The Network Structure of Occupations: Fragmentation, Differentiation, and Contagion[1]

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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 networks as a dynamic system in which between-occupation exchange is shaped by occupational similarities and occupational attributes are in turn responsive to mobility patterns. The authors illustrate this perspective with the exchange networks of detailed occupations. Their 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 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 coconstitutive and that a network perspective provides a unifying framework for the study of stratification and mobility.

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., Treiman 1977;

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Erikson and Goldthorpe 1992; Hauser and Warren 1997; Wright 1997; Weeden and Grusky 2005). Yet, scholars have long pointed out that mobility is critical in understanding the structure of the labor market (Blau and Duncan 1967; White 1970; Spilerman 1977; Breiger 1981). 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 (Toubøl and Larsen 2017; Cheng and Park 2020; 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, focuses on the flow of workers between occupations. 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; Weeden and Grusky 2005; Laurison and Friedman 2016). 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 by a wide range of occupational attributes beyond status proximity. We find that mobility is negatively associated with occupational dissimilarity in sex and

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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 and 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 wages 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 coconstitutive 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 in 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 (Weil 2014; Cobb and Lin 2017; Wilmers and Aeppli 2021). We also provide clear evidence that occupations requiring quantitative, social, and creative skills have become more specialized in recent years (Florida 2002; Liu and Grusky 2013; Deming 2017), 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 Microclasses

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 2010). Occupations are also sites for the formation of political preferences (Weeden and Grusky 2012; Kitschelt and Rehm 2014) and have far-reaching influences on household dynamics (e.g., Schneider 2012; McClintock 2017). 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., Treiman 1977; Hauser and Warren 1997). 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 Comparative Analysis of Social Mobility in Industrial Nations (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 neomarxian 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, p. 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 have been criticized as overly reductive in recent years (Pakulski and Waters 1996; Kingston 2000), and in response, scholars have introduced the concept of microclasses (Grusky and Sørensen 1998; Weeden and Grusky 2005; Weeden et al. 2007; Jonsson et al. 2009). 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), microclasses are more flexible in reflecting the distinctions between occupations and in capturing similarities in life conditions. Empirical studies also demonstrate that microclasses pick up meaningful variation that is masked by larger classes (e.g., Weeden et al. 2007; Laurison and Friedman 2016).

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 doubted that occupations can be unidimensionally scaled and advocate for a more comprehensive view of the occupational structure (e.g., Weeden and Grusky 2005, p. 148). More recently, Freeland and Hoey (2018) have shown that status is a multidimensional construct and cannot be summarized solely by income and education.[2]

Second, the class-based view entails the perennial questions of how many classes there are and how occupations should be categorized into different classes (Giddens 1973; Erikson, Goldthorpe, and Hällsten 2012). 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 microclasses, 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 guidance regarding when and how the class structure should be updated. As the U.S. labor 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.

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

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" (p. 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 preentry 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 (see Spenner, Otto, and Call 1982; Kerckhoff 1995).

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, Kriesi, and Buchmann (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. (2022) also showed that female-dominated jobs are more circuitously linked than male-dominated jobs in a sample of distribution centers.

Most recently, Villarreal (2020) advocated for a network approach to understand the occupational structure in the United States. Using factional analysis, he found that the U.S. 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.[3] 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 toward 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 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

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

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 (Lévi-Strauss 1969; Bearman 1997; 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.[4] Individuals with a given occupation are more likely to conduct transactions or communicate with those with certain occupations (Lin and Dumin 1986; Chan and Goldthorpe 2004; Lambert and Griffiths 2017). 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, 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, p. 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 (White 1970; Spilerman 1977). From this perspective, mobility does not indicate a lack of structure but represents the structure itself.

[4] 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 e-mail traffic (Kleinbaum, Stuart, and Tushman 2013; Goldberg et al. 2016) or job description (Hasan, Ferguson, and Koning 2015).

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 on the basis of 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" (Toubøl and Larsen 2017; Cheng and Park 2020) but is a result of assortativity in certain critical dimensions.

Furthermore, we view mobility not only 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 to be coconstitutive: 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 because of 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 (Stainback and Tomaskovic-Devey 2012; Rivera 2015).

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 nonmovers, 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 (Tilly 1998; Sorenson 2000; Weeden 2002). In the meantime, competition for the same workforce likely results in the convergence of employment practices (Tomaskovic-Devey 2013). For this reason, nonunionized workers used to benefit from the presence of unionized workers in the local labor market (Western and Rosenfeld 2011; Rosenfeld 2014).

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 because of 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, as 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, however, 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 becomes 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 2009*a*; Kalleberg 2011; Dwyer 2013; 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; Weil 2014; Cobb and Lin 2017). 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 setup, 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. Finally, we test how the network structure may affect 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 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 (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 individuals to change their occupation, they must first declare a job change.[5]

Our sample includes consecutively employed respondents ages 25–64 with valid sampling weights ($N = 1,880,071$).[6] We assign respondents 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 codes. 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).[7]

To ensure that the findings are not driven by a particular occupational classification or measurement error, we reclassify the respondents using more aggregated 1950 census codes (146 occupations, based on OCC1950 developed by the Integrated Public Use Microdata Series) and microclasses (82 classes; e.g., Jonsson et al. 2009; Jarvis and Song 2017). The findings are substantively similar (see app. 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 using the transition matrix (Blau and Duncan 1967). Figure 1*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

[5] 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.

[6] 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.

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

A

Prior Occupation \ Current Occupation	I	II	III	IV	V	VI	VII	Total
I	89	11	0	2	12	0	8	122
II	14	73	7	0	1	0	1	96
III	0	8	120	20	0	3	7	158
IV	5	0	17	98	18	1	0	139
V	0	3	12	0	138	38	23	214
VI	0	7	2	0	12	75	15	111
VII	4	0	0	10	25	19	102	160
Total	112	102	158	130	206	136	156	

B

Prior Occupation \ Current Occupation	I	II	III	IV	V	VI	VII
I	0.73	0.11	0	0.03	0.04	0	0.04
II	0.11	0.76	0.06	0	0.01	0.03	0
III	0	0.06	0.76	0.12	0.03	0.02	0.02
IV	0.03	0	0.12	0.71	0.05	0	0.03
V	0.04	0.01	0.03	0.05	0.64	0.15	0.13
VI	0	0.03	0.02	0	0.15	0.68	0.13
VII	0.04	0	0.02	0.03	0.13	0.13	0.64

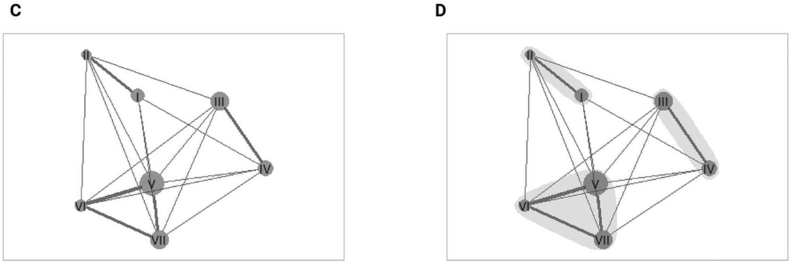

FIG. 1.—Hypothetical example of how we construct the networks. *A*, Hypothetical example of 1,000 workers moving among seven occupations. *B*, Counts transformed into an undirected, weighted adjacency matrix using equation (1). *C*, Network plotted using a Fruchterman-Reingold drawing. *D*, Communities of occupations identified using the Louvain community detection algorithm. Color version available as an online enhancement.

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 ($r > .999$).

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:

$$\mathrm{E}_{i\leftrightarrow j,p} = \frac{C_{i\to j,p}}{O_{i,p}} \times \frac{O_{i,p}}{O_{i,p}+O_{j,p}} + \frac{C_{j\to i,p}}{O_{j,p}} \times \frac{O_{j,p}}{O_{i,p}+O_{j,p}} = \frac{C_{i\to j,p}+C_{j\to i,p}}{O_{i,p}+O_{j,p}}, \qquad (1)$$

where $C_{i\to j,p}$ and $C_{j\to i,p}$ denote the population-weighted number of workers who moved between occupation i and occupation j during period p and $O_{i,p}$ and $O_{j,p}$ denote the sizes of last year's occupations i and j (i.e., the row margins in fig. 1*A*). Because $O_{i,p} + O_{j,p}$ limits $C_{i\to j,p} + C_{j\to i,p}$, $\mathrm{E}_{i\leftrightarrow j,p}$ ranges from 0 to 1, with larger values indicating higher rates of exchange.[8] Figure 1*B* presents the adjacency matrix calculated with equation (1). For example,

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

Figure 1*C* illustrates the network using figure 1*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. Figure 1*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 the occupational network evolves over time, we partition our data into three periods: 1983–92, 1993–2002, and 2008–17.[9] For each period, the mobility data from CPS-ASEC 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 1983–92, 10.2% during 1993–2002, and 8.57% during 2008–17). 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.[10] Apart from the three period-specific networks, we 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.

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

[9] We suspect that the structure of the 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 classifications 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.

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

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 and shortest distances. We log transform both measures because of the skewness of these distributions.

Figure 2*A* presents the distribution of direct exchanges using 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.

Figure 2*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., $\log(E_{i\leftrightarrow k1}) + \log(E_{k1\leftrightarrow k2}) + \ldots \log(E_{kn\leftrightarrow j})$). 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 (e.g., Fortunato and Hric 2016; Peel, Larremore, and Clauset 2017).[11] 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

[11] Another potential approach to detecting weak communities is block modeling, 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 on request.

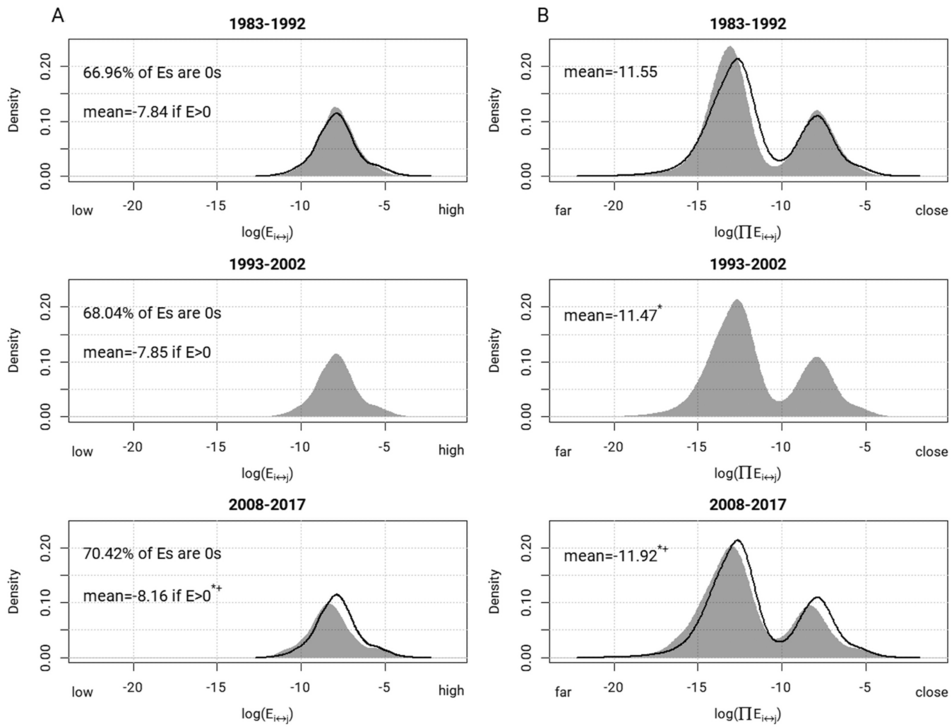

FIG. 2.—Distributions of exchanges (A) and shortest distances (B). A, Distribution of $\log(\mathrm{E}_{i\leftrightarrow j})$ when $\mathrm{E}_{i\leftrightarrow j} > 0$. B, Distribution of the shortest distances. For both panels, the solid lines represent the distribution in 1993–2002 for ease of comparison. We conduct bootstrap t-tests for each panel. The symbol * denotes a statistically significant difference ($P < .001$) from 1983 to 1992. The symbol + denotes a statistically significant difference ($P < .001$) from 1993 to 2002. The total number of observations for each period, including zeros, is $252 \times (252 - 1)/2 = 31{,}626$. Color version available as an online enhancement.

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 within groups than would be expected to occur at random.[12] 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 a divisive approach (Clauset, Newman, and Moore 2004; Newman 2006; Blondel et al. 2008; Bruch and Newman 2019).

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 (Rosvall and Bergstrom 2008; Cheng and Park 2020).

Although each algorithm follows a different procedure, they share a similar interpretation: the more the communities are identified, the more segmented the U.S. labor 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. Figure 3*A* shows that the walk-trap and infomap methods tend

[12] 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 a weakness when our goal is to detect the general, consensual divisions in the network.

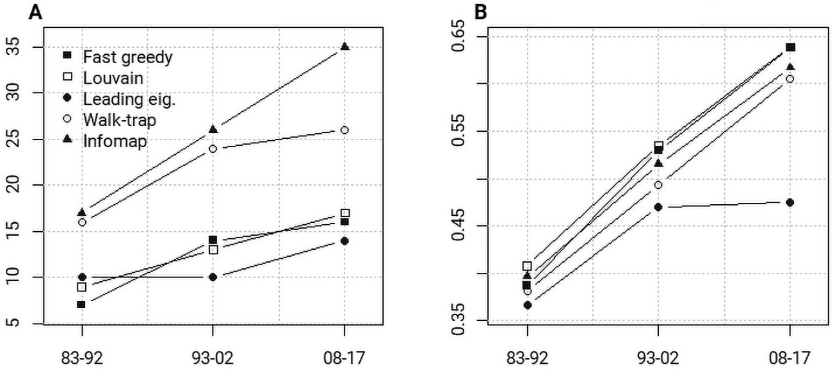

FIG. 3.—Number of communities (*A*) and modularity (*B*) by algorithm and period. We implement the five algorithms to three undirected, weighted networks generated from the CPS for 1983–92, 1993–2002, and 2008–17. Color version available as an online enhancement.

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.

Figure 3*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 the 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 1983–92 and 2008–17 using a Fruchterman-Reingold drawing. The more frequent the exchanges between two occupations, the closer they are in the figure.[13] Nine sets of occupations are identified for 1983–92. 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.

How has the U.S. labor market evolved since the 1980s? Figure 4*B* presents the configuration in 2008–17. 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.

[13] Like other force-directed graph drawings 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.

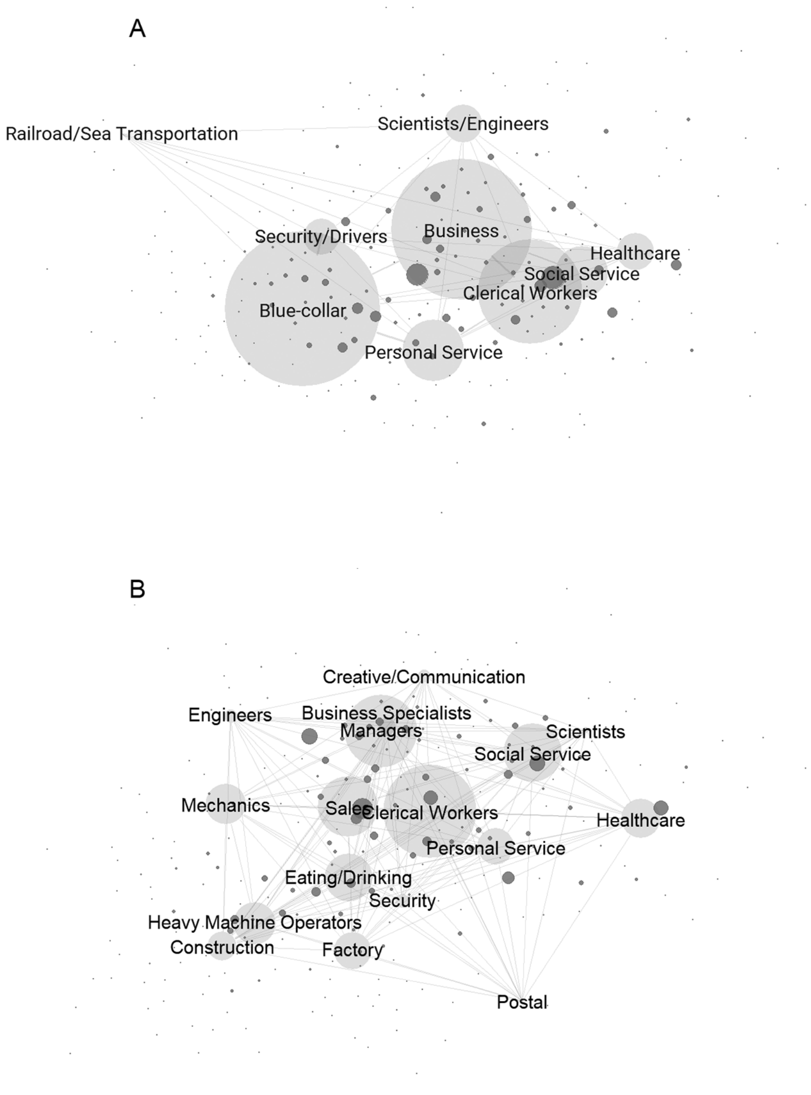

FIG. 4.—Main components of the U.S. labor market, 1983–92 (*A*) and 2008–17 (*B*). Each network has two layers. The first layer consists of detailed occupations (*solid circles*), which are located on the basis of weighted edges (not shown) using a Fruchterman-Reingold algorithm. The size reflects the number of workers holding the occupation. The second layer summarizes the occupations into the components (*shaded areas*) identified with the Louvain algorithm by combing the sizes and edges (shown) and taking the size-weighted average location. Color version available as an online enhancement.

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. The 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: 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:

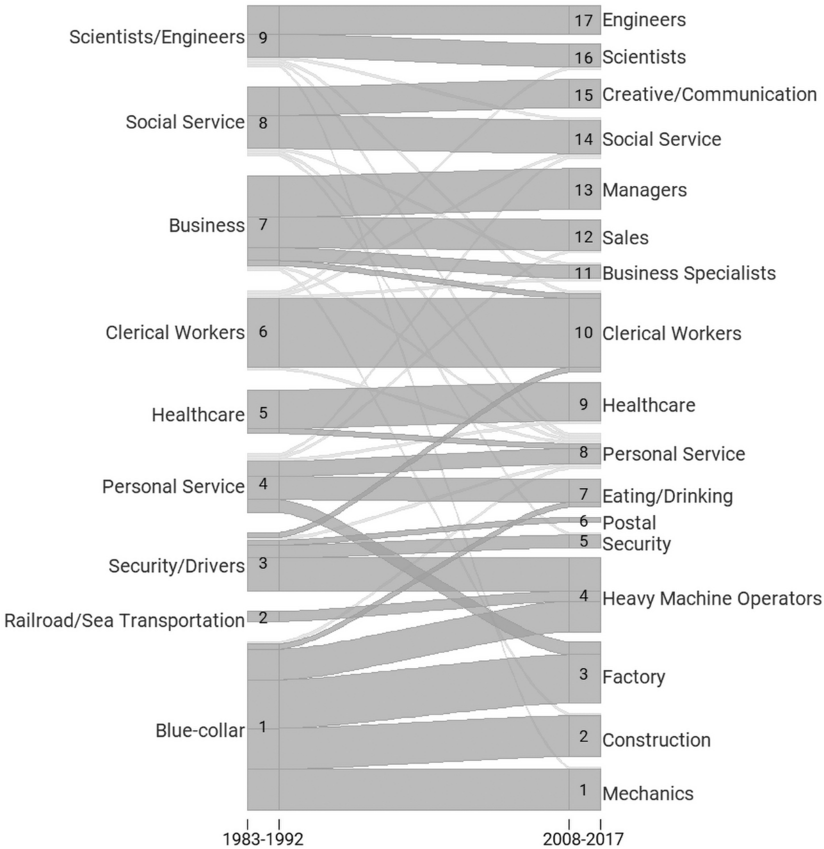

FIG. 5.—Fragmentation of communities from 1983–92 to 2008–17. Communities correspond to those identified in figure 4. Communities identified for 1983–92 are shown on the left, and those for 2008–17 are on the right. The width reflects the number of occupations, not the number of workers. We assign 42 singular movements (17% of all occupations) with light gray to simplify the presentation. These are cases in which only one occupation links two communities. Color version available as an online enhancement.

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 because of 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 eq. [1] for definition) by the 17 components (289 pairs) in 1983–92 and 2008–17. The percentage change $D_{i,j}$ between components i and j is calculated as

$$D_{i,j} = \left(\frac{\overline{\mathrm{E}_{i\leftrightarrow j,2008-17}} - \overline{\mathrm{E}_{i\leftrightarrow j,1983-92}}}{\overline{\mathrm{E}_{i\leftrightarrow j,1983-92}}} \right) \times 100. \tag{2}$$

Figure 6 shows that all but one of the 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

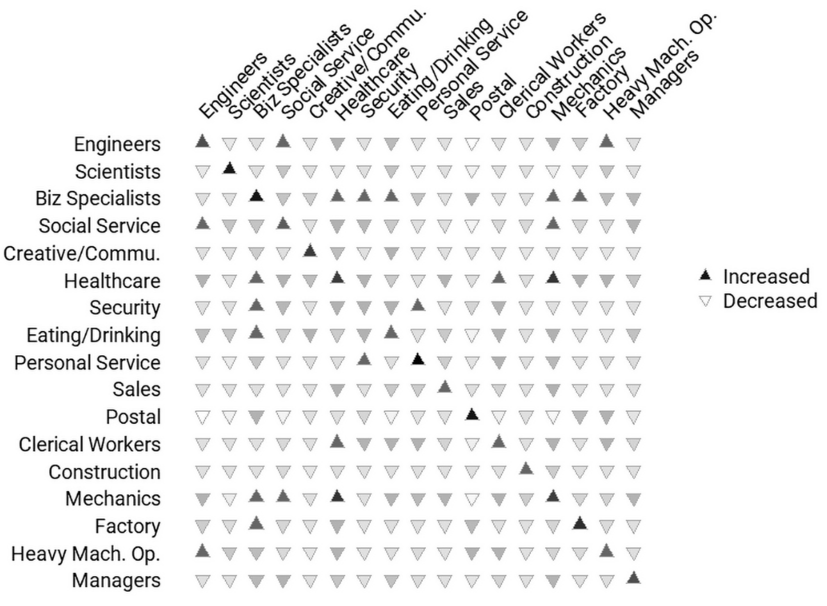

FIG. 6.—Percentage changes in average exchange rates by component pairs. We classify the detailed occupations into 17 components based on the Louvain method. An average exchange rate is calculated for all pairs of the 17 components for 1983–92 and for 2008–17. Changes are calculated using equation (3) 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 (∇) indicates a decrease. The density of color represents the magnitude of change.

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, the 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 the community detection methods. Together, these findings suggest that the documented increase in mobility (Kambourov and Manovskii 2008; Jarvis and Song 2017), 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 who 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.[14]

In addition, we draw a variety of items from the Occupational Information Network (O*NET; see Handel [2016*b*] for a recent review) to describe different dimensions of occupational content. The *cognitive* dimension includes the importance of verbal, quantitative, analytical, and 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.[15] Table 2 describes

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

[15] In cases in which 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.

TABLE 1
Occupational Attributes, CPS

Attribute/Period	Mean	SD	Max	Min
% Male:				
1983–92	60.75	31.22	Brick/block/stonemasons	Dental assistants
1993–2002 . . .	58.78	30.50	Loading machine operators	Secretaries
2008–17	58.76	29.17	Bus/truck mechanics	Dental hygienists
% White:				
1983–92	79.26	9.95	Vets	Parking lot attendants
1993–2002 . . .	73.91	11.54	Environmental scientists/ geoscientists	Parking lot attendants
2008–17	64.81	12.82	Vets	Packaging/filing machine operators
Median age:				
1983–92	38.21	2.41	Real estate brokers	Health practitioners
1993–2002 . . .	40.34	2.42	Librarians	Counter attendants
2008–17	43.05	2.62	Librarians	Bartenders
% College:				
1983–92	27.67	28.62	Dentists	Paving/surfacing equipment operators
1993–2002 . . .	29.15	29.19	Vets	Welding/soldering/brazing workers
2008–17	34.37	29.89	Judicial workers	Millwrights
Median ln wage:				
1983–92	3.00	.36	Dentists	Childcare workers
1993–2002 . . .	3.00	.37	Dentists	Childcare workers
2008–17	3.05	.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 in the last two columns.

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

$$\log_e(\mathrm{C}_{i\leftrightarrow j,p}) = \alpha_p + \sum_k^K \beta_{k,p}|A_{i,k,p} - A_{j,k,p}| + \beta_{1,p} I_{i,j,p} + \beta_{2,p}\log_e(O_{i,p} + O_{j,p}) + \varepsilon_{i\leftrightarrow j,p}, \quad (3)$$

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

TABLE 2
OCCUPATIONAL ATTRIBUTES, O*NET

Attribute	Item: Example	Item: N	Item: α	Max	Min
Cognitive:					
Verbal	Oral comprehension, written expression	4	.96	Management analysts	Vehicle cleaners
Quantitative	Mathematical reasoning, number facility	2	.97	Other math occupations	Maids
Analytical	Deductive reasoning, critical thinking	12	.96	Physicians/surgeons	Packagers
Creative	Originality, thinking creatively	3	.92	Artists	Maids
Spatial orientation	Spatial orientation, peripheral vision	8	.93	Taxi drivers/chauffeurs	Sales/street vendors
Physical:					
Control	Multilimb coordination, reaction time	7	.97	Crane operators	Management analysts
Strength	Gross body coordination, stamina	9	.97	Brick/stonemasons	Economists
Social:					
Interactive	Communicating outside organization, interpersonal relationships	8	.86	Social workers	Sewing machine operators
Supervising	Guiding and motivating subordinates, coaching and developing others	6	.95	Health service managers	Billing clerks
Environment:					
Discomfort	Extremely bright or inadequate lighting; cramped work space, awkward positions	6	.94	Bus/truck mechanics	Insurance underwriters
Physical Hazard	Exposed to hazardous equipment	4	.92	Electricians	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 following Liu and Grusky (2013). The occupations with the highest and the lowest values are listed in the last two columns.

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. When greater dissimilarity leads to fewer exchanges, $\beta_{k,p}$ and $\beta_{1,p}$ are expected to be negative.

Because dyads are nonindependent 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 squares and circles 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 on the basis of 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 1983–92 and 2008–17. Attribute-period interaction terms (shown in the fig. 7*C*) 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 nonsignificant in 1983–92 but turned significant in the later periods, suggesting a greater divide between older and younger occupations (Autor and Dorn 2009*b*).

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 remains 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.

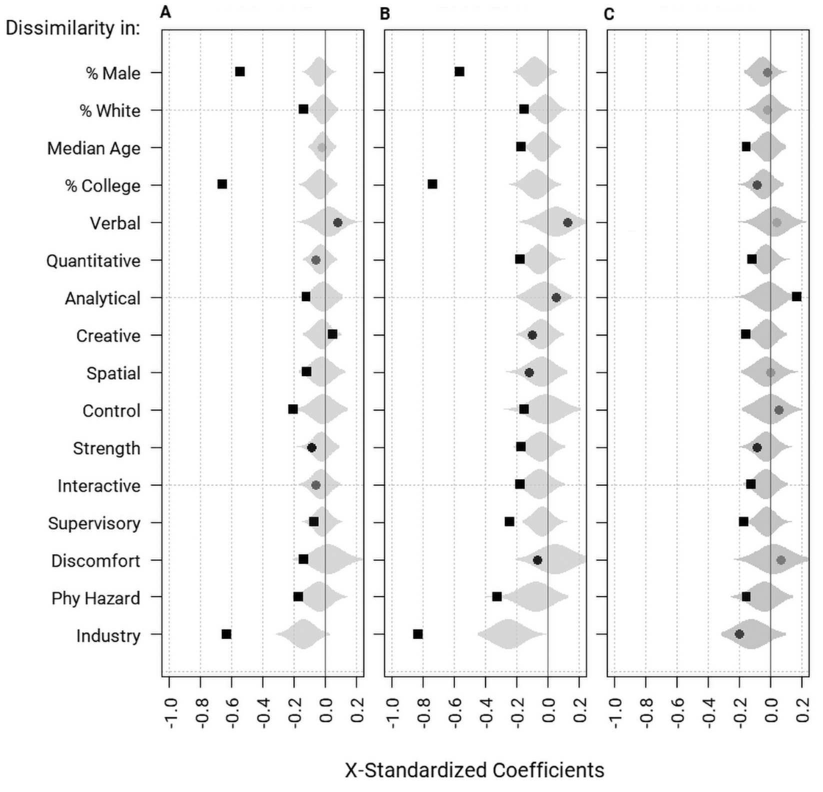

FIG. 7.—Negative binomial regressions predicting pairwise exchange: *A*, 1983–92; *B*, 2008–17; *C*, difference. Estimates are obtained from equation (3). All occupational attributes are standardized by period, except for industry, which is a dichotomous variable indicating whether the two occupations have different modal industries. The reference period is rotated to obtain period-specific estimates for *A* and *B*. *C*, Period-attribute interaction terms, which are the differences between 1983–92 and 2008–17. The null distributions are generated using the QAP 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 (●). Color version available as an online enhancement.

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 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 (Guvenen 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 1983–92 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 (fig. 5). Occupations that require strong spatial orientation tended to congregate, but the coefficient became nonsignificant in 2008–17. 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 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 ($N = 756$).[16] We first obtain an exchange-weighted average linked wage $G_{i,p}$ for each occupation period, defined as follows:

$$G_{i,p} = \frac{\sum_j^J (\mathrm{E}_{i\leftrightarrow j,p} W_{j,p})}{\sum_j^J \mathrm{E}_{i\leftrightarrow j,p}}, \tag{4}$$

where $\mathrm{E}_{i\leftrightarrow j,p}$, 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, $G_{i,p}$ varies by occupation and period, and it represents the exchange-weighted median wage of the linked occupations for occupation i in period p.

Because of 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 (Ord 1975; Leenders 2002). The first, a fixed effect (FE) model, is specified as

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

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, no 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

[16] 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.

the lagged dependent variable (LDV) for the second and third periods ($N = 504$):

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

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 wages 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 app. 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%–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 (fig. 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

TABLE 3
Partial Coefficients and Standard Errors Predicting Logged Median Wage

	FE		LDV	
	Equation (5)		Equation (6)	
Linked wage	.320**	(.110)	.225***	(.063)
Wage $t-1$			.725***	(.029)
Composition:				
% Male	.131	(.113)	.075***	(.022)
% White	.502***	(.120)	.209***	(.048)
Median age[a]	.274	(.282)	.224	(.162)
% College	.761***	(.116)	.182***	(.031)
Cognitive:				
Verbal			−.005	(.010)
Quantitative			−.006	(.007)
Analytical			.053***	(.012)
Creative			−.019**	(.006)
Spatial orientation			−.025**	(.009)
Physical:				
Control			.033**	(.012)
Strength[a]			.054	(.770)
Social:				
Interactive			.009	(.007)
Supervising			−.014**	(.005)
Environment:				
Discomfort			.016	(.014)
Physical hazard			−.022	(.011)
Period:				
1993–2002	.012	(.011)		
2008–17	.045	(.027)	.041***	(.011)
N	756		504	
R^2	.975		.955	

Note.—Occupation-clustered SEs are reported in parentheses. The occupational intercepts of the FE model are omitted from the table. Environmental wage is instrumented with the other linked attributes.

[a] Coefficient and SE are both multiplied by 100 to reduce decimal places.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

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 (see parts A and 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

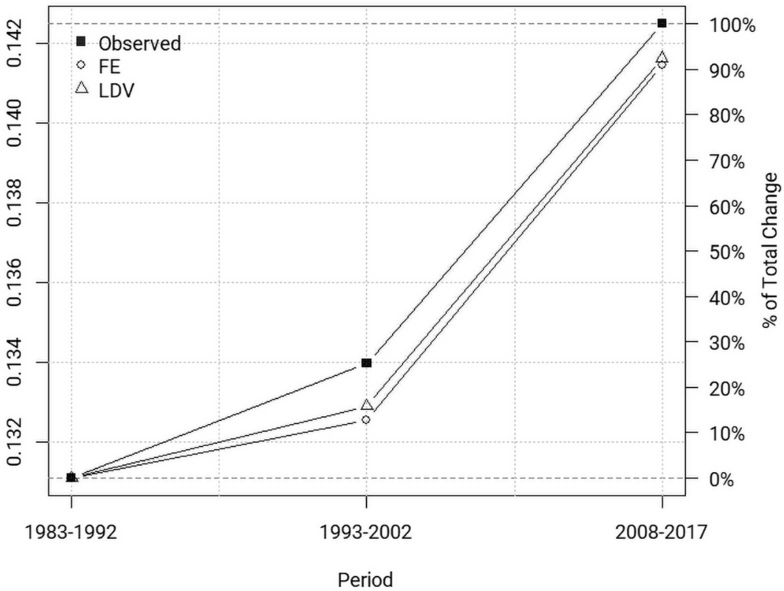

FIG. 8.—Observed and counterfactual between-occupation wage variance. Left axis indicates the between-occupation median logged wage variance. Right axis indicates the percentage of total change. Counterfactual trends are generated by (*a*) creating a data set in which the exchanges are constrained at their 1983–92 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. Color version available as an online enhancement.

occupational network remained as connected as in the initial period.[17] In practice, we constrain $E_{i\leftrightarrow j,p}$ at the 1983–92 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 1983–92.

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 the mobility pattern are associated with rising wage inequality in the U.S. labor market.

[17] 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 2010). 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 (2017) claim 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 the 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 earlier decades. It is no surprise that there has been an increase in emphasis on professional training in higher education and a divergence in returns 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 (fig. 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 (Osterman 1996; Cappelli 2015). 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 (Cappelli 1999; Bidwell 2011). Temporary or contractual work also makes it harder for workers 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 (Toubøl and Larsen 2017; Cheng and Park 2020), our article shows 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 other, nor is there 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.[18] The fractures observed in our analysis also

[18] In a separate analysis, we find quite a number of cases in which two closely linked occupations are assigned into two distinct microclasses. 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

suggest 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 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 adjacencies 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 the 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, however, 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 provides limited insights into individual mobility over the life course. Future studies may construct alternative networks with longer-term mobility and examine whether and in what ways the patterns differ. How to incorporate the concepts of trajectory (i.e., how past experience affects future

Workers, between Compliance Officers and Human Resources, Training, and Labor Relations Specialists; and 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 nonadjacent microclasses. These examples do not invalidate microclasses, 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 judgment can sometimes be made about how occupations should be grouped, a scientific study of occupational structure, ideally, should use all available evidence.

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 ascendancy of certain tasks was driven by increased productivity for these tasks or 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 started collecting information of tasks and skills in Occupational Requirement Surveys in 2018 for a limited set of occupations (Handel 2016*a*; Bureau of Labor Statistics 2020). When enough data are accumulated, these measures will not only 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., White 1970; Burris 2004; McDonald and Benton 2017). 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 the labor market.

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 microclasses (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.

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

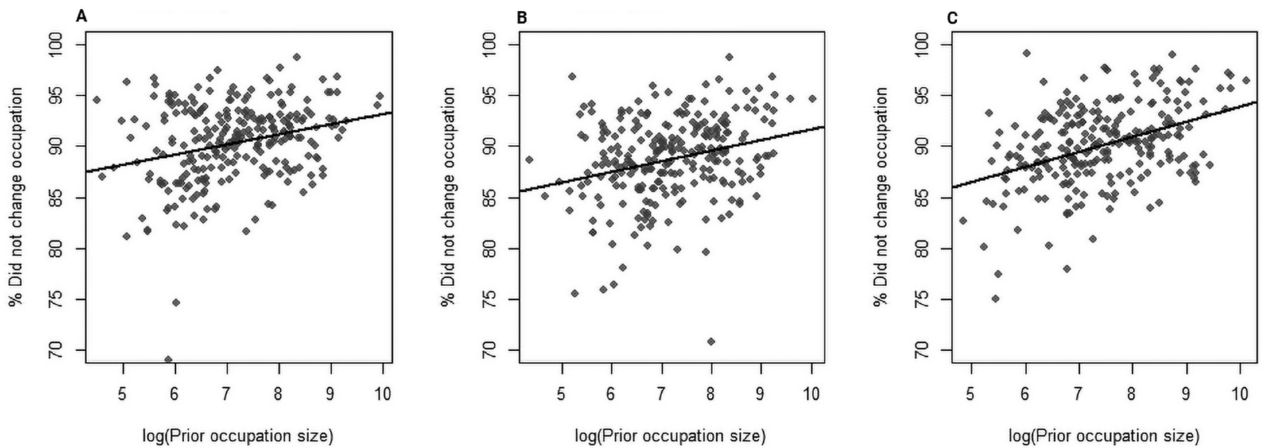

FIG. A1.—Distribution of occupation size and percentage remaining in the same occupation: *A*, 1983–92; *B*, 1993–2002; *C*, 2008–17. Color version available as an online enhancement.

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 (fig. 2) is robust when using more aggregated occupational classifications. Figure A2 presents the distribution of shortest distances when the 1950 code and microclasses are used for 2008–17 (depicted by the shading) and for 1983–92 (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 microclasses. 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.

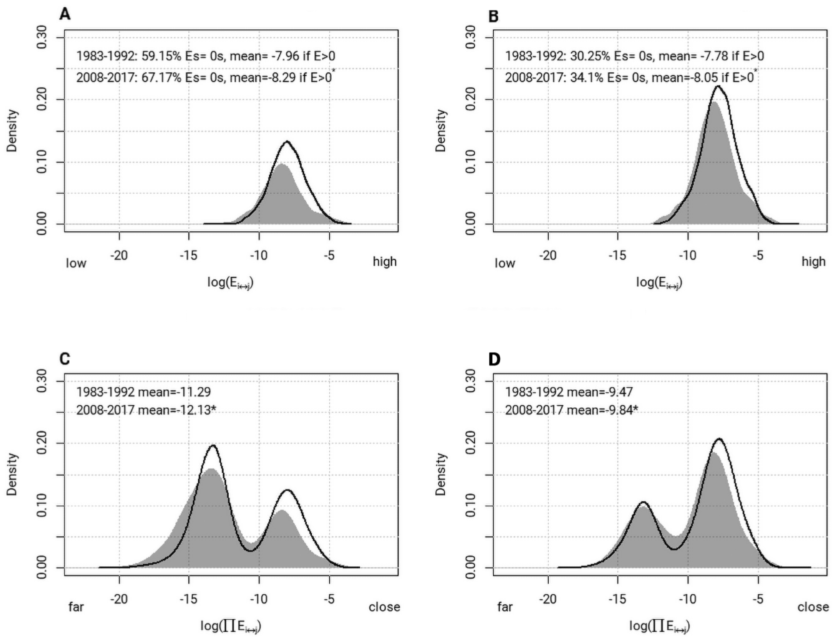

FIG. A2.—Distribution of exchanges and shortest distances, 2008–17 (*shading*) and 1983–92 (*solid line*): *A*, 1950 code direct exchanges; *B*, microclass direct exchanges; *C*, 1950 code shortest distances; *D*, microclass shortest distances. Color version available as an online enhancement.

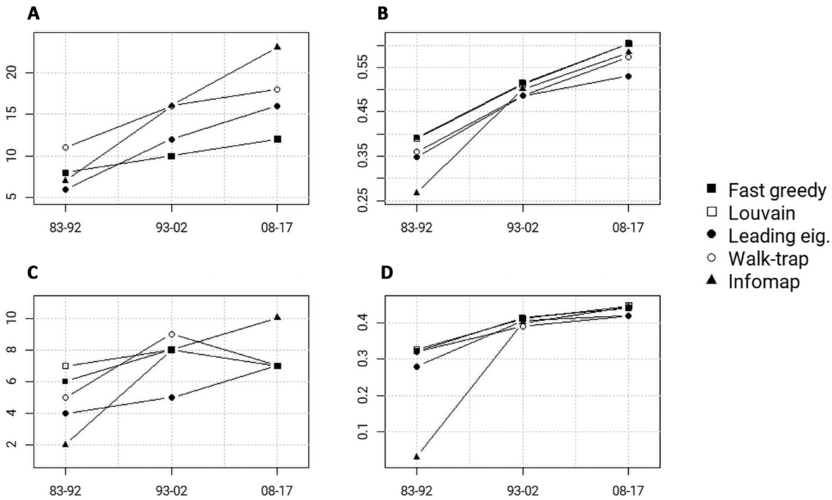

FIG. A3.—Number of communities and modularity scores by community detection algorithms: *A*, number of communities (1950 code); *B*, modularity (1950 code); *C*, number of communities (microclass); *D*, modularity (microclass). Color version available as an online enhancement.

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 microclasses 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 microclasses, 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.

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, and 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. Index R ranges from 0 (complete disagreement) to 1 (complete agreement).

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 (of which there are fewer) and the infomap communities (of which there are more; see fig. 3) for both the 1983–92 and 2008–17 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

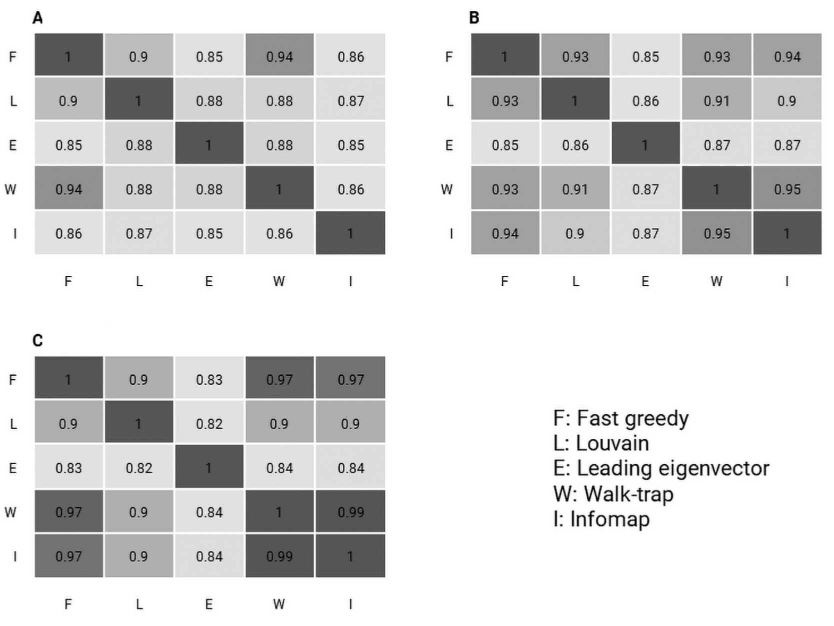

FIG. B1.—Rand Index comparing partition results: *A*, 1983–92; *B*, 1993–2002; *C*, 2008–17. Color version available as an online enhancement.

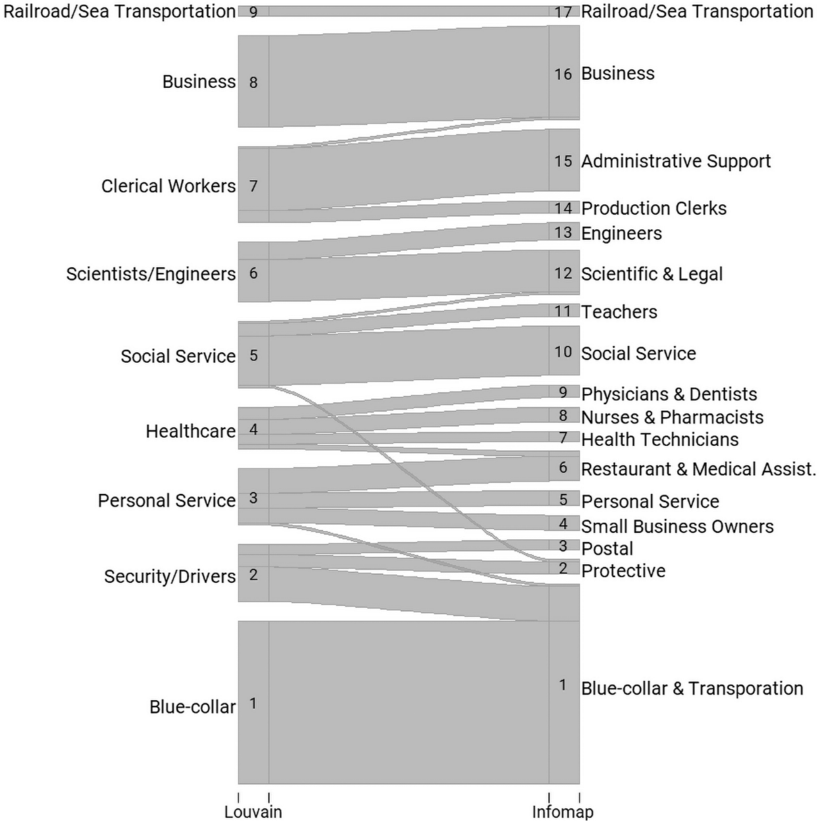

FIG. B2.—Comparing the Louvain and the infomap communities, 1983–92. Color version available as an online enhancement.

produces more communities (17 in 1983–92 and 35 in 2008–17), 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 indicates that 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.

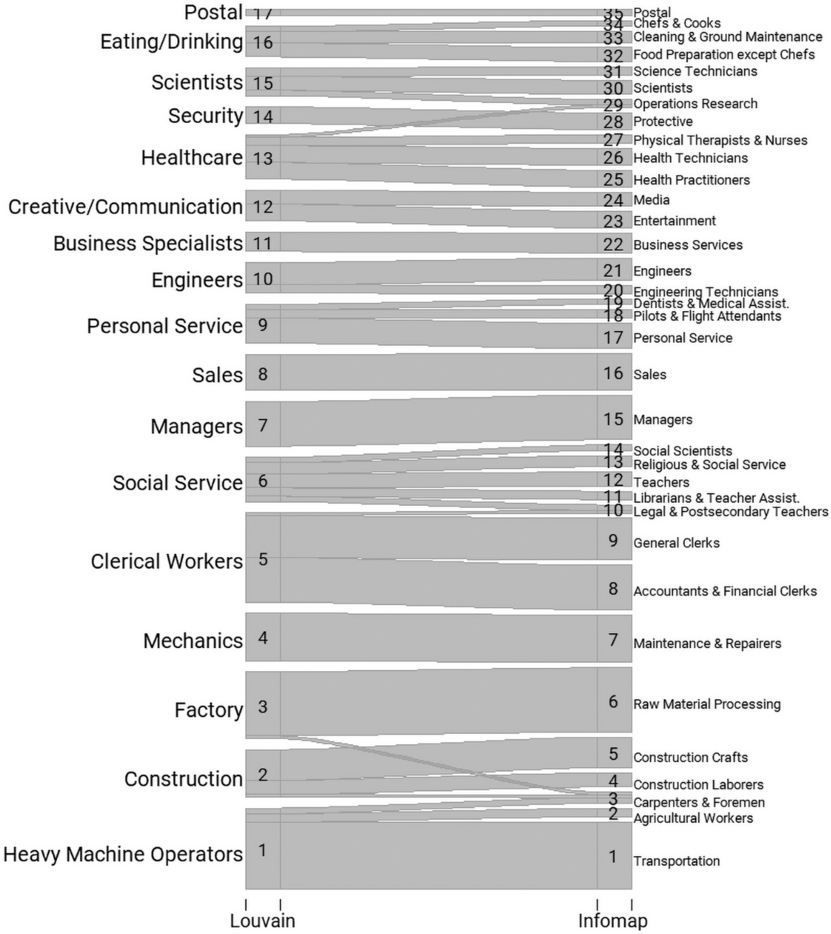

FIG. B3.—Comparing the Louvain and the infomap communities, 2008–17. Color version available as an online enhancement.

APPENDIX C

TABLE C1

FIRST-STAGE COEFFICIENTS AND CLUSTERED STANDARD ERRORS PREDICTING LINKED WAGE

	FE		LDV	
	Equation (5)		Equation (6)	
Wage $t-1$			.026***	(.005)
Linked attribute:				
% Male	.285***	(.065)	.307***	(.046)

TABLE C1 (*Continued*)

	FE		LDV	
	Equation (5)		Equation (6)	
% White	1.113***	(.203)	.967***	(.123)
Median age	.006	(.008)	.003	(.004)
% College	.838***	(.108)	.768***	(.059)
Cognitive:				
Verbal	−.060	(.042)	−.030	(.025)
Quantitative	.036	(.025)	−.00795	(.018)
Analytical	.177***	(.045)	.147***	(.022)
Creative	−.125***	(.024)	−.136***	(.015)
Spatial orientation	−.040	(.042)	−.028	(.021)
Physical:				
Control	−.003	(.048)	.066*	(.027)
Strength	−.087*	(.037)	−.099***	(.025)
Social:				
Interactive	−.014	(.036)	.083***	(.021)
Supervising	−.010	(.025)	−.020	(.013)
Environment:				
Discomfort	.191***	(.057)	−.015	(.041)
Physical hazard	−.038	(.060)	.141***	(.039)
Ego attribute:				
% Male	−.106**	(.034)	−.008	(.007)
% White	.008	(.040)	−.012	(.012)
Median age[a]	−.005	(.095)	−.111**	(.039)
% College	.036	(.035)	−.026***	(.008)
Cognitive:				
Verbal			−.002	(.003)
Quantitative			−.002	(.001)
Analytical			.002	(.003)
Creative[a]			−.007	(.163)
Physical:				
Spatial Orientation			.004	(.002)
Control			−.002	(.003)
Strength			−.005**	(.002)
Social:				
Interactive			−.001	(.002)
Supervising			.001	(.001)
Environment:				
Discomfort			−.007*	(.003)
Physical hazard			.003	(.003)
Period:				
1993–2002	.043*	(.021)		
2008–17	.135**	(.052)	.093***	(.016)
N	756		504	
R^2	.980		.983	

NOTE.—Occupation-clustered SEs are reported in parentheses. The occupational intercepts of the FE model are omitted from the table.

[a] Coefficient and SE are both multiplied by 100 to reduce decimal places.

* $P < .05$.

** $P < .01$.

*** $P < .001$.

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