer advantage to their members includes the establishment of strong personal networks among professional peers. While there is a large literature exploring the effect of network formation on material gain, these studies have primarily explored the variation of this social capital across classes (Granovetter 1973, 1974, 1978; Diani and McAdam 2003). For instance, it is well-established that upper-class and high-status individuals maintain larger networks with more high-status ties, resulting in greater levels of social capital (Bourdieu 1986; Lin 2005; Li et al. 2008; Lin and Hung 2022; Alecu 2022). However, high-status connections may yield social benefits without necessarily translating into professional advantages. As an example, being friends with a well-known artist may boost one's social status, yet this connection offers little guidance on market dynamics or job opportunities for someone working as a financial analyst. In this sense, my point is not purely about status but rather about occupational endogamy—particularly in the context of understanding job precarity.

I therefore draw on an important body of research in social network analysis that examines "multiplex" networks, in which nodes (individuals) are simultaneously connected through multiple types of ties (White 1976; Kivelä et al. 2014; Li et al. 2023). Within the context of this study, multiplex networks are understood as cases in which a coworker or member of one's same occupation is also considered to be a personal friend. While there are a few management scholars who have examined this phenomenon of multiplex networks in the workplace, these studies have primarily focused on job satisfaction (Hurlbert 1991) or job performance (Methot et al. 2016; Barroso 2022) as the dependent variable. Accordingly, this study integrates perspectives from both network stratification and multiplex networks by analyzing the stratification processes and consequences of workplace friendship.

To provide concrete verbiage for my theoretical framework, I borrow the term occupational embeddedness (OE) from the "Attachment Literature" of early 2000s management scholarship. OE has typically been utilized to predict employee turnover based on the overall "stuckness" created by various on- and off-the-job determinants (Mitchell et al. 2001; Ng and Feldman 2007, 2009).[3] OE has not been formally utilized outside of studies of employee turnover, but I argue that repurposing and redefining the concept can provide a useful framework for identifying a key mechanism underlying variation in job precarity. I formally define OE as occupational network homogeneity, measured by the extent to which an individual's social contacts belong to their same occupational group—that is, how multiplex or "overlapping" the professional and social ties are within the network. Variation in this measure is likely the result of differences in institutionalized

[3] Management scholars typically refer to "job" rather than "occupational" embeddedness (Mitchell et al. 2001). However, I use the term "occupational embeddedness" for conceptual clarity, in light of the difference between jobs and occupations (see the ILO's classification [2025] and Martin-Caughey [2021]).

processes and informal norms. For instance, occupational licensing, the typical number of hours worked per week, the existence of separate occupation-based networking channels, and the importance of formal training all contribute to whether the majority of an individual's close friends are also their professional colleagues. However, the primary focus of this paper is on describing the effects rather than the causes of this phenomenon, particularly as it relates to job security.

Mechanisms of Advantage

There are various ways that this concept of occupational embeddedness should *a priori* confer advantage to labor-market insiders. Primarily, however, I suggest that tightly knit professional networks allow socially skilled actors to establish a more secure position in the labor market through two key channels, one largely economic and the other more sociological. First, I propose that occupational groups lower transaction costs and more efficiently allocate actors into desirable positions when network homogeneity and density are high (Granovetter 1974). By this, I mean that occupations that have clearly defined (yet often informal) channels of communication are better positioned to allocate qualified actors to labor market positions, thus creating an effective safety net for insiders. Lawyers exemplify this argument, as legal professionals in the U.S. typically use an informal blog (*Above the Law*) to efficiently communicate occupation-specific information about firm and market dynamics. While these tightly knit occupational groups often resist new entrants, individuals who have acquired a certain degree of prestige tend to retain job security, even in periods when their roles do not fulfill a socially useful or economically demanded function.

While this first mechanism is not particularly novel, I more interestingly suggest that tighter and more homogenous occupational networks also facilitate the creation of work-related collective identities. The more time (on and off the clock) that actors spend with those whom they are professionally associated with, the more likely they are to conceptualize themselves as members of that group. This mechanism is not dissimilar from Neil Fligstein and Douglas McAdam's (2012) emphasis on the importance of a "shared understanding" of what is at stake within a given field. Occupations that can more effectively generate these shared understandings will promote stronger in-group sentiment and a general atmosphere of "homophily." This sentiment, in turn, contributes to a more pronounced protection of members as "one of us" during economic downturns or political threats. Following the natural logic of these two mechanisms, I expect the following:

Hypothesis 1: A stronger degree of overlap between personal and professional ties (*i.e.* a higher occupational embeddedness score) is associated with greater job security.

In this sense, my proposed analytical framework of relational, systematic jockeying for status has obvious affinities with field theory (Fligstein and McAdam 2012), as well as Andrew Abbott's (1988) path-breaking book on *The Systems of Professions*. I build particularly on Fligstein and McAdam's (2012) coherent synthesis, and I argue that occupational groups can be best understood as subfields nested within the broader field of the labor market. Just as incumbents and challengers vie for status and jurisdiction over particular kinds of knowledge, actors within occupational groups aim to build coalitions to establish or defend dominant positions. This framework therefore helps explain variation in network structures across occupational groups, particularly since incumbents are expected to more actively cultivate work-centered identities, networks, and closure mechanisms to exclude challengers.

While labor market competition has been widely studied, the majority of previous work has tended to focus on within-occupation and within-sector competition, rather than *across*-occupation conflict. To some extent, this traditional approach is warranted; occupations do not always compete with each other directly—plumbers and lawyers are likely not vying for domain over the same systems of knowledge—but this framework becomes more useful when the aim is to explain how occupations facing similar exogenous threats display marked differences in outcomes. As an example, the threat of artificial intelligence arguably threatens content creators and authors more than food service workers and Uber drivers, yet the increasing unionization of the former (such as actors' response to Hollywood's and Disney's experimentation with AI) has cultivated relative security, while the latter consistently remain subject to high job precarity. Ultimately, at its core, it appears that some occupations are more equipped than others to effectively solve the collective action problem. I therefore expect that incumbents (high-status occupations) will have higher rates of occupational embeddedness than challengers (low-status occupations).

Hypothesis 2: A stronger degree of overlap between personal and professional ties (*i.e.* a higher occupational embeddedness score) is associated with upper-class and high-status occupations.

4 Empirical Strategy

4.1 Data and Descriptive Statistics

To empirically evaluate this theory's validity, I examine the distribution of a constructed occupational embeddedness score across social groups, followed by an examination of this measure's relationship with job precarity. The analysis is primarily descriptive, but the findings are nonetheless relevant to testing the validity of the proposed theoretical framework. To do so, I draw on data from the most recent social networks module administered by the *General Social Survey* (GSS) in 2004. This module begins by asking respondents about the specific people they are closest to. The question is framed in the language of "strong ties" rather than casual acquaintances, asking: "From time to time, most people discuss important matters with others. Looking back over the last six months, who are the people with whom you discussed matters important to you?" Respondents were then asked to name up to five close contacts and report their characteristics. For the purposes of this study, I focus on two key attributes: (1) If a respondent's close contact is also their coworker, and (2) the respondent's frequency of meaningful interaction with this person.

As the primary explanatory variable, I operationalize occupational embeddedness, OE_i, as the share of a respondent's close social contacts who are also their coworkers. This measure captures the extent to which respondents' core interpersonal networks are embedded within their professional community. Since respondents were permitted to list fewer than five close contacts, the measure is expressed as a proportion of the number of total reported contacts (*i.e.* $\mathrm{OE}_i \in [0, 1]$). I also weight the OE_i score by the reported intensity of contact with each network tie.[4]

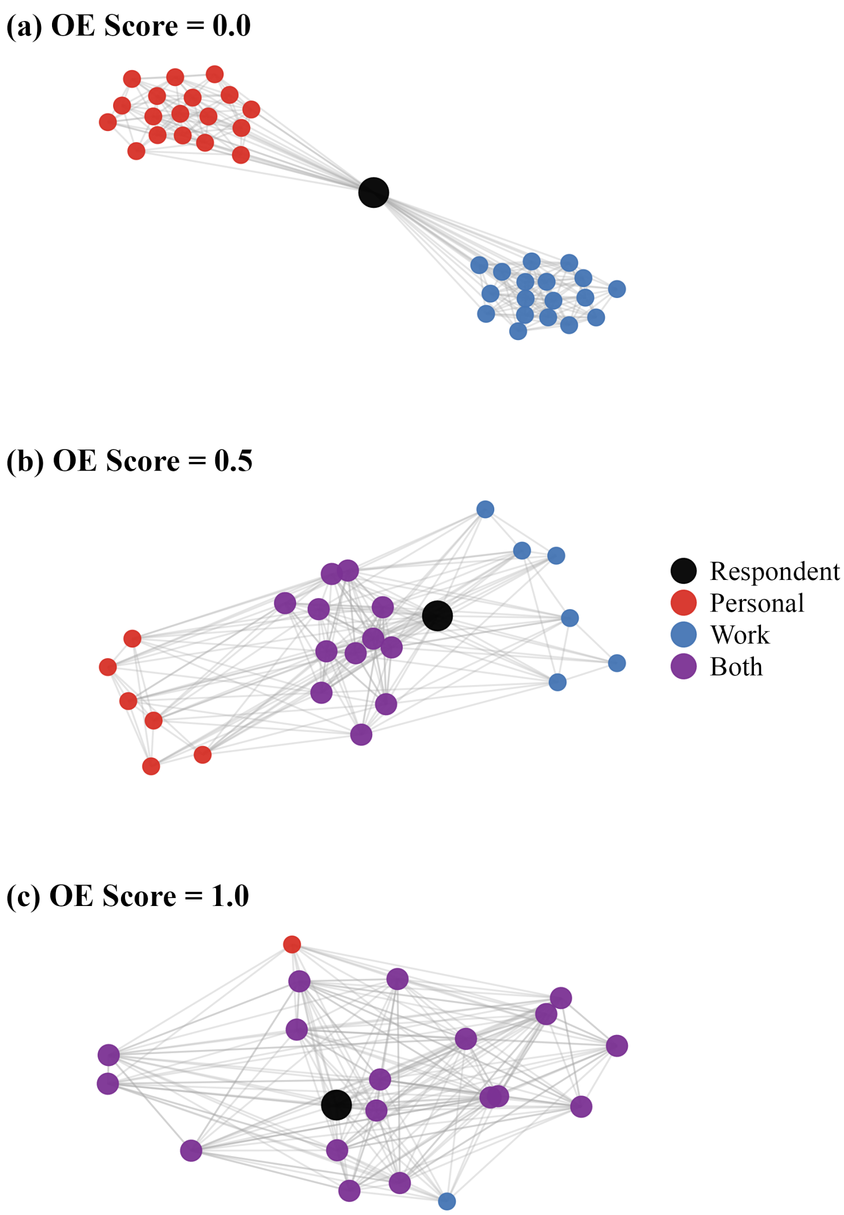
[4] Intensity of contact is measured by respondents' answers to the following question: "Thinking about how often you usually talk to (NAME), on average, do you talk to (him/her) almost every day (4), at least once a week (3), at least once a month (2), or less than once a month (1)?"

Formally, occupational embeddedness is defined as:

$$\text{Weighted OE Score}_i = \frac{\sum_{j=1}^{N_i} C_{ij}\, T_{ij}}{\sum_{j=1}^{N_i} T_{ij}}, \tag{1}$$

where C_{ij} is an indicator equal to 1 if contact (node) j is a coworker of respondent i, and 0 otherwise; T_{ij} denotes the intensity of contact between respondent i and node j (ranging from 1-4); and N_i is the number of total nodes reported by respondent i. To demonstrate the underlying network structures that these scores represent, I provide a visualization in Figure 1. In Panel A ($\text{OE}_i = 0.0$), the respondent's personal and work ties are fully separate, indicating no overlap. By contrast, Panels B ($\text{OE}_i = 0.5$) and C ($\text{OE}_i = 1.0$) show increasing integration, with Panel C depicting a personal network composed almost entirely of coworkers.

Figure 1: **Network Structures Underlying Occupational Embeddedness Scores**



It is worth noting, however, that this particular OE score presents a few limitations. First, with only up to five reported contacts, this metric can only measure strong rather than weak ties. Additionally, this particular operationalization may capture embeddedness at the organizational level rather than purely at the occupational level, since the question asks specifically about coworkers. However, under the assumption that coworkers are typically concentrated within similar occupational groupings, this measure provides the closest proxy for occupational network endogamy that is available in survey data.

Table 2: **OE Scores by Occupation and Class Position**

	Average Weighted OE Score	**N**
ISCO-88 Occupations (1-Digit)		
Legislators, senior officials and managers	0.186	119
Technicians and associate professionals	0.170	122
Professionals	0.167	153
Clerks	0.129	83
Plant and machine operators and assemblers	0.124	43
Service workers and shop and market sales workers	0.090	68
Craft and related trades workers	0.083	73
Elementary occupations	0.068	35
Skilled agricultural and fishery workers	0.000	8
Self-Reported Class Position		
Upper class	0.119	20
Middle class	0.142	378
Working class	0.145	294
Lower class	0.098	26
EGP Class Schema		
Higher-grade service class	0.170	158
Lower-grade service class	0.168	200
Routine non-manual workers	0.146	146
Skilled manual workers	0.167	2
Semi- and unskilled manual workers	0.085	91
Agricultural workers	0.082	87
Farmers	0.027	14

Notes: Average weighted job embeddedness scores measure the proportion of a respondent's close contacts who are also their coworkers, weighted by the intensity of contact (*i.e.* $\text{OE}_i \in [0, 1]$). Only respondents who have a job are included. Self-employed respondents are also excluded.

I next evaluate the distribution of this variable across occupational groups and social classes, thereby testing Hypotheses 2. As depicted in Table 2, OE appears to be concentrated in upper-class occupational groups as they are traditionally conceived (*i.e.* professionals, managers, technicians). For instance, an average of 18.6 (weighted) percent of legislators', senior officials', and managers' strong ties are also their coworkers, whereas this share is essentially zero for agricultural and fishery workers. Table 3 also presents a more detailed breakdown of OE by two-digit ISCO classifications, revealing even greater dispersion of this metric across occupations. Occupational networks also vary by class. While there is less variation among self-reported measures of social class, this is to be expected in light of the typically inaccurate self-identification of class position (Fernández-

Table 3: **OE Scores by ISCO-88 2-Digit Occupation**

	Average Weighted OE Score	**N**
General managers	0.320	29
Legislators and senior officials	0.308	4
Physical, mathematical and engineering science professionals	0.268	37
Physical and engineering science associate professionals	0.225	22
Precision, handicraft, craft printing and related trades workers	0.200	1
Drivers and mobile-plant operators	0.192	23
Other professionals	0.186	49
Life science and health professionals	0.184	24
Teaching associate professionals	0.167	3
Life science and health associate professionals	0.161	48
Other associate professionals	0.154	49
Models, salespersons and demonstrators	0.149	22
Office clerks	0.138	73
Corporate managers	0.135	86
Metal, machinery and related trades workers	0.123	45
Sales and services elementary occupations	0.090	16
Agricultural, fishery and related labourers	0.063	6
Personal and protective services workers	0.062	46
Customer services clerks	0.061	10
Machine operators and assemblers	0.053	17
Teaching professionals	0.050	43
Labourers in mining, construction, manufacturing and transport	0.043	13
Extraction and building trades workers	0.000	17
Market-oriented skilled agricultural and fishery workers	0.000	8
Other craft and related trades workers	0.000	8
Stationary-plant and related operators	0.000	3

Notes: Average weighted job embeddedness scores measure the proportion of a respondent's close contacts who are also their coworkers, weighted by the intensity of contact (*i.e.* OE Score $\in [0, 1]$). Only respondents who have a job are included.

Albertos and Kuo 2018). However, after translating the ISCO-88 codes into the well-known EGP class schema, I find further support for Hypothesis 2, as the service class exhibits the highest level of occupational network homogeneity—with almost entirely monotonic declines observed at successively lower positions in the class structure. In short, OE is clearly stratified across social and occupational groups, taking a higher value among the more privileged. This stylized fact likely reflects a variety of different mechanisms. For one, the shape of the distribution may represent the tendency for working class individuals to prefer authoritarian and structured relationships in the productive sphere of life (Lipset 1959; de Regt et al. 2012). The functional form may also represent work-related task characteristics, such as typical levels of interpersonal communication within occupations. It could even be that getting an upper-class job to begin with tends to require an insider connection. However, causality is not necessarily the point here, particularly since network formation is almost inherently endogenous. Rather, my primary aim is to demonstrate that building tight workplace networks confers some form of advantage, and that this benefit varies across occupational groups.

4.2 Regression Results

I next consider the relationship between occupational networks and job security, returning to the initially posed question and thereby testing Hypothesis 1. Although the GSS data are cross-sectional and likely subject to unobserved endogeneity stemming from organizational factors and individuals' personalities (*i.e.* extroversion vs. introversion), it is nonetheless interesting to consider the relationship between occupational embeddedness and job-related outcomes. I primarily focus on two survey questions, both related to perceptions of job security. The first asks respondents how likely they are to lose their job in the next twelve months,[5] and the second asks respondents whether they agree that their job security is "good."[6] Although I expect the relationship between these variables and OE to be comparable (yet reversed), I include both measures for robustness.

I control for a laundry list of covariates (descriptive statistics reported in Table 4), which include respondents' sociodemographics, party identification (0-7), income bracket, union membership, and government worker status. I also incorporate a job satisfaction variable as a proxy for broader organizational effects. From here, I estimate three models for each outcome: the first excludes covariates, the second includes all covariates and one-digit ISCO-88 occupation dummies,[7] and the third includes both occupation and social class dummies based on the EGP schema. The idea behind estimating these models separately is to show that, while OE tends to be clustered by occupation and social class, the measure retains predictive power *outside* of these factors as well. The models are formally represented with a simplistic Ordinary Least Squares (OLS) estimator,

$$Job\_Loss_i = \mathrm{OE}_i + \gamma X_i + \epsilon_i, \tag{2}$$

in which vector X_i represents the relevant controls described above and Job_Loss_i is exchanged for $Job\_Security_i$ in the second group of models. Table 5 reports the results. I find that the OE score is highly significant, and the effect becomes larger as occupational and class dummies are incorporated. Notably, this finding indicates that the association between job security and having friends

[5]Answers range from "very likely" (4) "fairly likely" (3), "not too likely" (2), or "not at all likely" (1).
[6]Respondents select from "very true" (4), "somewhat true" (3), "not too true" (2), and "not at all true" (1).
[7]The parameters and significance levels are unchanged when ISCO two-digit codes are specified instead.

Table 4: **Descriptive Statistics**

Variable	**N**	**Mean**	**Std. Dev.**	**Min**	**Max**
Weighted OE Score	222	0.129	0.263	0.000	1.000
Female	222	0.523	0.501	0.000	1.000
Age	222	40.802	12.227	18.000	75.000
Education (years)	222	14.387	2.751	5.000	20.000
Number of children	222	1.608	1.380	0.000	6.000
Household income bracket	222	11.324	1.879	1.000	12.000
Rural	222	0.063	0.244	0.000	1.000
Union member	222	0.090	0.287	0.000	1.000
Region: South	222	0.360	0.481	0.000	1.000
Government worker	222	0.171	0.378	0.000	1.000
ln Hours worked per week	222	3.646	0.518	0.693	4.489
Foreign-born	222	0.144	0.352	0.000	1.000
Party identification	222	4.023	2.055	0.000	7.000
Job satisfaction	222	3.324	0.792	1.000	4.000

at work is partially obscured by the clustering of OE across occupational groups—representative of the descriptive statistics above. The effects are also substantively large; in Model 6, moving from no overlap to complete overlap in friendship–coworker networks is associated with an increase of nearly one quarter of the full job security scale. Expectations of job loss function similarly, indicating that greater embeddedness in a work-centered identity is associated with increased confidence in one's position as a labor market insider.

Figure 2: **Effect of Occupational Embeddedness on Likelihood of Job Loss**

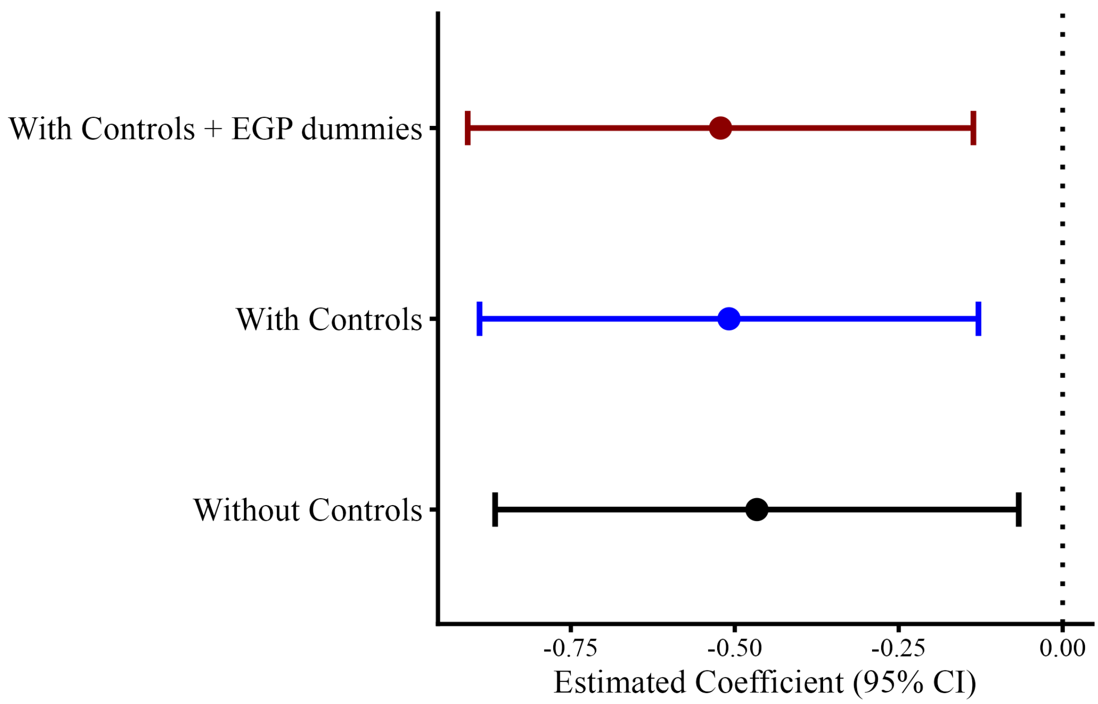


Table 5: **Occupational Embeddedness and Job Security**

	Job Loss Likelihood			**Job Security**		
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted OE score	-0.466*	-0.509**	-0.522**	0.595**	0.726***	0.788***
	(0.203)	(0.193)	(0.195)	(0.190)	(0.190)	(0.195)
Female		0.043	-0.005		0.086	0.108
		(0.110)	(0.112)		(0.108)	(0.112)
Age		-0.019	-0.005		-0.021	-0.019
		(0.026)	(0.026)		(0.026)	(0.027)
Age^2		0.000	-0.000		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Education (years)		-0.025	-0.029		-0.012	-0.015
		(0.025)	(0.025)		(0.024)	(0.025)
Married		-0.090*	-0.096*		0.072*	0.080*
		(0.037)	(0.037)		(0.036)	(0.037)
Number of children		0.018	0.007		0.036	0.028
		(0.044)	(0.046)		(0.044)	(0.046)
Household income bracket		-0.025	-0.033		0.007	0.004
		(0.031)	(0.031)		(0.030)	(0.031)
Rural		-0.211	-0.171		-0.240	-0.250
		(0.214)	(0.213)		(0.211)	(0.213)
Union member		-0.025	-0.054		-0.090	-0.045
		(0.187)	(0.187)		(0.184)	(0.186)
Government worker		0.134	0.174		0.188	0.204
		(0.150)	(0.150)		(0.148)	(0.151)
ln Hours worked per week		0.036	0.035		-0.078	-0.113
		(0.104)	(0.105)		(0.104)	(0.106)
Foreign-born		0.086	0.106		0.132	0.148
		(0.156)	(0.157)		(0.150)	(0.154)
Party identification (0–7)		0.079**	0.071**		-0.013	-0.017
		(0.026)	(0.026)		(0.026)	(0.027)
Job satisfaction		-0.282***	-0.281***		0.286***	0.285***
		(0.068)	(0.068)		(0.066)	(0.068)
Intercept	1.533***	3.343***	3.355***	3.385***	2.826***	3.050***
	(0.059)	(0.799)	(0.806)	(0.055)	(0.810)	(0.831)
Num. Obs.	222	222	222	223	223	223
R^2	0.024	0.287	0.327	0.043	0.224	0.247
Race Dummies		✓	✓		✓	✓
ISCO-88 (1-Digit) Dummies		✓	✓		✓	✓
EGP Social Class Dummies			✓			✓

$+p < 0.1$, $*p < 0.05$, $**\ p < 0.01$, $***p < 0.001$

Notes: Race is measured as a categorical variable that includes White (Non-Latinx), Black (Non-Latinx), Latinx, and Other. Self-employed and unemployed respondents are excluded.

5 Directions for Future Research

While these findings provide a useful starting point, GSS survey data present various limitations; the data are cross-sectional and relatively old (2004), and job security measures are self-reported. I therefore suggest that future analyses could complement traditional survey-based approaches with more innovative methodological approaches. For instance, I propose applying computational methods to LinkedIn data, with the primary objective of evaluating the extent to which individuals are embedded within their occupational networks. With this data, I would be able to aggregate information on individuals' contacts to the occupational level, thereby comparing differences in average OE scores across occupational groups. This approach facilitates both a larger sample size—which is necessary for the project's generalizability—while also extending the analysis past evaluations of only an individual's five closest friends.

Despite its strengths, however, LinkedIn data also presents numerous challenges. For one, selection into having a LinkedIn account is an obvious source of bias, given that white-collar workers are over-proportionately represented among its user base. However, with over 200 million U.S. users (Kumar 2025), there is evidence that the platform is growing in scope, particularly within the North American context. Second, it is likely that an individual's connections on LinkedIn are not perfectly analogous to their real-life social circle; as such, I expect that the reported OE score will be biased upward. Regardless of this measurement error, however, I nonetheless find it reasonable to assume that individuals generally connect with those whom they consider as friends, colleagues, or people they aim to emulate—especially since the platform's algorithm routinely recommends "People You May Know."

Scraping public LinkedIn data is also pragmatically difficult for non-authorized users—and in some contexts illegal—rendering API access necessary before the project can be carried out. However, previous researchers (Chinoy and Koenen 2024) have been able to access this data, and the recently updated *RLinkedIn* package could, in theory, be helpful in efficiently extracting the relevant information once API access is acquired. Nonetheless, this problem can be temporarily side-stepped for proof of concept, since individual users can freely download a list of their own connections. As such, I provide an example of the proposed methodology using my own LinkedIn connections, with the results presented in aggregate form for privacy concerns.

While calculating my personal OE score, I encountered the common issue that automated crosswalks are often inaccurate when mapping job titles to ISCO codes. Self-reported position titles do not always communicate the skills or tasks actually involved in a given job, a difficulty that is increasingly exacerbated in David Graeber's (2018) world of "bullshit" white-collar jobs. Additionally, as a form of labor self-commodification, LinkedIn presents further challenges since the platform incentivizes users to "oversell" themselves and therefore describe their current positions with more abstract language. For transparency's sake, however, I include the results from multiple translation methods and their accuracy compared to the manually coded results. In addition to manual coding, I employ three alternative, automated methods. First, I asked Chat-GPT (Version 5.0) to convert the position titles to ISCO codes. This approach was explicitly wrong (with 0.7% accuracy at the 4-digit level) and subsequently discarded. Then, I worked with LabourR, a package in R that uses fuzzy matching to crosswalk free-text descriptions to ISCO codes.[8] While

[8]While the package has been removed from the CRAN repository as of June 2025, it can still be downloaded externally through GitHub.

still relatively low, this approach is remarkably more accurate, and the coding agreement rates in my sample mirror those in Wan et al.'s (2023) overview of the precision in different automated methods of occupational coding. Finally, I use a large language model (LLM) accessed via the OpenAI API to translate job titles into ISCO-08 categories.[9] This approach provides the highest level of accuracy, suggesting that LLM-based classification is a promising tool for future research.

Table 6: **ISCO Agreement: Percentage of Matching With Manual Coding**

ISCO Level	LLM (%)	LabourR (%)	Chat-GPT 5.0 (%)
1-digit	71.68	50.0	13.9
2-digit	51.77	28.7	3.7
3-digit	37.61	22.5	1.1
4-digit	21.24	14.7	0.7

Then, describing myself as a "Sociologist" (ISCO-08 2632), I calculate my occupational network homogeneity score at the one through four digit levels, subsequently depicted in Table 7.[10] Similar to the measure constructed above, I operationalize OE as a continuous variable representing the degree of occupational similarity between the centroid and all other nodes (*i.e.* the proportion of one's personal contacts also located within their professional community). Although this exercise may appear somewhat self-indulgent, I suggest that, after collecting sufficient data, it will be possible to calculate the mean and spread of the OE variable across occupational groups. I then can match this data to occupational-level unemployment rates during economic shocks to test my theory's explanatory power.

Table 7: **Personal Occupational Embeddedness (OE) Scores**

ISCO Level	OE Score
1-digit	.491
2-digit	.131
3-digit	.067
4-digit	.045

6 Discussion

Through this analysis, I have mapped out a novel mechanism to help account for the uneven ability of occupational groups to protect their members from economic downturns: occupational embeddedness. Despite its high-status bias, I find that occupational embeddedness still retains a positive effect on perceptions of job security even after social class, occupational groupings, and income are controlled for—evidencing the robustness of the association between the two variables. I therefore suggest that "upper-class" occupational groups tangibly confer benefits to their members not only through pure income, industry, or educational effects but also through the creation of collective work-centered identities. As such, the proposed project implies that improving job stability for

[9] The associated prompt and coding procedures can be found at the Online Appendix here.
[10] I use the manually coded data in this exercise to maximize accuracy.

those in precarious sectors should involve the development of occupation-specific networks and communication channels. In future research, I plan to formulate more precise measurement strategies to minimize measurement error, with the ultimate aim of understanding the role of networks in labor market stratification.

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