Flows and Boundaries: A Network Approach to Studying Occupational Mobility in the Labor Market[1]

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Although stratification research has long recognized the importance of mapping out the underlying boundaries that govern the flow of workers in the labor market, the current literature faces two major challenges: (1) the determination of mobility boundaries and (2) the incorporation of changes in mobility boundaries. The authors propose a network approach to address these challenges. The approach conceptualizes the occupational system as a network, in which the nodes are occupations and the edges are defined by the volume and direction of workers who move between the nodes. A flow-based community detection algorithm is introduced to uncover mobility boundaries based on the observed mobility network. Applying this approach to analyze trends in intragenerational occupational mobility in the United States from 1989 to 2015, the authors find that the boundaries that constrain mobility opportunities have become increasingly rigid over time, while, at the same time, decoupled from the boundaries of big classes and microclasses. Moreover, these boundaries are increasingly sorting workers into clusters of occupations with similar skill requirements.

INTRODUCTION

That the labor market consists of a constellation of occupations connected by flows of workers has been a long-standing thesis in the scholarship on

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stratification, labor markets, and occupations. In the status attainment model, the opportunities of movement between job positions shape the patterns of intragenerational mobility, which determine individuals' subsequent socioeconomic attainment (Blau and Duncan 1967; Sørensen 1977; Featherman and Hauser 1978; Erikson and Goldthorpe 1992); in the literature on occupational classes, the latent boundaries that facilitate or constrain worker flow between different sets of occupations are considered a key structural aspect of the occupational system (Giddens 1973; Breiger 1981, 1990; Sørensen 2000; Weeden and Grusky 2005), and the rigidity of such boundaries reflects the fluidity of the labor market (Featherman and Hauser 1977; DiPrete 1993; Moscarini and Thomsson 2007; Jarvis and Song 2017); and in the scholarship on career processes, the labor market is depicted as a system of interconnected career lines linking job positions to one another, the structure of which separates these positions into different categories (Sørensen 1975; Spilerman 1977; Rosenfeld 1992).

Collectively, these strands of research illuminate the usefulness of mapping out the *boundaries* that govern the *flow* of workers to understand the occupational system. They have motivated decades of empirical research examining the structural constraints and opportunities that individuals face when they move from occupation to occupation.[2] Following this tradition, we treat the flows of workers and the boundaries constraining these flows as an analytical basis through which labor markets or occupational systems can be studied. Mobility boundaries partition occupations into groups within which mobility is frequent and across which mobility is rare. The *constellation* of mobility boundaries represents the opportunity structure faced by workers

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[2] For example, these research topics include the extent to which the movements of workers from job to job are constrained by structural boundaries (Hauser 1980; Hout 1984; DiPrete 1987; Stier and Grusky 1990), how jobs or occupations can be grouped into clusters by volumes of worker flows between them (Breiger 1981; Goodman 1981; Snipp 1985; Schmutte 2014; Melamed 2015; Toubøl and Larsen 2017), and how these boundaries shape the socioeconomic standings and life course trajectories among individuals traversing the stratification system (Sørensen 1977; DiPrete 2002; Kambourov and Manovskii 2009; Cheng 2014).

after entering the labor market; the extent to which the opportunity structure constrains the worker flow is, on the other hand, reflected in the *rigidity* of the mobility boundaries. We will refer to the clusters of occupations grouped together by mobility boundaries as *mobility classes*. We emphasize that mobility classes, as here defined, are distinct from *occupational classes* analyzed in previous work, as the former are explicitly defined in terms of mobility patterns while the latter are often not. Thus, mobility boundaries may crosscut, rather than coincide with, occupational class boundaries: transcending mobility boundaries does not necessarily involve changes in one's class position, nor does a change in one's class position necessarily involve movements across mobility boundaries. In sum, not only do mobility classes and occupational classes tap into different aspects of the occupational system, but the degree to which they are aligned or dealigned poses an important empirical question regarding the structure of the occupational system.

While the notion of flows and boundaries appears frequently in the literature, empirical researchers have faced two main challenges in operationalizing it. The first challenge is the determination of boundaries that constrain worker flows. Most research on occupational mobility starts from predetermined occupational classes, which are defined based on criteria such as the sectoral division of labor (Blau and Duncan 1967; Featherman and Hauser 1978; Erikson and Goldthorpe 1992), authority and control in the production process (Wright 1979; Western and Wright 1994), or the institutionalized division of labor at the microlevel (Weeden 2002; Weeden and Grusky 2005). While these analyses have made significant progress toward mapping out mobility patterns between occupational classes, insufficient attention has been paid to the detailed occupation-to-occupation flows that are essential for identifying the latent boundaries that directly constrain the mobility chances of workers at finer levels. Furthermore, any analysis that treats occupational classes as the starting point to examine mobility patterns will not be able to identify boundaries that cut through the class system: by starting from classes instead of detailed occupations, all identified mobility boundaries will necessarily lie between classes but never within them. This challenge has motivated empirical work to cluster occupations according to observed mobility patterns using various types of network algorithms (Snipp 1985; Schmutte 2014; Melamed 2015; Toubøl and Larsen 2017). However, an adequate account of mobility boundaries requires not only a framework to identify the barriers to observed worker flows but also a systematic approach for examining how the mobility boundaries deviate from class boundaries defined by other criteria as well as how these patterns change over time. This study addresses both aspects.

The second challenge, which is related to the first, is how to account for changes in the boundaries over time. One commonly adopted assumption in previous mobility studies is that the occupational classes remain stable and that only the rigidity of the class boundaries is subject to change. For example, mobility studies have examined changes in the fluidity of class boundaries by comparing between-class mobility rates under a time-invariant occupational class scheme (Featherman, Jones, and Hauser 1975; Erikson and Goldthorpe 1992; Xie 1992). However, standard methods for analyzing mobility trends under fixed occupational class schemes may not be readily applicable to the analysis of mobility boundaries, because the boundaries constraining mobility opportunities themselves constantly evolve, breaking down old clusters and forming new ones. Without adapting the boundaries to reflect such labor market changes, researchers may run the risk of conflating changes in boundaries themselves with changes in their rigidity. Hence, the over-time change in mobility boundaries necessitates the development of an approach that simultaneously deals with both changes in the constellation of mobility boundaries as well as changes in their rigidity. It also suggests that the relation between mobility boundaries and occupational class boundaries might change, with periods when class positions and mobility opportunities are tightly consolidated and periods when these two are only loosely coupled.

This article advances the literature on occupational mobility in the labor market by proposing a network approach for addressing these two challenges. We conceptualize the occupational system as a directed, weighted network in which the "nodes" are detailed occupations and the "edges" are defined by the volume of workers who move between the nodes, where the directions of edges align with the directions of worker flows. We then use a community detection algorithm, known as the Infomap (Rosvall and Bergstrom 2008), to inductively identify boundaries of occupational mobility based on a hypothetical flow on the network. Heuristically, the algorithm finds a partition scheme such that a hypothetical "random walker" who navigates the occupational system following the observed mobility rates will spend a long time within a given cluster before moving to a different cluster. This heuristic aligns with the notion of labor market boundaries we described at the beginning: a proper set of mobility boundaries should be such that the average worker will find it easier to move within the boundaries than to move across them.

We use the network approach to analyze trends in intragenerational occupational mobility in the United States from 1989 to 2015. Our empirical analysis serves two aims. The first aim is to detect mobility boundaries based on observed mobility patterns: we identify the boundaries of mobility classes based on a nationally representative sample of workers, describe how these boundaries have evolved over time, and use a generalized modularity measure to evaluate how the rigidity of these boundaries has changed.[3] The second aim

[3] Modularity is a widely used measure in the network literature that quantifies the strength of clustering structures. Formal definitions of modularity and their generalizations are presented in the data and measures section.

is to compare the detected mobility boundaries with other occupational classification schemes that are commonly adopted in the stratification literature. The comparison involves three aspects: (1) the level of agreement between the derived partition scheme based on mobility patterns and other class schemes, (2) the degree and trends in the rigidity of the derived mobility boundaries versus the rigidity of other class boundaries in constraining worker flows, and (3) the explanatory power of the mobility boundaries in predicting occupational and individual differences in labor market outcomes.

To anticipate the results, we find that the boundaries constraining worker flows have become increasingly dissimilar from the boundaries of big classes and microclasses. Further, the boundaries in the American labor market have become increasingly rigid in constraining the flow of workers, particularly in the post-2009 era. The growing barriers to occupational mobility are not fully captured by either big classes or microclasses, implying that analysis relying only on the between-class mobility rate may overstate the fluidity in the labor market and understate the growth of its rigidity over time. Finally, we find that occupational skill sets are becoming increasingly important in shaping the mobility pattern in the labor market. Overall, the findings not only illuminate the payoff of adopting the proposed network approach in the analysis of labor market mobility but also point to important substantive implications regarding the occupational system, which we discuss at the end of the article.

Flows and Boundaries as an Analytic Basis to Study the Occupational Systems

Boundaries that constrain worker flows have been long considered a core structural aspect of the labor market (Beshers and Laumann 1967; Sørensen 1977; Spilerman 1977; Breiger 1981). Following this tradition, we invoke the *occupation-to-occupation flows* and the latent *boundaries* that constrain these flows as an analytic basis for understanding labor market structures. The idea to use the containment of worker flows within mobility boundaries to group occupations might be traced back to Weber's discussion of *social classes*, which consist of "the totality of those class situations within which individual and generational mobility is easy and typical" ([1922] 1978, p. 302). A similar, although less explicit, view that points toward the importance of worker flow constraints can be found in neo-Marxists studies on the (im)permeability of class boundaries (Western and Wright 1994; Wright 1996). Stratification research has subsequently elaborated on the notion of flows and boundaries to shed light on how movements of workers transcend subdivisions of the labor market (Sorokin 1927; Giddens 1973; Breiger 1981; DiPrete et al. 1997; Schmutte 2014; Melamed 2015; Toubøl and Larsen 2017). For example, the inherent connection between flows and boundaries is articulated in Blau and Duncan's seminal study of the American occupational system and serves as a guiding principle throughout their analyses: "The structure of relations among these occupational groupings is defined in terms of the flow of manpower between them through time, either intergenerationally or intragenerationally. Each occupation is characterized by the inflow or recruitment of its manpower from various origins, on the one hand, and by the outflow or supply of sons to various destinations, on the other" (1967, p. 24).

Metaphorically, we might conceptualize the movement of workers as a flow through latent "channels" that connects different occupations to one another. Each of these channels will have its own "width," reflecting how easy it is for workers to move between a pair of occupations. Boundaries correspond to cleavages in the labor market across which channels for movement are absent or where their width is relatively narrow. In constraining the flow of workers, these boundaries partition the occupations into groups within which mobility is frequent and across which it is sparse. Hence, the widths of these channels and their constellation form a key structural aspect of the labor market in that they reflect the opportunities and constraints that workers face when moving through it (Sørensen 1977; Spilerman 1977; Kalleberg and Sorensen 1979; Breiger 1981; Rosenfeld 1992; Kalleberg and Mouw 2018).

The arrangements of the channels in the labor market are shaped by various factors, such as the movement of vacancies (White 1970; Chase 1991; Rosenfeld 1992), the structuration of career lines (Spilerman 1977), closure strategies (Weeden 2002; Redbird 2017), and the flow of job information (Rosenfeld 1992; Granovetter 1995), among others. The observed occupational worker flows are best described as the realization or manifestation of the underlying boundaries created and maintained through these mechanisms. The analysis of observed mobility patterns enables us, therefore, to depict where these boundaries are drawn, how rigid they are, and how they are aligned with or crosscut other dimensions of occupational stratification.

Finally, examining the flows and boundaries of intragenerational occupational mobility is conducive to documenting how the structure of the labor market as well as the process of stratification in society has shifted over time (Featherman and Hauser 1977; DiPrete 1993; Moscarini and Thomsson 2007; Jarvis and Song 2017). Further, given the critical role occupation plays in shaping socioeconomic inequality cross-sectionally (Mouw and Kalleberg 2010; Weeden and Grusky 2012; Zhou and Wodtke 2018), over the life course (Warren and Hauser 1997; Kambourov and Manovskii 2009), and across generations (Jonsson et al. 2009), examining the evolution of mobility boundaries and how they constrain worker flows will lend new insights into the trends in inequality more generally.

Mobility Boundaries as Distinct from Occupational Class Boundaries

In order to study occupational mobility, prior research has mainly relied on occupational class schemes as a starting point. There are two major types of occupational class regimes in the literature. The first is the *big-class regime*, organized around categories such as professional occupations, managerial occupations, proprietors, and routine nonmanual occupations. The boundaries of big classes may constitute barriers to occupational mobility. For example, it is rare for workers to move from the routine nonmanual class to the proprietors class, because the latter requires entrepreneurial skills and a specific set of cultural capital, which are often not developed within routine nonmanual occupations. The second is the *microclass regime*, which contends that the stratification system is organized around smaller, disaggregated occupational groups (i.e., microclasses; Jonsson et al. 2009; Weeden and Grusky 2012). The microclass regime predicts that the flows of workers are constrained by finer-grained barriers within the big classes. The main argument is that the major hurdles to occupational mobility—such as the operation of closure strategies, acquiring licenses or certificates, and occupational skills—are institutionalized at a much smaller scale than the macroclasses.

However, because the class boundaries in big-class and microclass regimes are not derived directly using the criterion of mobility, it is important to recognize that they may not provide an adequate representation of the latent boundaries that constrain worker flows. For example, labor market restructuring—shrinkage of certain types of occupations and expansion of others—can lead to flows of workers that cut across the boundaries of big classes. Consider, for instance, the falling cost of automating routine job tasks, which has relocated routine nonmanual labor to the low-skill service sector (Autor and Dorn 2013). When such relocation happens, the boundaries between the routine nonmanual and lower service classes may no longer represent the "true" barriers to mobility. A second example is the rising demand for programming skills that has expanded out of the information technology industry and spread to a broader range of professional occupations, such as jobs in the financial sector and business service sector (Cheng, Chauhan, and Chintala 2019). This means that individuals who possess programming skills are now able to move between jobs that belong to seemingly distant microclasses (e.g., from being a computer systems analyst to being a marketing analyst), and in consequence, the boundaries between these microclasses may no longer stand as a structural barrier to mobility.[4] Finally, geographic constraints

[4] Indeed, several other studies suggest that job switchers can carry their skill set across a broad range of occupations that belong to different sectors, given that they share some commonality in the skill requirements (Poletaev and Robinson 2008; Gathmann and Schönberg 2010).

on local labor markets may also bundle together seemingly disparate occupations into the same mobility class. The boom of the oil industry in rural North Dakota, for instance, may have created flows of local workers between low-skill service jobs such as cashiers in Walmart to fracking-related jobs in the expanding oil companies.[5] The above discussions corroborate the argument that mobility boundaries represent a unique dimension of occupational systems that is analytically distinct from the groupings defined by the big-class and microclass regimes. This argument underscores the value of analyzing mobility boundaries themselves, which is a primary goal of this study.

In addition to being distinctive from occupational class boundaries, the constraints on worker flows carry their own sociological significance for both individuals and theories of the labor market. First, adopting the viewpoint of individuals, being able to move more freely across segments of the labor market enables them to consider a greater set of options in their career decisions. Constraints on mobility may thus limit individuals' ability to select occupations and careers that best fit their training background and personal preference. Moreover, the mobility constraints faced by workers would influence their lives in a way that extends beyond job switches. For example, if some mobility clusters are concentrated within specific geographical regions, workers would face growing constraints in their ability to move geographically as the rigidity of mobility boundaries increases (Kleiner, Gay, and Greene 1982; Moretti 2012).

Second, adopting the viewpoint of the labor market as a whole, the rigidity of mobility boundaries affects aspects of the occupational system that are central to several theoretical perspectives on work and occupations. For theories on vacancy chains, rigid mobility boundaries can reduce the accessibility of job vacancies to workers located at different segments of the labor market, as some workers would have to overcome mobility barriers in order to move toward parts of the labor market where the vacancies are created. For theories on occupational closure, the constraints imposed by mobility boundaries may create new or reinforce preexisting categorical distinctions between occupations, making it easier for some groups to secure resources through closure strategies such as opportunity hoarding (Tilly 1998; Tomaskovic-Devey et al. 2009). If, for example, mobility boundaries around a cluster of managerial positions become more rigid over time, it will become harder for workers outside of the cluster to move into these occupations. Such constraints on access can give current practitioners in these occupations greater power to legitimate and exacerbate inequality between themselves and other segments of the labor market.

In sum, mobility boundaries induce a categorization of occupations that is analytically distinct from occupational class categories. Constraints on

[5] We thank the anonymous reviewer for directing our attention to geographical factors that influence mobility boundaries.

mobility have implications for individuals' lives as well as the labor market as a whole. Examining these mobility boundaries has the potential to add new depth and complexity to our understanding of the occupational system, beyond what we have already learned from the long-standing occupational class literature.

TWO CHALLENGES IN RESEARCH ON OCCUPATIONAL MOBILITY

The preceding discussion illustrates the theoretical relevance of flows and boundaries as the analytic basis for understanding the occupational system. We build on these long-established ideas and expand them to address challenges in the empirical analysis of labor market mobility. We begin by discussing two major challenges in empirical research on intragenerational occupational mobility. Thereafter, we describe in detail a network approach that helps address these challenges.

Challenge 1: How to Determine Boundaries of Worker Flows

The empirical analysis of occupational mobility often requires defining a scheme that aggregates detailed occupations into occupational groups. These aggregation schemes, also referred to as an "occupational class scheme," are usually determined *before* the analysis of mobility patterns. In the analysis of labor market mobility, the choice between aggregate versus disaggregated occupational classes involves, on the one hand, a trade-off between the granularity and the parsimony of the occupational class scheme and, on the other, a decision about the theoretical focus of the analysis (Erikson and Goldthorpe 1992; Grusky and Weeden 2001; Erikson, Goldthorpe, and Hällsten 2012). The accumulated theoretical and empirical knowledge about the occupational system helps lay out the most important properties that an aggregation scheme of occupations should satisfy. For example, a boundary could be drawn between the agricultural and nonagricultural occupations to represent the strong sector barrier (Blau and Duncan 1967; Xie and Killewald 2013); finer-grained boundaries can also be drawn within these sectors if one wants to capture the institutionalized division of labor (Weeden and Grusky 2005).

However, existing occupational class schemes are often not explicitly defined in terms of constraints on worker flows. Thus, the examination of between-class worker flows will reflect the constraints on mobility only to the extent that the defined class schemes coincide with the underlying barriers to mobility. For example, in the extreme case in which the labor market has "perfectly" rigid boundaries, in the sense that no worker is able to cross any of them, half of all occupational mobility would be labeled as between-class mobility if the defined occupational class boundaries and the mobility boundaries are orthogonal to each other. The flow of workers will appear to be fluid across class boundaries, while they are strictly constrained by mobility boundaries. To be sure, the extent to which class boundaries and mobility boundaries actually overlap with each other remains an empirical question—one that our empirical analysis later will shed light on—but the key point is that, in order to derive valid conclusions on the fluidity of the labor market, detecting the boundaries that constrain worker flows at the occupational, rather than class, level is an important prerequisite.

To address this challenge, Breiger (1981) and Goodman (1981) proposed an approach to defining occupational class schemes based on observed mobility patterns. They tackle the problem by postulating explicit criteria for testing why and whether certain categories in the occupational mobility table should be combined in light of the observed rates of mobility. While Breiger (1981) proposed a theoretically informed framework that incorporates testable principles, Goodman (1981) elaborated on various statistical strategies for testing these hypotheses. A guiding principle for this approach is the emphasis on the "duality with respect to interclass mobility and occupational mobility" (Breiger 1981, p. 603). That is, occupational origins and destinations should be independent within classes (indicating internal homogeneity), while between-class mobility is characterized by the dependence of destination class on origin class (indicating a structured class system; Breiger 1981; Goodman 1981).

This line of work presents an important step forward, as it allows researchers to start with not a single but instead several candidate class schemes. Moreover, the authors also provide theoretically meaningful criteria for selecting a preferred scheme out of a handful of candidate schemes that can be checked against the observed mobility patterns. However, these criteria may pose a significant computational challenge in their empirical implementation, because as the number of occupational categories gets larger, evaluating all possible partition schemes in the prevailing log-linear approach will be prohibitively intensive to compute.[6] These limitations call for an approach that is more flexible and efficient in detecting the groupings that reflect the occupational mobility structure. Notably, several previous studies have taken some first steps to inductively detect mobility boundaries based on observed occupational mobility patterns, relying on methods such as smallest space analysis (Snipp 1985), modularity-based community detection techniques (Schmutte 2014; Melamed 2015), and clique-based agglomerative algorithms (Toubøl and Larsen 2017).[7] Like these studies, ours employs a "bottom-up" approach for detecting

[6] We return to the technical details later in the section that compares the methodological differences between log-linear models and the approach adopted in this article.

[7] While an extensive review is beyond this study, we note that outside of sociology, the notions of networks, flows, distances, and boundaries have been adopted by other realms of mobility research in general, such as geographic mobility (Gallotti and Barthelemy 2014) and global trade (Fagiolo, Reyes, and Schiavo 2009).

boundaries using mobility data. Meanwhile, our approach advances this emerging literature by considering the time-varying nature of mobility boundaries and multistep connections between occupations.

Challenge 2: How to Incorporate Changes in Mobility Boundaries

The second challenge stems from another central focus of the stratification literature: the historical changes in the mobility system. To date, the literature has focused primarily on historical changes in the rigidity of between-class mobility patterns—that is, whether it has become more or less difficult to move from one occupational class to another across generations or individuals' careers. Yet, most studies assume, in effect, that the occupational classes themselves are invariant over time. This assumption is necessary to separate out changes in mobility patterns from changes in the underlying class structure. Consequently, discussions on over-time changes in the occupational system have focused almost exclusively on changes in between-class mobility patterns, such as between-class mobility rates, exchange mobility rates, and upward mobility rates, conditional on the assumption that class boundaries remain invariant over time (Featherman et al. 1975; Erikson and Goldthorpe 1992; Xie 1992).

However, the latent mobility boundaries that constrain worker flows themselves may evolve over time. While direct assessment of changing mobility boundaries is lacking, we know from ample empirical evidence that the opportunity structure of the labor market is constantly evolving in various ways.[8] These changes are likely to lead to changes in the opportunity structure that individuals face as they navigate through their careers and, in consequence, the boundaries to occupational mobility. For example, the enactment of licensing laws may create a set of institutional mechanisms that alter the locale and rigidity of occupational boundaries over time (Law and Kim 2005; Redbird 2017), and the proliferation of computer and information technology can increase the demand for programming-related skills in a large number of professional occupations, which may help reduce the mobility barriers for workers with such skills (Shaw 1987; Gathmann and Schönberg 2010; Cheng et al. 2019). In all likelihood, these mechanisms suggest that the boundaries that constrain the flow of workers may have shifted over time.

Provided that the underlying mobility boundaries can change, the assumption of time-invariant class boundaries may result in inaccurate

[8] These changes include, among others, the changing forms of closure strategies (Redbird 2017), the decline of unions (Western and Rosenfeld 2011; Rosenfeld 2014), the changing skill demand and the skill endowment of the workforce (Breen and Jonsson 2005), economic restructuring (DiPrete 1993; Autor and Dorn 2013), and the rise of precarious and nonstandard work (Kalleberg 2011).

accounts of the changing structure of the labor market. For example, suppose the labor market becomes more specialized so that a larger class C splits into two smaller but distinct mobility classes, $C1$ and $C2$. In other words, the boundary between $C1$ and $C2$ becomes more rigid over time, so that they end up separating into two sets of occupations between which workers rarely move. Also suppose that other parts of the occupational system remain unchanged. Then, if we stick to a time-invariant class scheme that aggregates $C1$ and $C2$ into a single class C, movements of workers within class C would be simply considered as within-class mobility. As a result, we would report no changes to the mobility pattern, whereas in fact the labor market has become more segmented. More complicated boundary changes can similarly occur, such as *migration* (a small group of occupations migrating from one class to another) or *merging* (several smaller classes combining into a larger class).

Thus, in order to understand changes in occupational mobility, it is necessary to move beyond time-invariant class schemes and, instead, allow for a more flexible account of changes in the occupational system. Along this line, a number of studies have examined whether different class schemes, such as big classes or microclasses, have become more or less powerful in explaining variations in socioeconomic outcomes over time (Weeden and Grusky 2005, 2012). While this approach is applicable to mobility patterns as well, it still relies on the assumption that each of the tested schemes remains fixed; it is only their explanatory power that changes. Hence, if we would find that the association of a class scheme with mobility patterns weakens, it would be impossible to know whether this is due to the dealignment of mobility boundaries with class boundaries or whether the rigidity of the mobility boundaries themselves has weakened. Indeed, as Weeden and Grusky thoughtfully noted, "If this scheme is progressively less accurate in capturing the true boundaries and institutionalized divides in class structure, we may see a decline in class effects simply because of ever-poorer measurement" (2012, p. 1765).[9]

To overcome these limitations, we use a fully flexible specification of the schemes to allow for changes in mobility boundaries over time. Specifically, not only do we use an algorithm to characterize the boundaries constraining worker flows, but we also allow the detected boundaries to change from year to year. This ensures that, when we examine the over-time trends of mobility, we will have simultaneously accounted for the changes in both the location and the rigidity of the mobility boundaries.

[9] In principle, it would be possible to implement the microclass scheme in a time-varying form to constantly update the scheme with the changing boundaries. Yet, we are not aware of a systematic effort to operationalize this time-varying form.

A NETWORK APPROACH TO STUDYING OCCUPATIONAL MOBILITY

The Mobility Table as a Weighted Network

We treat the patterns by which workers change their occupations as a weighted network, where the occupations are regarded as a set of nodes that are connected by directed and weighted edges. The weight of an edge (i, j) reflects how many workers changed their occupation from i to j. In general, the weight of the edge (i, j) is not necessarily equal to that of (j, i), as there might be more individuals moving from i to j than the other way around. It is not difficult to see that the adjacency matrix of such a network, W, with entries w_{ij} corresponding to the number of individuals moving from occupation i to j, is exactly the standard occupational mobility table. Hence, conceptualizing the mobility table as a weighted network is simply a different representation of the same information.

Still, conceptualizing the mobility table as a network has substantive implications. Most importantly, network scholars have long realized that networks carry flows on them in form of information (Granovetter 1973; Rapoport 1979), influence (French 1956; Friedkin and Johnsen 1990; Gould 1993), new ideas or innovations (Coleman, Katz, and Menzel 1957; Rogers 1995), or any other "stuff" (Freeman, Borgatti, and White 1991; Borgatti 2005). Accordingly, many measures and methods that are used to analyze networks were developed using an image of a hypothetical flow.[10] Indeed, it is precisely the reliance on hypothetical flows that allows network scholars to go beyond direct connections to consider multistep linkages between nodes. It is the flow that concatenates simple dyadic ties into multistep pathways, which are, in turn, able to incorporate information regarding the structure of the entire network.

The incorporation of multistep pathways is especially important when studying mobility patterns. Most prior work characterizes occupational mobility by one-step moves (i.e., transitions from an origin to a destination occupation). The proximity of two occupations is thus determined by the size of the worker flow from one to another across two adjacent time points. But the flow of workers between two occupations might take multiple steps to materialize. For example, while it is relatively unlikely for an accountant to become a financial manager immediately, he or she may first become a financial specialist, before eventually turning into a financial manager. Hence, occupations are connected to one another not only through adjacent

[10] For example, measures of node "centrality" depend on what kind of flow on the network is assumed: eigenvector centrality assumes a flow that follows a random walk, while betweenness centrality and closeness centrality are based on flows across the shortest paths between the nodes (Borgatti 2005). Degree centrality, however, takes into account only direct connections and, thus, might be perceived as being based on a flow that ends after taking one step.

movements of workers but also through paths in the mobility network that take several steps. This suggests that there can be multiple possible paths of flows between any two occupations—flows that run through other parts of the occupational network.

Even in cases in which we are not able to observe how the same workers switch occupations over their careers, a network approach is uniquely suited to analyze how the aggregate worker flow is interconnected across multiple occupations. The usefulness of a network approach to studying occupational mobility was recognized earlier in the stratification literature (Beshers and Laumann 1967; Breiger 1981, 1990). In particular, using simple Markovian random walks to study the social distance between occupations, Beshers and Laumann were able to "consider all possible paths (or flows) through the network, rather than restricting our attention to adjacent flows, or to flows directly between pairs of points that neglect possible flows over intermediate points" (1967, p. 226). While Beshers and Laumann were clearly innovative in their approach to occupational mobility, few followed their lead in conceptualizing occupational mobility patterns in terms of flows on networks. In addition, the work of Beshers and Laumann suffers from the same limitation that remains a challenge to most mobility studies to date: namely, they started their analysis of social distance using predetermined aggregated classes, rather than deriving class boundaries directly from the worker flow between occupations. Addressing this limitation is an important benefit of the approach presented here.

Identifying Mobility Boundaries Using Random Walks

In the network literature, the procedure of finding boundaries that cluster nodes into classes is referred to as *community detection* (Fortunato 2010). Usually, a node is assigned to one and only one class, such that the community structure can be expressed as a partition of the node set. To incorporate dependencies between occupations that go beyond one-step connections when deriving mobility boundaries, we rely on a simple hypothetical flow on the mobility network, namely, a random walk. Certainly, workers do not traverse the occupational system in a random manner. Instead, we treat the observed edge weights as proxies for the "opportunities" of movements, or the width of the latent channels that connect occupations to one another, and use the hypothetical flows to incorporate information regarding the structure of the full network to detect the boundaries. Ideally, we would directly observe the transition histories of a large number of workers between detailed occupational categories over their long-term careers (Spilerman 1977; Rosenfeld 1992). However, nationally representative mobility data with sufficiently large sample sizes are typically limited to shorter time windows, which arguably reflect, but not directly measure, long-term mobility opportunities. These data constraints lead us to consider hypothetical, rather than actual, flows.[11]

We use the Infomap algorithm to identify mobility boundaries from worker flows (Rosvall and Bergstrom 2008; Rosvall et al. 2009). The Infomap algorithm is one of the few network community detection algorithms that is explicitly based on random flows on networks and that is simultaneously able to incorporate both directed and weighted edges. Further, simulation studies show that Infomap is one of the best performing community detection algorithms (Lancichinetti and Fortunato 2009; Fortunato 2010). As such, it has found application not only in the physics and computer science literature but also in sociology, such as in studying clusters of scientific knowledge (e.g., Foster, Rzhetsky, and Evans 2015).

The Infomap algorithm is based on the "minimum description length principle" (Grünwald 2007) and can be intuitively explained as follows: imagine a person who starts at a random occupation and moves to other occupations that are connected to it, where the probability of choosing any specific destination is proportional to the observed number of workers who have moved to the destination from the current occupation. The hypothetical person uses this heuristic for every step of her journey, thereby creating a random tour across the nodes of the entire network. Now, suppose we want to encode the trace of this random walker into a code word that is as short as possible while being decodable by another person without loss of information. The most efficient way to do so is to assign short codes to occupations that are visited frequently and reserve the longer ones for occupations that are only rarely traversed. Yet, there is an additional way to compress the description length of the random walk: namely, to the extent that the occupational structure is clustered into classes whose boundaries are relatively difficult to cross, the random walker will spend a long time within each class before departing to the next. Hence, we could shorten the code word even further by assigning a unique code to each class and repeatedly using the same (short) codes for the nodes within each class. As long as we are able to tell the decoder when the random walker switches from one class to another, there will be no ambiguity in decoding her trajectory. In other words, there exists a duality between minimizing the description length of the random walk and finding boundaries in the network that constrain the flow. The minimization of the code word, therefore, leads to a partition of the occupations, such that between-class flow is rare and within-class flow is common. This is what the Infomap algorithm tries to achieve.[12]

[11] We discuss the data limitations in more detail in the data and measures section.

[12] Of course, the algorithm does not assign actual codes to the trace of hypothetical random flows. Instead, it relies on Shannon's (1948) source coding theorem that specifies the asymptotic lower bound of the expected code length from a random source. Note that the

In sum, by relying on a hypothetical flow of random walks, the Infomap algorithm is able to detect the boundaries that constrain the movement of workers. While observing the actual flow of workers through the occupational system would be ideal, we regard the utilization of a hypothetical flow as an important step forward in incorporating multistep connections between occupations in the detection of mobility barriers. Furthermore, as the Infomap algorithm recovers the boundaries inductively from observed data at any given time, we do not need to base our study on predefined classifications of occupational classes. In effect, this enables us to overcome the two major challenges: the detection of boundaries as well as their temporal changes.

COMPARING THE NETWORK APPROACH AND THE MOBILITY TABLE APPROACH

The network approach is closely related to standard approaches to analyze mobility tables. Indeed, the detailed occupation-to-occupation mobility matrix could be, in principle, analyzed directly using log-linear models. Hence, before moving on to the empirical analysis, we demonstrate how the network approach compares to log-linear models and how it overcomes some of the limitations of the latter in analyzing large mobility tables.

Conceptual Differences

As described above, the key strength of the flow-based approach lies in its ability to identify mobility boundaries by taking advantage of all multistep pathways in the occupational network. This feature also marks the main difference between the approach proposed here and other approaches, including those based on network-clustering algorithms, that focus exclusively on one-step connections. To demonstrate the difference, we create a hypothetical example in figure 1. In this example, we represent the occupational system first using a directed network (fig. 1*A*) and then a mobility table (fig. 1*B*). For simplicity, we assume the edge weights are equal. We then present two measures for the "proximity" between two occupations in this network: the probability that a random flow that starts from one occupation will reach another occupation by following the structure of the network over several steps (fig. 1*C*) and the expected number of visits that this flow will make to a given destination from the origin (fig. 1*D*).

optimal number of clusters in a network is also automatically determined when the algorithm derives the partition. For further details on the Infomap algorithm, see Rosvall and Bergstrom (2008) and Rosvall, Axelsson, and Bergstrom (2009). Finally, we note that many standard statistical procedures in the social sciences can be interpreted in light of the same duality of compressing information (i.e., minimizing the description length) and finding structure in the data (see, e.g., Grünwald 2007).

As figure 1 shows, the network representation of this occupation system reveals two clear clusters of occupations—(A, B, C, D, E) and (F, G, H, I, J)—based on the Infomap algorithm. However, the mobility table, which engages only one-step moves between pairs of occupations, does not reveal any clear clustering structure. Intuitively, this is because the mobility table masks a substantial amount of between-occupation connections that take more than one step to realize, while the Infomap algorithm successfully captures the containment of the flow within the two clusters. In particular, the circle A → B → C → D → E is hardly visible in the mobility table, although it implies that any flow that enters B has to spend a long time in the circle until it exits the cluster by reaching A again. Thus, the substantive interpretation of the same pattern in the mobility table might be different, depending on whether hypothetical flows or one-step moves are considered.

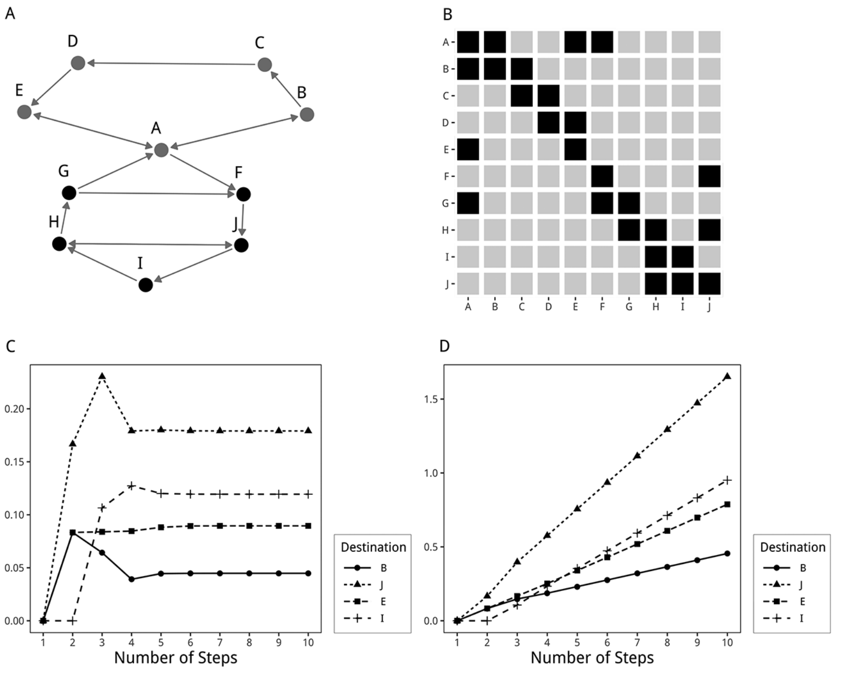


FIG. 1.—Conceptual differences between the flow-based network approach and the mobility table approach: *A*, network graph; *B*, mobility table; *C*, visiting probabilities from G to B, J, E, I; *D*, expected number of visits from G to B, J, E, I. For simplicity, all edge weights are assumed to equal. The visiting probability in panel *C* from occupation I to J is defined as the probability that a random flow starting from node *i* will be in node *j* after a given number of transition periods. The expected number of visits in panel *D* from occupation I to J is defined as the cumulative number of times that a random flow starting from node *i* is expected to visit node *j* after a given number of transition periods.

Figures 1*C* and 1*D* further illustrate this difference using measures for the proximity between two occupations. For example, although G is two steps apart from B, J and E, a random flow starting from G and following the edges on this network will have a higher probability of visiting B or J than E as the length of the random walk increases (see fig. 1*C*). Indeed, the probability would be higher for I than E, even though I is further away from G than E when only the shortest path length is counted. This is also apparent from the expected number of visits as shown in figure 1*D*. While the expected number of visits from G to I within the initial two periods is zero, the number increases faster than for B or E, so that after five periods a random walk starting from G will have a higher expected number of visits to I than to E or B.

As this hypothetical example demonstrates, the flow-based network approach and the mobility table approach can lead to quite different findings about the structure of mobility boundaries. Offering a richer picture of the clustering structure of worker flows—by grouping together occupations that can be easily reached not only in one step but within multiple steps—is a main payoff of using a flow-based approach.

Methodological Differences

We next highlight three methodological differences between the standard approaches to analyzing mobility tables and the network approach in recovering mobility boundaries. First, as noted above, the most important difference is that log-linear models fit parameters to one-step transitions of the mobility table without consideration of multistep connections. Thus, even though log-linear models can be used, in principle, to cluster the occupations into classes by using block diagonal design matrices, the recovered "class scheme" will be based solely on direct transitions.

Second, without prior aggregation, the mobility table of detailed occupations will have a large number of cells with zero frequency. In the presence of many sampling-zero cells, the asymptotic distribution of the two most commonly used statistics to assess the goodness of fit of a model—namely, the Pearson chi-squared statistic (χ^2) and the likelihood ratio statistic (G^2)—cannot be approximated by the chi-squared distribution (Reiser and Lin 1999; Nylund, Asparouhov, and Muthén 2007). While it has been suggested to fill the zero cells with a small positive value or a value proportional to the marginal shares (Clogg and Eliason 1987), these strategies artificially blur the mobility boundaries because the difficulty of crossing their barriers is not accounted for in assigning these values (Agresti and Yang 1987). In addition, for this strategy to work, the number of zero cells has to be small. Yet, when analyzing 350 occupational categories, the mobility table would have 122,500 cells, the majority of which will not be filled with any observations.

But, sparseness is the norm, rather than an abnormality, in network analysis, so that most community-detection algorithms are designed for exactly this kind of data. In fact, when trying to detect mobility boundaries, these algorithms automatically treat zero cells as informative data points in themselves, because the absence of flows between two nodes indicates that a mobility boundary may be drawn somewhere between them.

Third, an important limitation of the usage of log-linear models in the analysis of large mobility tables is that there are simply too many ways in which the occupations can be grouped together. Even with only 10 occupations there are 21,147 possible ways to partition the occupations into different clusters, starting from a scheme in which all occupations are in one cluster to the partition in which every occupation is its own class.[13] Thus, it is simply impossible to test all possible partition schemes unless the number of the analyzed occupations is extremely small.[14] Instead, what is called for is an algorithm that searches systematically through the possible partitions in order to find a clustering that best represents the boundaries of the mobility flow. As the minimum expected code length of a partition can be calculated very quickly, the Infomap algorithm implements a very effective stochastic procedure in which clusters are merged and split iteratively in a random sequential order. Applying the same algorithm using log-linear models would, in contrast, simply take too long, even with contemporary computational power. Table 1 summarizes the differences between the mobility table approach and the proposed flow-based network approach for studying intragenerational occupational mobility.

DATA AND MEASURES

Occupational Transitions

We rely on the March Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) to obtain data on intragenerational between-occupation transitions. The CPS-ASEC collects data on individuals' occupation in the current and previous year. We focus on the sample of

[13] If O is the set of occupations, then any partition of O into a collection of mutually exclusive "classes" defines an equivalence relation on O. It is well known that the number of possible equivalence relations on a set of size k is given by the kth Bell number. With $k \approx 400$ this number is enormous. To give the reader a sense of the order of the 400th Bell number, we note that the $B_1 = 1, B_2 = 2, B_{10} = 21,147$, and $B_{20} = 5,832,742,205,057$.

[14] Latent class approaches for analyzing mobility tables (e.g., Clogg 1981), however, are aimed at identifying classes of individuals and are therefore not identifying boundaries between occupations.

TABLE 1
Comparison between Previous Approaches and the Flow-Based Network Approach for Studying Occupational Mobility

	Challenge 1: Determining Boundaries	Challenge 2: Over-Time Changes
Challenges to current research:		
Conceptual	Analysis focuses on between-class mobility patterns rather than the detailed occupation-to-occupation worker flow; class boundaries are determined before calculating mobility patterns; mobility boundaries that are not aligned with the class boundaries cannot be detected	Class boundaries are assumed to remain fixed over time
Methodological	Topological log-linear models incorporate only one-step connections between occupations; distribution of goodness-of-fit statistic is unknown; computationally inefficient	Unable to detect changes in the mobility boundaries over time
How the network approach addresses the challenges:		
Conceptual	Mobility boundaries are detected inductively on the basis of the flow of workers between occupations; enables the detection of boundaries that cut through class schemes	Boundaries are allowed to change over time
Methodological	The community detection algorithm incorporates multistep connections between occupations; designed to analyze sparse mobility matrices; computationally efficient	Changes in both the constellation of mobility boundaries as well as their rigidity can be analyzed

prime-age workers between ages 25 and 54, which comes to a total of approximately 40,000–50,000 observations per year.[15]

Our main units of analysis are detailed occupational categories. Occupations at different periods were originally coded by different census coding schemes, and we use the harmonized 1990 coding scheme in all our samples for consistency (Meyer and Osborne 2005). We treat the occupation in the previous year as the "origin" and occupation in the current year as the "destination." As respondents who stayed in the same occupation over consecutive years do not contain information regarding the relations between occupations, we focus here on individuals who have changed their occupations. This is akin to using dummies to saturate the effect of diagonal cells and focusing on off-diagonal cells in log-linear models. Our analytic sample comes to a total of

[15] We obtained the data through the Integrated Public Use Microdata Series (Flood et al. 2017).

around 4,000–5,000 transitions per year and around 20,000–25,000 transitions for each five-year moving window. Because the CPS moved to a completely new processing system and adopted new imputation techniques in 1989, which substantively compromises the consistency of occupational transition measures before and after 1989 (Kambourov and Manovskii 2013), we focus on post-1989 years. We drop observations in which the current or previous occupation is imputed. Figure E1 (figs. C1, E1–E15 are available online) presents our analytic sample sizes and share of between-occupation transitions by year.

Two alternative data sets were also considered before we decided to use the CPS-ASEC. The first is the Panel Study of Income Dynamics (PSID). Despite its longitudinal design, the PSID has several limitations for the purpose of our study. Namely, it contains relatively small sample sizes, changed to biennial instead of annual surveys in later waves, and lacks frequent updates in the occupational classification to reflect more recent labor market changes (Kambourov and Manovskii 2013). A second alternative is the month-to-month matched samples of the CPS. This data set suffers, however, from selective attrition, as individuals who changed their occupations are more likely to move out of the household (Drew, Flood, and Warren 2014). The two data sets also suffer from measurement issues in recording occupational changes. This concern is indeed an important reason for using the retrospective measures in the ASEC supplement of CPS instead of alternative data sets such as the PSID and the matched CPS monthly data. In the ASEC data, respondents' previous occupation was reported retrospectively in the same survey in which current occupation was reported. An occupational transition will not be coded unless the individual (or the proxy reporter in that household) reports that the occupation in the previous year is different from the current occupation. This has been shown to significantly reduce the share of spurious occupational transitions (Kambourov and Manovskii 2013). In the PSID or the matched CPS monthly data, however, the respondent's previous and current occupations are coded independently, except for a few exceptional years in which dependent coding was used.[16] Thus, spurious occupational changes may appear if either the same job was described differently by the respondent in these two surveys or the occupation coders assigned different codes to the same job description.[17] Certainly, as is true with virtually all mobility studies, reporting and coding errors will not be completely eliminated despite the researchers' best efforts. Yet, we believe that the retrospective reports in the ASEC supplement are, by far, the best measure for studying occupational transitions on a national scale.

[16] See Kambourov and Manovskii (2013) for details.

[17] Indeed, our preliminary analysis suggests that the share of occupational transitions is substantially higher in the matched monthly CPS sample than in the retrospective measures in the ASEC.

Another issue that needs to be mentioned, affecting not only the PSID and the monthly CPS data but also the ASEC supplement, is the over-time changes in the occupational coding schemes adopted by the surveys. We use a modified version of the 1990 Census Bureau occupational classification scheme, which contains a total of 389 occupational categories. This classification system offers a consistent, long-term, detailed classification of occupations. Yet, the harmonization process still involves some decisions about assigning occupational titles. One is that a number of occupations that appeared in some coding schemes but not others are recategorized into an occupation with "not elsewhere classified" (n.e.c.) in the title (Meyer and Osborne 2005). For example, the harmonized scheme now includes an occupation titled "salespersons n.e.c.," which contains a variety of miscellaneous sales occupations that are coded differently in different census schemes. This somewhat arbitrary assignment of occupations into the n.e.c. categories introduces large heterogeneity into these categories. For instance, a worker might move into the "managers and administrators n.e.c." category by being promoted to a managerial position in a large international cooperation or becoming a store manager in a small coffee shop. Lumping highly heterogeneous jobs into a single category may thus introduce artificial fluidity into the occupational system that does not stem from actual worker mobility. Out of these considerations, we exclude all n.e.c. categories from our main analysis.[18]

Our empirical analysis is based on the occupational transition data from 1989 to 2015 as described above. We start with a description of the patterns of the occupational mobility network. We then fit the Infomap algorithm to the occupational transition data to detect mobility boundaries that are allowed to vary from year to year. Using the detected boundaries, we calculate measures for the rigidity of the mobility boundaries and class boundaries and examine their trends over time.

We then compare the detected mobility classes with alternative class schemes used in the literature. Following earlier work (Jonsson et al. 2009; Weeden and Grusky 2012; Jarvis and Song 2017), we consider two occupational class schemes under the big-class regime: the *macroclass scheme*, largely following Erikson-Goldthorpe's big-class tradition, contains five categories (professional-managerial, routine nonmanual, manual, primary, and military); and the *mesoclass scheme*, related most closely to the Featherman-Hauser scheme, further splits the professional-managerial macroclasses into three subcategories (managerial, professional, technicians), routine

[18] Similar concerns were raised in n. 10 of Jonsson et al. (2009). Further, we collapsed all "subject instructors" into one single category to ensure over-time consistency, because the census 2000 coding scheme does not differentiate between instructors of different subjects as the other schemes do (Meyer and Osborne 2005). Additionally, as the occupation "teacher's aides" was not included in the census 2000 coding scheme, we merged it into the "teachers n.e.c." category.

nonmanual into two subcategories (sales and administrative), and manual classes into three subcategories (craft, lower manual, service), which results in a total of 10 mesoclasses (including military and primary as two additional mesoclasses). Finally, the *microclass scheme* contains 82 categories.[19]

Measuring the Rigidity of Boundaries: Modularity and Bayesian Information Criterion

Our next task is to construct measures for evaluating the rigidity of a given class partition with respect to how strongly its boundaries constrain mobility. A widely adopted strategy in existing mobility research is to include log-multiplicative period effects in the log-linear models and use them as indicators of within-class persistence, net of changes in the marginal distribution of occupations.[20] However, this method is not suitable for our study for two reasons. Most importantly, to track changes in within-class persistence over periods, this method rests on the assumption that the class partition scheme does not change over time. Second, this method only accounts for one-step movements and ignores multistep connections.

We therefore turn to measures that can account for both over-time changes in the class scheme and multistep connections between occupations. We rely on a quality function known as *modularity* (Newman and Girvan 2004), which is, by far, the most widely used measure to quantify the strength of community structures in the network literature (Fortunato 2010). As such, it was applied to measure shared cultural schema and political belief systems (Goldberg 2011; Baldassarri and Goldberg 2014), salience of scientific communities (Shwed and Bearman 2010), or political polarization in U.S. Congress (Moody and Mucha 2013), among others. For a weighted and directed network and a class partition $C = \{C^{(1)}, C^{(2)}, \dots, C^{(K)}\}$ of the occupations into K classes, the modularity of the partition can be calculated by generalizing the formula given in Leicht and Newman (2008). This is done by substituting the adjacency matrix of a (unweighted) network by its weighted counterpart (Fortunato 2010). This gives

$$QC = \frac{1}{w}\sum_{i\in V}\sum_{j\in V}\left(w_{ij} - \frac{w_i^{\text{out}}w_j^{\text{in}}}{w}\right)\delta(C_i, C_j), \tag{1}$$

[19] In the original work by Weeden and Grusky (2005), the microclass scheme contains 126 categories, but we use the modified version in Jonsson et al. (2009) that aggregates some of the original microclasses. See table A2 in Jonsson et al. (2009) for the full list of macro-, meso-, and microclasses. We adapted these schemes so that they can be coded from the harmonized census 1990 occupation coding scheme.

[20] For example, see Stier and Grusky (1990) and Jarvis and Song (2017) for their applications in studying intragenerational mobility. This method can be seen as an application of the "log-multiplicative layer effect" model of Xie (1992), which is adapted from the row and column effects model of Goodman (1979).

where w_{ij} is the (i, j)th entry of the weighted adjacency matrix W, $w_i^{\text{out}} = \Sigma_j w_{ij}$ and $w_j^{\text{in}} = \Sigma_j w_{ij}$ are, respectively, the weighted in- and out-degrees of occupation i and j, and $w = \Sigma_i \Sigma_j w_{ij}$ is the total weight of the network. Finally, $\delta(C_i, C_j)$ is the Kronecker delta function, which is equal to 1 if both i and j belong to the same class and zero otherwise. Intuitively, equation (1) might be understood as the sum over the proportion of within-class transitions minus what would be expected under a random mixing model, where workers move randomly from occupation to occupation given the constraint that the weighted in- and out-degree of each occupation is preserved. A modularity of zero indicates that the classification scheme is no better than the random mixing model, while high values of Q indicate a tendency of transitions to be confined within the classes above what is expected by the random mixing model. As the expected proportions of transitions are calculated using the same partition as the observed proportions, the number of detected clusters is accounted for in the modularity measure. This ensures that, when we use modularity to trace the changes in the rigidity of mobility boundaries, changes in the number of classes over time will be automatically adjusted for.

Modularity $Q(\mathcal{C})$ suffers, however, from two shortcomings for our application. First, and most importantly, it accounts only for one-step connections on the network and is therefore inconsistent with a flow-based approach. Second, it has been demonstrated that the generalized modularity in equation (1) does not appropriately distinguish between the directions of the edges (Kim, Son, and Jeong 2010). In order to overcome these two problems, we use the LinkRank modularity (Kim et al. 2010), which is based on the idea of Google's PageRank algorithm (Brin and Page 1998) and can be formulated as

$$Q^{\text{lr}}(\mathcal{C}) = \sum_{i \in V} \sum_{j \in V} (L_{ij} - \pi_i \pi_j) \delta(C_i, C_j), \tag{2}$$

where $L_{ij} = \pi_i g_{ij}$, with g_{ij} the (i, j)th entry of the row-normalized adjacency matrix, G, and π_i the ith element of the PageRank (Perron) vector that satisfies $\pi^\top = \pi^\top G$. As all the rows of G sum to one, it is also equal to the transition matrix of a Markov chain generated by a random walk on the network—that is, the (i, j)th element gives the probability that a random flow would move to occupation j at time $t + 1$ given that it is at occupation i at time t.[21] Hence, the first term of the sum in equation (2), L_{ij}, is the

[21] For directed graphs, like the graph under study, a small teleportation probability, τ, is added in the definition G, so that $g_{ij} = (1 - \tau) w_{ij} / \Sigma_j w_{ij} + |V|^{-1}[(1 - \tau) I(\Sigma_j w_{ij} = 0) + \tau]$, where $|A|$ denotes the size of a set A and $I(v)$ is an indicator function that is equal to one if v is true and zero otherwise. This modification ensures that G is aperiodic and irreducible and, thus, the existence of a unique stationary distribution of the Markov chain characterized by G. In what follows, we set $\tau = .15$, as recommended by Kim et al. (2010).

probability that a random flow will move from occupation i to j in the stationary state of the Markov chain characterized by G. On the other hand, $\pi_i\pi_j$ is the probability of moving from i to j in a null model in which the random walker "jumps" freely around under the constraint that the PageRank of the nodes is conserved. Thus, equation (2) can be intuitively understood as the difference between the fraction of the time spent by a random walker within the class boundaries and the expected value of that fraction under the null model.[22] Finally, because of the absence of analytical results regarding the sampling distribution of $Q^{\mathrm{lr}}(\mathcal{C})$, we calculate confidence intervals for our key empirical estimates based on 1,000 bootstrap samples drawn from observed occupational transitions.

While modularity is the default criterion to compare the quality of community structures in the network literature, it is rarely used in mobility studies. To supplement the modularity measure, we also report the Bayesian information criterion (BIC) when comparing the performance of different partitions. The decision to use BIC instead of other goodness-of-fit statistic such as the deviance stems from the fact that the partition recovered from the Infomap algorithm is not necessarily nested in the other class schemes. All BIC values presented below are calculated from a log-linear model fitted to the observed mobility table. In the model we include row and column effects, effects for the diagonal entries of the mobility table, and "block diagonal" effects for the partition schemes. Details on the model specification are given in appendix B (apps. A–F are available online). It is important to note that BIC values are not comparable across models that are fitted to different data (Burnham and Anderson 2002). Therefore, we use BIC only to compare the performance of different schemes within each year and rely on modularity to examine changes in the rigidity of boundaries across years.

[21] For directed graphs, like the graph under study, a small teleportation probability, τ, is added in the definition G, so that $g_{ij} = (1 - \tau)w_{ij}/\Sigma_j w_{ij} + |V|^{-1}[(1 - \tau)I(\Sigma_j w_{ij} = 0) + \tau]$, where $|A|$ denotes the size of a set A and $I(v)$ is an indicator function that is equal to one if v is true and zero otherwise. This modification ensures that G is aperiodic and irreducible and, thus, the existence of a unique stationary distribution of the Markov chain characterized by G. In what follows, we set $\tau = .15$, as recommended by Kim et al. (2010).

[22] Notice that the PageRank of node i is proportional to the asymptotic visiting time of the random walker to i. Hence the product $\pi_i\pi_j$ might be thought of as the expected proportion of time the random walker moves from node i to j (or j to i) if only the marginal visiting times are taken into account. In this sense the term $\pi_i\pi_j$ corresponds to a dynamic counterpart of how "structural mobility" is measured—i.e., the expected cell count of the mobility table based on the marginal distribution alone. The quantity L_{ij}, however, represents the proportion of time the random flow would move from i to j, when the Markov chain follows the structure of the network. Hence, by comparing L_{ij} to $\pi_i\pi_j$, the LinkRank modularity compares the within-cluster flow based on the observed network with what is expected in a hypothetical scenario of structural mobility alone. In this way, it "nets out" the structural aspect of mobility. Finally, Kim et al. (2010) show that in the case of an undirected network, eq. (2) reduces to (1), so that $Q^{\mathrm{lr}}(\mathcal{C})$ can be considered a generalization of the modularity measure proposed by Leicht and Newman (2008).

EMPIRICAL RESULTS: MOBILITY BOUNDARIES IN THE AMERICAN LABOR MARKET FROM 1989 TO 2015

Descriptive Statistics

We start by describing key features of the analyzed mobility network. Figure 2 shows the in- and out-degree distributions—namely, the number of transitions into and out of occupations—for 1992–96, 2003–7, and 2011–15, respectively, where we pool observations across five years. A high degree suggests that a large number of workers are flowing into and out of the focal occupation. For each period, we also list the five occupations with the highest in- or out-degree, where the numbers in the parentheses stand for the weighted degrees of the corresponding occupations.[23] Two major observations can be made from the figure. First, the distributions of in- and out-degrees are right skewed, with most occupations having an in- and out-degree ranging between 0 and 30. Yet, there is still substantial variation within this range, indicating that occupations vary in terms of the volume of worker flows that go through them. The list of high-degree occupations contains nonmanual and manual jobs that require relatively low skills, such as "truck, delivery, and tractor drivers," "janitors," and "cashiers." These occupations typically recruit workers who are relatively easily replaced and involve more frequent worker turnovers. Second, quite consistently across periods, occupations with the highest in-degree also tend to have the highest out-degree and vice versa.[24]

We note, however, that this does not indicate that the recovered boundaries from the Infomap algorithm will be dominated by the few occupations with a high degree. For example, even if occupation A has a high out-degree, its influence on the clustering structure depends on which other occupations it is connected to. If A's connections are confined to a small number of occupations that are strongly connected among themselves, the influence of A on the overall clustering structure of the network would be limited. It is only if A is connected to very heterogeneous occupations, allocated to different clusters, that its high degree will pull occupations in the network closer together and, thus, blur the boundaries between them. Similarly, A will be allocated into the same cluster as B only to the extent that B also has a high outflow to A (i.e., if the tie is reciprocated) or if there are many cycles in the networks that connect the outgoing flow from A to B back to A. In short, the Infomap algorithm will detect mobility boundaries based on the constellation of all between-occupation transitions, not based on degrees alone.

[23] The weights of these degrees adjust for differential CPS sample sizes over time but do not affect the relative volumes of between-occupation transitions.

[24] For a distribution of edge weights, see fig. E2.

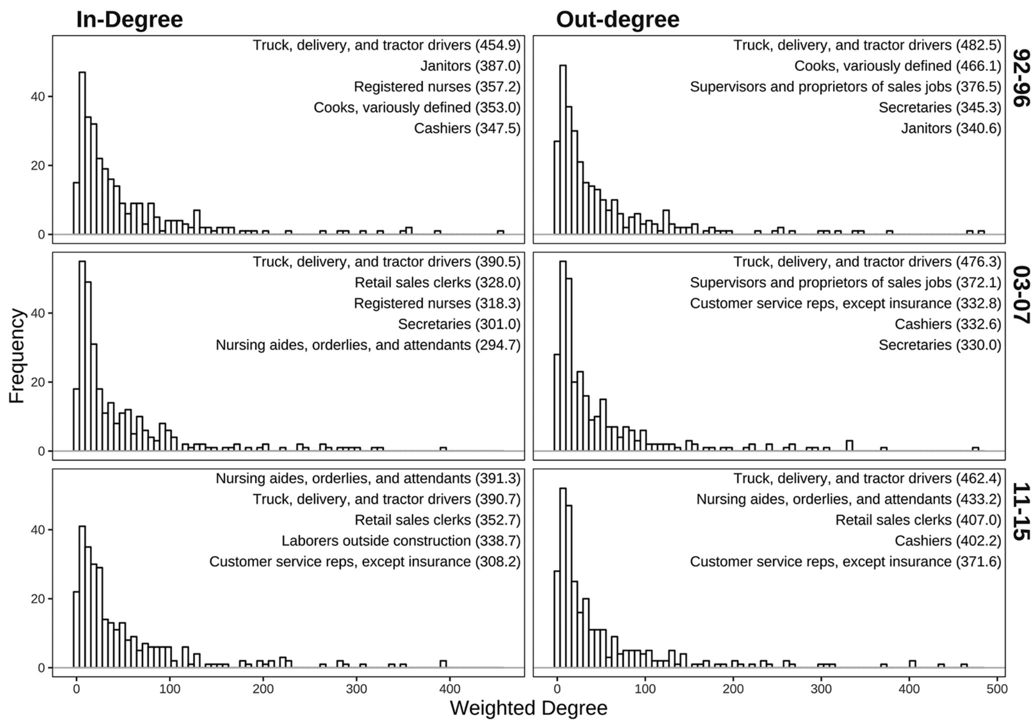


Fig. 2.—In- and out-degree distribution of occupations in 1992–96, 2003–7, and 2011–15. The in-degree is the number of transitions into an occupation; the out-degree is the number of transitions out of an occupation. Numbers in parentheses are weighted degrees of the corresponding occupations. Transitions are weighted such that the total number of observations in each year is equal to the total number of observations in 1989. Not-elsewhere-classified occupations are excluded.

Changes in Mobility Boundaries across Periods

Next, we examine the changes in detected mobility boundaries over these three periods. Figure 3 presents a cross-period mapping of identified mobility classes—that is, clusters of occupations identified by the Infomap algorithm based on observed worker flows. Each filled circle represents a mobility class. The sizes of the circles are proportional to the number of occupations in that class. The shades of the lines connecting two classes across two consecutive periods, C_t and C_{t+1}, are proportional to the percentage of occupations in C_{t+1} that have their origin in C_t (*left panel*) or the percentage of occupations that moved into C_{t+1} from C_t (*right panel*). These panels present a visualization of the changes in mobility classes over time, reflected in the regrouping, merging, and splitting of mobility classes from period to period. The number of classes identified also varies over time—26, 24, and 30 for the periods 1992–96, 2003–7, and 2011–15, respectively.[25]

We now zoom in and describe the over-time changes in mobility boundaries using some examples. The full lists of detailed occupations in each mobility class for the three periods are presented in tables D1, D2, and D3 (tables D1–D4, F1 are available online), respectively. Consider three occupations that belong to the largest mobility class (class 1) in the early 1990s: carpenters, auto body repairers, and drillers of oil wells. That these occupations belong to the same mobility class suggests that there are relatively dense flows of workers among them during this period. Then, in the early 2000s, these occupations split into three different mobility classes: carpenters appear in class 3, where they are grouped together with a number of other manual and craft occupations; auto body repairers appear in class 4, where they are grouped together with a number of automobile and machinery related occupations; drillers of oil wells appear in class 16, where they are grouped together with a number of other drillers or miners occupations. That is, new mobility boundaries have emerged between these occupations, separating them into smaller and more specialized clusters. To give another example, in the early 1990s, statisticians belonged to the same mobility class as a number of natural science professions, such as chemists, physicists, and astronomers. This is probably not surprising, given that these natural science professions are likely to require substantial knowledge about statistics. Yet, in the early 2010s, statisticians left the mobility class of natural science occupations and moved to the same mobility class as the a number of management related occupations, such as management analysts and personnel, human resources, training, and labor relations specialists. This may reflect a rising reliance on data and quantitative analysis in the business world. It is beyond the scope of this article to explain any particular case of boundary

[25] The number of detected mobility classes has increased over the studied period and is not a peculiarity of the three periods presented here (see fig. E3).

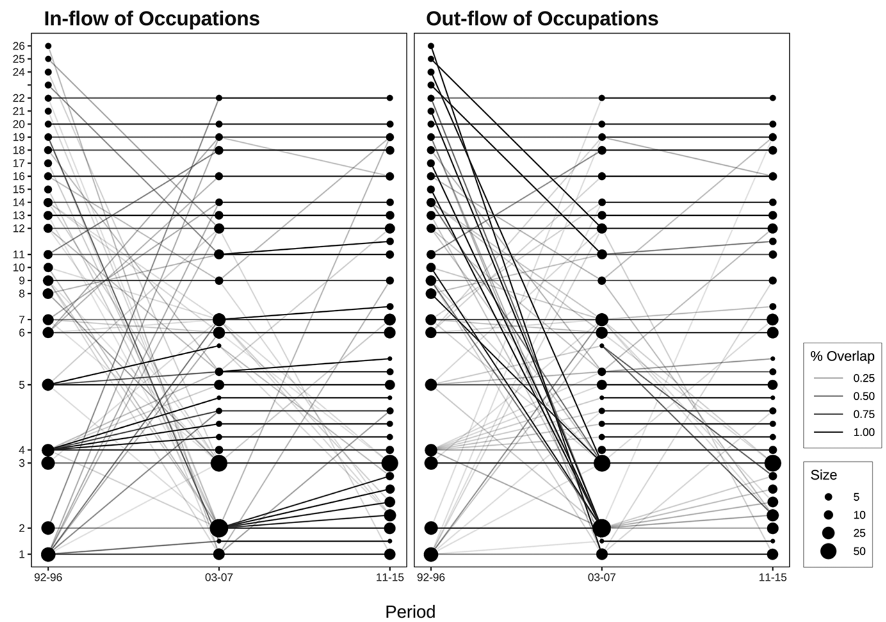


FIG. 3.—Evolving mobility boundaries over three periods: 1992–96, 2003–7, and 2011–15. Shades of lines connecting two mobility classes, C_t and C_{t+1}, in consecutive periods reflect the percentage of occupations in C_{t+1} that have their origin in C_t (*left*) or the percentage of occupations that moved into C_{t+1} from C_t (*right*). Two classes, C_t and C_{t+1}, in consecutive periods are labeled with the same number if more than 50% of the occupations in C_{t+1} come from C_t. The size of the points in the plot is proportional to the number of occupations in each cluster. The Infomap algorithm was fitted on the 304 occupations that consistently appeared in all five-year moving windows from 1989 to 2015 with not-elsewhere-classified occupations excluded, where transitions are weighted so that the total number of transitions in each year is equal to that of 1989. Mobility classes are detected by aggregating data over five consecutive years. The number of mobility classes in 1992–96, 2003–7, and 2011–15 is 26, 24, and 30, respectively. Labels for the mobility classes are sorted by the number of occupations in each class in 1992–96.

changes, but what we highlight with these descriptive patterns and examples is that where these mobility boundaries are drawn in the labor market has changed substantially.[26]

Trends in the Rigidity of Mobility Boundaries

Mobility boundaries can change over time, not just in terms of where they are but also in terms of how strongly they constrain worker flows. We next examine the over-time changes in the rigidity of the detected boundaries—that is, the degree to which mobility boundaries constrain the movements of workers in the occupational system. Figure 4 presents the trends in the LinkRank modularity, $Q^{\mathrm{lr}}(\mathcal{C})$, as well as bootstrapped pointwise 95% confidence intervals, under the partition schemes induced by the detected mobility boundaries. A higher value of modularity implies a stronger tendency for flows on the mobility network to be confined within the boundaries. As shown in the figure, the modularity remained relatively stable from 1989 to 2009 and took up an upward trend from 2009 onward, which resulted in an increase in modularity from around 0.35 in 2009 to over 0.45 in 2015. This suggests that, over the past decade, the rigidity of mobility boundaries in the U.S. labor market has increased substantially, so that it has become increasingly difficult for workers to switch occupations across these boundaries.[27]

The increasing rigidity of mobility boundaries proved to be robust to several different model specifications. Using the measure in equation (1) (fig. E4), using different sizes of moving windows and restricting the analysis to occupations that appear across all moving window sizes (fig. E5), including n.e.c. occupations (fig. E6), and using regression models to adjust for jumps in years when the occupational coding scheme changes (fig. E9) all lead to the same substantive conclusion. Another strategy to minimize the influence of occupational coding changes is to replicate our analysis using the harmonized 2010 occupation codes from 2003 onward, where the changes in occupational coding had been relatively minor compared to those in prior years.[28] The results exhibit a pattern consistent with our main findings—that is, modularity shows a consistent increase, implying stronger clustering of the

[26] Additional analyses, not discussed here in detail, suggest that the mobility boundaries have become more stable in recent years (see fig. E15). While the adjusted normalized mutual information between the mobility classes of two subsequent years was around 0.6 in the early 1990s, it increased to approximately 0.8 after 2010. The adjusted normalized mutual information measure is introduced below in eq. (3).

[27] In an analysis presented in app. C, we further split the sample by gender. The findings suggest that the trends in modularity are very similar for men and women and that the gender-specific trends are also very similar to that in the pooled sample.

[28] We use the harmonized, four-digit, 2010 occupational codes, instead of the raw occupation 2010 codes, because this ensures that we have consistent occupational coding for this period (CPS changed occupational coding from the 2000 to the 2010 census classification scheme in 2011).

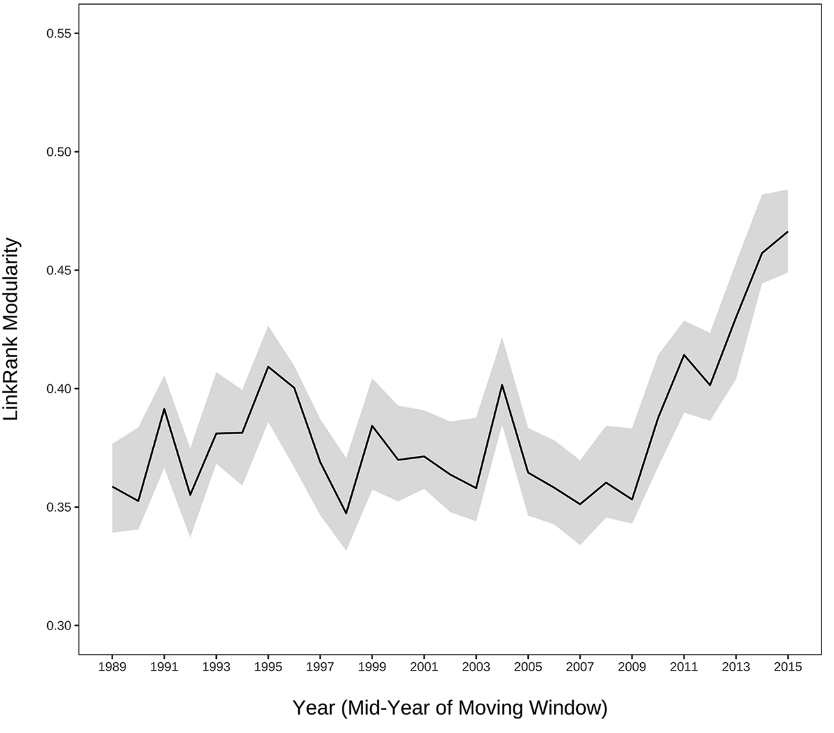


FIG. 4.—Trends in modularity based on boundaries detected by the Infomap algorithm. Line shows estimated LinkRank modularity, $Q^{\mathrm{lr}}(\mathcal{C})$, of the partition recovered from the Infomap algorithm in each year. Shaded area shows bootstrapped pointwise 95% confidence intervals calculated from 1,000 bootstrap samples of the observed transitions. Transitions used in the analysis are weighted such that the total number of transitions in each year is equal to the total number of transitions in 1989. Not-elsewhere-classified occupations are excluded from the analysis.

occupations, starting from the mid-2000s (fig. E7). In addition to using the count of between-occupation movers to define the edges, we have also used the proportion of the outflow from each occupation as the edge weights, where the size of an occupation (i.e., the denominator) was defined as the sum of movers and stayers. The results show a very similar trend in modularity (fig. E8).

COMPARING MOBILITY CLASSES WITH MACRO-, MESO-, AND MICROCLASSES

Comparison 1: Similarity between Mobility Boundaries and Other Class Boundaries

The first comparison focuses on the class boundaries themselves. Specifically, we examine whether the detected mobility classes have become more or less similar to the macro-, meso-, and microclasses over time. Table 2 presents the joint distribution of the occupations across 10 mesoclasses (rows) and 26 mobility classes (columns) in 1992–96 as an example of how the boundaries of these partitions crosscut one another.[29] There are more mobility classes than mesoclasses, but unlike the microclasses, the detected mobility classes are not simply nested within the mesoclasses. In fact, table 2 shows that a number of the mobility classes span across several mesoclasses. For example, the first column of the cross-tabulation represents the distribution of the 36 occupations in mobility class 1, which contains a set of lower-skill manual occupations such as truck, delivery, and tractor drivers, carpenters, material movers, and farm workers (see table D1 for the full list). Table 2 shows that these occupations span across four mesoclasses: one from mesoclass VI (service class, namely, ushers), eight from mesoclass VII (agricultural class, such as farm workers), six from mesoclass VIII (craft class, such as carpenters), and 21 from mesoclass IX (lower manual class, such as construction laborers). Carpenters and construction laborers are classified into different mesoclasses, but they are identified as belonging to the same mobility class, which suggests that workers move relatively frequently between these two occupations—either directly or through other pathways in the mobility network. A similar example is found in the column for mobility class 4, which contains a total of 24 occupations, 14 belonging to mesoclass II (professionals, such as physicists) and 10 to mesoclass III (technicians, such as chemical technicians). This implies that the boundaries between these professional and technical classes are quite permeable and, further, that for a subset of occupations belonging to these mesoclasses, mobility is more frequent across occupational class boundaries than within them. In sum, as the cross-tabulation in table 2 illustrates, the mobility flow tends to be contained within boundaries that are not necessarily aligned with or nested within the boundaries of occupational classes. Occupations in the same mobility class span across several mesoclasses, and the mobility boundaries, in general, crosscut the mesoclass boundaries. This corroborates our proposition that mobility boundaries represent an analytically distinct dimension of the occupational system, which need not perfectly align with that of occupational classes.

Table 2 presents a descriptive view on how the mobility boundaries crosscut mesoclass boundaries. But to compare the similarity between different class schemes and to study the trend in similarity over time, a summary index is needed. Because these class schemes define partitions over the same set of detailed occupations, and because each partition scheme

[29] The cross-tabulations for all three periods are shown in table D4, and the full list of occupations in each mobility class for the three periods is shown in tables D1–D3.

TABLE 2

Cross-Tabulation of Detailed Occupations by Mesoclasses and Mobility Classes for 1992–96

Mesoclass	Mobility Class																									
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
I		2			1				1	10							6									
II				14	20						8		8					6		4						
III				10							1												4			
IV									5				1								4					
V		28													6							4				
VI	1								6			8				6			5						3	
VII	8																									
VIII	6					16	16	13						9										4		
IX	21		30					2	2			1														3
X						1																				
Total	36	30	30	24	21	17	16	15	14	10	9	9	9	9	6	6	6	6	5	4	4	4	4	4	3	3

Note.—Mesoclasses are as follows: I = managerial, II = professional, III = technicians, IV = sales, V = administrative, VI = service, VII = agricultural, VIII = craft, IX = lower manual, and X = military. Mobility classes are sorted by the number of occupations in each class. All zero entries are omitted. Mobility classes were detected by fitting the Infomap algorithm on the aggregated mobility data over 1992–96.

induces a probability distribution of occupations over the classes, the problem of measuring the similarity between two class schemes can be approached as a problem of examining the mutual dependence of the two probability distributions. To measure such mutual dependence, we rely on the *mutual information*, which, as the name suggests, captures the shared information content between two distributions. Using Π_1 and Π_2 to denote the probability distributions induced by two class schemes, we write the mutual information between two partitions as $I(\Pi_1, \Pi_2)$. Mutual information equals zero if and only if two distributions are independent; otherwise, it is strictly positive. A higher value of mutual information indicates greater similarity between the two partitions.

For reasons detailed in appendix A, we use a variant of the mutual information, called the adjusted mutual information (AMI; Vinh, Epps, and Bailey 2010), to compare the mobility classes with other partitions of the occupations:

$$\mathrm{AMI}\left(\Pi_1, \Pi_2\right) = \frac{I(\Pi_1, \Pi_2) - \mathrm{E}[I(\Pi_1, \Pi_2)]}{\mathrm{HM}\{H(\Pi_1), H(\Pi_2)\} - \mathrm{E}[I(\Pi_1, \Pi_2)]}, \tag{3}$$

where $\mathrm{E}[I(\Pi_1, \Pi_2)]$ denotes the expected mutual information when the partitions are generated at random under the constraint that the number of classes as well as the number of occupations within each class remains the same, $H(\Pi_1)$ and $H(\Pi_2)$ are the entropies of the two partitions, and $\mathrm{HM}\{H(\Pi_1), H(\Pi_2)\}$ denotes the harmonic mean of the entropies. The AMI statistic adjusts the mutual information in two ways. First, it normalizes the mutual information to lie between zero and one and, second, adjusts it for the expected value of randomly generated partitions with the same number and sizes of clusters in each partition. The AMI is zero if the mutual information between the two partitions is no better than what is expected when the partitions are formed at random given the fixed marginals and equals one if the two partitions are identical.

Results of the comparison are presented in figure 5. Each line shows the AMI between the partition defined by the mobility boundaries, on the one hand, and the partitions defined by the macro-, meso-, and microclass schemes, on the other. The first point to notice is that the AMI remains below 0.65 across most of the years, indicating that the boundaries of mobility classes and the other classes are never in full agreement. By this measure, the derived mobility classes align most closely with microclasses, followed by mesoclasses and then macroclasses. Because the macro-, meso-, and microclass schemes were largely based on the occupational class structure of the 1970s and that "effectively freezes the class structure in the 1970s" (Weeden and Grusky 2012, p. 1765), whereas the mobility boundaries derived using our framework adapt from year to year, we would expect the mobility classes to align more closely with the other class schemes in earlier

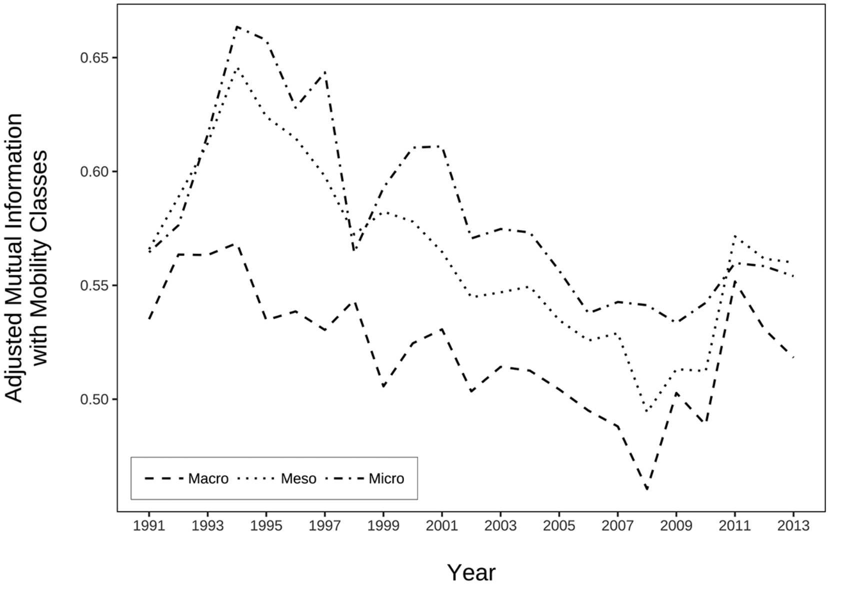


FIG. 5.—AMI between mobility classes and macro-, meso-, and microclasses. Each year on the X-axis shows the midpoint of moving windows created by aggregating data over five consecutive years. The adjusted normalized mutual information is calculated on 304 occupations that consistently appeared in all five-year moving windows throughout 1989–2015. Not-elsewhere-classified occupations were excluded from the analysis. The macroclass scheme contains 5 categories; the mesoclass scheme, 10 categories; and the microclass scheme, 82 categories. The average number of clusters detected by the Infomap algorithm is 27.59 over the analyzed period.

years and grow increasingly dissimilar to the other class schemes over time. The AMI measure shows a trend that is largely consistent with this expectation: over the studied period, the adjusted normalized mutual information between mobility classes and macro-, meso-, and microclasses has followed downward trends, suggesting that the mobility boundaries have become increasingly dissimilar to the big-class and microclass boundaries. The overall decline in mutual information, however, stalled around 2008 and started to climb up since around 2009, especially for the macro- and mesoclasses. This suggests that the mobility boundaries started to become more closely aligned with the boundaries of the other classes in recent years. This recent increase, however, is not large enough to reverse the long-term trend of a declining similarity between mobility boundaries and class boundaries that started in the mid-1990s. In sum, after showing a peak of similarity in the mid-1990s, the mobility classes have become increasingly different from the macro-, meso-, and microclasses.

Comparison 2: How Strongly Do Class Boundaries Constrain Worker Flows?

The second round of comparison examines the rigidity of the class boundaries defined by different class schemes. As the preceding results indicate, the mobility boundaries we derived are not perfectly aligned with the other occupational class boundaries. This discrepancy suggests that mobility boundaries are able to capture the constraints on worker flows that are not fully incorporated by the other class schemes. Therefore, we should expect two outcomes: first, between-occupation flows should be more strongly constrained by the mobility boundaries than by the other class boundaries. This implies that, for each given year, we expect the partition defined by mobility boundaries to exhibit the highest modularity. We hasten to note that such a finding should not be interpreted as a shortcoming of the previous occupational class schemes, as they were not specifically designed to capture mobility patterns. Rather, we use these class schemes as a reference point to which we compare the mobility classes, as these schemes have important theoretical groundings and were often used in previous mobility studies (e.g., Jonsson et al. 2009; Jarvis and Song 2017). Second, as discussed earlier, the other class schemes are based largely on the occupational system in the 1970s, whereas the mobility boundaries are able to adapt to over-time changes in the labor market boundaries. This implies that, the difference in modularity between the mobility boundaries and the other class schemes should increase over time. The following analysis examines these two expectations.

Before we present the results, it bears reiterating that the mobility boundaries are not derived by direct modularity maximization. This is important because if they were, then using modularity as the criterion to compare them with other class schemes would simply induce circular reasoning—that is, we would be setting as our criterion a metric that our approach optimizes. But we do not have this problem here: as described earlier, the mobility boundaries are detected by minimizing the description length of a hypothetical random walk on the occupational network. Modularity, however, is used only to evaluate the rigidity of the detected boundaries.

Figure 6*A* presents the modularity trends of the four partitions defined by the mobility boundaries and the macro-, meso-, and microclass schemes. As expected, the mobility boundaries consistently yield the highest modularity values, followed by the macro- and mesoclass schemes and, finally, the microclass scheme. Also, while the modularity for the mobility classes shows a clear upward trend, after a period of stability, the modularity trends for the three other class schemes show a less clear pattern. Figure 6*B* presents the difference in modularity between the three occupational class schemes and the mobility classes. Not only do the mobility classes outperform the other three class schemes in terms of identifying the barriers to worker flows (as indicated by

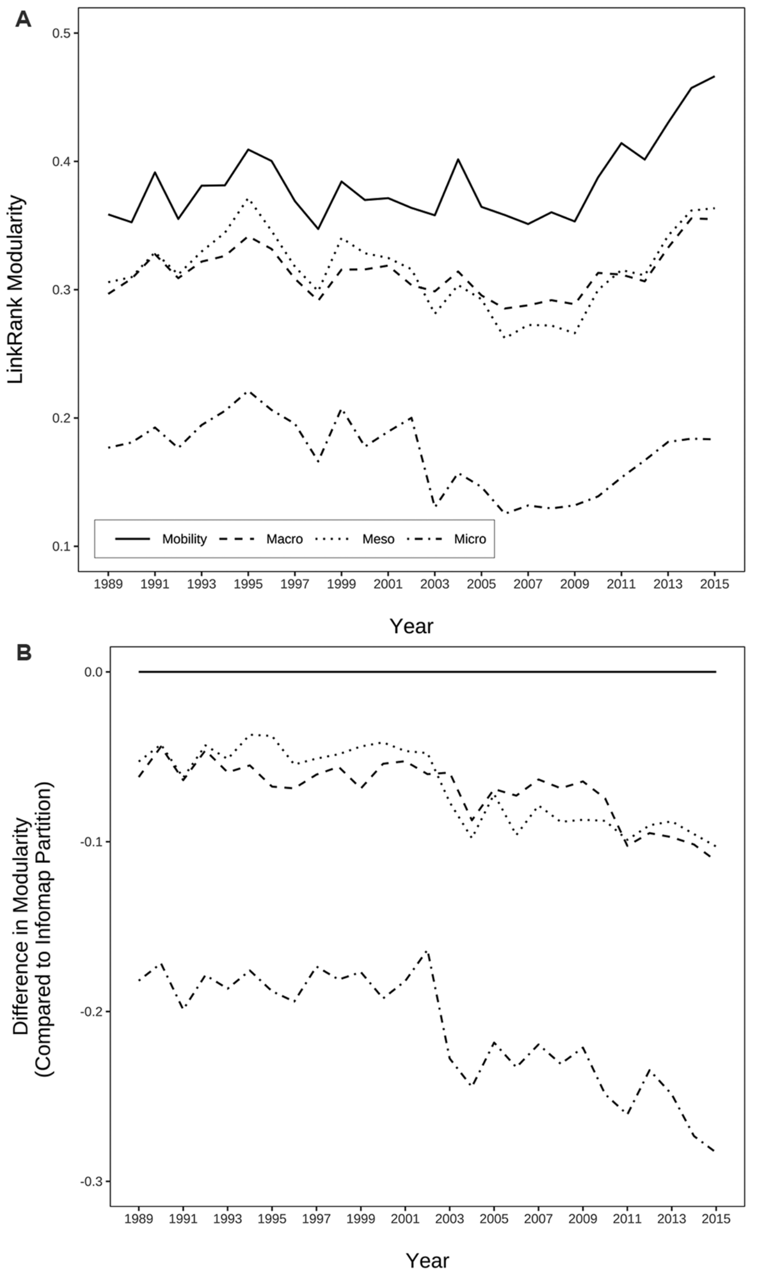


FIG. 6.—Comparison of modularity based on mobility boundaries and macro-, meso-, and microclass schemes: *A*, trends of modularity, $Q^{\mathrm{lr}}(\mathcal{C})$; *B*, difference in modularity between the macro-, meso-, and microclass schemes and the Infomap scheme. Transitions used in the analysis are weighted such that the total number of transitions in each year is equal to the total number of transitions in 1989. Not-elsewhere-classified occupations were excluded from the analysis; The macroclass scheme contains 5 categories; the mesoclass scheme, 10 categories; and the microclass scheme, 82 categories. The average number of clusters detected by the Infomap algorithm is 27.59 over the analyzed period.

the negative differences), but these differences also increase over time, suggesting that the time-invariant class schemes have become increasingly inaccurate in capturing the constraints on mobility flows.[30]

Similar conclusions are reached when we compare these partition schemes using BIC (fig. 7). Here, the BIC statistics are scaled such that in each year the mean of the four schemes equals zero.[31] A smaller BIC value indicates a better model fit of the scheme. The figure suggests that, in almost all years, and increasingly so from 2009 onward, the BIC statistics consistently favor the partition defined by mobility boundaries. That is, even when we consider only one-step connections in the mobility table, the origin-destination association captured by the classes defined by mobility boundaries still provides a better fit to the observed frequencies.[32]

Comparison 3: Explaining Variations in Labor Market Outcomes

As the foregoing analyses suggest, adopting an inductively detected, flexible, and flow-based mobility class scheme allows us to better capture the boundaries that contain the flow of workers. Next, we extend beyond the mobility domain and examine the association of the class schemes with labor market outcomes. To compare the performance of the partitions, we focus on two fit measures: the *R*-squared and BIC statistics. We present results for both of these measures, as they serve different purposes and complement each other.[33]

[30] The decline in the relative performance of the macro-, meso-, and microclass schemes compared to the mobility classes does not contradict the finding that the occupational class schemes themselves show an upward trend in modularity since around 2007. This is because even though the occupational class schemes are largely based on occupational codes from the 1970s, the modularity for these class schemes can still increase if mobility patterns show a tendency to become increasingly contained within the boundaries of these occupational classes. Yet, it is the decline in the relative performance of these class schemes (i.e., fig. 6*B*) that indicates that they have become increasingly less accurate compared to "what could be done" with alternative approaches, such as the one adopted here, that explicitly capture mobility constraints.

[31] As described earlier, log-linear models are fitted to the observed occupational mobility data, with row and column effects, diagonal effects, and class-specific dummies to capture within-class persistence.

[32] Using the Akaike information criterion (AIC) instead of BIC to assess the performance of the models did not change the conclusions of the analysis (see fig. E11).

[33] The *R*-squared statistic shows the proportion of the variation in the outcome that is accounted for by a model. While this statistic has the benefit of being easily interpretable, it shows only the accounted variation for this particular sample and, further, does not differentiate between the signal and the noise in the sample. For instance, we could increase the *R*-squared statistic of a model that regresses an outcome on dummy variables of a class scheme by "randomly" splitting each class into two smaller classes. With each random split, the *R*-squared statistic would increase, even though the split is purely random. Hence, the *R*-squared statistic, despite being a useful descriptive statistic, will favor models that overfit the data and has its limitations in accessing how well a model will perform

We first examine how well the classification schemes account for the variation in various skill and task measures across occupations. We measure occupational skills on the three-digit detailed occupational level, using data from the Occupational Information Network (O*NET), which provides measures of key attributes of occupations in the United States and is widely used in the literature on occupational skills (Liu and Grusky 2013; Cheng et al. 2019).[34] Using the procedure described in detail in appendix F, we assign O*NET items to different skill categories and conduct confirmatory factor analysis to obtain 10 occupational skill measures: verbal, quantitative, analytic, creative, programming, general computer knowledge, science and engineering, miscellaneous technical, managerial, and care work.

Figure 8A reports the R-squared statistics of linear regression models in which the skill measures are regressed on indicator variables representing the class categories. As the skill ratings for the occupations as well as the macro-, meso-, and microclass schemes are time invariant, the R-squared trends are flat over time. In contrast, the R-squared values for mobility classes vary from year to year as the mobility boundaries change. Overall, the microclass scheme has the highest R-squared across all skill measures, followed by the mobility, meso-, and macroclasses.[35] The only exception is managerial skills, for which the mesoclass partition outperforms the mobility partition in most of the years. Interestingly, we find that the R-squared statistics for the mobility classes increase over time for almost all skill measures, particularly in recent years. This suggests that the boundaries constraining worker flows are increasingly drawn between occupations that require different skills.

in general. The BIC statistic, however, tries to find the model with the highest posterior odds by approximating the marginal likelihood of the data under each candidate model given a multivariate normal prior on the parameters (Raftery 1995). This approach penalizes models with larger dimensionality and thus prevents overfitting. Hence, although BIC relies on its own assumptions, it offers a principled approach to model selection and is widely used in the social sciences. In sum, we believe that both the R-squared and the BIC statistics are useful in accessing different aspects of fitted models and, therefore, present both statistics in the analyses that follow.

[34] Version 21.3 of the O*NET database, on which our analysis is based, includes data collected from 2003 to 2016. The occupational attributes are constructed using ratings by incumbents, occupational experts, and analysts. Ideally, we would want to use occupation- and time-specific measures of skill requirement. However, to date, consistent time-series measures of within-occupation changes in skills and tasks are not available for our period of analysis (Autor 2013; Liu and Grusky 2013; Handel 2016).

[35] We note that the ordering in terms of the R-squared of micro-, meso-, and macroclasses is not very informative, as these schemes are nested—i.e., by design, the R-squared of the microclasses cannot be smaller than that of the meso- or macroclasses. Hence, only the comparisons between the mobility classes, on the one hand, and the macro-, meso-, and microclasses, on the other, are meaningful for the R-squared measure.

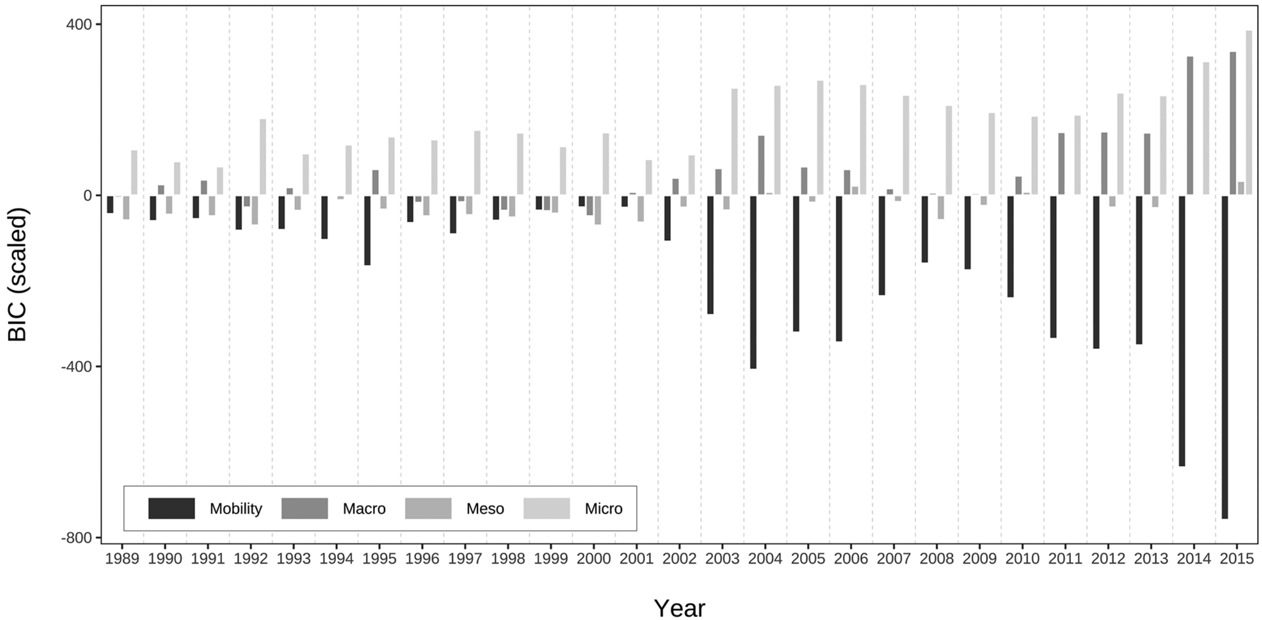


Fig. 7.—Comparison of BIC in log-linear models fitted to observed mobility tables based on mobility boundaries and macro-, meso-, and microclass schemes. BIC statistics calculated using the log-linear model specification in appendix B. BIC statistics are scaled such that the mean in each year is equal to zero. Log-linear models were fitted to unweighted transitions. Not-elsewhere-classified occupations excluded from analysis. The macroclass scheme contains 5 categories; the mesoclass scheme, 10 categories; and the microclass scheme, 82 categories. The average number of clusters detected by the Infomap algorithm is 27.59 over the analyzed period.

To incorporate the complexities of the models in the assessment of their fit, we calculate the BIC statistics for all partitions, which are shown in figure 8*B*.[36] Here, we highlight three observations. First, in terms of the comparison between different class schemes, figure 8*B* tells a different story from figure 8*A*. According to the BIC statistics, the microclasses perform the worst (i.e., highest BIC) among all the class partitions, implying that fitting a model with 82 microclasses turns out to be especially costly and results in potential overfitting of the data. In general, mesoclasses and mobility classes show the lowest BIC values, suggesting that they provide a better fit to the data than the other two schemes. Second, there are also some variations by skill type: mobility classes perform better on the programming, science and engineering, and care work skills, while mesoclasses perform better on verbal, creative, and managerial skills. Third, focusing on the trends for mobility classes, we see a downward trend in BIC (i.e., signaling improving model fit) for three types of skills: programming, science and engineering, and managerial. This finding is consistent with the trend in the R-squared results we observed in figure 8*A* and suggests that the flow of workers in the labor market is increasingly contained within groups of occupations that share requirements similar to programming, science and engineering, and managerial skills. In other words, mobility boundaries have changed in such a manner that it became less likely for workers to experience changes in occupational skills when they move within the constraints of these boundaries. Of course, both the R-squared and the BIC statistics are noisy signals of model performance. Also, in contrast to BIC, AIC prefers the microclass scheme over other partitions for most of the skills and across most of the years.[37] Overall, therefore, we are hesitant to reach any definitive conclusion regarding which class scheme best explains occupational skills. Rather, we treat these results as strong indications that the mobility boundaries are becoming increasingly aligned with the differentiation of skill requirements between occupations. Importantly, these findings point to a strengthening relationship between occupational skills and the occupations into which workers can and do move, a trend that would have been lost if we had relied on the assumption of time-invariant boundaries.

Next, we examine the extent to which the different class schemes account for inequality in individuals' annual labor income. Here, we use the

[36] As noted above, BIC values cannot be compared across models that are fitted to different data. Yet, as the skill measures do not change over time, we are here fitting different models (partitions) to the same outcome. Therefore, the BIC values can be directly compared to each other.

[37] The only exceptions are programming skills and care work skills, for which AIC prefers the mobility classes over the microclasses in the post-2005 period and in the last year of analysis, respectively. Full results of the analysis can be found in fig. E12.

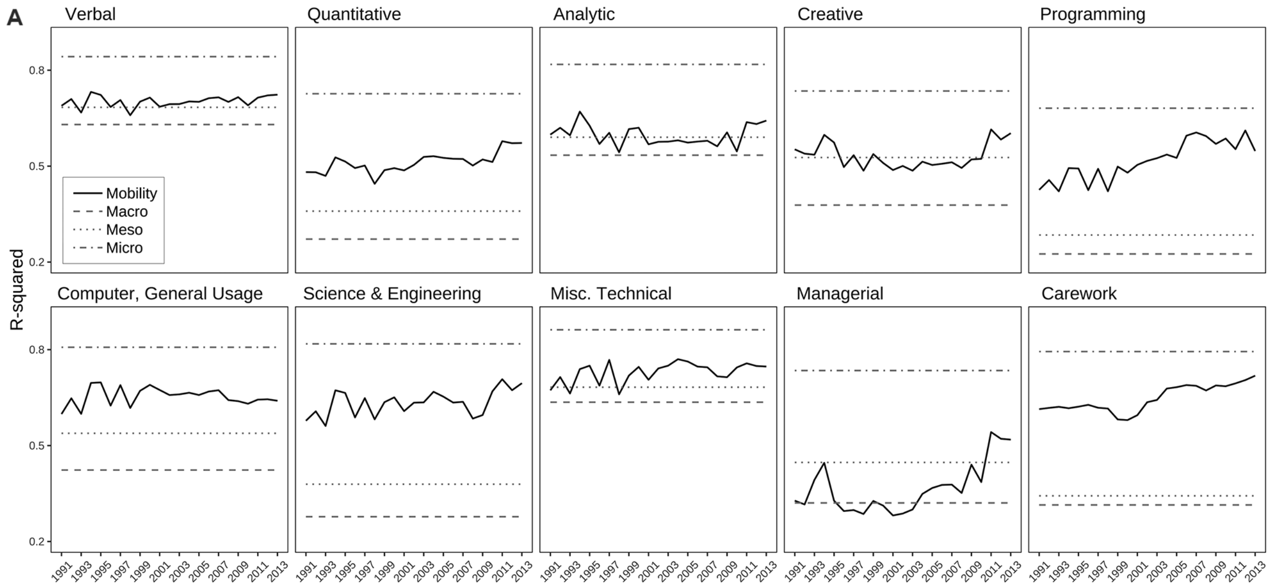


FIG. 8.—R-squared (A) and BIC (B) statistics based on linear regression models predicting occupation-level skill measures by different class schemes. Occupation-level skill measures are constructed on the three-digit detailed occupational level, using data from O*NET. The R-squared and BIC statistics are obtained from fitting an OLS regression, where occupation-level skill scores are regressed on indicator variables for the classes of each partition scheme. The X-axis shows the midpoint of moving windows created by aggregating data over five consecutive years. The models are estimated using the 304 occupations that consistently appeared across all five-year moving windows. The macroclass scheme contains 5 categories; the mesoclass scheme, 10 categories; and the microclass scheme, 82 categories. The average number of clusters detected by the Infomap algorithm is 27.59 over the analyzed period.

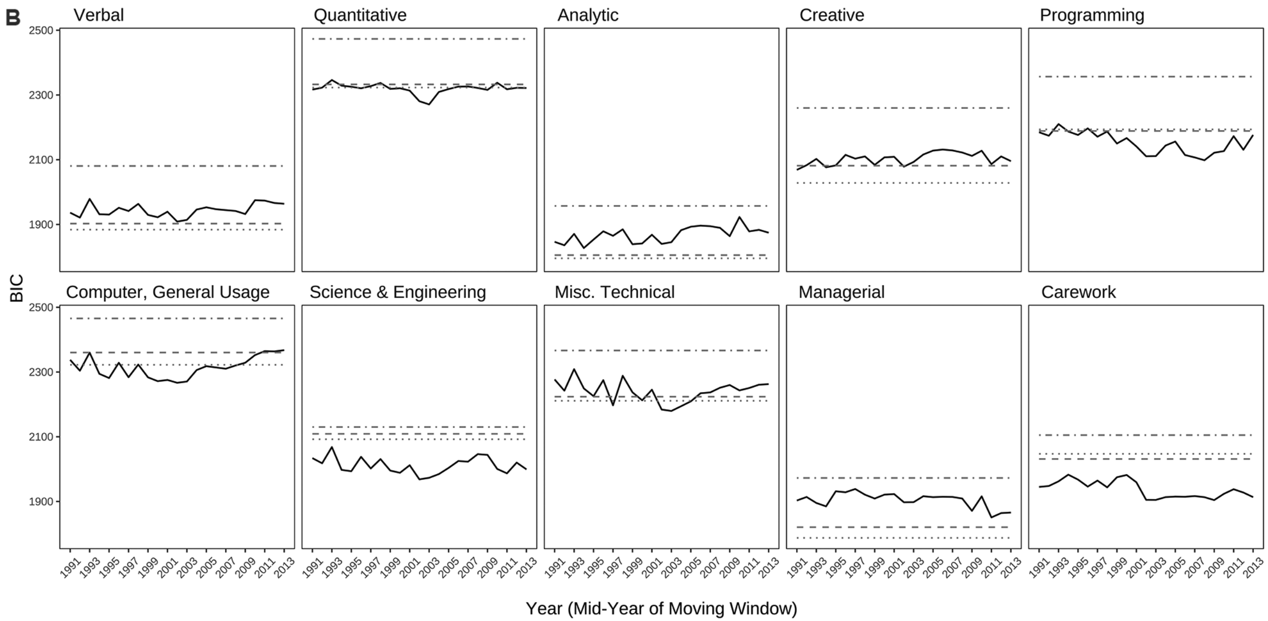
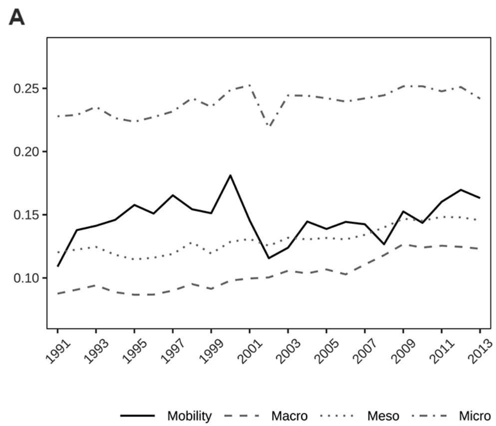


FIG. 8.—(*Continued*)

individual-level data from the CPS-ASEC. The outcome variable is measured as the personal annual wage and salary income, converted to 1999 dollars and log transformed. We excluded imputed income from the analysis because of potential biases introduced by the Census Bureau's imputation methods (Mouw and Kalleberg 2010). As before, we regress the annual log income on indicator variables representing the classes of each scheme and present both R-squared and BIC statistics. These results, presented in figure 9, suggest that the R-squared of mobility classes is slightly above that of the mesoclass scheme but lower than that of the microclass scheme. Using the incremental R-squared from models that control for demographic and educational attributes yields similar findings (see fig. E13). For all four classification schemes, the R-squared grew moderately over time, indicating a growing share of income inequality explained by between-class differences, regardless of how the class boundaries are specified. Both the R-squared and the BIC statistics suggest that the microclass scheme offers the best model for annual income across all the years, followed by the mobility, meso-, and macroclasses. Similar conclusions are reached when we examine the AIC values of the models (results shown in fig. E14). Hence, in terms of predicting annual income, the microclass scheme seems to offer the best model among the four class schemes considered here, followed in order by the mobility, meso-, and macroclasses.

LIMITATIONS

We note several limitations of our analyses. First, since our primary goal is to detect the boundaries between occupations, rather than the trajectories of individuals, we have focused on occupations as the basic units of analysis. Consequently, our analyses have relied on the "movers" who switched occupations rather than "stayers." If future studies are to take the perspective of individuals, additional adjustments will be needed to take into account the possibility that the movers may differ systematically from the stayers in characteristics that are simultaneously associated with their labor market prospects. Second, driven by the availability of data, our analyses have relied on the transition matrix between two consecutive years and the random walk assumption to incorporate multistep connections between occupations. We believe that this is an important step forward to go beyond analyzing one-step moves and incorporate more complex ways in which two occupations can be "close to" or "distant from" one another. Ideally, large-sample, longitudinal data on individuals' job histories would enable the analysis of workers' career lines, which would give us richer information on mobility boundaries. While we are not aware of a suitable longitudinal data set that has sufficient sample size on a national scale, such analysis may be possible when large data sets such as resume data or employer-employee



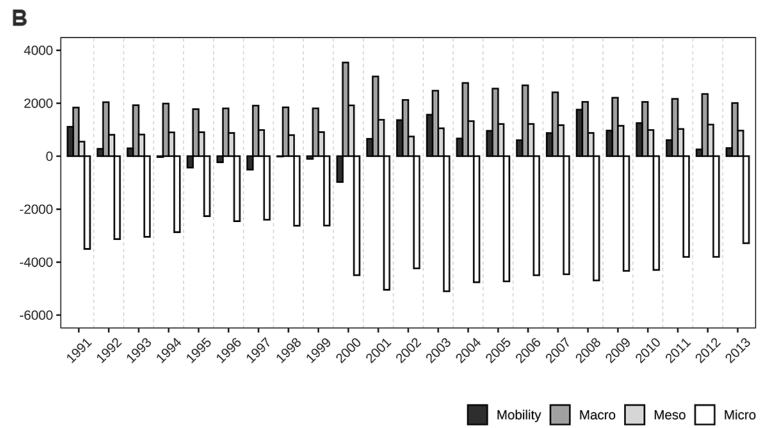


FIG. 9.—R-squared (A) and BIC (B) statistics based on linear regression models predicting logged annual labor income by different class schemes. All models are estimated from individual-level data of the CPS-ASEC. R-squared and BIC values are calculated from linear regression models in which logged annual earning is regressed on indicator variables for the clusters in each partition scheme. BIC statistics are scaled such that the mean in each year is equal to zero. The outcome variable is the annual wage and salary income, converted to 1999 dollars and log transformed. Imputed income values are excluded. The X-axis shows the midpoint of moving windows created by aggregating data over five consecutive years. The models are estimated using the 304 occupations that consistently appeared across all five-year moving windows. The macroclass scheme contains 5 categories; the mesoclass scheme, 10 categories; and the microclass scheme, 82 categories. The average number of clusters detected by the Infomap algorithm is 27.59 over the analyzed period.

matched data become available in the future. In those cases, the approach used here can be generalized to incorporate second- or even higher-order dependencies across multiple transitions of the same workers. Third, we have mainly focused on mobility boundaries in the general population. Future research is needed to further investigate subgroup variations, such as difference by gender, race, immigration status, and education.

DISCUSSION OF SUBSTANTIVE FINDINGS

Finally, what new substantive knowledge have we gained from applying the network approach to study occupational mobility? The approach not only helps solve some of the major methodological challenges in literature, but it also advances our understanding of the structure, continuity, and changes of the occupational system. We now move on to discuss the implications of our key substantive findings.

Changes in Mobility Boundaries

Have the movements of workers become more stringently constrained by mobility boundaries in the labor market? This is one of the most important questions in stratification research. Recent research suggests that the rates of intragenerational mobility across aggregate and disaggregate occupational classes have increased since the early 1970s up to around 2009 (e.g., Kambourov and Manovskii 2008; Jarvis and Song 2017), indicating growing permeability of these class boundaries in the United States. Similarly, we find a moderate decline of the rigidity of big-class and microclass boundaries up to around 2009, after which it increased.[38] However, these studies have mainly focused on occupational mobility across class boundaries, rather than the boundaries that constrain the detailed occupation-to-occupation worker flows. It is one of the major contributions of this article to go beyond between-class movements and directly examine the boundaries that structure the flows of workers at the occupational level—boundaries that might crosscut, rather than being aligned with, the boundaries defined by the occupational class schemes. Indeed, we find that barriers to occupational mobility have become increasingly dealigned from the both the macro- and microclasses after the mid-1990s, while simultaneously growing in their rigidity. Thus, while the rate at which workers move from one big class or microclass to another has increased or remained largely stable, a growing share of these occupational switches are happening within structural barriers to mobility that

[38] The recent increase in the rigidity was not captured in previous work because of the different time span that was analyzed. For example, Kambourov and Manovskii (2008) focused on the period before 1997 and Jarvis and Song (2017) focused on the period before 2011.

cut through the occupational class system. The methodological approach adopted here, in relaxing the reliance on a predetermined classification of occupations, enables the detection of these mobility boundaries as well as the measurement of their rigidity.

Further, what has also been changing over time is where these mobility boundaries are drawn. Transformations of the labor market are accompanied by the creation of new channels through which workers can easily flow and the blockage of existing ones that were frequently traversed in the past. Such changes in the labor market structure determine which occupations are bundled together by dense flows of workers and which occupations are separated by mobility barriers. Going beyond previous approaches that rely on time-invariant occupational groupings, we have uncovered mobility boundaries that reflect these changes. For example, among the professional occupations, technological changes have increased demand for the same set of skills across microclass boundaries (Liu and Grusky 2013; Alabdulkareem et al. 2018). Hence, job switchers who possess these "portable" and highly demanded skills are able to switch jobs across microclass boundaries, whereas at the same time, their job mobility may be increasingly confined within clusters of jobs that share similar skill requirements. Indeed, our findings shown earlier in figure 8 support this view: mobility boundaries are not only becoming more powerful in constraining worker flows, but they are increasingly sorting workers into clusters with similar skill requirements. Theses changes would have been overlooked if we had relied on time-invariant occupational groupings.

Labor Market Trends and Flows and Boundaries: Directions for Future Research

What are the potential drivers of the changes in mobility boundaries? Here, we draw on our findings as well as the literature to speculate about some potential factors and point toward directions of future work. First, job polarization—the growth of jobs at the bottom and top ends of the skill distribution and the shrinkage of routine nonmanual jobs at the middle—may have played a role in the strengthening of mobility boundaries. To the extent that the "middle jobs" can serve as stepping-stones for individuals to move from relatively lower to higher skill jobs, the "hollowing out" of the middle may have deepened the divide between high- and low-skill occupations by closing up these the potential mobility pathways (Autor and Dorn 2013; Dwyer 2013; Alabdulkareem et al. 2018). Our results showing that mobility opportunities are increasingly constrained by skill requirements provide some suggestive evidence in support of this possibility, and we believe that the linkage between job polarization and labor market mobility is a compelling topic for future research.

A second labor market trend that may have played a role is the rise of precarious labor and nonstandard employment relations (Cappelli 1998; Kalleberg 2011) and the decline of unions (Western and Rosenfeld 2011). With the shift of labor market risks from employers toward individual workers and the decline of unions in protecting workers' power, workers face increased uncertainty in their careers and may need to go through more frequent occupational changes to figure out their career pathways. Yet, low-skill workers who are disproportionately affected by the growing job precariousness may be increasingly stuck in dead-end occupations that provide little training, which hampers efficient accumulation of human capital at work that is instrumental for upward career mobility (Finegold, Levenson, and Van Buren 2003; Kalleberg 2011). In this sense, we might expect an increase in the rigidity of labor market boundaries around groups of low-skilled occupation, a topic that warrants future investigation.

Third, the trends in mobility boundaries also have broader implications for earnings inequality. How mobility boundaries relate to earnings inequality depends on the degree to which mobility classes are consolidated with earnings differences. In the case of strong consolidation—that is, mobility boundaries group together occupations of relatively similar earnings levels—high earners who circulate within their mobility boundaries will stay high earners, while low earners will face substantial barriers to their advancement into higher-paying occupations that are outside of their own mobility class. If, however, mobility boundaries group together occupations of quite heterogeneous earnings levels, individuals will move between jobs of quite different earnings levels, even if their movements are confined within the mobility boundaries. Our findings shed light on this relationship. As presented earlier in figure 9, an increasing portion (from around 10% to 15%) of the variations in annual labor income can be accounted for by differences across the mobility classes. This implies that workers are increasingly circulating within clusters of occupations with similar earnings, rather than switching between occupations of different earning levels. This finding raises concerns that opportunities to move into higher-paying jobs may have become increasingly limited, a topic that calls for future research.

CONCLUSION

The overarching aim of this study was to formulate a network approach for understanding occupational mobility in the labor market and examine what implications it brings to the literature on theoretical, substantive, and methodological levels. We started our study with the long-established thesis that the underlying boundaries that govern worker flows form a key structural aspect of the labor market. Building on this analytic basis, we illustrated that current scholarship on labor market mobility faces two major challenges—namely, determining mobility boundaries and tracing the over-time changes in them.

These challenges motivated us to propose a network approach to address them. A defining feature of the approach is that it emphasizes the detailed occupation-to-occupation flows and the latent boundaries that constrain these flows as the starting point for analyzing occupational mobility. The advantage of this approach is threefold. First, it allows us to inductively uncover the underlying boundaries governing worker flows based on detailed occupation-to-occupation mobility patterns, rather than starting from aggregated occupational classes. This enables us to identify barriers to mobility that crosscut the occupational class system, either at the big-class or microclass level. Second, instead of being restricted to a fixed set of boundaries over time, it allows us to adopt a flexible specification that varies from year to year as the labor market evolves. Third, instead of focusing exclusively on one-step movements between occupations, it allows us to identify the boundaries by incorporating the information of the entire occupational network.

We show that conceptualizing the occupational system as a network that carries flows of workers—and the labor market structure as a set of boundaries constraining these flows—can change the way we approach occupational mobility. While previous occupational class schemes are defined in terms of key properties of the occupational system, such as resources, tasks, authority relations, or the division of labor, we argue that mobility boundaries present a unique structural dimension of the labor market that is distinct from the previous class schemes. Further, we show how the long-standing notion of "flows and boundaries" can be formulated into a formal framework that connects central questions in the stratification literature with community detection techniques from the network literature. We emphasize that the most relevant data for analyzing mobility boundaries is the pattern of labor market flows itself, which provides a tight fit between the theoretical approach and the empirical analysis. Of course, this does not mean that previous approaches to occupational classes are less useful. Rather, the existing class schemes and the one we uncover complement each other, as they emphasize different aspects of the occupational system. Compared to previous approaches to occupational mobility, the proposed network-based approach is more informative about the latent boundaries that constrain and facilitate individuals' mobility opportunities, how this opportunity structure changes over time, and the extent to which the mobility boundaries separate individuals into occupations that vary in terms of skill requirements or earnings.

Substantively, our empirical analysis showed evidence on the growing rigidity of mobility boundaries in the occupational network in recent years. This finding may seem to contradict earlier work that documented rising occupational mobility rates across big-class and microclass boundaries. Yet, once it is recognized that mobility boundaries are distinct from occupational classes, it becomes clear that both findings might be true: indeed, while big-class and microclass boundaries may have become more permeable over time, we show that the movements of workers are increasingly constrained by the structural barriers in the labor market that crosscut these class boundaries. The question, however, remains far from settled as to how and why exactly the underlying boundaries in the labor market have become more rigid over the last decade. These questions call for a research agenda focusing directly on the underlying mechanisms. Earlier, we speculated about potential factors behind the shifting mobility boundaries and their growing rigidity, including the role of technological change, demand for skills, job polarization, the rise of precarious employment, and the decline of unions. Moving forward, research could take advantage of the temporal and historical variations in these conditions to examine their impact on the flows and boundaries in the labor market.

Finally, on the methodological level, our study reveals the promise of introducing methods developed in the field of network science into research on stratification and mobility. Whereas the conceptualization of the labor market as a network of occupations and their interconnections is a long-established idea in the sociological literature on stratification, the network approach proposed in this study makes a unique contribution to this scholarship by introducing new analytical tools for overcoming some important challenges to the operationalization of these ideas. We believe that uncovering the latent structure of the occupational system will continue to be a fruitful area of sociological research on stratification and mobility. With the advances in computational capacity, the enhancement of techniques for handling large data sets, and the growing availability of high-quality stratification and mobility data (Grusky, Smeeding, and Snipp 2015), there will be new opportunities for updating our knowledge of long-standing topics using new approaches.

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