The Network Structure of Occupations:
Fragmentation, Differentiation, and Contagion

Ken-Hou Lin

University of Texas at Austin

Koit Hung

University of Texas at Austin

Keywords: occupational structure; network; labor market; inequality

Forthcoming, *American Journal of Sociology* 127(5)

We thank Dustin Avent-Holt, Siwei Cheng, Emily Erikson, James Kitts, Barum Park, David Pedulla, Kelly Raley, Art Sakamoto, Michael Schultz, Patrick Sheehan, Donald Tomaskovic-Devey, and reviewers for their comments on the earlier drafts of this paper. We also thank the colloquium series at the University of Massachusetts-Amherst, and the Center for Empirical Research on Stratification and Inequality at Yale University for their valuable inputs. This research was supported by grant, P2CHD042849, Population Research Center, awarded to the Population Research Center at The University of Texas at Austin by the Eunice Kennedy Shriver National Institute of Child Health and Human Development.

ABSTRACT

Occupational structure is commonly viewed as either hierarchical or organized around stable classes. Yet, recent studies have proposed to describe occupational structure as a network, where the mobility of workers demarcates boundaries. Moving beyond boundary detection, this article develops occupational network as a dynamic system in which between-occupation exchange is shaped by occupational similarities, and occupational attributes are in turn responsive to mobility patterns. We illustrate this perspective with the exchange networks of detailed occupations. Our analysis shows that the U.S. occupational structure has become more fragmented. The division was in part associated with the emerging importance of age composition, as well as those of quantitative, creative, and social tasks. The fragmentation reduced wage contagion and therefore contributed to a greater between-occupation wage dispersion. These results indicate that occupational attributes and mobility are co-constitutive, and that a network perspective provides a unifying framework for the study of stratification and mobility.

INTRODUCTION

Occupational structure has been central to the study of social stratification and inequality. Conventional studies conceive occupational structure as either hierarchical or organized around stable classes (e.g., Erikson and Goldthorpe 1992; Hauser and Warren 1997; Treiman 1977; Weeden and Grusky 2005; Wright 1997). Yet, scholars have long pointed out that mobility is critical in understanding the structure of labor market (Blau and Duncan 1967; Breiger 1981; Spilerman 1977; White 1970). Based on this insight, recent studies have proposed to analyze occupational structure as a network, in which occupations are linked by the movement of workers (Cheng and Park 2020; Toubøl and Larsen 2017; Villarreal 2020).

The network perspective is distinct from traditional approaches with its emphasis on mobility in delineating occupational structure. Both the hierarchical and class frameworks focus on certain occupational attributes such as prestige, authority, or skill level to locate occupations. The network perspective, in contrast, focus on the flow of workers between occupation. Furthermore, the strata and class perspectives necessitate the assignment of occupations into discrete categories, and much debate has centered around how and to what extent occupations should be aggregated (e.g., Breiger 1981; Laurison and Friedman 2016; Weeden and Grusky 2005). The network approach does not require *a priori* classification; it allows for the dynamic association of occupations.

This article further develops occupational structure as a dynamic system in which mobility is shaped by occupational similarities, and occupational attributes are in turn

responsive to network configuration. We go beyond describing occupational structure as a network and examine whether it indeed *operates* as a network, in which nodes and ties are mutually constitutive. By examining the interdependence between occupational attributes and mobility patterns, we develop a unifying framework for the study of stratification and mobility.

Empirically, we examine the exchange networks of 252 detailed occupations between 1983 and 2017 through three sets of analysis. First, we describe how occupational networks have evolved over time. Consistent with prior studies (Cheng and Park 2020; Villarreal 2020), we find that the U.S. labor market has become more fragmented in the past decades. Both first- and higher-order connectivity declined. The number of distinct “communities” also increased. The fragmentation was driven by both the increase of mobility within and the decline of mobility between these communities.

Second, we test how between-occupational exchange is shaped a wide range of occupational attributes beyond status proximity. We find that mobility is negatively associated with occupational dissimilarity in sex, racial, educational, and industrial composition. Occupations that involve motion control or supervisory tasks as well as those in hazardous environments are also distant from other occupations. Notably, a new array of differentiating factors—such as age composition, quantitative, creative, and social tasks—have emerged to suppress the mobility of workers between occupations dissimilar in these

regards. Analytical tasks, while associated with higher wages (Liu and Grusky 2013), became less important in regulating mobility net of educational composition.

The last set of analysis considers contagion, that is, how exchange may generate convergence in occupational attributes. Specifically, we examine whether occupational median wage is associated with those of linked occupations. The findings indicate that, net of changes in workforce composition, occupational content, and class membership, the median wages of linked occupations are robustly correlated. This suggests that mobility structure could influence the level of wage dispersion among occupations. We estimate that about 10% of the increase in between-occupation wage inequality could be attributed to the fragmentation of occupational networks.

Together, these findings illustrate that the network perspective is not merely a “novel” approach but one that provides distinct insights. The findings also suggest the co-constitutive nature of occupational attributes and mobility. Mobility, after all, requires structural basis: it is facilitated by one or multiple dimensions of similarity between the origin and destination. In the meantime, occupational attributes are malleable, shaped by the influx and outflow of workers to other occupations.

Substantively, our findings indicate that the entry point to the labor market has become more restrictive in determining one’s career trajectory than the earlier decades. This is consistent with previous findings on the divergence in returns to college education across different areas of study (Altonji, Kahn, and Speer 2014; Kim, Tamborini, and Sakamoto

2015) and increased organizational barriers between core and peripheral positions (Cobb and Lin 2017; Weil 2014; Wilmers and Aeppli 2021). We also provide clear evidence that occupations requiring quantitative, social, and creative skills have become more specialized in recent year (Deming 2017; Florida 2002; Liu and Grusky 2013), leading to a decrease in the exchange between occupations that are dissimilar in these regards.

The fragmentation of occupational structure provides a plausible explanation for the uneven impacts of the recent recessions (Redbird and Grusky 2016) and expanding wage inequality in the U.S. labor market (Weeden and Grusky 2014). Reduced connectivity may limit the reallocation of workers to new demands. A shortage of labor and a shortage of jobs could therefore exist contemporaneously in different segments of the market.

The rest of the article is organized as follows: we first summarize the canonical views of occupational structure and some early insights regarding the linkages among occupations. The discussion then pivots to recent studies that have analyzed the occupational structure as a network and how we further advance this line of inquiry. After introducing our data sources, we present the main findings from three sets of questions. First, what is the topological structure of occupations in the United States, and how has it evolved since the 1980s? Second, does between-occupation mobility vary by occupational similarities and which are the critical dimensions? Third, does network location influences occupational attributes? We conclude with a discussion on the implications of our findings and future research directions.

OCCUPATIONAL STRUCTURE

Hierarchy, Big Classes, and Micro-classes

Occupations are critical institutions through which economic and social resources are allocated across individuals. Between-occupation wage variation accounts for a substantial portion of rising wage inequality in the United States (Lemieux 2008; Mouw and Kalleberg 2010a). Occupations are also sites for the formation of political preferences (Kitschelt and Rehm 2014; Weeden and Grusky 2012) and have far-reaching influences on household dynamics (e.g., McClintock 2017; Schneider 2012). Occupational structure, therefore, has garnered perennial interest.

A common way to depict occupational structures is to rank occupations in a hierarchy or sort them into strata (e.g., Hauser and Warren 1997; Treiman 1977). The two most popular measures for the ranking of occupations are prestige and status, both rooted in the Weberian tradition of social differentiation. Hierarchy serves as the backbone for studying social stratification and mobility, as social mobility is defined according to one's position in hierarchical structure. Individuals are considered upwardly mobile when their current occupation has higher prestige or status than their previous one.

A second way to formulate occupational structure is through the lens of social class. In this view, occupations are grouped into a smaller number of classes, with individuals in each class supposedly holding similar life chances and social experiences. The CASMIN class schema (Erikson and Goldthorpe 1992) is a paradigmatic example for this approach. The

schema shifted in theoretical focus over time, from market and work situations to the specificity of human capital and the difficulty of monitoring (Breen 2005). Yet, it provides a stable analytical framework for classifying occupations based on sector, employment relations, and skill specificity.

Another influential example of grouping occupations into social classes is the neo-Marxian framework developed by Wright (1997, 2005). Recognizing the inadequacy in Marx’s original formulation, Wright sought to develop a model to better reflect the “actual variations in the concrete ways in which people are located within class relations (2005:15),” while preserving an emphasis on exploitation. The main axes in Wright’s later class schema are the control or possession of property, expertise, and authority.

These big-class schemata are criticized as overly reductive in recent years (Kingston 2000; Pakulski and Waters 1996), and in response, scholars have introduced the concept of micro-classes. (Grusky and Sørensen 1998; Jonsson et al. 2009; Weeden et al. 2007; Weeden and Grusky 2005). Market is the main site for forming class relations in this framework. By defining exploitation as the control over rent-producing financial or human assets (Sorenson 2000), micro-classes are more flexible in reflecting the distinctions between occupations and in capturing similarities in life conditions. Empirical studies also demonstrate that micro-classes pick up meaningful variation that is masked by larger classes (e.g., Laurison and Friedman 2016; Weeden et al. 2007).

Both the hierarchical and class-based frameworks have generated important insights regarding the stratification systems in the United States and in other countries (e.g., Ganzeboom, De Graaf, and Treiman 1992; Jonsson et al. 2009). Nevertheless, some critical issues remain. First, how to measure occupational status is a lingering concern in the examination of occupational hierarchy. Researchers have casted doubt that occupations can be unidimensionally scaled and advocate for a more comprehensive view of the occupational structure (e.g., Weeden and Grusky 2005:148). Most recently, Freeland and Hoey (2018) show that status is a multi-dimensional construct and cannot be summarized solely by income and education.¹

Second, the class-based view entails the perennial questions of how many classes there are and how occupations should be categorized into different classes (Erikson, Goldthorpe, and Hällsten 2012; Giddens 1973). Both could be difficult to determine. When classifying occupations into classes, researchers often have relatively clear principles to construct “big” classes, but this is less the case for micro-classes, which require a significant amount of discretion.

Most importantly, since the class framework assumes a relatively stable occupational structure, it has limited capability to capture dynamism. There is also little theoretical guideline regarding when and how the class structure should be updated. As the U.S. labor

¹ Lynn and Ellerbach (2017) also points out that occupational prestige is less consensual than commonly assumed and systematically biased—individuals with higher education tend to favor training-intensive occupations.

market has transformed significantly since some of these frameworks were first developed, it is unclear to what extent existing categories continue to reflect the key divisions in the occupational structure.

Linked Occupations

While the hierarchical and class-based views largely focus on occupational traits in formulating occupational structure, between-occupation mobility has attracted recurring interest. A canonical example is Blau and Duncan (1967), who stated that “processes of social mobility from one generation to the next and from career beginnings to occupational destinations are considered to reflect the dynamics of the occupational structure” (1967:1). Using a series of transition matrices, they observed that occupations are nonindependently linked through inter- or intragenerational mobility.

White (1970) contended that concrete organizational contexts are important for understanding mobility observed in national surveys. Mobility should not be considered a product of “weak” structure or an “open” system; it reflects opportunity chains established within a bureaucratic system or an institutional field. Similarly, Spilerman (1977) proposed that socioeconomic attainment is not solely a product of pre-entry characteristics but largely unfolds on institutionalized pathways. Although familial or educational backgrounds are important in determining the entry point, subsequent advancement is largely shaped by the opportunity structure in the labor market. Thus, observing mobility patterns is of great importance in understanding the structure of labor market (c.f., Kerckhoff 1995; Spenner, Otto, and Call 1982).

Breiger (1981; see also Goodman 1981) pointed out that the mobility patterns a researcher observes largely depend on how occupations are aggregated into distinct categories. Following a Weberian premise that mobility is suppressed by class boundaries, he argued that mobility across different categories should be low when occupations are (properly) sorted by social classes. Minimizing between-category mobility, therefore, could be one reasonable way to detect occupational structure.

A Network Turn

With methodological advancement, a number of contemporary studies have expanded these insights and begun to empirically untangle the threads connecting occupations. For example, Sacchi et al. (2016) argued that the Swiss labor market consists of occupational mobility chains (OMCs): groups of linked occupations that share similar skill requirements and workforce. They found that individual mobility is driven by OMC-specific demand, not market-wide demand. McDonald and Benton (2017) noted that high-inequality establishments have fewer mobility pathways into high-wage jobs than their low-inequality counterparts in a national grocery store chain. Wilcox et al. (2021) also showed that female-dominated jobs are more circuitously linked than male-dominated jobs in a sample of distribution centers.

Most recently, Villareal (2020) advocated for a network approach to understand the occupational structure in the United States. Using factional analysis, he found that the US labor market has become more segmented, with more exchange occurring within sets of occupations. Following Breiger’s earlier proposition, Toubøl and Larsen (2017) showed that

social class boundaries could be detected by the absence of mobility between occupations.² Similarly, Cheng and Park (2020) explored the shifting “mobility classes” with a community-detection algorithm. They contrasted these occupational communities with conventional class schemata and found that the mobility boundaries in the U.S. labor market have changed over time, deviating from the conventional class boundaries and becoming more rigid in shaping the flow of workers.

While all these studies point towards a network turn in the study of occupational structure, there are three main challenges in advancing this line of inquiry. First, network analysis has been primarily treated as a methodological, instead of a conceptual, intervention. Both Toubøl and Larsen (2017) and Cheng and Park (2020) continued to operate within a group-based framework that maps occupational structure as a collection of clearly distinguishable (mobility) classes. Yet, both studies relied on a single algorithm. It is unclear to what extent the classification and the number of “classes” are sensitive to the algorithm in use. If the classification of occupation varies by algorithm, we quickly return to the earlier dilemma of determining the “true” number of classes.

Second, there tended to be a somewhat circular reasoning about the relationship between mobility and boundary. Researchers observed “latent boundaries” by the absence of mobility, yet they also contended that the mobility is absent because of these latent

² See also Melamed (2015) for using community detection methods in network science to understand intergenerational occupational mobility.

boundaries. It is left unanswered what facilitates or deters the mobility of workers. It is similarly unclear what may lead these boundaries to change over time.

Third, and perhaps most importantly, even though prior studies have described the occupational structure as a network, it is yet to be tested whether the structure indeed *operates* as a network. Neither Toubøl and Larsen (2017) nor Cheng and Park (2020) developed theoretical propositions or testable hypotheses for their analysis. Our view is that the network perspective would remain a novelty if it solely “maps” the occupational structure without demonstrating unique explanatory power.

Our study departs from the existing studies by addressing these challenges. We conceptualize the occupational structure as a network, not a collection of network-derived groups or classes. While we still use community-detection methods to describe the contour of the U.S. labor market, our analysis of occupational attributes and mobility leverages the full network information, not simply the algorithm-derived groups. Furthermore, while prior studies view mobility mostly as a reflection of latent boundaries, we argue that the exchange of workers is both a cause and a consequence of occupational similarities. As such, we investigate what constitutes the latent boundaries and how mobility may in turn shape occupational attributes. In the next section, we begin to develop a conceptual framework to advance a network perspective of occupational structure.

OCCUPATIONAL STRUCTURE AS A SYSTEM OF EXCHANGE

We view occupational structure as an adaptive system of generalized exchange. The system consists of durable positions with time-variant attributes. These positions are linked, differentially, by the exchange of workers between positions. The underlying structure of the labor market can thus be delineated by the circulation of workers. The exchange is generalized in that it need not to be reciprocal between any two positions (Bearman 1997; Lévi-Strauss 1969; Takahashi 2000). The system is adaptive in that both occupational attributes and between-position exchanges respond to exogenous shocks, as well as endogenous network processes: similarity between positions tends to produce exchange, and exchange tends to converge the attributes of the two positions.

Certainly, the movement of workers is not the only tie that bounds occupations.³ Individuals with a given occupation are more likely to conduct transactions or communicate with those with certain occupations (Chan and Goldthorpe 2004; Lambert and Griffiths 2017; Lin and Dumin 1986). Some occupations more regularly situate in the same organization (Tomaskovic-Devey and Avent-Holt 2019) or industry (Hartmann et al. 2019). All these forms of association could be used to construct occupational networks. However,

³ We thank a reviewer for pointing out that network analysis has been used to understand organizational structures. In addition to mobility, these networks could be constructed via email traffic (Goldberg et al. 2016; Kleinbaum, Stuart, and Tushman 2013) or job description (Hasan, Ferguson, and Koning 2015).

the exchange of workers represents a restrictive and unambiguous form of exchange that is highly indicative of other forms of exchange (Blau and Duncan 1967:48).

Our perspective departs from the existing approaches in three important ways. First, whereas hierarchical and class-based frameworks focus solely on occupational characteristics (e.g., prestige, status, skill specificity, and authority), we consider the exchange of workers between occupations as the fiber constituting occupational structure (Spilerman 1977; White 1970). From this perspective, mobility does not indicate a lack of structure but represents the structure itself.

Second, instead of classifying occupations with a fixed number of classes or strata, our perspective allows for the organic association of occupations, thereby providing a more dynamic and realist depiction of which occupations are bound together and which drift apart. That is, the framework does not require *a priori* partition of occupations, and allows the occupational structure to change over time based on the mobility patterns.

Third, this very flexibility provides the potential to examine how the differences in a wide range of occupational attributes may shape the level of exchange and, conversely, how the exchange of workers may affect occupational attributes. In our view, between-occupation mobility does not merely reflect some “latent boundaries” (Cheng and Park 2020; Toubøl and Larsen 2017) but a result of assortativity in certain critical dimensions.

Furthermore, we view mobility not as an outcome but as actively shaping the origin and destination. This distinguishes our approach from the canonical mobility analysis, which

uses a fixed set of occupational strata that are assumed stable and unaffected by the mobility pattern. In contrast, we consider occupational attributes and between-occupation mobility are co-constitutive: similar occupations are more likely to form exchanges, and exchanges could be conducive to the convergence of occupational attributes.

Indeed, existing studies have suggested that the flow of workers is guided by occupational similarities. Occupations that perform related tasks or require comparable credentials tend to form exchanges (Gathmann and Schönberg 2010; Sanders 2012; Yamaguchi 2012). Mobility is also more likely to occur between occupations in the same organization or industry due to frequent interaction and shared knowledge. In workplaces such as banks, factories, hospitals, and cooperatives, formal job rotation is frequently implemented to reduce fraud, injury, or burnout as well as to increase learning opportunities (Eriksson and Ortega 2006; Ho et al. 2009; Sobering 2019; Wilmers 2020). Similarities in demographic composition or social background also affect the exchange between economic positions because group-specific inclusion or exclusion remains a key mechanism in producing occupational segregation in the United States (Rivera 2015; Stainback and Tomaskovic-Devey 2012).

In the meantime, occupations are outward-looking, attending to the practices in adjacent occupations: their compensation practices, skill requirements, cultures, and other traits are influenced by the occupations their workers come from as well as where they leave for. The exchange of workers also fosters social networks spanning different occupations,

which could serve as conduits for the flow of knowledge and norms (Collet and Hedström 2013). Linked occupations, even for non-movers, represent external benchmarks to be leveraged by employees for higher compensation (DiPrete, Eirich, and Pittinsky 2010) or by employers to justify wage or benefit cuts (Dube and Kaplan 2010; Kochan and Riordan 2016).

Reducing access from lower-resource occupations, or social closure, therefore has been a key mechanism through which incumbents secure economic resources or elevate status (Sorenson 2000; Tilly 1998; Weeden 2002). In the meantime, competition for the same workforce likely results in the convergence of employment practices (Tomaskovic-Devey 2013). For this reason, non-unionized workers used to benefit from the presence of unionized workers in the local labor market (Rosenfeld 2014; Western and Rosenfeld 2011).

The exchange of workers between occupations generates resemblance, which in turn facilitates exchange. Consequently, sets of occupations tend to congregate into identifiable communities, in which frequent, routinized exchange occurs. These communities may appear as careers from a micro perspective, and as labor market segments or “fields” from a macro perspective. Community formation is conducive to the isomorphic emergence of shared knowledge; norms; and, to some extent, common political or economic interests (DiMaggio and Powell 1983). Meanwhile, new barriers could emerge due to technological and institutional changes. Incumbents of advantageous positions may also activate new forms of

differentiation to suppress exchange and defend against convergence (Collins 1979; Fligstein and McAdam 2012; Horowitz 2018).

While the occupational network consists of identifiable communities, they do not necessarily organize as a collection of “cliques” in modern societies. Exchanges between communities do occur, so does the transmission of norms and practices. As in the case of exchanges between occupations, a community may exchange with some communities more frequently than others. As such, the occupational network could be shaped by the tension between contagion and differentiation at various levels.

The tension situates the occupational network along a spectrum of connectivity. In a dense network that features frequent and less selective exchange, local contagion is more efficient in leading to a system-wide convergence in attributes. A sparse network, on the other hand, reduces the reach of each position and therefore enables divergence (Tomaskovic-Devey 2013). In real-world networks, density is rarely uniform but unevenly distributed. The global structure become looser (or more cohesive) as occupations or communities dissociate (or conjoin).

A number of studies have suggested that the U.S. labor market has become more fragmented. Some argue that the labor market is now bifurcated, a trend driven by weakening demand for middle-skilled workers and widening divides between standard and nonstandard employment (Autor and Dorn 2009a; Dwyer 2013; Kalleberg 2011; Pedulla 2020). Others have argued that internal labor markets and on-the-job training that used to

promote upward mobility have been weakened in the pursuit of efficiency and flexibility (Cappelli 1999; Cobb and Lin 2017; Weil 2014). Moreover, it becomes harder to move out from low-wage jobs (Schultz 2019), and the linkages between field of study and career trajectories have strengthened among high-skilled workers (Kim et al. 2015). These trends signal that new fault lines may have emerged among occupations.

Following a description of our empirical set up, we begin to test the occupational structure as a system of exchange. The analysis also illustrates how occupational structure could be examined as a full network, and not merely a collection of (network-derived) groups. Our empirical analysis consists of three parts. Part A describes the general structure of occupational networks. We pay specific attention to how the connectivity of occupational networks and how the number of communities have changed over time. In contrast to prior studies, we employ multiple community-detection algorithms and present the consensus.

Part B tests the proposition that occupational network operates under the principle of assortativity. That is, the level of exchange among occupations is associated with occupational similarity. Our analysis goes beyond status proximity and considers a wide range of occupational attributes. We identify which dimensions of similarity are significant in shaping the mobility of workers and how these dimensions evolved in the past decades. The analysis also provides insights into what constitutes the “latent boundaries” and why the occupational structure has become more fragmented.

Part C turns attention to the contagion process—how the level of exchange may affect occupational attributes. Specifically, we test whether occupational median wage is correlated with that of linked occupations, while considering compositional similarities, skill requirements, and shared class membership. Lastly, we test how the network structure may impact between-occupation wage distributions through contagion.

SETUP

Our primary data source is the Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) from 1983 to 2017 (Flood et al. 2018). The CPS-ASEC, although is designed for cross-sectional analysis, serves the purpose of this study, as two useful pieces of information are collected from a representative sample of respondents: 1.) the job they held in the week before the survey and about 2.) the longest job they held in the previous year. This information permits us to link detailed occupations across time.

Compared with other surveys such as the Panel Study of Income Dynamics, the CPS-ASEC is uniquely useful for its large representative sample and *dependent coding* technique. The former allows us to examine the mobility patterns among more detailed occupations. The latter reduces the inflation of mobility due to inconsistent occupational coding, a common issue in longitudinal data sets (Kambourov and Manovskii 2013; Wolf and Lockard 2018). Specifically, after the respondents are asked about their current job, question 46 in the CPS-ASEC asks respondents whether the longest job they held in the *prior calendar year* was the same. If it was, the system prefills last year’s occupation with the current

occupation. If not, question 47 asks them what that job was, including information about the occupation, industry, and class of worker. In other words, for an individual to change their occupation, they must first declare a job change.⁴

Our sample includes consecutively employed respondents aged 25–64 with valid sampling weights ($N = 1,880,071$).⁵ We assign each respondent two occupational codes: one for their prior job, and one for their current job. The codes are derived from three-digit 2010 census occupational classification code. Some detailed occupations are merged when the number of observations is too small, do not exist consistently over the period, or experienced a sharp change in size when the occupational classification scheme was revised. We disaggregate two large occupations— “managers, not elsewhere classified” and “truck drivers”—by nine industrial sectors to add specificity. The harmonization produces a total of 252 occupations (see Online Supplement A for more discussion about the harmonization process).⁶

⁴ Inconsistent coding may still occur among respondents who switched employers, which potentially inflates occupational mobility. However, the two jobs are coded by the same person at the same time, instead of by different persons at different times as in most longitudinal data. We also checked the imputation rate of occupation over the period, which ranges from 0.13% to 2.74%. The exclusion of these observations does not change our substantive findings.

⁵ Because the CPS interviews only civilians, individuals who currently serve in the military do not appear in the survey. We therefore exclude individuals who held a military position in the prior year but a civilian position in the current year.

⁶ Certainly, by harmonizing occupations over time, our analysis is unable to capture the dynamics related to the disappearance and emergence of occupations. Although it may be possible to compare networks with different numbers of nodes, it would be difficult to

To ensure that the findings are not driven by a particular occupational classification or measurement error, we reclassify the respondents based on more aggregated 1950 census codes (146 occupations, based on OCC1950 developed by the IPUMS) and micro-classes (82 classes, cf. Jarvis and Song 2017; Jonsson et al. 2009). The findings are substantively similar (see Appendix A for a comparison of different classification schemes). We prefer less aggregated occupations because they provide more detailed information about mobility patterns (Breiger 1981).

[Figure 1](#) illustrates how we construct the networks based on the transition matrix (Blau and Duncan 1967). Panel A provides a hypothetical example of 1,000 workers moving across seven occupations during a given period. The rows index last year’s occupations, and the columns index current occupations. In this example, 112 workers reported Occupation I as their current occupation (the column margin). Among these workers, 89 reported that they worked in the same occupation in the previous year, 14 in Occupation II, and none in Occupation III. Because all transitions took place within a one-year interval in the CPS-ASEC, the row margins are similar to the column margins (corr. > .999).

We calculate the weighted, undirected ties between occupations i and j during period p as the average between-occupation mobility rate weighted by last year’s occupational size, which could be simplified as joint movement over joint size:

distinguish whether any change is driven by the actual change in mobility patterns or differences in occupational classification.

$$E_{i \leftrightarrow j, p} = \frac{C_{i \rightarrow j, p}}{O_{i, p}} \cdot \frac{O_{i, p}}{O_{i, p} + O_{j, p}} + \frac{C_{j \rightarrow i, p}}{O_{j, p}} \cdot \frac{O_{j, p}}{O_{i, p} + O_{j, p}} = \frac{C_{i \rightarrow j, p} + C_{j \rightarrow i, p}}{O_{i, p} + O_{j, p}}, \quad (1)$$

where $C_{i \rightarrow j, p}$ and $C_{j \rightarrow i, p}$ denote the population-weighted number of workers who moved between occupation i and occupation j during period p . $O_{i, p}$ and $O_{j, p}$ denote the sizes of last year's occupations i and j (i.e., the row margins in Panel A). Because $O_{i, p} + O_{j, p}$ limits $C_{i \rightarrow j, p} + C_{j \rightarrow i, p}$, $E_{i \leftrightarrow j, p}$ ranges from 0 to 1, with larger values indicating higher rates of exchange.⁷ Panel B presents the adjacency matrix calculated with Equation (1). For example,

$$E_{A \leftrightarrow B, p} = \frac{C_{A \rightarrow B, p} + C_{B \rightarrow A, p}}{O_{A, p} + O_{B, p}} = \frac{11 + 14}{122 + 96} \cong 0.12. \quad (1a)$$

Panel C illustrates the network based on Panel B, in which nodes with a stronger association are placed closer to one another. The widths of the ties indicate the strength of association. It shows that mobility occurs more often between Occupations I and II; between III and IV; and among V, VI, and VII. Panel D identifies three distinct sets in which occupations are more densely connected to one another. We refer to these sets as “clusters,” “components,” or “communities” below.

To examine how network evolves over time, we partition our data into three periods: 1983–1992, 1993–2002, and 2008–2017.⁸ For each period, the mobility data from CPS-ASEC

⁷ The unweighted arithmetic average or geometric average of $\frac{C_{i \rightarrow j, p}}{O_{i, p}}$ and $\frac{C_{j \rightarrow i, p}}{O_{j, p}}$ would give disproportional weight to smaller occupations. In contrast, our measure is more robust and readily interpretable.

⁸ We suspect that the structure of labor market changes little year to year. Pooling data over time also ensures that the mobility pattern is less sensitive to measurement error. The periods are selected to avoid the years in which the CPS revised occupational classification and therefore generated abnormally large numbers of movers. Because we do not distinguish employers, this measure accounts for both within- and between-firm occupational changes.

are pooled together to construct a 252×252 matrix. Across the three periods, around 9% of the observations had different occupational codes between the prior year and the reference week (8.68% during 1983–1992, 10.2% during 1993–2002, and 8.57% during 2008–2017). The higher between-occupation mobility during the 1990s likely reflects the economic boom at the time.

For simplicity, our analysis does not consider the directionality of exchange, which will be of clear importance in subsequent studies.⁹ Besides the three period-specific networks, we also construct two panel data sets: one at the dyad level, and one at the occupation level. The former contains 94,878 observations of occupation dyads ($252 \times [252 - 1] / 2$ unique pairs $\times$ 3 periods), whereas the latter includes 756 observations (252 occupations $\times$ 3 periods). These data sets are used to test the endogenous association between exchange and occupational attributes.

EMPIRICAL ANALYSIS

Part A: The Network Structure of Occupations

We begin our analysis by assessing the overall connectivity of the three occupational networks. A more connected network features higher frequency of exchanges and shorter distances among occupations. [Figure 2](#) describes the distributions of dyad-level exchange

⁹ In general, the exchange tends to be bidirectional instead of unidirectional. The correlation of the two-directed flows (e.g., A->B and B->A) between two positions is about .5 in all three periods. Change and Park (2020) also find that, consistently across periods, occupations with highest in-degrees also tend to have highest out-degrees.

and shortest distances. We log-transform both measures due to the skewness of these distributions.

Panel A presents the distribution of direct exchanges based on Equation (1). Exchanges between any two occupations have become less frequent in the recent period, as shown by the proportion of empty cells and the average intensity. The proportion of empty cells (not plotted), in which no direct exchange occurred between a pair of occupations, increased from nearly 67% to more than 70%. Among nonzero exchanges, the average intensity also declined. The mean of $\log(E_{i \leftrightarrow j})$ dropped from -7.84 to -8.16 ($p < .001$, bootstrap t -test). Both measures suggest that the first-order connectivity of the occupational network has weakened over time.

Panel B presents the shortest distances between all pairs of occupations. The shortest distance is calculated by the weighted sum of both direct and indirect connections. For pairs of occupations that are directly connected (i.e., $E_{i \leftrightarrow j} \neq 0$), the shortest distance is $\log(E_{i \leftrightarrow j})$. For pairs that are indirectly connected, the distance is a combination of all the exchanges along the shortest path in the network (i.e., $\log(E_{i \leftrightarrow k1}) + \log(E_{k1 \leftrightarrow k2}) + \dots \log(E_{kn \leftrightarrow j})$). It shows that the average distance between occupations lengthened from -11.55 to -11.92 ($p < .001$, bootstrap t -test). The average distance increased for occupations that were directly connected to each other (the right cluster) as well as occupations that were indirectly connected (the left cluster). Together, these results confirm previous finding (Cheng and Park 2020; Villarreal 2020) that the connectivity among occupations has become weaker in

recent decades. In Appendix A, we show that more aggregated occupational schemes produce similar results.

The statistics in Figure 2 summarize the overall network connectivity, but they reveal little about how the network configuration has changed. To explore the shifting structure, we use multiple community detection algorithms that are commonly used in analyzing large, complex networks (cf. Fortunato and Hric 2016; Peel, Larremore, and Clauset 2017).¹⁰ These algorithms help to identify which occupations are clustered and how the main components of the network have changed over time, thereby allowing us to qualitatively describe the evolution of occupational structure. While Toubøl and Larsen (2017) and Cheng and Park (2020) have taken a similar approach to detect the boundaries in occupational networks, both studies relied on only a single algorithm. We instead exploit two classes of methods and five distinct algorithms to dissect the occupational network.

The first class of algorithms is based on modularity maximization. A common measure for the effectiveness of division in a complex network (Newman and Girvan 2004), modularity is defined as the actual fraction of exchanges occurring within groups minus the hypothetical fraction of such exchanges if they were to distribute at random. Modularity ranges from -1 to 1 , with positive and higher values indicating that more exchanges occur

¹⁰ Another potential approach to detecting weak communities is blockmodeling, which is more computationally intensive for weighted/valued networks and assigns occupations probabilistically into different communities. We implemented the stochastic block model routine developed by Leger (2016) and found similar patterns of fragmentation. The results are available upon request.

within groups than would be expected to occur at random.¹¹ We use three algorithms from this class: *Fast greedy*, *Louvain (multilevel)*, and *Leading eigenvector*. Each of these algorithms seeks to optimize modularity by either an agglomerative or divisive approach (Blondel et al. 2008; Bruch and Newman 2019; Clauset, Newman, and Moore 2004; Newman 2006).

The second class of algorithms detects network clusters based on random walk. The intuition is that a random walker is more likely to wander in the same community than to travel to a different community. We use two algorithms from this class. First, the *Walk-trap* method measures the closeness of two nodes by the probability that they will reach each other in a given number of steps (Pons and Latapy 2006). We present the finding with three steps but using four or five steps produces similar results. Second, the *Infomap (map equation)* method considers an infinite random walk, which tends to circle in a community until moving to another; this method seeks to balance the number of communities and the number of unique identifiers in each community so that the itinerary of the random walker can be most succinctly recorded (Cheng and Park 2020; Rosvall and Bergstrom 2008).

Although each algorithm follows a different procedure, they share similar interpretation: the more the communities are identified, the more segmented the U.S. labor

¹¹ Modularity is known to have a limited resolution, preventing the method from identifying the correct scale of the communities, even when the latter are very pronounced. Thus, it is not a perfect measure to identify detailed communities. That said, this is less of weakness when our goal is to detect the general, consensual divisions in the network.

market is. That said, the resulting communities are best understood as *heuristic tools* that provide a digestible summary of a complex network. Contrary to the claims made in prior studies (e.g., Toubøl and Larsen 2017), we do not view them as unambiguous divisions among occupations. As Moody and Coleman (2015) noted, identifying groups in a network requires arbitrary stopping criteria, which vary across these algorithms. As such, we focus on the *consensus*, not any specific partition.

[Figure 3](#) presents the results produced by the five community detection algorithms. Panel A shows that the Walk-trap and Infomap methods tend to yield significantly more communities than modularity maximization methods. For instance, the Infomap method produces 17, 26, and 35 communities across the three periods, while the Louvain method produces only 9, 13, and 17 communities respectively. These differences suggest that the number of communities could be sensitive to the algorithm in use.

Even though the number of communities identified is different across the algorithms for a given period, they all demonstrate the same pattern: for every algorithm, *more* communities are identified in the later period than in the earlier period. This suggests a steady increase in fragmentation in the U.S. labor market. Exchange is now more common within a smaller set of occupations.

Panel B presents the results based on modularity score. When larger communities split into smaller communities, they also became more cohesive. Among the five algorithms and across the three periods, the Louvain method consistently produces the partitions with

the highest modularity score (i.e., the division is most effective in blocking the exchange), with the Fast greedy and Infomap close behind. The Leading eigenvector, in contrast, generates the partitions with the lowest modularity scores.

In Appendix B, we further compare the communities produced by the five algorithms. The results indicate that, although different numbers of communities are identified, most algorithms agree with one another about 90% of the time. While more communities are identified by Infomap and Walk-trap methods, these communities are nested within the Louvain and Fast greedy communities. That is, the cleavages identified by simpler community structures are also present in more fine-grained communities. The differences across these algorithms suggest that occupational networks are best viewed as hierarchically clustered. Detailed communities identified by more sensitive algorithms are often nested with the larger clusters identified by other methods.

Because the Louvain algorithm performed well in past simulation studies (Lancichinetti and Fortunato 2009; Yang, Algesheimer, and Tessone 2016), and in the current data (with a high modularity and a parsimonious grouping), we use it to provide a stylized description of how occupational network has evolved. We stress again that the dissection of the network structure by any algorithm is somewhat arbitrary, and all communities are defined in relative terms. The occupational network is best viewed as a continent with an uneven contour, instead of a collection of islands.

[Figure 4](#) presents the structure of the U.S. labor market in 1983–1992 and 2008–2017 using a Fruchterman-Reingold drawing. The more frequent exchanges between two occupations, the closer they are in the figure.¹² Nine sets of occupations are identified for 1983–1992. An inspection of their members suggests that they can be labeled as Scientists/Engineers (24 detailed occupations), Social Services (27), Healthcare (17), Clerical Workers (31), Railroad/Sea Transportation (4), Blue-collar Workers (66), Personal Service (23), Business (37), and Security/Drivers (23). During this period, about 53% of all movements occurred within these nine communities. In Online Supplement B, we present the specific location and community membership of each detailed occupation.

With mobility being the sole input, these components are organized in a familiar pattern. Manual and industrial occupations congregate on the left side of Figure 4, and business and service occupations are on the right. Occupations that are considered high-skilled or require more formal education cluster in the upper half. Business sector serves as the hub for most occupations, whereas Railroad/Sea Transportation occupations form a niche distant from the rest.

¹² Like other force-directed graph drawing or multidimensional scaling methods, Fruchterman-Reingold generally places vertices with more exchanges closer to one another and therefore provides an intuitive visual summary of the network. However, this approach has two limitations. First, casting a multicore network onto a two-dimensional space unavoidably introduces distortion. Second, because the minimization is calculated at the network level, it does not guarantee an intuitive relationship between spatial distance and the exchange rate in subgraphs.

How has the U.S. labor market evolved since the 1980s? Panel B of Figure 4 presents the configuration in 2008–2017. In this period, the number of communities has increased from 9 to 17. Yet, within-community movement also increased from 53% to 65% of all movements. This suggests that mobility is now more likely to occur within a more limited set of occupations. The result is also consistent with our previous finding that the network as a whole has become less connected.

[Figure 5](#) summarizes the changes in communities between the two periods with an alluvial diagram (Bojanowski and Edwards 2018), where the width represents the number of occupations in the community. Healthcare (16 detailed occupations) and Clerical (32) sectors remain largely stable, but other sectors have split. The previous Blue-collar sector is separated into four different communities (with number of occupations shown in parentheses): Construction (17); Mechanics, including repairers and installers (17); Factory Workers (24); and Heavy Machine Operators (29), which absorbed Railroad/Sea Transportation occupations. To some extent, this division reflects different production relations with machines: workers who build or maintain machines, workers who work alongside machines in mass production, and workers who operate large machines. Similarly, the Business sector is divided into Managers (16); Sales (13); and Business Specialists (7), such as compliance officers, analysts, and human resource professionals.

Divergence among other communities is also evident. Notably, the earlier Scientists/Engineers diverged into two distinct communities (10 and 11), indicating a

separation between research- and application-oriented occupations. Security-related occupations (6), such as firefighters, correctional, and police officers, formed an enclave. Drivers and Carriers largely merged with Heavy Machine Operators, while Postal occupations (2) became isolated from the rest of the labor market. Consistent with Florida’s (2002) observation, Creative/Communication occupations (11), such as reporters, writers, photographers, and public relations specialists, emerged as a distinguishable community from other Social Service occupations. The Personal Service sector also experienced changes. Eating/Drinking occupations (11) emerged as a distinct niche, and a number of occupations (e.g., bakers and butchers) were absorbed into the Factory segment due to increasing mass production of household goods.

Because these communities are detected in relative terms, the fragmentation could be driven by either increasing cohesiveness within communities of occupations (within-component exchanges) or decreasing exchanges between these communities (between-component exchanges). Figure 6 presents the percentage changes in the exchange rate between and within different components. We average pairwise exchange rates (see Equation (1) for definition) by the 17 components (289 pairs) in 1983–1992 and 2008–2017. The percentage change $D_{i,j}$ between component i and j is calculated as

$$D_{i,j} = \left(\frac{E_{i \leftrightarrow j, 2008-2017} - E_{i \leftrightarrow j, 1983-1992}}{E_{i \leftrightarrow j, 1983-1992}} \right) \times 100. \quad (2)$$

[Figure 6](#) shows that all but one new communities emerged because of *both* increased within-component exchange (diagonal) and decreased between-component exchange (off-

diagonal). The consolidation is particularly strong within Personal Service occupations, a finding that is consistent with the emergence of the care economy (Dwyer 2013). The exchange between the two Postal occupations (i.e., postal service clerks and postal mail carriers) also strengthened, signaling the fortification of an internal labor market at the U.S. Postal Service. Security is the only exception from the general pattern, in which the niche was formed largely because of the high stability of these occupations and the lack of exchanges with other occupations.

Consistent with the findings of decreasing overall connectivity in Figure 2, there are fewer exchanges between these new communities. The mobility between Scientists and Engineers declined. Creative occupations had fewer exchanges with all other communities in the later period than in the earlier one, as did the Construction and Postal occupations. The only substantial increase in exchanges is between Mechanics and Healthcare-related occupations, which may reflect that the healthcare industry became more capital-intensive, requiring more mechanics to maintain and repair in-house technological devices (Glied, Ma, and Solis-Roman 2016).

In sum, occupational network has become more scattered between the 1980s and the 2010s. Not only did first- and higher-order connectivity decline, but more segments emerged in the later period than the earlier one, regardless of community detection methods. Together, these findings suggest that the documented increase in mobility (Jarvis and Song 2017;

Kambourov and Manovskii 2008), even when crossing conventional class boundaries, may take place within small occupational communities.

A second insight from the analysis is that occupational network is not a collection of cliques but is best described as hierarchically clustered. By comparing the results from multiple algorithms, we show that smaller communities are nested within larger communities. An attempt to reduce the occupational network into network-derived groups, therefore, would again encounter the issues of how many communities there are, as well as which algorithm should be used. There are no clear answers to these questions. As such, we treat occupational structure as a full network, not mobility classes, in the following analysis.

Part B: Differentiation and Dyadic Exchange

Our second analysis considers the assortative tendency in occupational networks. Past studies have shown that mobility is more likely to occur among occupations of similar status. However, status is unlikely the sole factor that determines mobility. Because the network perspective is not restricted to any particular occupational attribute, we take an agnostic approach and select a wide variety of attributes. We use these attributes to identify the dimensions of similarity that pull two occupations toward each other (or the differences that drive them apart). By observing the changes in association across periods, we also explore factors that may have contributed to the fragmentation observed in the previous section.

We obtain five occupational attributes from the CPS-ASEC with sampling weights: median age; the percentage of workers that were male, white, and college-educated; and the

modal industry. [Table 1](#) presents the means and standard deviations of the first four variables by period. We also list the occupations with the highest and lowest values for each variable.¹³

In addition, we draw a variety of items from the Occupational Information Network (O*NET; see Handel 2016 for a recent review) to describe different dimensions of occupational content. The *cognitive* dimension includes the importance of verbal, quantitative, analytical, creative skills (Liu and Grusky 2013), and spatial orientation. The *physical* dimension includes the requirement for motion control and strength. The *social* dimension includes interactive and supervising tasks (Bacolod 2017; Deming 2017). The *environmental* dimension considers the degree to which the working condition is discomforting and whether the workers are exposed to physical hazards (Choi et al. 2012; Fujishiro et al. 2013). All O*NET measures are time-invariant and standardized in the analysis.¹⁴ [Table 2](#) describes the variables related to occupational content. Online Supplement C details the items used to construct these variables.

To systematically assess the association between exchange and occupational attributes, we test the level of exchange as a function of occupational dissimilarity in these

¹³ We do not include percentage unionized or covered by a union contract because the variable is not available before 1990 in the CPS-ASEC.

¹⁴ In cases where we use a more aggregate occupational category, we average the items by the relative size of detailed occupations. It is plausible that these attributes changed over time, so treating them as constant could be problematic. Our analysis assumes that, although these attributes could change, between-occupation differences may remain similar.

attributes and allow the association to vary by period. Specifically, we estimate a negative binomial regression using the dyadic data set ($N = 94,878$):

$$\begin{aligned} \log_e(C_{i \leftrightarrow j, p}) = & \alpha_p + \sum_k^K \beta_{k, p} |A_{i, k, p} - A_{j, k, p}| + \beta_{1, p} I_{i, j, p} \\ & + \beta_{2, p} \log_e(O_{i, p} + O_{j, p}) + \varepsilon_{i \leftrightarrow j, p} \end{aligned} \quad (3)$$

where $C_{i \leftrightarrow j, p}$ denotes the count of workers who moved between occupation i and occupation j in period p ; α_p denotes period-specific intercepts; $A_{i, k, p}$ denotes the attribute k for occupation i ; $I_{i, j, p}$ represents a dichotomous variable indicating whether the two occupations have different modal industries (Hartmann et al. 2019); and $\log_e(O_{i, p} + O_{j, p})$ represents the exposure term that adjusts for the combined size of the two occupations. In essence, we capture how the rate of exchange for a pair of occupations is associated with the absolute differences in occupational attributes ($\beta_{k, p}$) and industrial membership ($\beta_{1, p}$), while allowing the association to vary by period. $\beta_{k, p}$ and $\beta_{1, p}$ are expected to be negative when greater dissimilarity leads to fewer exchanges.

Because dyads are non-independent observations, standard errors based on the independence assumption are inappropriate. We therefore use the quadratic assignment procedure (QAP) to determine statistical significance (Krackardt 1987; Krackhardt 1988). The QAP randomly reassigns the values in the dependent variable (along with the exposure term) to different observations by i and j (to preserve row and column dependence). Equation (3) is then estimated with the “scrambled” data set to obtain a set of coefficients. Doing so

iteratively, the QAP produces a null distribution for each $\beta_{k,t}$ and $\beta_{1,t}$, which represents the potential noise in the data set.

[Figure 7](#) presents the regression estimates from Equation (3), with dots representing point estimates $\beta_{k,p}$ and $\beta_{1,p}$, and shaded areas representing the null distributions generated by the QAP with 1,000 iterations. Statistical significance is judged based on the likelihood of observing the coefficient in the noise. The farther an estimate is from the null distribution (shaded areas), the more confident we are that the coefficient is statistically meaningful. We rotate the reference period to obtain the main coefficients for 1983–1992 and 2008–2017. Attribute-period interaction terms (shown in the right panel) are used to test the differences in coefficients between the two periods.

The first four rows in Figure 7 show the extent to which demographic attributes shape the exchanges between occupations over time. When the sex and racial composition is dissimilar between a pair of occupations, fewer exchanges are observed between them, net of other occupational differences (Stainback and Tomaskovic-Devey 2012). Educational dissimilarity remains important in regulating mobility. Whereas the coefficients of gender, race, and education do not significantly differ between the two periods, the importance of median age has increased. The coefficient for dissimilarity in median age was non-significant in 1983–1992 but turned significant in the later periods, suggesting a greater divide between older and younger occupations (Autor and Dorn 2009b).

Two concurring trends could suppress the exchange between older and younger occupations. One is that certain occupations could develop distinct age preferences. Recent studies have also suggested that age discrimination remain prevalent and has been on the rise in the United States (Roscigno et al. 2007; Rosenblatt 2017). The second is that, as the traditional types of jobs rapidly declined and new types of jobs emerged, older and younger cohorts of workers could become more segregated even in the absence of age discrimination.

We now turn to the four dimensions of occupational content that may shape exchange (see Table 2). Among the cognitive skills, dissimilarity in verbal skills, net of education, does not appear to correlate with the level of exchange among occupations. The importance of quantitative skills increased significantly, but the that of analytical skills decreased. The rising importance of quantitative skills in forming closure is consistent with higher returns for math-related skills (Mitra 2002), as well as the finding that workers without quantitative skills tend to seek employment far from the occupations with high math demands (Güvenen et al. 2020). In Figure 5, we also see the separation of Business Specialists (e.g., accountants and analysts) from other occupations in the Business sector that involve less quantitative tasks.

Creative occupations mingled with noncreative occupations in 1983–1992 but became more isolated in the later period. This trend corresponds to the emergence of the Creative/Communication community and the professionalization of these occupations (Figure 5). Occupations that require strong spatial orientation tended to congregate, but the

coefficient became nonsignificant in 2008–2017. This is likely a result of the wide implementation of location tracking and environment sensing technologies, which reduces related cognitive demands.

Physical demands are consistently important in regulating between-occupation exchanges. Occupations that necessitate motion control or strength tend to share a similar workforce. The importance of interactive and supervising tasks increased, driving occupations that involve more social activities away from other occupations (Wyant, Manzoni, and McDonald 2018). One example is the division in the Business sector, where managerial occupation became a distinct and expanding career (Goldstein 2012). Segregation by work environment is also evident. Workers tend to switch between workplaces with similar levels of discomfort or hazard. Finally, occupations that share the same modal industry have higher rates of exchange, indicating the importance of production-specific knowledge and organizational context in facilitating mobility.

Overall, Figure 7 illustrates the importance to go beyond status proximity and consider multiple dimensions in understanding mobility. By observing how the levels of exchange vary by occupational dissimilarities, the findings also reveal the types of differentiation that are meaningful in generating the boundaries among occupations. Education, gender, and race-based closures were stable. However, the importance of age composition, quantitative, creative, and social skills has increased over time. These new

forms of differentiation are consistent with the fragmentation observed in the previous section.

Part C: Contagion and Between-Occupational Wage Dispersion

In canonical mobility analysis, occupations are assumed to be stable in their attributes and unaffected by mobility. This section considers potential contagion of occupational attributes among linked occupations. That is, we examine whether an occupation’s attribute could be a consequence of exchanges with other occupations. Linked occupations are likely to share similar knowledge and culture as a result of the routinized movement of individuals. The competition for workers may also lead to a convergence in employment practices.

Specifically, we test how occupational median wage may be correlated with that of linked occupations using the occupation-period panel data set ($N = 756$).¹⁵ We first obtain an exchange-weighted average linked wage $G_{i,p}$ for each occupation-period, defined as follows:

$$G_{i,p} = \frac{\sum_j^J (E_{i \leftrightarrow j,p} W_{j,p})}{\sum_j^J E_{i \leftrightarrow j,p}}. \quad (4)$$

where $E_{i \leftrightarrow j,p}$, derived from Equation (1), denotes the strength of exchange between i and j in period p ; and $W_{j,p}$ denotes the period-specific logged median wage of occupation j . In sum,

¹⁵ We use median wage as the dependent variable because using a compositional variable, such as those in Table 1, may produce obvious or even tautological results. For example, occupations that form exchanges with women-dominated occupations are likely to have more women.

$G_{i,p}$ varies by occupation and period, and it represents the exchange-weighted median wage of the linked occupations for occupation i in period p .

Because the endogenous nature between occupational attribute and exchange, we instrument $G_{i,p}$ with other attributes of linked occupations (also weighted by exchange), including both the workforce composition (Table 1) and occupational content (Table 2) discussed in the previous section. The assumption is that linked attributes do not influence the focal wage except indirectly through either (a) $G_{i,p}$ or (b) ego attributes, both of which are accounted for in our models.

Because our period is rather long (i.e., a decade), we focus on the contemporaneous association between $G_{i,p}$ and $W_{j,p}$. Analysis with more fine-grained data may consider the potential lagged relationship between $G_{i,p-1}$ and $W_{j,p}$. We estimate two network autocorrelation models (Leenders 2002; Ord 1975). The first, a fixed-effect (FE) model, is specified as:

$$\log(W_{i,p}) = \alpha_p + \alpha_i + \beta_1 \log(\hat{G}_{i,p}) + \sum_m^M \beta_m D_{i,m,p} + \varepsilon_{i,p}, \quad (5)$$

where $W_{i,p}$ denotes the median wage of occupation i ; α_p and α_i denote period- and occupation-specific intercepts; $D_{i,m,p}$ denotes time-variant occupational characteristics; and $\hat{G}_{i,p}$ denotes linked wage instrumented by other linked attributes. We expect β_1 to be positive. That is, the within-occupation, between-period variation of median wage is a function of both the median wages of linked occupations and changing occupational attributes. It should be noted that occupational intercepts also absorb the effects of class

membership, not matter which schema we consider. Thus, the estimate of β_1 is net of shared class membership.

Because the exchange of workers and the linked wages could be driven by the median wages in the prior period, we estimate another model with the lagged dependent variable (LDV) for the second and third periods ($N = 504$):

$$\begin{aligned} \log(W_{i,p}) = & \alpha_p + \log(W_{i,p-1}) + \beta_2 \log(\hat{G}_{i,p}) + \sum_m^M \beta_m D_{i,m,p} + \\ & \sum_n^N \beta_n S_{i,n} + \varepsilon_{i,p}, \end{aligned} \tag{6}$$

where occupation intercepts in Equation (5) are replaced with the median wage at $p - 1$, and time-invariant attributes $S_{i,n}$ are added to the equation. Again, we expect β_2 to be positive. That is, conditional on prior wages and occupational attributes, the median wage is correlated with those of linked occupations. In a separate analysis, we also estimate a first-differenced model and find substantively similar results.

[Table 3](#) presents the partial coefficients, with standard errors clustered by occupations (first-stage estimates are reported in Appendix C). Linked wage, obtained with Equation (4), is positively associated with occupational median wage across both specifications. A 10% increase in the median wage of linked occupations is connected to a 2.5% to 3.7% increase in the median wage of the focal occupation. These estimates suggest that wages may be contagious through exchange: the higher the wages of linked occupations, the higher the wage of the focal occupation. The correlation is robust when we account for the changes in workforce composition, occupational content, the median wage in the earlier

period, and time-constant unobserved characteristics (including class membership). Additionally, Table 3 shows that the median wage is associated with racial and educational compositions. Occupations dominated by whites and workers with college degrees tend to have higher median wages than other occupations. The LDV model also indicates that occupations with more men tend to receive higher wages than those with more women (Levanon, England, and Allison 2009).

Because the measures of occupational content do not vary over time in our data, they are only present in the LDV model. Consistent with Liu and Grusky (2013), we find that analytical skills are associated with a wage premium, whereas creative skills are associated with a penalty. We also find that workers in occupations that require motion control (e.g., machine operators) tend to receive higher wages, whereas jobs that demand spatial orientation skills or supervising tasks pay less net of educational composition. Overall, the attributes regulating the flow of the workers (Figure 7) do not have consistent wage consequences. Dissimilarity in creative or supervising skills increasingly prohibited the flow of workers, but this closure led to a decline in wages among creative and supervising occupations. By contrast, even though analytical skills declined in their importance in shaping the exchange, they are positively associated with wages. These findings indicate that occupational closure is not always beneficial and should always be considered in relational terms.

The notion of wage contagion suggests that network structure affects wage distribution at the global level (Tomaskovic-Devey 2013). In particular, the fragmentation of occupational structure means that occupations increasingly form exchanges within a smaller and more homogenous set of other occupations (Part A & B). Local wage contagion, therefore, would not be as effective in constraining global wage dispersion.

To gauge the consequence of structural change, we compare the observed trend with what the occupational wage distribution would be if the occupational network remained as connected as in the initial period.¹⁶ In practice, we constrain $\mathbf{E}_{i \leftrightarrow j, p}$ at the 1983–1992 level and use the coefficients in Table 3 and Appendix C to generate two sets of predicted wages: one based on Equation (5), and another based on Equation (6). We then add the error terms back in the predicted wages to restore the variance. This procedure produces counterfactual wages that are identical to the observed wages for the 1983–1992 period.

[Figure 8](#) presents the observed and counterfactual trends of wage variance. It shows that wage variance would have grown at a lower rate in the absence of fragmentation. About 10% of the rise in between-occupation variance could be attributed to the changing occupational linkages. This result indicates that the changes in mobility pattern are associated with rising wage inequality in the U.S. labor market.

¹⁶ Although wages do vary within each occupation, previous studies have shown that between-occupation wage differences account for much of the increase in wage inequality (e.g., Lemieux 2008; Mouw and Kalleberg 2010b). That said, among college graduates, there is also a substantial increase in within-occupation income inequality (Xie, Killewald, and Near 2016).

DISCUSSION

Building on the past and contemporary literature on linked occupations, this article develops occupational structure as a dynamic system in which occupations are connected through the exchange of workers. Our perspective is distinct in its emphasis on the relational nature of occupations and the interdependence between mobility and occupational attributes: similar occupations tend to form exchanges, and parties of exchange are likely to converge in their attributes.

Consistent with prior studies (Cheng and Park 2020; Villarreal 2020), our analysis shows that the U.S. labor market has become more fragmented. The overall connectivity declined, and new segments emerged in both industrial and service sectors. The division is driven by *both* the increase of exchanges within and the decrease of exchanges between occupational communities. In other words, when individuals change occupations, they now stay within a limited set of occupations more so than in earlier periods. The finding contradicts Jarvis and Song’s claim (2017) that intragenerational mobility has increased. A possible explanation is that the increase in between-class mobility may take place within small occupational communities.

We show that occupational network operates under the principles of assortativity and contagion. Specifically, we identify a number of occupational attributes that regulate the flow of workers. Gender, racial, and educational compositions are stable bases of differentiation. Age composition, as well as quantitative, creative, and social tasks emerged

as significant distinctions that prohibit exchange. We also show that occupations influence one another through the mobility of workers. The fragmentation of occupational structure, as such, has led to wider between-occupation wage dispersion.

Why did the occupational network become more fragmented? Functionalists may see this fragmentation as reflecting the advancement of economic or technological development, whereby increasing specialization inhibits the mobility of workers between dissimilar occupations. The entry point into the labor market, thus, becomes more significant in determining one's economic trajectory than in the earlier decades. It is no surprise that there has been an increase in emphasis on professional trainings in higher education and a divergence in return to college education across areas of study (Altonji et al. 2014; Kim et al. 2015).

Skeptics perhaps wonder about the extent to which the fragmentation was driven by the fragile demand for workers in the aftermath of the Great Recession—a time when there were not many openings and all job advertisements mandated experience. In other words, rather than indicating structural change, network connectivity could reflect the business cycle. While we agree that labor demand affects mobility patterns, the level of fragmentation also increased in 1993–2002 (Figure 3), a period with a long economic boom.

Institutionalists would view these results as consistent with recent changes in employment practices. The demise of internal labor markets and the lack of on-the-job training narrowed existing organizational pathways through which individuals could acquire

a diverse set of skills and advance their careers (Cappelli 2015; Osterman 1996). The preference for external and horizontal hiring over internal promotion limits the potential pool of candidates and leads to greater labor costs for high-level positions (Bidwell 2011; Cappelli 1999). Temporary or contractual work also makes it harder for worker to move from peripheral to core functions (Cobb and Lin 2017; Godechot et al. 2020; Pedulla 2020). Together, these practices not only erect organizational barriers that suppress mobility but also promote between-workplace inequality (Tomaskovic-Devey et al. 2020; Wilmers and Aeppli 2021). Indeed, the workplaces of low-wage workers have become more occupationally homogeneous in recent years, and the level of workplace occupational homogeneity is negatively associated with the wages of these workers (Handwerker 2020).

Clearly, more historical or comparative studies are needed to assess these interpretations. A historical analysis could help illustrate the long-run relationship between network structure and business cycles, as well as how rapid economic changes could disrupt existing structure. Cross-national studies could offer insights regarding how economic configuration may produce different network structures. In economies where school-to-work linkages are robust or closure mechanisms are prevalent, occupational networks may be both more segmented and stable (Bol and Weeden 2015; DiPrete et al. 2017).

Similar to prior studies (Cheng and Park 2020; Toubøl and Larsen 2017), we show that community-detection algorithms could be useful in describing the occupational structure. However, our findings indicate that the divisions between these communities are

not as definitive as previously suggested. The number of communities is in part determined by the algorithm in use. There is no clear rationale to favor one set of communities over the others, nor a single metric to judge which algorithm performs better. Future studies should take the full network into consideration, instead of focusing solely on network-derived groups.

For this reason, we also do not view network communities as “classes,” which assume a significant level of homogeneity within the community. That said, the development and evaluation of class schema should consider the permeability within and between classes instead of focusing solely on occupational characteristics.¹⁷ The fractures observed in our analysis also suggests that big classes may be less capable of capturing contemporary differentiation than are disaggregated class schemes.

Our analysis illustrates that between-occupation mobility is shaped by a multitude of factors. We report the average associations between exchange and dissimilarity for the

¹⁷ In a separate analysis, we find quite a number of cases in which two closely linked occupations are assigned into two distinct micro classes. For example, there is a high degree of exchange between *Fishing and Hunting Workers* and *Forest and Conservation Workers*, between *Chefs and Cooks* and *First-Line Supervisors of Food Preparation and Serving Workers*, between *Compliance Officers* and *Human Resources, Training, and Labor Relations Specialists*, between *Pharmacists* and *Health Diagnosing and Treating Practitioners*. In all these cases, the exchange between the two occupations is higher than the 99th percentile of all exchanges but the two occupations are assigned into two non-adjacent micro-classes. These examples do not invalidate micro-classes, as these classes do not promise the absence of mobility. What we propose is that the level of exchange can serve as one data point for class theorists to develop a more persuasive schema. If there is a high frequency of exchange, further investigation may be needed to assess whether the mobility is meaningful enough to be viewed as “between-class” mobility. While sound judgement can sometimes be made about how occupations should be grouped, a scientific study of occupational structure, ideally, should utilize all available evidence.

labor market as a whole. This does not preclude the possibility that the associations could differ across segments. The attributes considered in our analysis are by no means exhaustive. Geographical as well as organizational adjacency obviously shape the flow of workers between occupations. Future studies should explore potential variation and additional factors that govern mobility.

We view increased fragmentation as a plausible explanation for the uneven impacts of recent recessions (Redbird and Grusky 2016), as well as persistent wage inequality in the U.S. labor market (Weeden and Grusky 2014). The canonical economic model predicts that the supply of workers will respond to changing demands. Yet, fragmentation limits both the level and speed of this adjustment. A shortage of labor and a shortage of jobs, thus, could exist simultaneously in different segments of the market. An old lesson to relearn is that friction is what constitutes the market. Aggregate supply and demand say little about labor market dynamics, given that multiple equilibrium states could be sustained by these barriers.

Our findings also suggest that facilitating between-occupation mobility could be crucial in reducing between-occupation wage dispersion. Of course, a distinction between within- and between-community mobility must be made. Increased mobility within a community may simply indicate employment instability while doing little to disrupt the existing wage structure. Expanding the exchanges between middle- and high-wage communities, on the other hand, could broaden the supply of labor and moderate aggregate wage inequality.

Our occupational network is constructed with short-term mobility. While this approach is useful in demonstrating the overall occupational structure, it sheds limited insights into individual mobility over the life course. Future studies may construct alternative networks with longer-term mobility and examine if and in what ways the patterns differ. How to incorporate the concepts of trajectory (i.e., how past experience affect future mobility, net of current occupation) into the network perspective is certainly a promising direction. Individual mobility is unlikely to follow a Markov chain (Cheng and Park 2020) but unfolds with memory (Rosenbaum 1979).

Another limitation of our data is that many occupational attributes are time-invariant. It is therefore unclear whether the ascendance of certain tasks was driven by increased productivity for these tasks or that the between-occupation skill differences have widened substantially. Further studies should seek to construct time-variant measures that reflect changing occupational content. For example, the Bureau of Labor Statistics has started collecting information of tasks and skills in Occupational Requirement Surveys in 2018 for a limited set of occupations (Handel 2016a; The Bureau of Labor Statistics 2020). When enough data are accumulated, these measures not only will be more precise, but also provide an opportunity to examine whether occupational contents are similarly contagious.

This article provides an example of how the organization of economic positions could be analyzed through the exchange of workers. Although detailed occupations may be useful in illustrating the approach, our findings are still limited by the unit of observation. In places

where large administrative data sets are available, researchers could construct more detailed networks with the flow of workers between different jobs. Such networks would discover how organization and occupation jointly shape mobility and inequality (Tomaskovic-Devey and Avent-Holt 2019).

We focus on the U.S. labor market as a whole, but a similar approach could be extended to other countries, an industry, or a firm that consists of locally meaningful positions and attributes (e.g., Burris 2004; McDonald and Benton 2017; White 1970). Future studies should investigate how mobility interacts with positions in different economic and organizational contexts. The abundance of possibilities indicates that our analysis is rather preliminary in unpacking the inner structure of labor market.

REFERENCES

- Altonji, Joseph G., Lisa B. Kahn, and Jamin D. Speer. 2014. "Trends in Earnings Differentials across College Majors and the Changing Task Composition of Jobs." *American Economic Review* 104(5):387–93. doi: 10.1257/aer.104.5.387.
- Autor, David, and David Dorn. 2009a. *The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market. Working Paper*. 15150. National Bureau of Economic Research.
- Autor, David, and David Dorn. 2009b. "This Job Is 'Getting Old': Measuring Changes in Job Opportunities Using Occupational Age Structure." *The American Economic Review; Nashville* 99(2):45–51. doi: <http://dx.doi.org/10.1257/aer.99.2.45>.
- Bacolod, Marigee. 2017. "Skills, the Gender Wage Gap, and Cities." *Journal of Regional Science* 57(2):290–318. doi: 10.1111/jors.12285.
- Bearman, Peter. 1997. "Generalized Exchange." *American Journal of Sociology* 102(5):1383–1415. doi: 10.1086/231087.
- Bidwell, Matthew. 2011. "Paying More to Get Less: The Effects of External Hiring versus Internal Mobility." *Administrative Science Quarterly* 56(3):369–407. doi: 10.1177/0001839211433562.
- Blau, Peter M., and Otis Dudley Duncan. 1967. *The American Occupational Structure*. New York: John Wiley.
- Blondel, Vincent D., Jean-Loup Guillaume, Renaud Lambiotte, and Etienne Lefebvre. 2008. "Fast Unfolding of Communities in Large Networks." *Journal of Statistical Mechanics: Theory and Experiment* 2008(10):P10008.
- Bojanowski, Michal, and Robin Edwards. 2018. "Alluvial: R Package for Creating Alluvial Diagrams. 2016." *R Package Version: 0.1-2*.
- Bol, Thijs, and Kim A. Weeden. 2015. "Occupational Closure and Wage Inequality in Germany and the United Kingdom." *European Sociological Review* 31(3):354–69. doi: 10.1093/esr/jcu095.
- Breen, Richard. 2005. "Foundations of a Neo-Weberian Class Analysis." Pp. 31–50 in *Approaches to class analysis*, edited by E. O. Wright. New York: Cambridge University Press.

- Breiger, Ronald L. 1981. "The Social Class Structure of Occupational Mobility." *American Journal of Sociology* 87(3):578–611.
- Bruch, Elizabeth E., and M. E. J. Newman. 2019. "Structure of Online Dating Markets in U.S. Cities." *Sociological Science* 6:219–34. doi: 10.15195/v6.a9.
- Burris, Val. 2004. "The Academic Caste System: Prestige Hierarchies in PhD Exchange Networks." *American Sociological Review* 69(2):239–64.
- Cappelli, Peter. 1999. "The New Deal at Work: Managing the Market-Based Employment Relationship." *Harvard Business School Press. Capelli, P.(2000). Managing without Commitment. Organizational Dynamics* 28(4):11–24.
- Cappelli, Peter H. 2015. "Skill Gaps, Skill Shortages, and Skill Mismatches: Evidence and Arguments for the United States." *ILR Review* 68(2):251–90.
- Chan, Tak Wing, and John H. Goldthorpe. 2004. "Is There a Status Order in Contemporary British Society? Evidence from the Occupational Structure of Friendship." *European Sociological Review* 20(5):383–401.
- Cheng, Siwei, and Barum Park. 2020. "Flows and Boundaries: A Network Framework for Understanding Occupational Mobility in the Labor Market." *American Journal of Sociology*.
- Choi, Yoon-Hyeong, Howard Hu, SangWoo Tak, Bhramar Mukherjee, and Sung Kyun Park. 2012. "Occupational Noise Exposure Assessment Using O*NET and Its Application to a Study of Hearing Loss in the US General Population." *Occupational and Environmental Medicine* 69(3):176–83. doi: 10.1136/oem.2011.064758.
- Clauset, Aaron, Mark EJ Newman, and Cristopher Moore. 2004. "Finding Community Structure in Very Large Networks." *Physical Review E* 70(6):066111.
- Cobb, J. Adam, and Ken-Hou Lin. 2017. "Growing Apart: The Changing Firm-Size Wage Effect and Its Inequality Consequences." *Organization Science*.
- Collet, Francois, and Peter Hedström. 2013. "Old Friends and New Acquaintances: Tie Formation Mechanisms in an Interorganizational Network Generated by Employee Mobility." *Social Networks* 35(3):288–99. doi: 10.1016/j.socnet.2013.02.005.
- Collins, Randall. 1979. "The Credential Society. New York: Academic Press."
- Deming, David J. 2017. "The Growing Importance of Social Skills in the Labor Market." *The Quarterly Journal of Economics* 132(4):1593–1640. doi: 10.1093/qje/qjx022.

- DiMaggio, Paul J., and Walter W. Powell. 1983. "The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields." *American Sociological Review* 48(2):147–60. doi: 10.2307/2095101.
- DiPrete, Thomas A., Thijs Bol, Christina Ciocca Eller, and Herman G. van de Werfhorst. 2017. "School-to-Work Linkages in the United States, Germany, and France." *American Journal of Sociology* 122(6):1869–1938. doi: 10.1086/691327.
- DiPrete, Thomas A., Gregory M. Eirich, and Matthew Pittinsky. 2010. "Compensation Benchmarking, Leapfrogs, and the Surge in Executive Pay1." *American Journal of Sociology* 115(6):1671–1712. doi: 10.1086/652297.
- Dube, Arindrajit, and Ethan Kaplan. 2010. "Does Outsourcing Reduce Wages in the Low-Wage Service Occupations? Evidence from Janitors and Guards." *Industrial & Labor Relations Review* 63:287–306.
- Dwyer, Rachel E. 2013. "The Care Economy? Gender, Economic Restructuring, and Job Polarization in the US Labor Market." *American Sociological Review* 78(3):390–416.
- Erikson, Robert, and John H. Goldthorpe. 1992. *The Constant Flux: A Study of Class Mobility in Industrial Societies*. Oxford University Press, USA.
- Erikson, Robert, John H. Goldthorpe, and Martin Hällsten. 2012. "No Way Back up from Ratcheting down? A Critique of the 'Microclass' Approach to the Analysis of Social Mobility." *Acta Sociologica* 55(3):211–29. doi: 10.1177/0001699312447633.
- Eriksson, Tor, and Jaime Ortega. 2006. "The Adoption of Job Rotation: Testing the Theories." *ILR Review* 59(4):653–66. doi: 10.1177/001979390605900407.
- Fligstein, Neil, and Doug McAdam. 2012. *A Theory of Fields*. Oxford University Press.
- Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, and J. Robert Warren. 2018. *Integrated Public Use Microdata Series, Current Population Survey: Version 6.0 [Dataset]*. Minneapolis, MN: IPUMS.
- Florida, Richard. 2002. *The Rise of the Creative Class*. Basic books.
- Fortunato, Santo, and Darko Hric. 2016. "Community Detection in Networks: A User Guide." *Physics Reports* 659:1–44.
- Freeland, Robert E., and Jesse Hoey. 2018. "The Structure of Deference: Modeling Occupational Status Using Affect Control Theory." *American Sociological Review* 83(2):243–77. doi: 10.1177/0003122418761857.

- Fujishiro, Kaori, Ana V. Diez-Roux, Paul A. Landsbergis, Nancy Swords Jenny, and Teresa Seeman. 2013. "Current Employment Status, Occupational Category, Occupational Hazard Exposure and Job Stress in Relation to Telomere Length: The Multiethnic Study of Atherosclerosis (MESA)." *Occupational and Environmental Medicine* 70(8):552–60. doi: 10.1136/oemed-2012-101296.
- Ganzeboom, Harry B. G., Paul M. De Graaf, and Donald J. Treiman. 1992. "A Standard International Socio-Economic Index of Occupational Status." *Social Science Research* 21(1):1–56. doi: 10.1016/0049-089X(92)90017-B.
- Gathmann, Christina, and Uta Schönberg. 2010. "How General Is Human Capital? A Task-Based Approach." *Journal of Labor Economics* 28(1):1–49. doi: 10.1086/649786.
- Giddens, Anthony. 1973. *The Class Structure of the Advanced Societies*. Hutchinson London.
- Glied, Sherry, Stephanie Ma, and Claudia Solis-Roman. 2016. "Where The Money Goes: The Evolving Expenses Of The US Health Care System." *Health Affairs* 35(7):1197–1203. doi: 10.1377/hlthaff.2015.1356.
- Godechot, Olivier, Paula Apascaritei, István Boza, Lasse Folke Henriksen, Are Skeie Hermansen, Feng Hou, Naomi Kodama, Alena Křížková, Jiwook Jung, and Marta M. Elvira. 2020. *The Great Separation: Top Earner Segregation at Work in High-Income Countries*. MaxPo Discussion Paper.
- Goldberg, Amir, Sameer B. Srivastava, V. Govind Manian, William Monroe, and Christopher Potts. 2016. "Fitting In or Standing Out? The Tradeoffs of Structural and Cultural Embeddedness." *American Sociological Review* 81(6):1190–1222. doi: 10.1177/0003122416671873.
- Goldstein, Adam. 2012. "Revenge of the Managers Labor Cost-Cutting and the Paradoxical Resurgence of Managerialism in the Shareholder Value Era, 1984 to 2001." *American Sociological Review* 77(2):268–94. doi: 10.1177/0003122412440093.
- Goodman, Leo A. 1981. "Criteria for Determining Whether Certain Categories in a Cross-Classification Table Should Be Combined, with Special Reference to Occupational Categories in an Occupational Mobility Table." *American Journal of Sociology* 87(3):612–50. doi: 10.1086/227498.
- Grusky, David B., and Jesper B. Sørensen. 1998. "Can Class Analysis Be Salvaged?" *American Journal of Sociology* 103(5):1187–1234. doi: 10.1086/231351.
- Guvenen, Fatih, Burhan Kuruscu, Satoshi Tanaka, and David Wiczer. 2020. "Multidimensional Skill Mismatch." *American Economic Journal: Macroeconomics* 12(1):210–44. doi: 10.1257/mac.20160241.

- Handel, Michael J. 2016a. "Dynamics of Occupational Change: Implications for the Occupational Requirements Survey."
- Handel, Michael J. 2016b. "The O*NET Content Model: Strengths and Limitations." *Journal for Labour Market Research* 49(2):157–76. doi: 10.1007/s12651-016-0199-8.
- Handwerker, Elizabeth Weber. 2020. "Outsourcing, Occupationally Homogeneous Employers, and Growing Wage Inequality in the United States."
- Hartmann, Dominik, Cristian Jara Figueroa, Mary Kaltenberg, and Paulo Gala. 2019. *Mapping Stratification: The Industry-Occupation Space Reveals the Network Structure of Inequality. SSRN Scholarly Paper*. ID 3399239. Rochester, NY: Social Science Research Network.
- Hasan, Sharique, John-Paul Ferguson, and Rembrand Koning. 2015. "The Lives and Deaths of Jobs: Technical Interdependence and Survival in a Job Structure." *Organization Science* 26(6):1665–81. doi: 10.1287/orsc.2015.1014.
- Hauser, Robert M., and John Robert Warren. 1997. "Socioeconomic Indexes for Occupations: A Review, Update, and Critique." *Sociological Methodology* 27(1):177–298. doi: 10.1111/1467-9531.271028.
- Ho, Wen-Hsien, Ching Sheng Chang, Ying-Ling Shih, and Rong-Da Liang. 2009. "Effects of Job Rotation and Role Stress among Nurses on Job Satisfaction and Organizational Commitment." *BMC Health Services Research* 9(1):8. doi: 10.1186/1472-6963-9-8.
- Horowitz, Jonathan. 2018. "Relative Education and the Advantage of a College Degree." *American Sociological Review* 83(4):771–801.
- Jarvis, Benjamin F., and Xi Song. 2017. "Rising Intragenerational Occupational Mobility in the United States, 1969 to 2011." *American Sociological Review* 82(3):568–99. doi: 10.1177/0003122417706391.
- Jonsson, Jan O., David B. Grusky, Matthew Di Carlo, Reinhard Pollak, and Mary C. Brinton. 2009. "Microclass Mobility: Social Reproduction in Four Countries." *American Journal of Sociology* 114(4):977–1036. doi: 10.1086/596566.
- Kalleberg, Arne L. 2011. *Good Jobs, Bad Jobs: The Rise of Polarized and Precarious Employment Systems in the United States, 1970s-2000s*. Russell Sage Foundation.
- Kambourov, Gueorgui, and Iouri Manovskii. 2008. "Rising Occupational and Industry Mobility in the United States: 1968–97*." *International Economic Review* 49(1):41–79. doi: 10.1111/j.1468-2354.2008.00473.x.

- Kambourov, Gueorgui, and Iouri Manovskii. 2013. "A Cautionary Note on Using (March) Current Population Survey and Panel Study of Income Dynamics Data to Study Worker Mobility." *Macroeconomic Dynamics* 17(1):172–94.
- Kerckhoff, Alan C. 1995. "Institutional Arrangements and Stratification Processes in Industrial Societies." *Annual Review of Sociology* 21(1):323–47. doi: 10.1146/annurev.so.21.080195.001543.
- Kim, ChangHwan, Christopher R. Tamborini, and Arthur Sakamoto. 2015. "Field of Study in College and Lifetime Earnings in the United States." *Sociology of Education* 88(4):320–39. doi: 10.1177/0038040715602132.
- Kingston, Paul W. 2000. *The Classless Society*. Stanford University Press.
- Kitschelt, Herbert, and Philipp Rehm. 2014. "Occupations as a Site of Political Preference Formation." *Comparative Political Studies* 47(12):1670–1706. doi: 10.1177/0010414013516066.
- Kleinbaum, Adam M., Toby E. Stuart, and Michael L. Tushman. 2013. "Discretion within Constraint: Homophily and Structure in a Formal Organization." *Organization Science* 24(5):1316–36.
- Kochan, T. A., and C. A. Riordan. 2016. "Employment Relations and Growing Income Inequality: Causes and Potential Options for Its Reversal." *Journal of Industrial Relations* 58(3):419–40. doi: 10.1177/0022185616634337.
- Krackardt, David. 1987. "QAP Partialling as a Test of Spuriousness." *Social Networks* 9(2):171–86. doi: 10.1016/0378-8733(87)90012-8.
- Krackhardt, David. 1988. "Predicting with Networks: Nonparametric Multiple Regression Analysis of Dyadic Data." *Social Networks* 10(4):359–81. doi: 10.1016/0378-8733(88)90004-4.
- Lambert, Paul, and Dave Griffiths. 2017. *Social Inequalities and Occupational Stratification: Methods and Concepts in the... Analysis of Social Distance*. Springer.
- Lancichinetti, Andrea, and Santo Fortunato. 2009. "Community Detection Algorithms: A Comparative Analysis." *Physical Review E* 80(5):056117. doi: 10.1103/PhysRevE.80.056117.
- Laurison, Daniel, and Sam Friedman. 2016. "The Class Pay Gap in Higher Professional and Managerial Occupations." *American Sociological Review* 81(4):668–95. doi: 10.1177/0003122416653602.

- Leenders, Roger Th. A. J. 2002. "Modeling Social Influence through Network Autocorrelation: Constructing the Weight Matrix." *Social Networks* 24(1):21–47. doi: 10.1016/S0378-8733(01)00049-1.
- Leger, Jean-Benoist. 2016. "Blockmodels: A R-Package for Estimating in Latent Block Model and Stochastic Block Model, with Various Probability Functions, with or without Covariates." *ArXiv:1602.07587 [Stat]*.
- Lemieux, Thomas. 2008. "The Changing Nature of Wage Inequality." *Journal of Population Economics* 21(1):21–48. doi: 10.1007/s00148-007-0169-0.
- Levanon, Asaf, Paula England, and Paul Allison. 2009. "Occupational Feminization and Pay: Assessing Causal Dynamics Using 1950–2000 U.S. Census Data." *Social Forces* 88(2):865–91. doi: 10.1353/sof.0.0264.
- Lévi-Strauss, Claude. 1969. *The Elementary Structures of Kinship*. Beacon Press.
- Lin, Nan, and Mary Dumin. 1986. "Access to Occupations through Social Ties." *Social Networks* 8(4):365–85. doi: 10.1016/0378-8733(86)90003-1.
- Liu, Yujia, and David B. Grusky. 2013. "The Payoff to Skill in the Third Industrial Revolution." *American Journal of Sociology* 118(5):1330–74. doi: 10.1086/669498.
- McClintock, Elizabeth Aura. 2017. "Occupational Sex Composition and Gendered Housework Performance: Compensation or Conventionality?: Occupational Sex Composition and Gendered Housework." *Journal of Marriage and Family* 79(2):475–510. doi: 10.1111/jomf.12381.
- McDonald, Steve, and Richard A. Benton. 2017. "The Structure of Internal Job Mobility and Organizational Wage Inequality." *Research in Social Stratification and Mobility* 47:21–31. doi: 10.1016/j.rssm.2016.03.005.
- Melamed, David. 2015. "Communities of Classes: A Network Approach to Social Mobility." *Research in Social Stratification and Mobility* 41:56–65. doi: 10.1016/j.rssm.2015.05.001.
- Mitra, Aparna. 2002. "Mathematics Skill and Male–Female Wages." *The Journal of Socio-Economics* 31(5):443–56. doi: 10.1016/S1053-5357(02)00130-0.
- Moody, James, and Jonathan Coleman. 2015. "Clustering and Cohesion in Networks: Concepts and Measures."

- Mouw, Ted, and Arne L. Kalleberg. 2010a. "Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s." *American Sociological Review* 75(3):402–31. doi: 10.1177/0003122410363564.
- Mouw, Ted, and Arne L. Kalleberg. 2010b. "Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s." *American Sociological Review* 75:402–31. doi: Doi 10.1177/0003122410363564.
- Newman, M. E. J., and M. Girvan. 2004. "Finding and Evaluating Community Structure in Networks." *Physical Review E* 69(2):026113. doi: 10.1103/PhysRevE.69.026113.
- Newman, Mark EJ. 2006. "Finding Community Structure in Networks Using the Eigenvectors of Matrices." *Physical Review E* 74(3):036104.
- Ord, Keith. 1975. "Estimation Methods for Models of Spatial Interaction." *Journal of the American Statistical Association* 70(349):120–26. doi: 10.1080/01621459.1975.10480272.
- Osterman, Paul S. 1996. *Broken Ladders: Managerial Careers in the New Economy*. New York: Oxford University Press.
- Pakulski, Jan, and Malcolm Waters. 1996. *The Death of Class*. Sage.
- Pedulla, David. 2020. *Making the Cut: Hiring Decisions, Bias, and the Consequences of Nonstandard, Mismatched, and Precarious Employment*. Princeton University Press.
- Peel, Leto, Daniel B. Larremore, and Aaron Clauset. 2017. "The Ground Truth about Metadata and Community Detection in Networks." *Science Advances* 3(5):e1602548. doi: 10.1126/sciadv.1602548.
- Pons, Pascal, and Matthieu Latapy. 2006. "Computing Communities in Large Networks Using Random Walks." *J. Graph Algorithms Appl.* 10(2):191–218.
- Rand, William M. 1971. "Objective Criteria for the Evaluation of Clustering Methods." *Journal of the American Statistical Association* 66(336):846–50.
- Redbird, Beth, and David B. Grusky. 2016. "Distributional Effects of the Great Recession: Where Has All the Sociology Gone?" *Annual Review of Sociology* 42(1):185–215. doi: 10.1146/annurev-soc-073014-112149.
- Rivera, Lauren A. 2015. *Pedigree: How Elite Students Get Elite Jobs*. Princeton; Oxford: Princeton University Press.

- Roscigno, Vincent J., Sherry Mong, Reginald Byron, and Griff Tester. 2007. "Age Discrimination, Social Closure and Employment." *Social Forces* 86(1):313–34. doi: 10.1353/sof.2007.0109.
- Rosenbaum, James E. 1979. "Tournament Mobility: Career Patterns in a Corporation." *Administrative Science Quarterly* 24(2):220–41. doi: 10.2307/2392495.
- Rosenblatt, Lauren. 2017. "If You Weren't Raised in the Internet Age, You May Need to Worry about Workplace Age Discrimination." *Los Angeles Times*. Retrieved August 5, 2021 (<https://www.latimes.com/business/la-na-pol-age-discrimination-trends-20170626-htmlstory.html>).
- Rosenfeld, Jake. 2014. *What Unions No Longer Do*. Cambridge, Massachusetts; London, England: Harvard University Press.
- Rosvall, Martin, and Carl T. Bergstrom. 2008. "Maps of Random Walks on Complex Networks Reveal Community Structure." *Proceedings of the National Academy of Sciences* 105(4):1118–23.
- Sacchi, Stefan, Irene Kriesi, and Marlis Buchmann. 2016. "Occupational Mobility Chains and the Role of Job Opportunities for Upward, Lateral and Downward Mobility in Switzerland." *Research in Social Stratification and Mobility* 44:10–21. doi: 10.1016/j.rssm.2015.12.001.
- Sanders, Carl. 2012. *Skill Uncertainty, Skill Accumulation, and Occupational Choice*. 633. Society for Economic Dynamics.
- Schneider, Daniel. 2012. "Gender Deviance and Household Work: The Role of Occupation." *American Journal of Sociology* 117(4):1029–72. doi: 10.1086/662649.
- Schultz, Michael A. 2019. "The Wage Mobility of Low-Wage Workers in a Changing Economy, 1968 to 2014." *RSF: The Russell Sage Foundation Journal of the Social Sciences* 5(4):159–89. doi: 10.7758/RSF.2019.5.4.06.
- Sobering, Katherine. 2019. "The Relational Production of Workplace Equality: The Case of Worker-Recuperated Businesses in Argentina." *Qualitative Sociology* 42(4):543–65. doi: 10.1007/s11133-019-09434-y.
- Sorenson, Aage B. 2000. "Toward a Sounder Basis for Class Analysis." *American Journal of Sociology* 105(6):1523–58. doi: 10.1086/210463.
- Spenner, Kenneth I., Luther B. Otto, and Vaughn RA Call. 1982. *Career Lines and Careers*. Vol. 3. Lexington Books.

- Spilerman, Seymour. 1977. "Careers, Labor Market Structure, and Socioeconomic Achievement." *American Journal of Sociology* 83(3):551–93. doi: 10.1086/226595.
- Stainback, Kevin, and Donald Tomaskovic-Devey. 2012. *Documenting Desegregation: Equal Opportunity in Private Sector Employment Since the Civil Rights Act of 1964*. Russell Sage Press.
- Takahashi, Nobuyuki. 2000. "The Emergence of Generalized Exchange." *American Journal of Sociology* 105(4):1105–34. doi: 10.1086/210400.
- The Bureau of Labor Statistics. 2020. "Occupational Requirements Survey." in *The Handbook of Methods*. Washington, D.C.: The Bureau of Labor Statistics.
- Tilly, Charles. 1998. *Durable Inequality*. 1st ed. University of California Press.
- Tomaskovic-Devey, Donald. 2013. "What Might a Labor Market Look Like?" Pp. 45–80 in *Networks, Work and Inequality*. Emerald Group Publishing Limited.
- Tomaskovic-Devey, Donald, and Dustin Avent-Holt. 2019. *Relational Inequalities: An Organizational Approach*. Oxford University Press.
- Tomaskovic-Devey, Donald, Anthony Rainey, Dustin Avent-Holt, Nina Bandelj, István Boza, David Cort, Olivier Godechot, Gergely Hajdu, Martin Hällsten, Lasse Folke Henriksen, Are Skeie Hermansen, Feng Hou, Jiwook Jung, Aleksandra Kanjuo-Mrčela, Joe King, Naomi Kodama, Tali Kristal, Alena Křížková, Zoltán Lippényi, Silvia Maja Melzer, Eunmi Mun, Andrew Penner, Trond Petersen, Andreja Poje, Mirna Safi, Max Thaning, and Zaibu Tufail. 2020. "Rising Between-Workplace Inequalities in High-Income Countries." *Proceedings of the National Academy of Sciences*. doi: 10.1073/pnas.1918249117.
- Toubøl, Jonas, and Anton Grau Larsen. 2017. "Mapping the Social Class Structure: From Occupational Mobility to Social Class Categories Using Network Analysis." *Sociology* 51(6):1257–76. doi: 10.1177/0038038517704819.
- Treiman, Donald J. 1977. *Occupational Prestige in Comparative Perspective*. Academic Press.
- Villarreal, Andrés. 2020. "The U.S. Occupational Structure: A Social Network Approach." *Sociological Science* 7:187–221. doi: 10.15195/v7.a8.
- Weeden, Kim A. 2002. "Why Do Some Occupations Pay More than Others? Social Closure and Earnings Inequality in the United States." *American Journal of Sociology* 108:55–101. doi: 10.1086/344121.

- Weeden, Kim A., and David B. Grusky. 2005. "The Case for a New Class Map." *American Journal of Sociology* 111(1):141–212. doi: 10.1086/428815.
- Weeden, Kim A., and David B. Grusky. 2012. "The Three Worlds of Inequality." *American Journal of Sociology* 117(6):1723–85. doi: 10.1086/665035.
- Weeden, Kim A., and David B. Grusky. 2014. "Inequality and Market Failure." *American Behavioral Scientist* 58(3):473–91. doi: 10.1177/0002764213503336.
- Weeden, Kim A., Young-Mi Kim, Matthew Di Carlo, and David B. Grusky. 2007. "Social Class and Earnings Inequality." *American Behavioral Scientist* 50(5):702–36. doi: 10.1177/0002764206295015.
- Weil, David. 2014. *The Fissured Workplace*. Harvard University Press.
- Western, Bruce, and Jake Rosenfeld. 2011. "Unions, Norms, and the Rise in U.S. Wage Inequality." *American Sociological Review* 76(4):513–37. doi: 10.1177/0003122411414817.
- White, Harrison C. 1970. *Chains of opportunity system models of mobility in organizations*. Cambridge, Mass.: Harvard University Press.
- Wilcox, Annika, Steve McDonald, Richard A. Benton, and Donald Tomaskovic-Devey. 2021. "Gender Inequality in Relational Position-Taking: An Analysis of Intra-Organizational Job Mobility Networks." *Social Science Research*.
- Wilmers, Nathan. 2020. "Job Turf or Variety: Task Structure as a Source of Organizational Inequality." *Administrative Science Quarterly* 65(4):1018–57.
- Wilmers, Nathan, and Clem Aeppli. 2021. "Consolidated Advantage: New Organizational Dynamics of Wage Inequality." *American Sociological Review*.
- Wolf, Michael G., and C. Brett Lockard. 2018. "Occupational Separations: A New Method for Projecting Workforce Needs." *Monthly Labor Review* 1–25.
- Wright, Erik Olin. 1997. *Class Counts: Comparative Studies in Class Analysis*. Cambridge University Press.
- Wright, Erik Olin. 2005. "Foundations of a Neo-Marxist Class Analysis." Pp. 4–30 in *Approaches to class analysis*, edited by E. O. Wright. New York: Cambridge University Press.
- Wyant, Amanda, Anna Manzoni, and Steve McDonald. 2018. "Social Skill Dimensions and Career Dynamics." *Socius* 4:2378023118768007. doi: 10.1177/2378023118768007.

- Xie, Yu, Alexandra Killewald, and Christopher Near. 2016. “Between-and within-Occupation Inequality: The Case of High-Status Professions.” *The Annals of the American Academy of Political and Social Science* 663(1):53–79.
- Yamaguchi, Shintaro. 2012. “Tasks and Heterogeneous Human Capital.” *Journal of Labor Economics* 30(1):1–53. doi: 10.1086/662066.
- Yang, Zhao, René Algesheimer, and Claudio J. Tessone. 2016. “A Comparative Analysis of Community Detection Algorithms on Artificial Networks.” *Scientific Reports* 6:30750. doi: 10.1038/srep30750.

Figure 1. A Hypothetical Example of 1,000 Workers and Seven Occupations

Note. The panels provide a hypothetical example of how we construct the networks. Panel A shows a hypothetical example of 1,000 workers moving among seven occupations. Panel B transforms the counts into an undirected, weighted adjacency matrix using Equation (1). Panel C plots the network using a Fruchterman-Reingold drawing. Panel D identifies the communities of occupations using the Louvain community detection algorithm. [Return to Text](#)

Figure 2. The Distributions of Exchanges and Shortest Distances

Note. Panel A presents the distribution of $\log(E_{i↔j})$ when $E_{i↔j} > 0$. Panel B presents the distribution of the shortest distances. For both panels, the solid lines represent the distribution in 1993–2002 for the ease of comparison. We conduct bootstrap t -tests for each panel. The symbol * denotes statistically significant difference ($p < .001$) from 1983–1992. The symbol + denotes a statistically significant difference ($p < .001$) from 1993–2002. The total number of observations for each period, including 0s, is $252 \times (252 - 1) / 2 = 31,626$. [\[Return to Text\]](#)

Figure 3. The Number of Communities and Modularity Scores by Community Detection

Algorithms

Note. The figure presents the number of communities and modularity by algorithm and period. We implement the five algorithms to three undirected, weighted networks generated from the CPS for the periods 1983–1992, 1993–2002, and 2008–2017. [Return to Text](#)

Figure 4. Main Components of the U.S. Labor Market, 1983–1992 and 2008–2017

A. 1983-1992

B. 2008-2017

Note. Each network has two layers. The first layer consists of detailed occupations (solid dots), which are located based on weighted edges (not shown) using a Fruchterman-Reingold algorithm. The size reflects the number of workers holding the occupation. The second layer summarizes the occupations into the components (shaded areas) identified with the Louvain algorithm by combining the sizes and edges (shown) and taking the size-weighted average location. [\[Return to Text\]](#)

Figure 5. The Fragmentation of Communities from 1983–1992 to 2008–2007

Note. The communities correspond to those identified in Figure 4. The communities identified for 1983–1992 are shown on the left, and those for 2008–2007 are on the right. The width reflects the number of occupations, not the number of workers. We assign 42 singular movements (17% of all occupations) with light gray to simplify the presentation. These are cases where only one occupation links two communities. [\[Return to Text\]](#)

Figure 6. Percentage Changes in Average Exchange Rates by Component Pairs

Note. We classify the detailed occupations into 17 components based on the Louvain method. An average exchange rate is calculated for all pairs of the 17 components for 1983–1992 and for 2008–2017. The changes are calculated using Equation (3) and are presented as a symmetric matrix, with each element indicating the change for a pair of components and the diagonal showing the within-component cross-period difference. The delta symbol (Δ) indicates an increase in exchange and the nabla symbol (∇) indicate a decrease. The density of color represents the magnitude of change. [\[Return to Text\]](#)

Figure 7. Negative Binomial Regressions Predicting Pairwise Exchange

Note. This figure presents the estimates obtained from Equation (3). All occupational attributes are standardized by period, except for industry, which is a dichotomous variable indicating whether the two occupations have different modal industries. The reference period is rotated to obtain period-specific estimates for the first two panels. The third panel represents period-attribute interaction terms, which are the differences between 1983–1992 and 2008–2017. The null distributions are generated using the quadratic assignment procedure with 1,000 iterations. Statistically significant ($p < .05$) coefficients are shown with the solid square symbols (■), and nonsignificant coefficients are indicated with the solid circle symbols (●). [\[Return to Text\]](#)

Figure 8 Observed and Counterfactual Between-Occupation Wage Variance

Note. The left axis indicates the between-occupation median logged wage variance. The right axis indicates the percentage of total change. Counterfactual trends are generated by (a) creating a data set in which the exchanges are constrained at their 1983–1992 level, (b) using the coefficients from Equations (5) and (6) to predict wages, and (c) adding the error terms back to the predicted wages so that the predicted variance is not deflated. [\[Return to Text\]](#)

Table 1. Occupational Attributes, CPS

Attributes	Period	Mean (SD)	Max (Min)
% Male	1983-1992	60.75 (31.22)	Brick/Block/Stonemasons (Dental Assistants)
	1993-2002	58.78 (30.5)	Loading Machine Operators (Secretaries)
	2008-2017	58.76 (29.17)	Bus/Truck Mechanics (Dental Hygienists)
%White	1983-1992	79.26 (9.95)	Vets (Parking Lot Attendants)
	1993-2002	73.91 (11.54)	Environ. Scientists/Geoscientists (Parking Lot Attendants)
	2008-2017	64.81 (12.82)	Vets (Packaging/Filing Machine Operators)
Median Age	1983-1992	38.21 (2.41)	Real Estate Brokers (Health Practitioners)
	1993-2002	40.34 (2.42)	Librarians (Counter Attendants)
	2008-2017	43.05 (2.62)	Librarians (Bartenders)
% College	1983-1992	27.67 (28.62)	Dentists (Paving/Surfacing Equipment Operators)
	1993-2002	29.15 (29.19)	Vets (Welding/Soldering/Brazing Workers)
	2008-2017	34.37 (29.89)	Judicial Workers (Millwrights)
Median Ln Wage	1983-1992	3.00 (0.36)	Dentists (Childcare Workers)
	1993-2002	3.00 (0.37)	Dentists (Childcare Workers)
	2008-2017	3.05 (0.38)	Dentists (Counter Attendants)

Note. The variables are calculated from the Current Population Survey. Wages are inflation-adjusted with 2017 dollars. The occupations with the highest and the lowest values are listed on the right.

Table 2. Occupational Attributes, O*NET

Attributes	Example Items	Items (alpha)	Max (Min)
<i>Cognitive</i>			
Verbal	Oral Comprehension	4	Management Analysts
	Written Expression	(0.96)	(Vehicle Cleaners)
Quantitative	Mathematical Reasoning	2	Other Math Occupations
	Number Facility	(0.97)	(Maids)
Analytical	Deductive Reasoning	12	Physicians/Surgeons
	Critical Thinking	(0.96)	(Packagers)
Creative	Originality	3	Artists
	Thinking Creatively	(0.92)	(Maids)
Spatial Orientation	Spatial Orientation	8	Taxi Drivers/Chauffeurs
	Peripheral Vision	(0.93)	(Sales/Street Vendors)
<i>Physical</i>			
Control	Multilimb Coordination	7	Crane Operators
	Reaction Time	(0.97)	(Management Analysts)
Strength	Gross Body Coordination	9	Brick/Stonemasons
	Stamina	(0.97)	(Economists)
<i>Social</i>			
Interactive	Communicating Outside Organization	8	Social Workers
	Interpersonal Relationships	(0.86)	(Sewing Machine Operators)
Supervising	Guiding and Motivating Subordinates	6	Health Service Managers
	Coaching and Developing Others	(0.95)	(Billing Clerks)
<i>Environment</i>			
Discomfort	Extremely Bright or Inadequate Lighting	6	Bus/Truck Mechanics
	Cramped Work Space, Awkward Positions	(0.94)	(Insurance Underwriters)
Physical Hazard	Exposed to Hazardous Equipment	4	Electricians
		(0.92)	(Insurance Sales Agents)

Note. The variables represent the common factors of related O*NET items. Items with the two highest factor loadings are shown as examples. See Online Supplement C for the full list of items for each variable. Analytical and creative skills are constructed based on Liu and Grusky (2013). The occupations with the highest and the lowest values are listed on the right.

Table 3. Partial Coefficients and Standard Errors Predicting Logged Median Wage

Equation	FE		LDV	
	(4)		(5)	
Linked Wage	0.320**	(0.110)	0.225***	(0.063)
Wage t-1			0.725***	(0.029)
<i>Composition</i>				
% Male	0.131	(0.113)	0.075***	(0.022)
% White	0.502***	(0.120)	0.209***	(0.048)
Median Age†	0.274	(0.282)	0.224	(0.162)
% College	0.761***	(0.116)	0.182***	(0.031)
<i>Cognitive</i>				
Verbal			-0.005	(0.010)
Quantitative			-0.006	(0.007)
Analytical			0.053***	(0.012)
Creative			-0.019**	(0.006)
Spatial Orientation			-0.025**	(0.009)
<i>Physical</i>				
Control			0.033**	(0.012)
Strength†			0.054	(0.770)
<i>Social</i>				
Interactive			0.009	(0.007)
Supervising			-0.014**	(0.005)
<i>Environment</i>				
Discomfort			0.016	(0.014)
Physical Hazard			-0.022	(0.011)
<i>Period</i>				
1993-2002	0.012	(0.011)		
2008-2017	0.045	(0.027)	0.041***	(0.011)
N	756		504	
R-sq.	0.975		0.955	

Note. Occupation-clustered standard errors are reported. The occupational intercepts of the FE model are omitted from the table. Environmental wage is instrumented with the other linked attributes. Symbol † denotes that the coefficient and standard error are both multiplied by 100 to reduce decimal places. * $P < .05$. ** $P > .01$. *** $P < .001$.

APPENDICES

APPENDIX A. ALTERNATIVE CLASSIFICATION SCHEMES

We considered three classification schemes for the analysis: the 2010 occupation code (252 occupations, described in Online Supplement A), the 1950 occupation code (146 occupations), and micro-classes (82 classes). We prefer the 2010 code because it requires the least aggregation (Breiger 1981), but we also conducted a series of robustness checks to ensure that our findings are not driven by this decision.

Figure A1. The Distribution of Occupation Size and Percentage Remaining in the Same Occupation

Our first concern was that some occupations could be too small for us to capture mobility. Figure A1 presents the distribution of prior occupation size and the percentage of workers who had the same current occupation based on the 2010 code. The figure shows that we can observe some mobility for the smaller occupations. In fact, the larger an occupation is, the more likely its incumbents stay in that occupation.

We also tested whether the overall decline in connectivity (Figure 2) is robust when using more aggregated occupational classifications. Figure A2 presents the distribution of shortest distances when the 1950 code and micro-classes are used for 2008–2017 (depicted by the shading) and for 1983–1992 (depicted by the solid line). The figure shows that combining occupations into more aggregated categories results in fewer empty cells and more direct exchanges between categories. The difference is particularly clear when we contrast the results in Figure 2 and the results here using micro-classes. In the former case, about 30% of the occupation-pairs have direct exchanges; in the latter case, the number increases to about 70%. Nevertheless, the occupational network is less connected across the three periods even when more aggregated classifications are used, as indicated by the increased number of empty cells, the decreased intensity of exchanges, and the lengthened distances.

Figure A2. The Distribution of Exchanges and Shortest Distances, 2008–2017

Finally, we explore whether the community detection algorithms perform similarly with alternative classification schemes. Figure A3 presents the number of communities and modularity scores when the 1950 code and micro-classes are used. For the 1950 code, the results are very similar to our main findings. Across the three periods, all algorithms produce more communities and higher modularity scores. In the case of micro-classes, which are much more aggregated than the 2010 and 1950 codes (i.e., 82 classes, compared with 252 and 146 occupations, respectively), we do not see a consistent pattern regarding the number of communities; two of the five algorithms indicate an increase. This finding suggests that

certain differentiation may be masked by the aggregation. However, the increase in the modularity score still indicates that mobility increasingly occurs within instead of between communities.

Figure A3. The Number of Communities and Modularity Scores by Community Detection

Algorithms

APPENDIX B. COMMUNITY DETECTION METHODS

This appendix compares the partitions generated by different community detection algorithms. We begin by assessing the similarity of these partitions using the Rand Index R (Rand 1971), defined as follows:

$$R = \frac{\alpha_{11} + \alpha_{00}}{\alpha_{11} + \alpha_{00} + \alpha_{10} + \alpha_{01}},$$

where α_{11} denotes the number of pairs of occupations that are classified in the same group in both partitions; α_{00} denotes the number of pairs that are classified in different groups in both partitions; α_{10} and α_{01} denote the numbers of pairs that are classified in the same group in one partition but in different groups in the other. R ranges from 0 (complete disagreement) to 1 (complete agreement).

Figure B1. Rand Index Comparing Partition Results

Figure B1 presents the results, displaying great similarities among the Fast greedy, Louvain, Walk-trap, and Infomap communities. These algorithms tend to agree with one another about 90% of the time across the three periods. The Leading eigenvector partitions are less similar to other partitions, but they still agree with other partitions at least 82% of the time. These results indicate that even though these methods produce different numbers of communities, the partitions are largely consistent with one another.

To further assess the similarity among these partitions, we more closely compare the Louvain communities (which there are fewer) and the Infomap communities (which there are more; see Figure 3) for both the 1983–1992 and 2008–2017 periods. The resulting patterns

are displayed in Figures B2 and B3, where the width reflects the number of occupations in a given Louvain and a given Infomap community. The figures show that although Infomap produces more communities (17 in 1983–1992 and 35 in 2008–2017), these communities are mostly nested within the Louvain communities for both periods.

The side-by-side comparison suggests that the occupational network is likely to be hierarchically clustered. While the Louvain method identified the primary communities, and within each community, the Infomap method indicate there are smaller communities. Since there is no clear reason to favor one set of communities over another, we do not believe the network can be easily divided into distinct groups.

In sum, the findings here indicate that the results of different community detection methods show great consistency. The divisions identified by the Louvain method reflect cleavages in the occupational networks that are also identified by other algorithms. That said, different algorithms do yield communities that vary in the level of detail. Without a set of criteria, it is unclear which set of communities should be preferred.

Figure B2. Comparing the Louvain and the Infomap Communities, 1983–1992

Figure B3. Comparing the Louvain and the Infomap Communities, 2008–2017

APPENDIX C. FIRST-STAGE COEFFICIENTS AND CLUSTERED STANDARD ERRORS PREDICTING LINKED WAGE

Equation	FE (4-1)		LDV (5-1)	
Wage t-1			0.026***	(0.005)
<i>Linked Attributes</i>				
% Male	0.285***	(0.065)	0.307***	(0.046)
% White	1.113***	(0.203)	0.967***	(0.123)
Median Age	0.006	(0.008)	0.003	(0.004)
% College	0.838***	(0.108)	0.768***	(0.059)
<i>Cognitive</i>				
Verbal	-0.060	(0.042)	-0.030	(0.025)
Quantitative	0.036	(0.025)	-0.00795	(0.018)
Analytical	0.177***	(0.045)	0.147***	(0.022)
Creative	-0.125***	(0.024)	-0.136***	(0.015)
Spatial Orientation	-0.040	(0.042)	-0.028	(0.021)
<i>Physical</i>				
Control	-0.003	(0.048)	0.066*	(0.027)
Strength	-0.087*	(0.037)	-0.099***	(0.025)
<i>Social</i>				
Interactive	-0.014	(0.036)	0.083***	(0.021)
Supervising	-0.010	(0.025)	-0.020	(0.013)
<i>Environment</i>				
Discomfort	0.191***	(0.057)	-0.015	(0.041)
Physical Hazard	-0.038	(0.060)	0.141***	(0.039)
<i>Ego Attributes</i>				
% Male	-0.106**	(0.034)	-0.008	(0.007)
% White	0.008	(0.040)	-0.012	(0.012)
Median Age†	-0.005	(0.095)	-0.111**	(0.039)
% College	0.036	(0.035)	-0.026***	(0.008)
<i>Cognitive</i>				
Verbal			-0.002	(0.003)
Quantitative			-0.002	(0.001)
Analytical			0.002	(0.003)
Creative†			-0.007	(0.163)
<i>Physical</i>				
Spatial Orientation			0.004	(0.002)
Control			-0.002	(0.003)
Strength			-0.005**	(0.002)
<i>Social</i>				

Interactive			-0.001	(0.002)
Supervising			0.001	(0.001)
<i>Environment</i>				
Discomfort			-0.007*	(0.003)
Physical Hazard			0.003	(0.003)
<i>Period</i>				
1993-2002	0.043*	(0.021)		
2008-2017	0.135**	(0.052)	0.093***	(0.016)
N		756		504
R-sq.		0.980		0.983

Note. Occupation-clustered standard errors are reported. The occupational intercepts of the FE model are omitted from the table. † denotes that the coefficient and standard error are both multiplied by 100 to reduce decimal places. * $P < .05$. ** $P < .01$. *** $P < .001$.

Online Supplement for

The Network Structure of Occupations: Fragmentation, Differentiation, and Contagion

Prepared by Ken-Hou Lin & Koit Hung

University of Texas at Austin

A. HARMONIZATION OF OCCUPATIONAL CODE

Several steps were taken to ensure that our findings are not driven by the way we classify occupations. The harmonization was executed independently by a researcher experienced with the census occupation classification system and its changes over time. The priorities were placed on maximizing the number of occupations while maintaining sufficient cell sizes for the observation of mobility patterns. The researcher also checked to ensure that the harmonized occupations were consistent over time by examining the trends in the number of observations. Because harmonization is never an objective procedure, a separate researcher conducted the network analysis presented in the paper, thereby avoiding an artificial link between harmonization and our findings. (Appendix B shows that the findings are similar when two other, more aggregated classification schemes are used.)

Specifically, we use the variables OCC2010 (current occupation) and OCC10LY (prior occupation) from the IPUMS-CPS as the starting point of harmonization. Both variables are based on the 2010 census occupational classification, but some occupations are combined in public-use microdata and are merged for consistent categories across time. There are 540 occupations in the 2010 census occupational classification, 493 occupations in the public-use microdata, and 452 occupations in OCC2010 and OCC10LY.

OCC2010 and OCC10LY allow zero counts in some periods. Thus, we have no observation in early years for occupations that have emerged recently, and we have no observation in recent years for occupations that are shrinking over time because they are

merged with other occupations to ensure confidentiality. As such, we have to merge these and other smaller detailed occupations with other occupations. Table A1 documents the detailed occupations that are combined in the main analysis. To add specificity to two large occupations, we separate “managers, not elsewhere classified” and “truck drivers,” by nine industrial sectors.

Table A1. Harmonization of Occupational Code

Occupation merged with	Occupations to be merged
Managers, n.e.c. (430)	General and Operations Managers (20), Administrative Services Managers (100), Computer and Information Systems Managers (110), Industrial Production Managers (140), Transportation, Storage, and Distribution Managers (160), Constructions Managers (220), Architectural and Engineering Managers (300), Food Service and Lodging Managers (310), Gaming Managers (330), Natural Science Managers (360), Social and Community Service Managers (420)
Purchasing Agents (530)	Procurement Clerks (5150)
Business Operations and Management Specialists (730)	Cost Estimators (600), Logisticians (700), Meeting and Convention Planners (720)
Insurance Underwriters (860)	Insurance Claims and Policy Processing Clerks (5840)
Financial Specialists, n.e.c. (950)	Appraisers and Assessors of Real Estate (810), Budget Analysts (820), Credit Analysts (830), Financial Analysts (840), Personal Financial Advisors (850), Financial Examiners (900), Credit Counselors and Loan Officers (910), Tax Examiners and Collectors (930), Tax Preparers (940)
Computer Scientists and Systems Analysts (1000)	Database Administrators (1060), Network and Computer Systems Administrators (1100)
Computer Programmers (1010)	Software Developers, Applications and Systems Software (1020)

Mathematical Science Occupations, n.e.c. (1240)	Statisticians (1230)
Electrical and Electronics Engineers (1410)	Computer Hardware Engineers (1400)
Civil Engineers (1360)	Environmental Engineers (1420)
Biological Technicians (1910)	Agricultural and Food Science Technicians (1900)
Life, Physical, and Social Science Technicians, n.e.c. (1960)	Geological and Petroleum Technicians, and Nuclear Technicians (1930)
Religious Workers, n.e.c. (2060)	Directors, Religious Activities and Education (2050)
Legal Support Workers, n.e.c. (2150)	Paralegals and Legal Assistants (2140) ^a
Librarians (2430)	Library Technicians (2440)
Education, Training, and Library Workers, n.e.c. (2550)	Archivists, Curators, and Museum Technicians (2400) ^a
Media and Communication Workers, n.e.c. (2860)	Announcers (2800) ^a , Broadcast and Sound Engineering Technicians and Radio Operators (2900) ^a , Television, Video, and Motion Picture Camera Operators and Editors (2920)
Therapists, n.e.c. (3240)	Audiologists (3140), Radiation Therapists (3200), Recreational Therapists (3210)
Health Diagnosing and Treating Practitioners, n.e.c. (3260)	Chiropractors (3000), Physician Assistants (3110) ^a , Podiatrists (3120)
Health Diagnosing and Treating Practitioner Support Technicians (3410)	Diagnostic Related Technologists and Technicians (3320), Emergency Medical Technicians and Paramedics (3400)
Medical Assistants and Other Healthcare Support Occupations, n.e.c. (3650)	Nursing, Psychiatric, and Home Health Aides (3600), Occupational Therapy Assistants and Aides (3610), Physical Therapist Assistants and Aides (3620)
Supervisors, Protective Service, n.e.c. (3730)	First-Line Supervisors of Correctional Officers (3700)
Law Enforcement Workers, n.e.c. (3950)	Animal Control (3900), Private Detectives and Investigators (3910)
Waiters and Waitresses (4110)	Food Servers, Nonrestaurant (4120)
Food Preparation and Serving Related Workers, n.e.c. (4130)	Combined Food Preparation and Serving Workers, Including Fast Food (4050), Dishwashers (4140), Host and Hostesses, Restaurant, Lounge, and Coffee Shop (4150)

Entertainment Attendants and Related Workers, n.e.c. (4430)	First-Line Supervisors of Gaming Workers (4300), Animal Trainers (4340), Gaming Services Workers (4400), Gaming Cage Workers (5130)
Funeral Service Workers and Embalmers (4460)	Funeral Directors (320)
Personal Appearance Workers, n.e.c. (4520)	Barbers (4500) ^a , Hairdressers, Hairstylists, and Cosmetologists (4510) ^a
Personal Care and Service Workers, n.e.c. (4650)	Massage Therapists (3630), Personal Care Aides (4610), Residential Advisors (4640)
Reservation Agents and Travel Clerks (5410)	Travel Agents (4830)
Sales and Related Workers, n.e.c. (4965)	Telemarketers (4940)
Communications Equipment Operators, n.e.c. (5030)	Switchboard Operators, Including Answering Service (5010)
Bank Tellers (5160)	Financial Clerks, n.e.c. (5165), Brokerage Clerks (5200), Credit Authorizers, Checkers, and Clerks (5230), New Account Clerks (5340)
Information and Record Clerks, n.e.c. (5420)	Court, Municipal, and License Clerks (5220), Customer Service Representatives (5240)
Shipping, Receiving, and Traffic Clerks (5610)	Cargo and Freight Agents (5500)
Brickmasons, Blockmasons, and Stonemasons (6220)	Reinforcing Iron and Rebar Workers (6500)
Paving, Surfacing, and Tamping Equipment Operators (6300)	Highway Maintenance Workers (6730), Rail-Track Laying and Maintenance Equipment Operators (6740)
Painters, Construction and Maintenance (6420)	Paperhangers (6430)
Construction Workers, n.e.c. (6765)	Fence Erectors (6710), Hazardous Materials Removal Workers (6720)
Computer and Office Machine Repairers (7010)	Computer Support Specialists (1050)
Electronic Repairs, n.e.c. (7125)	Electronic Equipment Installers and Repairers, Motor Vehicles (7110), Electronic Home Entertainment Equipment Installers and Repairers (7120), Security and Fire Alarm Systems Installers (7130)
Aircraft Technicians (7140)	Avionics Technicians (7030), Aircraft Structure, Surfaces, Rigging, and Systems Assemblers (7710)

Automotive Body and Related Repairers (7150)	Automotive Glass Installers and Repairers (7160)
Vehicle Mechanics, Installers, and Repairers, n.e.c. (7260)	Small Engine Mechanics (7240) ^a
Telecommunications Line Installer and Repairer (7420)	Electrical Power-Line Installers and Repairers (7410)
Installation, Maintenance, and Repair Workers, n.e.c. (7630)	Precision Instrument and Equipment Repairers (7430) ^a , Coin and Vending Machine Repairers (7410), Locksmiths and Safe Repairers (7540) ^a , Manufactured Building and Mobile Home Installers (7550), Riggers (7560), Helpers--Installation, Maintenance, and Repair Workers (7610) ^a
Assemblers and Fabricators, n.e.c. (7750)	Engine and Other Machine Assemblers (7730)
Food Processing, n.e.c. (7855)	Food and Tobacco Roasting Machine Operators (7830) ^a , Food Batchmakers (7840) ^a , Food Cooking Machine Operators and Tenders (7850)
Metal Workers and Plastic Workers, n.e.c. (8220)	Extruding and Drawing Machine Operators (7920), Forging Machine Operators (7930), Drilling and Boring Machine Tool Operators (7960), Metal Furnace Operators (8040), Model Makers and Patternmakers (8060), Heat Treating Equipment Operators (8150), Tool Grinders, Filers, and Sharpeners (8210)
Textile, Apparel, Furnishings Workers, n.e.c. (8460)	Shoe Machine Operators and Tenders (8340)
Production Workers, n.e.c. (8965)	Tire Builders (8940)
Railroad Conductors and Yardmasters (9240)	Railroad Brake, Signal, and Switch Operators (9230)
Transportation Workers, n.e.c. (9420)	Automotive and Watercraft Service Attendants (9360), Transportation Inspectors (9410)

Note. n.e.c. = not elsewhere classified.

^a The occupational code to be merged consistently exists between 1983 and 2017, but it is merged to the “not elsewhere classified” code that emerges later in the classification scheme.

B. DETAILED OCCUPATIONAL NETWORK

Here we provide the location of detailed occupations corresponding to Figure 4. Each occupation is assigned with a color and a numeral ID. The colors correspond to the community membership in 1983–1992 and 2008–2017. The IDs are sequentially assigned by the 1983–1992 membership and do not change between the two periods. Thus, one may more easily trace the change in community membership as in Figure 5. The occupation titles in the legends are shortened because of space constraints. Full titles are available upon request.

Figure B1. Detailed Occupational Network, 1983–1992

1 Chemical Engineers	64 Health Technicians	127 Other Electronic Repairers	190 Electrical Assemblers
2 Electrical Engineers	65 Dieticians	128 Maintenance & Repair Workers	191 Tailors/Dressmakers
3 Surveyors & Surveying Technicians	66 Other Therapists	129 Radio Installers/Repairers	192 Bakers
4 Engineering Techs	67 Dental Assistants	130 Vehicle Mechanics	193 Other Business Specialists
5 Architects & Marine Engineers	68 Medical Assistants	131 Industrial Mechanics	194 Buyers & Purchasing Agents
6 Drafters	69 Other Math/Science Occupations	132 Bus/Truck Mechanics	195 HR Specialists
7 Other Engineers	70 Claim Consultants	133 Mechanics/Repairers Supervisors	196 Compliance Officers
8 Aerospace Engineers	71 Teacher Assistants	134 Aircraft Service Techs/Mechanics	197 Management Analysts
9 Mechanical Engineers	72 Hotel Clerks	135 Car Body Repairers	198 Funeral Workers/Embalmers
10 Industrial Engineers	73 Office Support Workers	136 Other Installation/Maintenance Workers	199 Real Estate Brokers
11 Civil & Geological Engineers	74 Office Tech Operators	137 Telecommunications Installers	200 Parts Salespersons
12 Biological Techs	75 Office Worker Supervisors	138 Heavy Vehicle Service Mechanics	201 Sales Rep (Manufacturing)
13 Medical/Life Scientists	76 Account Collectors	139 Welding/Soldering/Brazing Workers	202 Retail Salespersons
14 Phys. Scientists	77 Human Resources Assistants	140 Metal/Plastic Workers	203 Sale Supervisors
15 Operations Research Analysts	78 Interviewers	141 Bookbinders/Printing Operators	204 Counter Clerks
16 Biological Scientists	79 File Clerks	142 Crushing/Polishing Workers	205 Insurance Sales Agents
17 Environ. Scientists/Geoscientists	80 Production/Planning Clerks	143 Inspectors/Sorters/Samplers	206 Ad Sales Agents
18 Social Science Techs	81 Record Clerks	144 Machinists	207 Sales/Street Vendors
19 Chemical Techs	82 Correspondent/Order Clerks	145 Painters	208 All Other Sales Workers
20 Chemists	83 Library Assistants	146 Textile Workers	209 Securities Sales Agents
21 Judicial Workers	84 Communication Equipment Operators	147 Plant & System Operators	210 Sales Rep
22 Pilots & Controllers	85 Shipping/Traffic Clerks	148 Assemblers & Fabricators	211 Insurance Underwriters
23 Legal Support Workers	86 Ticket/Travel Agents	149 Woodworkers	212 Financial Specialists
24 Computer Scientists & Programmers	87 Office Clerks	150 Laundry/Dry-Cleaning	213 Building Inspectors
25 Economists/Researchers	88 Bookkeepers/Auditing Clerks	151 Packaging/Filing Machine Operators	214 Transportation Managers, NEC
26 Psychologists	89 Data Entry Keyers	152 Production Supervisors	215 Financial Managers
27 Clergy & Religious Workers	90 Dispatchers	153 Photo Process Workers/Machine Operators	216 Retail Managers, NEC
28 Pre-K & K Teachers	91 Stock Clerks	154 Jewelers	217 Finance/Business Managers, NEC
29 Training/Library Workers	92 Bank Tellers	155 Sewing Machine Operators & Pressers	218 Personal/Entertainment Managers, NEC
30 Secondary School Teachers	93 Secretaries	156 Machine Setters/Operators/Tenders	219 Public Admin. Managers, NEC
31 Social Scientists	94 Measurers & Recordkeeping	157 Production Workers	220 Public Communication Managers
32 Social Workers	95 Computer Operators	158 Material Movers	221 Purchasing Managers
33 Librarians	96 Typists	159 Truck/Tractor Operators	222 Professional Service Managers, NEC
34 Postsecondary Teachers	97 Receptionists	160 Crane Operators	223 Natural Resource Managers, NEC
35 Primary School Teachers	98 Accountants/Auditors	161 Laborers & Freight/Stock Movers	224 Education Admins
36 Special Ed Teachers	99 Billing Clerks	162 Fishermen	225 Health Service Managers
37 Counselors	100 Railroad Conductors/Yardmasters	163 Forest Conservation Workers	226 Property Managers
38 Other Teachers	101 Transportation Workers	164 Agricultural Workers	227 HR Managers
39 News Reporters/Correspondents	102 Sailors/Ship Engineers	165 Packagers	228 Construction Managers, NEC
40 Communication Workers	103 Train Engineers/Operators	166 Vehicle/Equip. Cleaners	229 Manufacturing Managers, NEC
41 Athletes/Officials	104 First-Line Supervisor Maintenance	167 Extraction workers	230 Firefighters
42 PR Specialists	105 Grounds Maintenance Workers	168 Construction Supervisors	231 Security Guards
43 Actors/Producers/Directors	106 Animal Trainers	169 Loading Machine Operators	232 Correctional Officers
44 Photographers	107 Roofers	170 Social Service Specialists	233 Protective Serv. Supervisors
45 Writers	108 Pipelayers/Plumbers/Pipefitters	171 Opticians	234 Police
46 Musicians	109 Carpenters	172 Food Prep Workers	235 Transport. Supervisors
47 Designers	110 Sheet & Structural Metal Workers	173 Waiters	236 Postal Service Mail Carriers
48 Entertainers (incl. Sports)	111 Construction Laborers	174 Maids	237 Postal Service Clerks
49 Artists	112 Construction Workers	175 Chefs	238 Mail Clerks
50 Law Enforcement	113 Cement/Concrete Finishers	176 Counter Attendants	239 Couriers/Messengers
51 Recreation/Fitness Workers	114 Electricians	177 Bartenders	240 Recyclable Material Collectors
52 Physicians/Surgeons	115 Construction Trades	178 Janitors	241 Wholesale & Retail Truck Drivers
53 Optometrists	116 Carpet/Tile Installers	179 Food Service Workers	242 Parking Lot Attendants
54 Health Practitioners	117 Painters/Construction Maintenance	180 Food Prep Supervisors	243 Business Truck Drivers
55 Dental Hygienists	118 Insulation Workers	181 Personal Service Supervisors	244 Transp. Utilities Truck Drivers
56 Health Techs	119 Paving/Surfacing Equipment Operators	182 Childcare Workers	245 Public Sector Truck Drivers
57 Pharmacists	120 Brick/Block/Stonemasons	183 Flight Attendants/Transport. Workers	246 Prof. Serv. Truck Drivers
58 Vets	121 Drywall Installers	184 Entertainment Attendants	247 Agricultural Truck Drivers
59 Licensed Nurses	122 Construction Equipment Operators	185 Other Personal Service Workers	248 Construction Truck Drivers
60 Physical Therapists	123 Car Service Techs/Mechanics	186 Personal Appearance Workers	249 Manufacturing Truck Drivers
61 Dentists	124 Office Tech Repairers	187 Cashiers	250 Service Truck Drivers
62 Registered Nurses	125 Heating/AC Mechanics/Installers	188 Butchers	251 Ambulance/Bus Drivers
63 Lab Techs	126 Millwrights	189 Food Processers	252 Taxi Drivers/Chauffeurs

Figure B2. Detailed Occupational Network, 2008–2017

1 Chemical Engineers	60 Physical Therapists	81 Record Clerks	145 Painters
2 Electrical Engineers	61 Dentists	82 Correspondent/Order Clerks	146 Textile Workers
3 Surveyors & Surveying Technicians	62 Registered Nurses	83 Library Assistants	147 Plant & System Operators
4 Engineering Techs	63 Lab Techs	84 Communication Equipment Operators	148 Assemblers & Fabricators
5 Architects & Marine Engineers	64 Health Technicians	85 Shipping/Traffic Clerks	149 Woodworkers
6 Drafters	65 Dieticians	86 Ticket/Travel Agents	150 Laundry/Dry-Cleaning
7 Other Engineers	66 Other Therapists	87 Office Clerks	151 Packaging/Filing Machine Operators
8 Aerospace Engineers	171 Opticians	88 Bookkeepers/Auditing Clerks	152 Production Supervisors
9 Mechanical Engineers	50 Law Enforcement	89 Data Entry Keyers	153 Photo Process Workers/Machine Operators
10 Industrial Engineers	230 Firefighters	90 Dispatchers	154 Jewelers
11 Civil & Geological Engineers	231 Security Guards	91 Stock Clerks	155 Sewing Machine Operators & Pressers
12 Biological Techs	232 Correctional Officers	92 Bank Tellers	156 Machine Setters/Operators/Tenders
13 Medical/Life Scientists	233 Protective Serv. Supervisors	93 Secretaries	157 Production Workers
14 Phys. Scientists	234 Police	94 Measurers & Recordkeeping	188 Butchers
15 Operations Research Analysts	104 First-Line Supervisor Maintenance	95 Computer Operators	189 Food Processers
16 Biological Scientists	105 Grounds Maintenance Workers	96 Typists	190 Electrical Assemblers
17 Environ. Scientists/Geoscientists	172 Food Prep Workers	97 Receptionists	191 Tailors/Dressmakers
18 Social Science Techs	173 Waiters	98 Accountants/Auditors	192 Bakers
19 Chemical Techs	174 Maids	99 Billing Clerks	100 Railroad Conductors/Yardmasters
20 Chemists	175 Chefs	211 Insurance Underwriters	101 Transportation Workers
69 Other Math/Science Occupations	176 Counter Attendants	212 Financial Specialists	102 Sailors/Ship Engineers
25 Economists/Researchers	177 Bartenders	238 Mail Clerks	103 Train Engineers/Operators
70 Claim Consultants	178 Janitors	239 Couriers/Messengers	158 Material Movers
193 Other Business Specialists	179 Food Service Workers	107 Roofers	159 Truck/Tractor Operators
194 Buyers & Purchasing Agents	180 Food Prep Supervisors	108 Pipelayers/Plumbers/Pipefitters	160 Crane Operators
195 HR Specialists	22 Pilots & Controllers	109 Carpenters	161 Laborers & Freight/Stock Movers
196 Compliance Officers	51 Recreation/Fitness Workers	110 Sheet & Structural Metal Workers	162 Fishermen
197 Management Analysts	67 Dental Assistants	111 Construction Laborers	163 Forest Conservation Workers
21 Judicial Workers	68 Medical Assistants	112 Construction Workers	164 Agricultural Workers
26 Psychologists	72 Hotel Clerks	113 Cement/Concrete Finishers	165 Packagers
27 Clergy & Religious Workers	106 Animal Trainers	114 Electricians	166 Vehicle/Equip. Cleaners
28 Pre-K & K Teachers	181 Personal Service Supervisors	115 Construction Trades	167 Extraction workers
29 Training/Library Workers	182 Childcare Workers	116 Carpet/Tile Installers	168 Construction Supervisors
30 Secondary School Teachers	183 Flight Attendants/Transport. Workers	117 Painters/Construction Maintenance	169 Loading Machine Operators
31 Social Scientists	184 Entertainment Attendants	118 Insulation Workers	240 Recyclable Material Collectors
32 Social Workers	185 Other Personal Service Workers	119 Paving/urfacing Equipment Operators	241 Wholesale & Retail Truck Drivers
33 Librarians	186 Personal Appearance Workers	120 Brick/Block/Stonemasons	242 Parking Lot Attendants
34 Postsecondary Teachers	198 Funeral Workers/Embalmers	121 Drywall Installers	243 Business Truck Drivers
35 Primary School Teachers	235 Transport. Supervisors	122 Construction Equipment Operators	244 Transp. Utilities Truck Drivers
36 Special Ed Teachers	187 Cashiers	213 Building Inspectors	245 Public Sector Truck Drivers
37 Counselors	199 Real Estate Brokers	24 Computer Scientists & Programmers	246 Prof. Serv. Truck Drivers
38 Other Teachers	200 Parts Salespersons	123 Car Service Techs/Mechanics	247 Agricultural Truck Drivers
71 Teacher Assistants	201 Sales Rep (Manufacturing)	124 Office Tech Repairers	248 Construction Truck Drivers
170 Social Service Specialists	202 Retail Salespersons	125 Heating/AC Mechanics/Installers	249 Manufacturing Truck Drivers
39 News Reporters/Correspondents	203 Sale Supervisors	126 Millwrights	250 Service Truck Drivers
40 Communication Workers	204 Counter Clerks	127 Other Electronic Repairers	251 Ambulance/Bus Drivers
41 Athletes/Officials	205 Insurance Sales Agents	128 Maintenance & Repair Workers	252 Taxi Drivers/Chauffeurs
42 PR Specialists	206 Ad Sales Agents	129 Radio Installers/Repairers	214 Transportation Managers, NEC
43 Actors/Producers/Directors	207 Sales/Street Vendors	130 Vehicle Mechanics	215 Financial Managers
44 Photographers	208 All Other Sales Workers	131 Industrial Mechanics	216 Retail Managers, NEC
45 Writers	209 Securities Sales Agents	132 Bus/Truck Mechanics	217 Finance/Business Managers, NEC
46 Musicians	210 Sales Rep	133 Mechanics/Repairers Supervisors	218 Personal/Entertainment Managers, NEC
47 Designers	236 Postal Service Mail Carriers	134 Aircraft Service Techs/Mechanics	219 Public Admin Managers, NEC
48 Entertainers (incl. Sports)	237 Postal Service Clerks	135 Car Body Repairers	220 Public Communication Managers
49 Artists	23 Legal Support Workers	136 Other Installation/Maintenance Workers	221 Purchasing Managers
52 Physicians/Surgeons	73 Office Support Workers	137 Telecommunications Installers	222 Professional Service Managers, NEC
53 Optometrists	74 Office Tech Operators	138 Heavy Vehicle Service Mechanics	223 Natural Resource Managers, NEC
54 Health Practitioners	75 Office Worker Supervisors	139 Welding/Soldering/Brazing Workers	224 Education Admins
55 Dental Hygienists	76 Account Collectors	140 Metal/Plastic Workers	225 Health Service Managers
56 Health Techs	77 Human Resources Assistants	141 Bookbinders/Printing Operators	226 Property Managers
57 Pharmacists	78 Interviewers	142 Crushing/Polishing Workers	227 HR Managers
58 Vets	79 File Clerks	143 Inspectors/Sorters/Samplers	228 Construction Managers, NEC
59 Licensed Nurses	80 Production/Planning Clerks	144 Machinists	229 Manufacturing Managers, NEC

C. O*NET ITEMS USED FOR OCCUPATIONAL MEASURES

We construct a series of measures using items from the O*NET. Because the study does not focus on any single attribute, we prioritize representativeness over comprehensiveness: we aim to select important measures in various dimensions rather than exhaust any single dimension. Although more measures could certainly be included in the list, we believe that most of them are correlated with existing measures and therefore provide little additional information. Table C1 provides detailed description of our measures.

Table C1. O*NET Items used for Occupational Content

Measures	O*NET variable	Variable description
Cognitive		
Verbal	Oral comprehension	The ability to listen to and understand information and ideas presented through spoken words and sentences.
	Written comprehension	The ability to read and understand information and ideas presented in writing.
	Oral expression	The ability to communicate information and ideas in speaking so others will understand.
	Written expression	The ability to communicate information and ideas in writing so others will understand.
Quantitative	Math reasoning	The ability to choose the right mathematical methods or formulas to solve a problem.
	Number facility	The ability to add, subtract, multiply, or divide quickly and correctly.
Analytical	Fluency of ideas	The ability to come up with a number of ideas about a topic (the number of ideas is important, not their quality, correctness, or creativity).
	Problem sensitivity	The ability to tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing there is a problem.

	Deductive reasoning	The ability to apply general rules to specific problems to produce answers that make sense.
	Inductive reasoning	The ability to combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
	Information ordering	The ability to arrange things or actions in a certain order or pattern according to a specific rule or set of rules.
	Critical thinking	Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.
	Active learning	Understanding the implications of new information for both current and future problem-solving and decision-making.
	Learning strategies	Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.
	Judging qualities	Assessing the value, importance, or quality of things or people.
	Processing information	Compiling, coding, categorizing, calculating, tabulating, auditing, or verifying information or data.
	Evaluating information to determine compliance with standards	Using relevant information and individual judgment to determine whether events or processes comply with laws, regulations, or standards.
	Analyzing data or information	Identifying the underlying principles, reasons, or facts of information by breaking down information or data into separate parts.
Creative	Originality	The ability to come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
	Thinking creatively	Developing, designing, or creating new applications, ideas, relationships, systems, or products, including artistic contributions.

	Innovation	Job requires creativity and alternative thinking to develop new ideas for and answers to work-related problems.
Spatial Orientation	Spatial orientation	The ability to know your location in relation to the environment or to know where other objects are in relation to you.
	Visualization	The ability to imagine how something will look after it is moved around or when its parts are moved or rearranged.
Physical		
Motion Control	Control precision	The ability to quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.
	Multilimb coordination	The ability to coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.
	Response orientation	The ability to choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part.
	Rate control	The ability to time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.
	Reaction time	The ability to quickly respond (with the hand, finger, or foot) to a signal (sound, light, picture) when it appears.
	Wrist-Finger speed	The ability to make fast, simple, repeated movements of the fingers, hands, and wrists.
	Limb movement	The ability to quickly move the arms and legs.
Strength	Static strength	The ability to exert maximum muscle force to lift, push, pull, or carry objects.
	Explosive strength	The ability to use short bursts of muscle force to propel oneself (as in jumping or sprinting), or to throw an object.

Dynamic strength	The ability to exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.
Trunk strength	The ability to use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without 'giving out' or fatiguing.
Extent flexibility	The ability to bend, stretch, twist, or reach with your body, arms, and/or legs.
Dynamic flexibility	The ability to quickly and repeatedly bend, stretch, twist, or reach out with your body, arms, and/or legs.
Gross body Coordination	The ability to coordinate the movement of your arms, legs, and torso together when the whole body is in motion.
Gross body equilibrium	The ability to keep or regain your body balance or stay upright when in an unstable position.
Sensory abilities	Abilities that influence visual, auditory and speech perception
Stamina	The ability to exert yourself physically over long periods of time without getting winded or out of breath.

Social

Interactive	Interpreting meaning of information for others	Translating or explaining what information means and how it can be used.
	Communicating with supervisors, peers, or subordinates	Providing information to supervisors, co-workers, and subordinates by telephone, in written form, e-mail, or in person.
	Communicating with persons outside organization	Communicating with people outside the organization, representing the organization to customers, the public, government, and other external sources. This information can be exchanged in person, in writing, or by telephone or e-mail.
	Establishing and maintaining relationships	Developing constructive and cooperative working relationships with others, and maintaining them over time.
	Assisting and caring for Others	Providing personal assistance, medical attention, emotional support, or other

		personal care to others such as coworkers, customers, or patients.
	Selling or influencing Others	Convincing others to buy merchandise/goods or to otherwise change their minds or actions.
	Resolving conflicts and negotiating with others	Handling complaints, settling disputes, and resolving grievances and conflicts, or otherwise negotiating with others.
	Performing for or working directly with the public	Performing for people or dealing directly with the public. This includes serving customers in restaurants and stores and receiving clients or guests.
Supervising	Coordinating the work and activities of others	Getting members of a group to work together to accomplish tasks.
	Developing and building teams	Encouraging and building mutual trust, respect, and cooperation among team members.
	Training and teaching Others	Identifying the educational needs of others, developing formal educational or training programs or classes, and teaching or instructing others.
	Guiding, directing, and motivating subordinates	Providing guidance and direction to subordinates, including setting performance standards and monitoring performance.
	Coaching and developing others	Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills.
	Provide consultation and advice to others	Providing guidance and expert advice to management or other groups on technical, systems-, or process-related topics.
Environment		
Discomfort	Sounds and noise levels	How often does this job require working exposed to sounds and noise levels that are distracting or uncomfortable?
	Very hot or cold temperatures	How often does this job require working in very hot (above 90 F degrees) or very cold (below 32 F degrees) temperatures?
	Extremely bright or inadequate lighting	How often does this job require working in extremely bright or inadequate lighting conditions?

Physical Hazards	Exposed to contaminants	How often does this job require working exposed to contaminants (such as pollutants, gases, dust or odors)?
	Cramped work space	How often does this job require working in cramped work spaces that requires getting into awkward positions?
	Whole body vibration	How often does this job require exposure to whole body vibration?
	High places	How often does this job require exposure to high places?
	Hazardous conditions	How often does this job require exposure to hazardous conditions?
	Hazardous equipment	How often does this job require exposure to hazardous equipment?
	Exposed to minor burns, cuts, bites, or stings	How often does this job require exposure to minor burns, cuts, bites, or stings?