

A Position with a View: Educational Status and the Construction of the Occupational Hierarchy

American Sociological Review
2017, Vol. 82(1) 32–58
© American Sociological
Association 2016
DOI: 10.1177/0003122416671743
journals.sagepub.com/home/asr



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Abstract

The differentiation of occupations is of central concern to stratification scholars studying class and mobility, yet little is known about how individuals actually see the occupational landscape. Sociologists have long collected data on individual perceptions of where occupations stand relative to one another, but these data are rarely used to study the logics that individuals employ when categorizing occupations. Using the 1989 GSS occupational prestige module, we investigate how cognitive maps of the occupational hierarchy vary in terms of content and structure. The results show that maps are more homogeneous among individuals with more versus less education. This increased consensus arises, in part, because better educated respondents are more likely to set aside training-intensive occupations as a relatively elite set of occupations at the top of the hierarchy. In contrast, less educated respondents generate more gradational classification systems that are significantly less sensitive to training intensiveness as a basis for categorical distinction. This study contributes to our empirical knowledge of valuation and raises new questions about how individuals organize and navigate social structures.

Keywords

occupational prestige, valuation, cognitive maps, symbolic boundaries, categorization

Like ‘being,’ according to Aristotle, the social world can be uttered and constructed in different ways.

– Pierre Bourdieu (1985:726)

Can the student of social structure enjoy the advantages of the survey without neglecting the relationships which make up that structure?

– James Coleman (1958:28)

Considered the backbone of the macro-stratification system in contemporary society, the occupational hierarchy is of central concern to stratification scholars studying social class

and social mobility (see Blau and Duncan 1967; Erikson and Goldthorpe 1992; Featherman and Hauser 1976; Torche 2015; Weeden and Grusky 2012; Wright 1985). A central line of research in this tradition involves the measurement of occupational prestige vis-à-vis individual perceptions of where occupations stand relative to one another (Duncan 1961;

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Hauser and Warren 1997; Treiman 1977; for a review, see Nakao and Treas 1994). In the classic approach, researchers ask a sample of individuals to sort occupational titles into ordered piles based on occupations' social standing or prestige (Nakao and Treas 1994; Treiman 1977).¹

Despite the extensive efforts dedicated to measuring occupational prestige, we argue that sociologists have neglected to approach these data for what they intrinsically are: individual-level maps of the occupational landscape. Instead, stratification scholars have treated individuals' prestige ratings primarily as votes to be averaged, an approach that by definition gives rise to a single rank order of occupations from which researchers can locate the relative standing of any given occupation (Nakao and Treas 1994; see also Zhou 2005). A key empirical finding is that upon averaging individuals' votes, the ordering of occupations at the aggregate level tends to be roughly the same across cultures and historical periods (Treiman 1977).² In 2002, when members of RC28³ met to summarize five decades worth of research contributions in the field of social stratification, they coined this discovery the *Treiman constant*, which they described as the "only universal sociologists have discovered—not just in stratification, but in sociology as a whole" (Hout and DiPrete 2006:3).

The point of this study is not to take issue with this characterization per se, but rather to argue that sociologists have focused almost entirely on how beliefs aggregate to define occupations to the detriment of exploring the nature and origins of the belief systems themselves. We suspect this is because many scholars assume that the stability observed at the aggregate level (i.e., the Treiman constant) stems from uniformity at the level of individual beliefs. Thus, even though sociologists have repeatedly asked individuals to "make sense" of occupations according to their relative standing, little effort has been devoted to unpacking the underlying logics that individuals use when categorizing occupations (for notable exceptions, see Coxon and Jones 1978; Zhou 2005).

When individuals are tasked with vertically differentiating a set of occupations, their responses, as we noted earlier, are typically aggregated by occupation; here, we explicitly keep the data disaggregated and instead treat each respondent's pile sort outcome as the object of study. Building on recent work on the social construction of value (Lamont 2012; Zuckerman 2012), we view a respondent's entire response set as representing how that individual values a broad sample of occupations in a relational sense (e.g., "occupation A is more prestigious than occupation B"). These classification systems are reflective of cultural understandings regarding the structure of occupations.

Previous literature suggests that individuals develop an understanding of the occupational hierarchy through a variety of socialization and interactional processes, including exposure to the media, diffusion of information through networks, and interactional experiences with incumbents of these occupations (e.g., being taught by a teacher, being examined by a doctor, or receiving mail from the postal service carrier) (see Boltanski and Thévenot 1983; DeFleur and DeFleur 1967; Martin 2000; Stockard and McGee 1990). Our goal is not to disentangle these processes, but rather to investigate the mental maps of occupations that emerge from the complex mixture of these processes. Not only are framing and categorization processes of sociological interest in their own right (e.g., Brubaker, Loveman, and Stamatov 2004; Lamont 1992, 2002; Morning 2011; Wimmer 2008; Young 2006), but a deeper understanding of how occupations are cognitively organized tells us something about how occupational stratification is experienced "on the ground." More broadly, because actors navigate social life on the basis of their mental representations of "how the world works" (Porac and Thomas 1990; Porac et al. 1995), studying how individuals conceptualize the occupational hierarchy may help shed light on *why* individuals pursue education and work opportunities in the ways they do (Asad and Bell 2014; Young 2006).

To this end, we contend that some important questions related to occupational perceptions come to light only when conceiving of ratings data as mental maps. For example, are some individuals more likely than others to be “on the same page” in their view of the occupational system? How do individuals vary in how they draw boundaries around certain types of occupations? Moreover, how much gradation do individuals see in terms of occupational value? These questions, which are orthogonal to the knowledge encapsulated by the Treiman constant, are the focus of this study. Similar to how different camera lenses and angles applied to the same landscape give us different images of the truth, the goal of examining mental maps of the occupational hierarchy is not to introduce mere nuance, but rather to create a multidimensional understanding of a complex cultural construct.

Data for our empirical analyses come from the occupational prestige module of the 1989 General Social Survey (GSS) (see Nakao and Treas 1994), in which respondents ($n = 1,166$) were asked to rank the “social standing” of 110 occupations with respect to a prestige ladder of nine rungs. We begin by describing how these pile sort data constitute classification systems, and we then define three system-level properties of theoretical interest: homogeneity, the presence of symbolic boundaries, and the level of differentiation. Our general proposition is that an individual’s position in the macro-social hierarchy, which we operationalize in terms of educational attainment, will shape the structure and content of her mental map regarding occupations. We find that more highly educated respondents tend to set aside the most training-intensive occupations into a relatively elite category of occupations that sits opposed to a grouping of all other occupations—a type of either/or mapping that generates inter-respondent consensus in how occupations are pile-sorted. In contrast, less educated respondents generate more gradational ranking systems that (1) vary in content more from person to person and (2) are far less sensitive to training intensiveness as a basis for classifying occupations.

MAPPING THE OCCUPATIONAL HIERARCHY

At first blush, some might argue that—precisely because of the Treiman constant—there is little reason to investigate how individuals make sense of occupations. For example, Treiman (1977) suggests that most members of society will recognize occupational hierarchy in generally the same way because (1) occupations naturally differ in terms of skill, authority, and economic control, such that (2) most everyone awards prestige on the basis of an occupation’s objective importance to society. In other words, Treiman expects a single, worldwide prestige hierarchy because the division of labor is rooted in natural and functional imperatives, and prestige ratings are simply a reflection of this natural ordering.

We, however, see compelling reasons to explore occupational mappings at the individual level despite observed “patterns of invariance” at the aggregate level (Hout and DiPrete 2006:2). First, the stability of rankings across time and space does not necessarily imply that everyone sees the world in the same way. Consider a population in which we are told that the average individual sees the world through a green lens. A green-hued average could emerge if most individuals in most time periods do in fact use a green lens, but green could also represent the average because half the population filters the world through a blue lens while the other half uses a yellow lens. Again, the point is simply that stable rankings at the aggregate level can coexist with heterogeneity at the level of individual beliefs (see Coxon and Jones 1978).

Second, conceiving of occupational prestige ratings as mental maps gives rise to new sociological questions pertaining to the nature and origins of heterogeneity in the maps themselves (see Harding 2007). To be sure, early investigations of inter-individual variation in occupational prestige perceptions have generally been dismissed as trivial, and indeed most of those discoveries were far less impressive compared to the stability of the

occupation-level correlations across time and space (Hout and DiPrete 2006; Treiman 1977).⁴ Zhou's (2005) reanalysis of the 1989 GSS occupational prestige module, however, showed that early studies were, in a sense, asking the wrong questions. Moving beyond simple cognitive biases, Zhou theorizes that occupations associated with either a scientific background or a position of authority are ranked higher by individuals who have effectively "bought into the system," compared to individuals who are less incorporated into institutions like higher education. Accordingly, he finds that white men, compared to women and minorities, are more likely to elevate the prestige of occupations characterized by authority, and to a lesser degree occupations related to science, when ranking occupations.

In the current study, we broaden this line of thinking by examining multiple properties of how occupations are mapped in relation to one another. We approach ratings data as the observable outcome of an interpretive process—an exercise in commensuration (Espeland and Stevens 1998) that might be carried out in different ways across individuals. When considering the many research areas that address cognitive mapping, conceptualization, and boundary-drawing,⁵ two clear themes emerge. First, individuals develop mental maps of physical (e.g., Lloyd and Heivly 1987; Tversky 1981; Tversky and Schiano 1989) and social (e.g., Bail 2008; Lamont 2002; Morning 2011; Porac et al. 1989) phenomena through various cognitive processes in which complex streams of information and experiences are simplified (Laszlo et al. 1993; Tversky 1981). Second, precisely because environments are complex, interpretation often varies across individuals, as data can be framed according to different logics (see Bail 2008; Morning 2011; Tversky 1992). Consequently, maps likely differ in a number of ways, such as how the content is organized relationally and where certain boundaries are drawn (see Lamont and Molnar 2002).

Indeed, past research gives us reason to believe that the division of labor in society is not simply a straightforward reflection of

objective differences in occupational contributions, but rather a socially constructed system of beliefs around "what *kinds* of people do what *kinds* of things" (Martin 2000:223; see also Bielby and Baron 1986; Boltanski and Thévenot 1983; Lauer 1974; Simmons and Rosenberg 1971). Studies demonstrate, for example, how occupational literacy is shaped by images and stereotypes portrayed by the media (e.g., DeFleur and DeFleur 1967; Stockard and McGee 1990; Wright et al. 1995), how occupational aspirations are shaped through learned gender roles (e.g., Miller and Budd 1999; Teig and Susskind 2008; Tremaine and Schau 1979; Tremaine, Schau, and Busch 1982), and how the value assigned to specific occupations is affected by participation in certain institutional settings (Binder, Davis, and Bloom 2016; Zhou 2005).

The question thus arises: how do individuals filter these experiences and develop a framework for where occupations belong relative to each other? Broadly, we expect that how actors see the occupational landscape is related to their position in the macro-social hierarchy. A central idea to emerge from sociological research on status is that an actor's position in a group's status hierarchy can shape or constrain that actor's (subsequent) behavior and the strategies she adopts (e.g., Phillips and Zuckerman 2001; Whyte 1943; see also Drea and Wallen 1999).⁶ In a similar vein, we expect that an actor's status position also influences the manner in which the social world itself is defined and articulated (see Bourdieu 1985).

In this study, we operationalize status position vis-à-vis educational attainment. Although education is not the only route to accruing wealth and social respect in the modern U.S. context, most would consider it a major pathway, if not *the* main pathway (Hout 2012). An actor's educational attainment corresponds to a relative position in a broadly recognized ordinal hierarchy of educational credentials (e.g., high school diploma < bachelor's degree < graduate degree) (Collins 1979). Earning these degrees requires experiences with educational institutions (Bourdieu and Passeron 1990); individuals with a master's degree, for

example, have typically accrued six additional years of shared experiences vis-a-vis the educational system, relative to individuals with a high school diploma but no postsecondary experience.

We suspect that three map-related outcomes are significantly shaped by a respondent's level of educational status. First, we hypothesize that more highly educated respondents will exhibit greater consensus in their views of the occupational hierarchy relative to lower-status individuals. Second, we posit that individuals with higher degree status will likely draw sharper boundaries around education-intensive occupations relative to less educated individuals, an exclusion mechanism that gives rise to *categorical* distinctions in terms of occupational prestige. Third, we explore the extent to which individuals with high or low degree status differentiate the value of occupations in different parts of the hierarchy. Although our results turn out not to support this hypothesis, prior literature almost uniformly suggests that differentiation in taxonomies should be most pronounced in spaces in which individuals are most familiar. In summary, the first analysis examines the amount of pile sort consensus within groups, and the second and third analyses describe the form this consensus takes. We discuss each hypothesis in detail in the following sections.

Pile Sort Consensus

The first question we address concerns the extent to which members of a collective exhibit more or less homogeneity in their classification systems as a whole. Coleman (1958:31) long ago put forth the idea of "boundaries of homogeneity" as a method of using survey data to study social structure. The idea of connectedness is most often associated with network analysis, wherein a collection of nodes is characterized as being more or less connected on the basis of direct social relations (Krackhardt 1994). For example, a network analyst might characterize the connectedness of students in a given school vis-à-vis the density of friendship ties. But a collection of individuals can also be

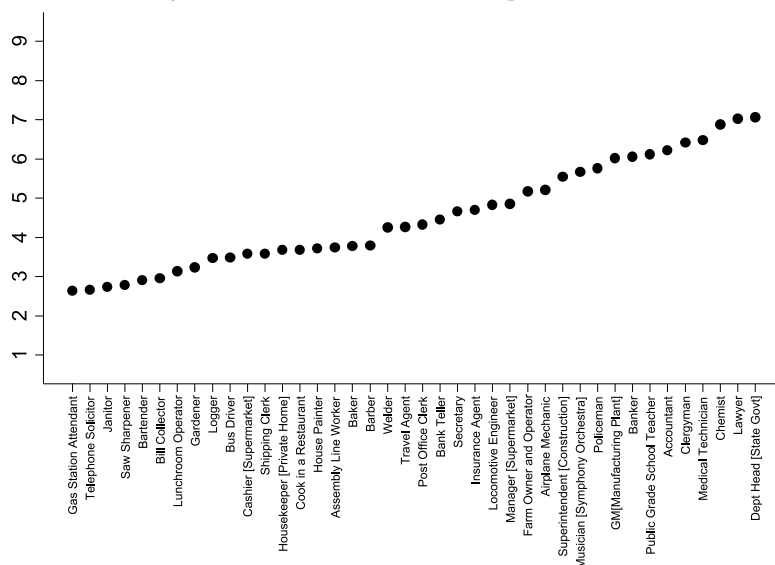
characterized as more or less cohesive on the basis of shared understandings, shared approaches, and shared behavior, regardless of whether they actually know each other.

To illustrate the concept of homogeneity with respect to occupational prestige ratings, consider Figure 1, which provides two contrasting images of the prestige ratings for the 40 occupations given to all raters in the 1989 GSS. Panel a depicts the mean rating of each occupation and orders the occupations from the least prestigious to the most prestigious, which corresponds roughly to how these data have been used in the past as an independent or dependent variable.⁷ Panel b, in contrast, shows the *distribution* of the ratings for the same 40 occupations. The boxplots in panel b are clearly consistent with the fact that some occupations are rated more highly on average than others, but they simultaneously suggest there is a non-trivial amount of dispersion around the mean.

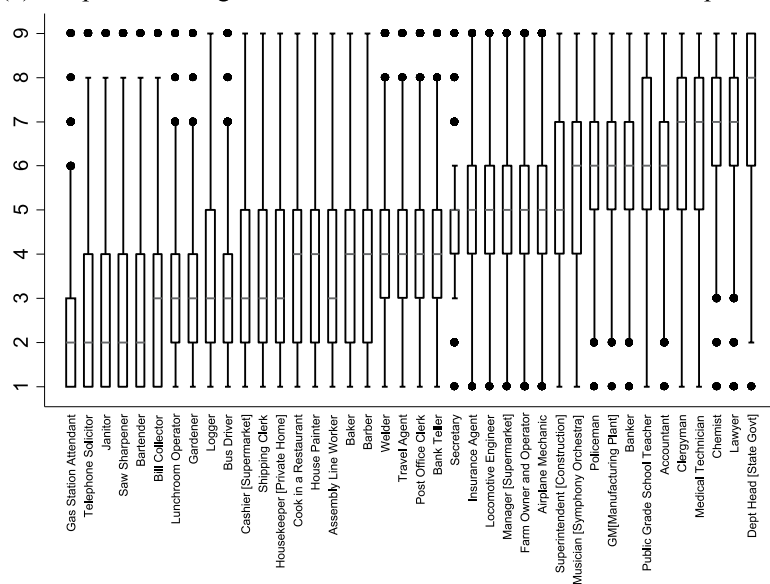
Figure 2 then plots the rating system of two specific individuals (persons A and B) alongside the mean rank. The mean rating (gray line) takes into account both individuals by definition (i.e., the mean is the average of all raters), but note how the two individuals' perceptions (diamonds versus circles) are not well-aligned *with each other*. In this study, rather than average out these differences, we are explicitly interested in exploring why pile sorts are more or less similar.

Our first analysis thus concerns the origins of homogeneity: why would some pairs of individuals have more similar understandings than others? We posit that individuals with college or advanced degrees will map the occupational hierarchy more similarly than will lesser educated individuals. Previous research points to actors' participation in institutional settings as a socialization process that fundamentally shapes their logics of action (McPherson and Sauder 2013; Meyer and Hammerschmid 2006; Thornton and Ocasio 1999). To the extent that higher education serves as an agent of socialization and imparts certain logics,⁸ we hypothesize that participation in the system should lead to convergence on specific views (e.g., science

(a) Mean Rating for Common Core of 40 Occupations



(b) Boxplot of Ratings Distribution for Common Core of 40 Occupations

**Figure 1.** Prestige Ratings for 40 Occupations

Note: In both figures, occupations are presented in ascending order based on mean rank. The boxplots are based on standard definitions: the box represents the interquartile range, the midline corresponds to the median, and the whiskers correspond to 1.5 times the interquartile range.

and authority should be rewarded with prestige), which should create greater within-group consensus in occupational perceptions. In contrast, we expect relatively more heterogeneity among individuals who have not been

incorporated into the educational system. Although the views of individuals with less experience in the education system might be shaped by some other institutional setting (e.g., a religious organization, the military), it

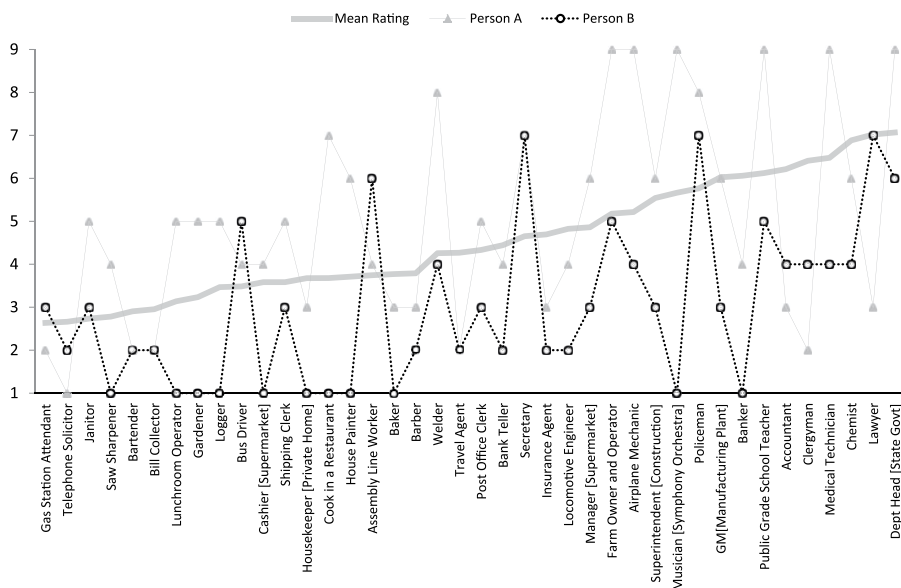


Figure 2. Mean Rating versus Ratings of Two Respondents, Common Core of 40 Occupations

is unlikely that any of these institutions will cast as wide a net as the education system. As a result, the views of individuals with lower levels of education are likely to be more diverse than, say, a group of college graduates (see Converse 1964; Harding 2007).

Boltanski and Thévenot (1983), for example, explore how mental structures of class hierarchy are shared among the French. Participants were asked to sort cards representing individuals with occupational profiles into different piles. They found that individuals with higher educational attainment tended to sort cards into categories that corresponded to official state occupational classifications, which generated piles that were more similar to each other relative to individuals with less educational experience.

Symbolic Boundaries: Segregating Occupations Based on Education-Intensiveness

If higher-status individuals do indeed express more homogeneous views regarding the occupational hierarchy (research question 1), what substantive themes unify their views? On what dimensions do their classification

systems converge? As noted earlier, Zhou's (2005) work documents the differential importance of knowledge-based and authority-based claims as the bases for prestige. Pushing this idea even further, how salient are such attributes to the perception of categorical distinctions among occupations? For example, the salience of certain attributes may affect not only how highly such occupations are ranked on the prestige scale, but also the extent to which individuals set aside certain occupations as a distinct and protected grouping.

We suspect, for example, that high-degree-status individuals may be motivated to draw sharper symbolic boundaries around occupations associated with knowledge and authority claims precisely because such occupations typically require more education (Coxon and Jones 1978; Zhou 2005). For example, if educated individuals map occupations with high training requirements as an exclusive set of occupations, this view, in effect, becomes a cognitive tool that reinforces the rules of a game in which they have already performed well. Protecting the purity of education-intensive occupations could be characterized as a form of social closure (Weber [1922] 1978;

see also Weeden 2002), albeit in cultural space. In effect, this would constitute a sorting mechanism that protects one set of occupations from being tainted or tarnished by another set of occupations. We see this, for example, in Rao, Monin, and Durand's (2005) discussion of the initial separation of *nouvelle* and classical French cuisine, enacted by conventional French chefs to maintain the purity of the latter.

In the case of our nine-rung prestige ladder, the extent to which the educational intensiveness of an occupation is a basis for categorical distinction is rooted, in part, in the extent to which respondents are unwilling to let occupations of various training requirements share a given rung. We examine a simple form of segregation: the extent to which occupations that require a relatively substantial amount of education (HIGH) are placed in the same rung with those that require less education (LOW). If a respondent engages in a great deal of segregation when pile-sorting HIGH and LOW occupations on the nine-rung ladder, this would indicate the presence of a strong symbolic boundary based on training time.⁹ Thus, in Analysis 2, we first merge occupational titles with their average training time using England and Kilbourne's (1988) dataset on occupational attributes. We then explore the extent to which respondents pile sort occupations on the basis of training time, where HIGH is defined with respect to various percentiles of the training-time distribution.

Differentiation Between- and Within-Categories

Analysis 2 allows us to measure the extent to which a particular set of occupations is treated as a distinct set of objects, but the mere presence of a boundary reveals nothing about (1) how the categories on either side of the boundary are juxtaposed relative to one another or (2) the shape or distribution of either category. For example, the presence of a categorical divide does not tell us if the two resulting categories are placed side-by-side (in their relevant conceptual space) or as far

apart as possible. Obviously, in the latter case, the nature of the divide could be characterized as cognitively deeper and more salient than in the former. A related but distinct concern is the extent of differentiation *within* categories on either side of a categorical divide. That is, how much dispersion are respondents seeing in various parts of the occupational landscape? An examination of boundaries coupled with between- and within-category differentiation gives us a more holistic understanding of how classification systems are structured.

To illustrate this point, Figure 3 displays the pile sort outcomes for 12 randomly selected respondents in the form of a histogram. By displaying the raw ratings in this manner, it becomes clear that mental maps can vary dramatically in terms of various structural characteristics, including their shape, central tendency, and spread. For example, a striking feature of Figure 3 is that some individuals spread occupations across all rungs of the ladders, whereas others see relatively little differentiation in occupational prestige, even for the same set of occupations. Take respondent 1, who distributes occupations across all nine rungs of the ladder. Although there is clearly a modal category in respondent 1's distribution, the other occupations are distributed relatively evenly in the remaining eight rungs. In contrast, respondent 5 lumps the vast majority of occupations into the lowest rung, with a sparsely populated right tail of superior occupations. Respondents 6 and 8 assign occupations to only a select portion of the ladder (four and five total rungs, respectively).

Figure 4 builds on Figure 3 by conceptualizing various possibilities in light of a strong versus weak categorical distinction based on a given occupational attribute. In Figure 4, the "x" and "o" markers represent hypothetical occupations that differ in the presence (yes/no) or intensity (high/low) of a single occupational attribute. Many different configurations are possible even in such a simple scenario, but we illustrate six that are useful to consider in the context of our data. The four systems in the top two rows of Figure 4 (a through d) are equivalent in terms of being

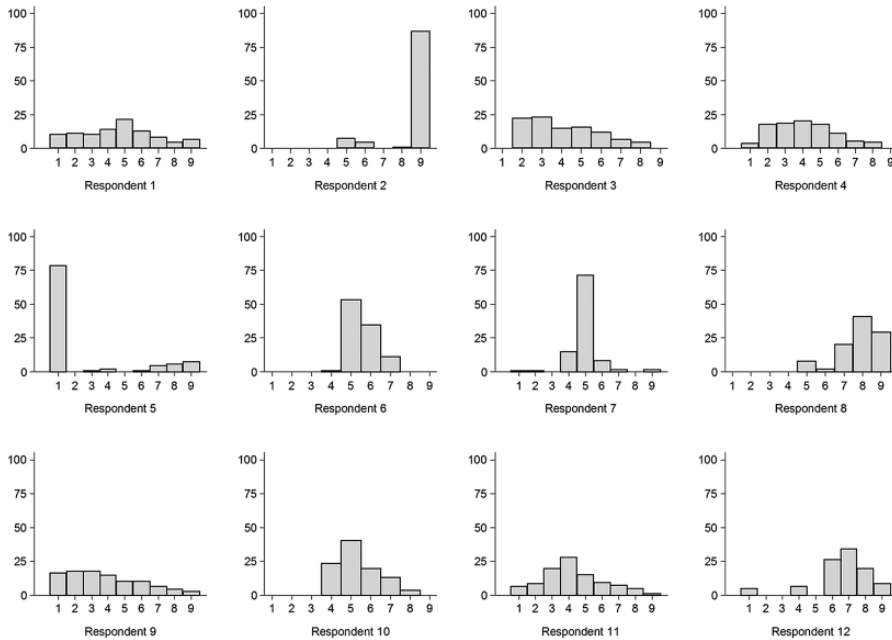


Figure 3. Twelve Respondents and Their Pile Sort Results, All Occupations

Note: The y-axis corresponds to percentage of occupations placed in each rung. The x-axis corresponds to the nine-rung ladder on which respondents were asked to sort occupational titles (nine = most prestigious).

organized around a sharp (in this case, perfect) boundary, such that “x” occupations are never in the same category as “o” occupations; they differ, however, with respect to between- and within-group differentiation. In system 4a, the categorical divide is deepest insofar as there is no differentiation within categories but maximal differentiation between categories. The categorical divide in pile sort 4c, however, is arguably weaker than in 4a due to a greater degree of *within*-category variation in 4c compared to 4a. The categorical divide is also weaker in 4b relative to 4a because *between*-group variation is vastly reduced in 4b. Pile sort 4d illustrates an asymmetrical scenario with respect to within-category differentiation. If a respondent considers “o” to be in-group occupations, 4d represents a mapping in which the out-group is homogenized but the in-group is differentiated. Finally, 4e and 4f correspond to respondents who do not use the x/o attribute as a basis for categorization but vary in their degree of overall differentiation.

The existing research strongly suggests that we should find two empirical regularities when analyzing between- and within-category differentiation with respect to education-intensive occupations. Again, Zhou (2005) documents that individuals with higher education are more likely to elevate the prestige of occupations characterized by a position of authority or a foundation in science. We further hypothesize that individuals with higher educational attainment will place the means of the aforementioned HIGH and LOW occupational categories further apart relative to lower-status individuals. In other words, not only will the mean of the HIGH occupations be higher, the difference in category means will be exaggerated as well. Polarizing the category means would be a way of reifying the distinction between HIGH and LOW training-time occupations.

With respect to within-category differentiation, research from a diverse set of areas almost uniformly suggests that we should expect more differentiation among

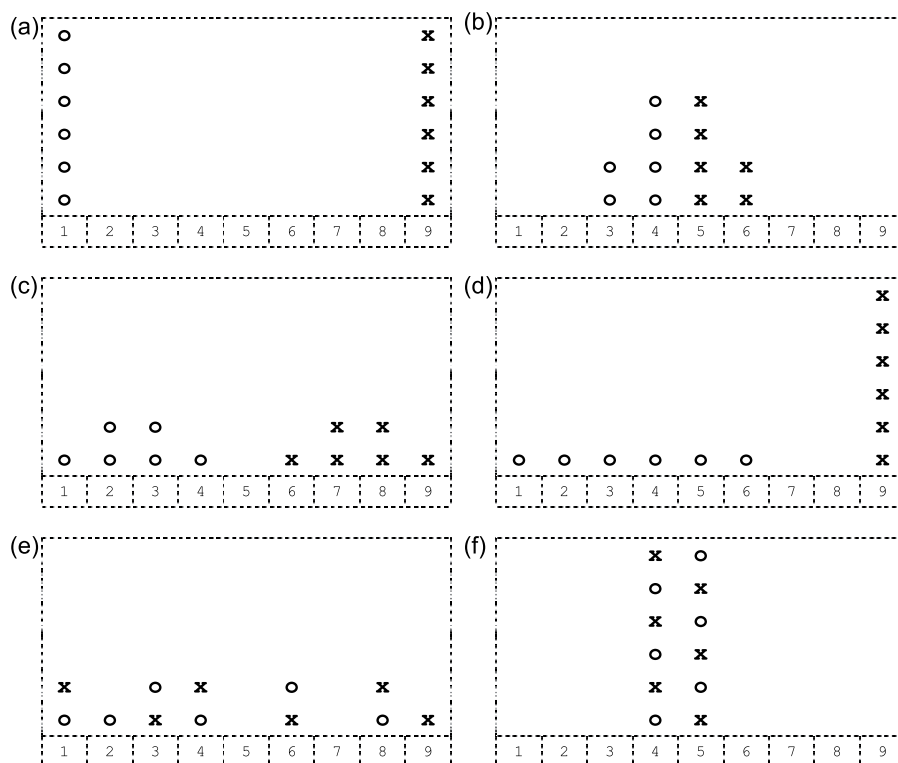


Figure 4. Conceptual Illustration of Between- and Within-Category Differentiation

occupations that respondents claim as part of their in-group and less differentiation among those viewed as occupations of the out-group. A central theme, for example, in Porac and colleagues' (Porac and Thomas 1990; Porac et al. 1989; Porac et al. 1995) research on how firms develop cognitive taxonomies of rivals is that greater taxonomic complexity will exist in organizations that are most familiar to decision-makers. Abbott (2001:11) echoes this theme in his theory of fractal distinctions and his expectation that individuals are "hazy about matters further away." The issue of differentiation has also been studied in depth by social psychologists in their research on inter-group perceptions and out-group homogenization (Tajfel 2010; Tajfel and Turner 1979). The theory suggests that actors have a richer set of experiences upon which to base perceptions of members of their group and they tend to emphasize more "individuating information" for in-group members, in part to be able to distinguish themselves from others within the in-group (e.g., Brauer 2001; Linville,

Fischer, and Salovey 1989; but see Pickett and Brewer 2001). Taken together, we expect respondents to exhibit more differentiation in their mental maps of occupations in locations in which they have greater knowledge. Thus, we expect to find that less educated respondents disperse LOW occupations across a greater number of rungs relative to individuals with higher degree status, whereas high-degree-status individuals should exhibit greater dispersion among HIGH occupations.

DATA AND METHODS

We address our three research questions using the raw ratings from the occupational prestige module of the 1989 GSS.¹⁰ Respondents ($n = 1,166$) were asked to rank 110 occupations with respect to a prestige ladder with nine rungs (nine = most prestigious). The original question wording is provided in Part A of the online supplement. In this module, respondents were divided into one of 10 subsamples. Every respondent was asked to rank a common core

Table 1. Descriptive Summary of Key Measures

| Respondent Characteristics | | | | |
|--|--------|-------|------|------|
| Highest Degree Earned | | | | |
| Less Than High School | | | | 20% |
| High School | | | | 54% |
| Junior College | | | | 7% |
| Bachelor's Degree | | | | 13% |
| Advanced Degree | | | | 6% |
| Female | | | | 57% |
| Race | | | | |
| White | | | | 87% |
| Black | | | | 10% |
| Other | | | | 4% |
| Subjective Class | | | | |
| Lower | | | | 4% |
| Working | | | | 42% |
| Middle | | | | 49% |
| Upper | | | | 4% |
| Age | | | | |
| 18 to 29 years | | | | 23% |
| 30 to 54 years | | | | 49% |
| 55+ years | | | | 28% |
| Pile Sort Characteristics | | | | |
| | Mean | SD | Min. | Max. |
| Number of Occupations Ranked | 102.25 | 19.27 | 5 | 110 |
| Mean Rank: All Occupations Ranked | 4.50 | 1.06 | 1 | 9 |
| Mean Rank: HIGH Training-Time Occupations | 6.25 | 1.24 | 1 | 9 |
| Mean Rank: LOW Training-Time Occupations | 4.30 | 1.12 | 1 | 9 |
| Standard Deviation: All Occupations Ranked | 1.92 | .60 | 0 | 3.68 |
| Standard Deviation: HIGH Training-Time Occupations | 1.69 | .74 | 0 | 4.24 |
| Standard Deviation: LOW Training-Time Occupations | 1.80 | .59 | 0 | 3.68 |
| Between-Group Density | .17 | .18 | .02 | 1 |

Note: $N = 1,148$. In this table, HIGH refers to a training time greater than the 90th percentile of the TRAIN variable in England and Kilbourne's (1988) dataset on occupational attributes. LOW training-time occupations are those with TRAIN scores at or below the 90th percentile.

of 40 occupations and then 70 more occupations unique to their subsample.¹¹ Respondents were allotted 15 minutes to complete the pile sort task, which corresponds to roughly eight seconds per occupational title if a respondent ranked all the titles in the subset.¹² See Nakao and Treas (1994) for details of the survey procedure. Respondents' occupational ratings were then merged with respondent characteristics from the main 1989 GSS survey.

As noted earlier, respondents' status is operationalized with respect to educational attainment, which is measured according to their highest degree earned: less than a high school diploma, a high school diploma or equivalent, junior college or associate's degree, or

bachelor's degree or graduate-level degree. Table 1 provides a descriptive summary of this variable along with all other key variables used in the following three analyses.

Outcomes

Pile sort (dis)similarity. Our first analysis is concerned with the extent to which respondents sort occupational titles in exactly the same way. That is, how far apart are two respondents in terms of how they place occupations on the nine-rung ladder? Dissimilarity in pile sorts can emerge for two broad reasons. First, dissimilarity can be due to scaling-related issues, such as when rater A assigns

doctor and nurse to 9 and 7, respectively, and rater B uses a downshifted ratings system of 5 and 3, respectively. But dissimilarity can also arise when two respondents differ substantively in how they interpret the relation between two occupations. For example, rater A and rater B differ in their understanding of “doctor” and “nurse” in the occupational landscape if A places doctor and nurse in rungs 9 and 2, respectively, whereas B assigns both to category 5. Drawing on Boutyline (forthcoming), the first example could be characterized as a situation in which A and B share a latent understanding of how occupations relate to one another, but they deploy those understandings in slightly different forms (i.e., with scaling and shift differences). In the second example, raters A and B do not appear to abide by the same latent understanding of the occupational hierarchy.

We thus calculate dissimilarity in pile sorts using two approaches. First, using the raw ratings, we calculate the Manhattan distance between respondents i and j , which is the absolute difference between rank_i and rank_j for occupation k summed over all occupations; this corresponds to what we consider total dissimilarity. Next, we convert raw scores to z -scores and then compute the Manhattan distance again; this second dissimilarity score thus takes into account differences with respect to pile sort mean and spread. For example, say that rater A assigns doctor to rung 9, nurse to rung 7, and mechanic to rung 5, whereas rater B assigns doctor, nurse, and mechanic to rungs 3, 2, and 1, respectively. The standardized ratings for both raters would be $z = +1$, $z = 0$, and $z = -1$ for doctor, nurse, and mechanic, respectively. Using raw scores, their dyadic distance would be: $(|9-3|) + (|7-2|) + (|5-1|) = 15$ rungs. However, using standardized scores, person A and person B have a Manhattan distance of 0.

Regardless of whether raw or z -scores are used, a group of individuals of size n with a mean dyadic distance that is closer to 0 exhibits a greater degree of consensus relative to a group with a mean dyadic distance that is significantly larger. We focus here on calculating dyadic distance with respect to the

common core of 40 occupations where the groups of interest correspond to highest degree earned. Because dissimilarity is symmetrical ($\text{distance}_{ij} = \text{distance}_{ji}$) and ties to self are undefined, the total number of dyads per group is given by $(n[n-1])/2$. For the 949 respondents who pile-sorted all 40 occupations in the common core, the mean distance based on raw ranks is 78.9 ($sd = 28.5$), and the mean distance based on standardized ranks is 31.3 ($sd = 8.3$).

Segregation based on training time.

Of the 725 occupational titles included in the prestige module, we were able to classify 703 with respect to the 1980 census occupational classification system.¹³ For these 703 titles, we merged the 1980 occupational codes with England and Kilbourne's (1988) dataset on occupational attributes, which includes characteristics such as average training time, mean wages, and physical demands.

Following Zhou (2005), we operationalize an occupation's educational-intensiveness with the variable “training time” (TRAIN), which is defined as “the amount of general educational development and specific vocational preparation required of a worker to acquire the knowledge and abilities necessary for average performance in a particular job-worker situation” (U.S. Department of Labor 1972:209). This variable is measured in months and ranges from 1 to 105 months. A lawyer, for example, is associated with 81 months, or roughly 6.75 years of overall training time, and a public grade-school teacher is associated with roughly 22 months. As Zhou (2005) notes, the training-time variable is effectively a combination of “general educational development” (GED) and “special vocational preparation” (SVP).¹⁴

In England and Kilbourne's (1988) dataset, the distribution of training times was right-skewed with a mean of 29.9 months and a median of 25.5 months ($sd = 23.4$). Rather than choose a single threshold for what constitutes HIGH training time, we explore a spectrum of cutoff values, such as the 95th, 90th, 75th, and 50th percentiles of the TRAIN variable. Whatever cutoff is used,

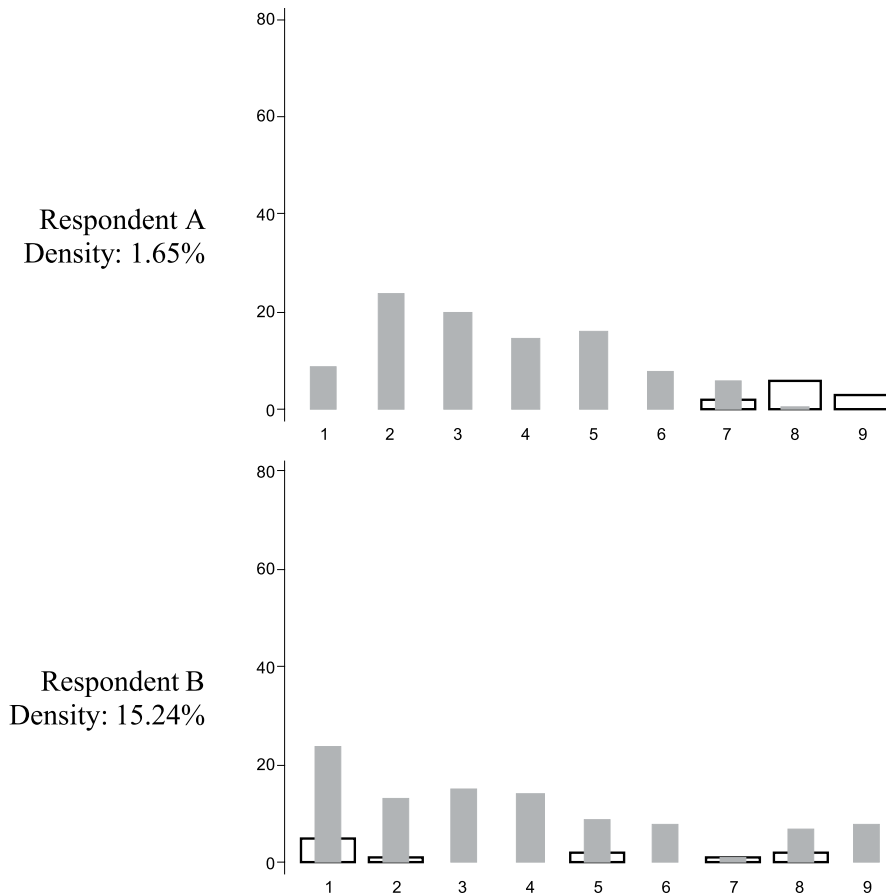


Figure 5. Variation in Between-Category Density, Two Respondents

Note: The y-axis corresponds to raw frequency in each rung. The white bars indicate the distribution of HIGH occupations (i.e., above the 90th percentile); gray bars indicate the placement of LOW occupations.

the dichotomization produces two sets of occupations, which we refer to as HIGH versus LOW occupations. The question of interest is the extent to which a boundary is drawn between HIGH and LOW occupations.

We define the extent of segregation in terms of between-category density; segregation is high when between-category density is low. Between-category density is simply the number of observed LOW-HIGH pairings divided by the total number of possible LOW-HIGH pairings. For example, when using the 90th percentile of TRAIN as the cutoff, 11 occupations are coded as HIGH, 99 occupations are coded as LOW, and thus we have a total of $99 \times 11 = 1,089$ LOW-HIGH dyads. To illustrate, Figure 5 displays the histogram of HIGH (white bars) and LOW (gray bars)

for two respondents. Respondent A clearly has a low between-category density (1.65 percent) with only 18 observed LOW-HIGH pairings out of 1,089. In rung 8, only one LOW occupation is mixed with six HIGH occupations (i.e., six LOW-HIGH pairings) and then in rung 7, six LOW occupations are mixed with two HIGH occupations (i.e., 12 LOW-HIGH pairings); LOW and HIGH occupations are otherwise segregated. For respondent B in Figure 5, however, between-group density is substantially higher. Overall, between-group density is zero when HIGH and LOW occupations are fully segregated, and it approaches one the more that HIGH occupations overlap with many LOW occupations. The distribution of between-group density for one particular definition of HIGH

training time (above 90th percentile) is summarized in Table 1.

Between-category differentiation. Regardless of whether the boundary around training-intensive occupations is strong or weak, a separate issue is the average placement of those two types of occupations (HIGH versus LOW) on the nine-rung ladder. We measure placement as the mean rung associated with HIGH training-time occupations and the mean rung for LOW training-time occupations. The mean of either category, of course, is contingent on what threshold is used to define HIGH and LOW. However, regardless of how HIGH and LOW are defined, between-category differentiation is higher when there is a greater distance between the mean of HIGH and the mean of LOW.

Within-category differentiation. Contingent on our definition of HIGH and LOW training times, we measure the extent to which each set of occupations is spread out or dispersed over the ladder versus clustered in a single rung. To quantify dispersion, we calculate the sample standard deviation of HIGH and LOW occupations separately. In this context, the standard deviation is the average distance between a typical occupation in a set and the mean occupation in that set. The sample standard deviation is zero when respondents place all occupations in a given set in a single rung. A respondent who clusters occupations into only two consecutive rungs will have a standard deviation closer to zero relative to a respondent who distributes occupations across multiple rungs spread throughout the ladder.¹⁵ Table 1 summarizes between- and within-category differentiation measures when HIGH is defined with respect to the 90th percentile of the TRAIN distribution.

Analytic Plan

In Analysis 1, we explore whether more highly educated individuals are characterized by greater within-group homogeneity in their views of the occupational landscape relative to less educated individuals. As noted, pile sort similarity is a dyad-level property, which

we aggregate to a group-level outcome by averaging pairwise distances across all dyads within a specific group of individuals. We then compare mean within-group similarities/distances *across* status groupings. As hypothesized earlier, we suspect that groups of higher-status individuals will be characterized by a greater degree of consensus compared to groups of lower-status individuals.

In Analysis 2, we use a fractional probit model to estimate differences in between-category density based on training time as a function of respondents' highest educational degree and several covariates. We control for the GSS subset of occupations (subset 1 to 10) to which the respondent was assigned as well as a host of demographic characteristics, including the respondent's sex (male or female), self-reported race (white, black, other), and age (mean = 44.5, sd = 17.4, range = [18, 89]), which we divide into three categories: 18 to 29, 30 to 54, and 55 to 89. Our models also include self-reported social class position (lower, working, middle, upper). We also control for the standard deviation of the entire rating system; the extent of segregation is likely to be lower if a respondent places a large number of occupations into just a few rungs. Table 1 provides descriptive summaries of these variables.

Analysis 3 (between- and within-category differentiation) uses OLS regression methods to explain four distinct outcomes: (1) the mean rank of HIGH occupations, (2) the difference in the mean rank between HIGH and LOW occupations, (3) the standard deviation in the ratings of HIGH occupations, and (4) the standard deviation in the ratings of LOW occupations. Similar to Analysis 2, each outcome in Analysis 3 is modeled as a function of the respondent's highest educational degree, the respondent's background characteristics (sex, race, age, and self-reported class), and GSS subset to which the respondent was assigned.

RESULTS

Analysis 1: Pile Sort Consensus

As predicted, Figure 6 shows that groups of individuals with higher educational

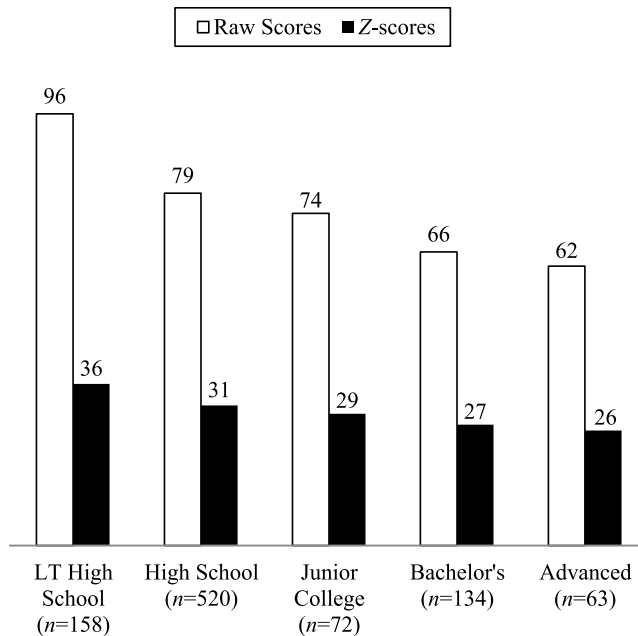


Figure 6. Mean Within-Group Manhattan Distance by Highest Degree Earned

attainment exhibit a greater deal of consensus in how they map the occupational landscape. Greater consensus is indicated by lower dyadic distances averaged within the group. The white bars in Figure 6 plot the average within-group Manhattan distance with respect to raw ranks, and the black bars correspond to mean distance based on standardized ranks. For example, among the 134 respondents with a bachelor's degree ($n = 8,911$ dyads), their ratings' vectors are 66 rungs apart from one another, on average, across all pairwise comparisons in the group; for the 158 respondents with less than a high school diploma, the average dyadic distance is nearly 50 percent higher (96 rungs). We note that dyadic distance based on z-scores (black bars) is lower for all status groups but still conforms to the same pattern; the average dyadic distance based on z-scores is 33 percent higher for the bachelor's group compared to the less than high school group. This indicates that while scaling-related dissimilarity is a significant portion of total dissimilarity for all groups, there is still evidence of stronger consensus among individuals with higher degrees in terms of how occupations are

placed relationally even after the noise of scaling issues is removed.¹⁶

In summary, degree status generates formal categories of persons on the basis of a shared level of education, but it is also true that individuals with higher levels of education are more internally cohesive in terms of their rankings of occupational hierarchy compared to individuals with less education. Part C of the online supplement goes a step further and tests whether this pattern of results holds even after controlling for a respondent's likelihood of obtaining postsecondary education. The concern is that it is not participation in the educational system that gives rise to homogeneity, but rather a set of shared background factors that give rise to both educational participation and shared valuation systems. Thus, drawing on the logic of propensity score matching methods, Part C of the supplement provides a more robust test of our convergence hypothesis by testing whether within-group distance differs by bachelor's degree status within strata of individuals with similar propensities of obtaining a bachelor's degree. Although by no means definitive, these results at least suggest that the pattern

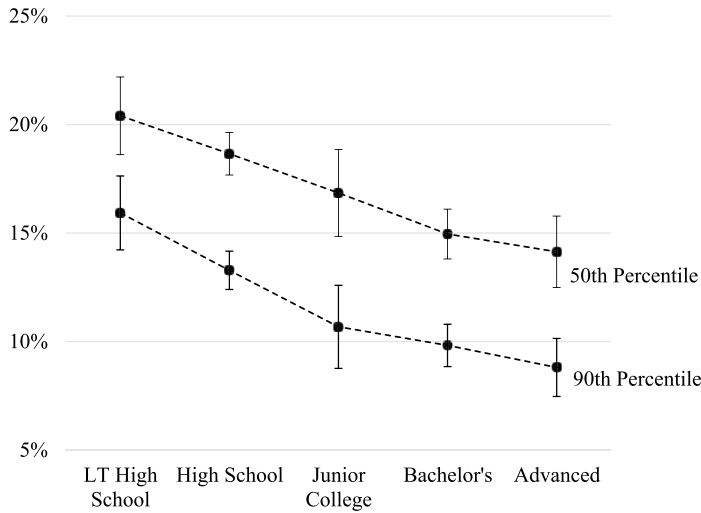


Figure 7. Predicted Between-Category Density by Highest Degree Earned

Note: Estimates are based on the fractional probit regressions shown in Part D of the online supplement. The y-axis corresponds to between-category density with respect to HIGH and LOW occupations; higher percentages indicate boundary weakness. The error bars refer to the 95 percent confidence interval for the mean. The top line indicates boundary weakness between HIGH and LOW occupations at the 50th percentile of the TRAIN distribution; the lower line corresponds to the 90th percentile. See Part D of the supplement for the regression results on which these estimates are based.

of results in Figure 6 is not simply a byproduct of self-selection, and instead that participation in the educational system does indeed have a homogenizing effect. We return to the broader implications of this point in the Discussion.

Analysis 2: Segregation Based on Training Time

Could the homogeneity patterns documented above be due, in part, to how respondents segregate or draw boundaries around certain kinds of occupations? We hypothesized earlier that respondents with more education would be more likely to protect the categorical purity of occupations that require a high level of training. The use of such a logic could generate more pile sort consensus within a group of raters.

Using a fractional probit to model variation in between-category density (a measure of HIGH and LOW overlap), we find that individuals with higher degree status are more likely to segregate occupations with respect to training-time eliteness than are individuals

with lower degree status. Figure 7 plots the predicted between-category densities for each degree grouping when HIGH is defined as above the 90th or 50th percentile. Part D of the online supplement shows the full regression results for three different definitions of HIGH.¹⁷ For example, when the 90th percentile of TRAIN is used as the cutoff between HIGH and LOW occupations, the expected between-category density is roughly 16 percent for “less than high school” and 13 percent for “high school,” both of which are significantly larger than the expected densities for individuals with a bachelor’s or more advanced degree (10 and 9 percent, respectively).

Analysis 3: Between- and Within-Category Differentiation

We hypothesized that higher-educated respondents would not only segregate occupations to a greater degree based on training time (Analysis 2), but also place HIGH occupations higher on the ladder, on average, relative to LOW occupations. At the same time, in terms of within-group differentiation, we

expect to see greater dispersion in the prestige rankings of occupations with which individuals are more familiar; respondents with more degree status will see greater dispersion among HIGH training-time occupations, whereas respondents with lower degree status will articulate more dispersion among LOW training-time occupations.

Table 2 reports regression results for four distinct outcomes related to the placement of HIGH and LOW training-time occupations, where HIGH is defined with respect to the 90th percentile of the TRAIN distribution. In Model 1, the outcome is the mean rank of the HIGH occupations; in Model 2 the outcome is the *difference* between the mean rank of the HIGH versus LOW occupations. The dummy variables for “less than high school” and “high school” are both negative and statistically significant, indicating that respondents in the reference category (bachelor’s degree or higher) tend to give HIGH occupations higher prestige scores on average. This finding is consistent with Zhou’s (2005) results.

Importantly, Model 2 clarifies that this finding is not a simple byproduct of a vertical shift in means: respondents with higher degree status not only give HIGH occupations higher scores on average (Model 1), they tend to polarize the means of the HIGH and LOW categories to a significantly greater extent than do respondents without postsecondary experience. For example, compared to a respondent with a bachelor’s or advanced degree, a respondent with less than a high school diploma places the mean of HIGH and the mean of LOW .995 rungs ($p < .000$) *closer together* on the nine-rung ladder, controlling for race, sex, subjective class, age, and GSS subset.

Models 3 and 4, however, do *not* support our hypothesis regarding out-group homogeneity. Respondents do not appear to have greater discriminatory power for occupations that are arguably closer to their in-group. The outcomes in Models 3 and 4 are the standard deviation of the HIGH and LOW occupations, respectively. Our results suggest that the two groups with the lowest degree status

exhibit *greater* differentiation with regard to both HIGH and LOW occupations relative to the reference category (bachelor’s or graduate degree).¹⁸

Taken together, our results converge on one main finding. As we address in the Discussion (see Figure 9), these results show that less educated respondents pile sort their cards with simply far less attention to the HIGH versus LOW distinction relative to the more educated respondents, who do tend to separate HIGH from LOW. That is, relative to more educated respondents, lower-educated respondents pile sort with more within-HIGH and within-LOW variation relative to between-category variation.

Supplemental Analysis: The Relative Importance of Training Time as an Organizing Principle

The question arises, does training time constitute a salient basis for categorical distinction *relative* to other dimensions of occupational variation (e.g., occupational income)? That is, respondents may indeed sort occupations on the basis of training time, but other occupational attributes may be as important, if not more important, foundations with respect to how individuals map the organizational hierarchy.

Drawing on Analyses 2 and 3, our findings suggest that high-degree-status respondents reify the symbolic boundary between HIGH and LOW training-time occupations in multiple ways. For example, high-status respondents are more likely to segregate HIGH occupations from LOW occupations (low between-group density) *and* more likely to concentrate HIGH occupations in fewer rungs. We can thus combine these two dimensions into a composite measure of exclusivity by taking, for example, the ratio of within-HIGH density (the proportion of HIGH occupations placed in exactly the same rung) to between-group density. Using this ratio measure of within-HIGH density to between-category density to indicate the presence of a boundary, we can begin to compare different

Table 2. OLS Estimates of Between- and Within-Category Differentiation

| | M1 | M2 | M3 | M4 |
|------------------------|--------------------|--|--------------------|--------------------|
| | Mean Rank HIGH | Difference in Means (HIGH – LOW) | Std. Dev. HIGH | Std. Dev. LOW |
| Degree | | | | |
| Less Than High School | –.747*** (.131) | –.995*** (.133) | .388*** (.075) | .287*** (.058) |
| High School | –.306*** (.087) | –.466*** (.090) | .152** (.053) | .081* (.039) |
| Junior College | .056 (.134) | –.121 (.139) | .003 (.081) | .038 (.064) |
| Female | .098 (.075) | .400*** (.078) | .124** (.042) | .129*** (.033) |
| Race | | | | |
| Black | .116 (.156) | –.258 (.160) | .231** (.082) | .271*** (.065) |
| Other | –.140 (.258) | –.358 (.269) | .117 (.110) | .079 (.059) |
| Subjective Class | | | | |
| Lower | .007 (.217) | –.036 (.226) | .261* (.130) | .257* (.106) |
| Working | –.174* (.079) | –.215** (.082) | .025 (.044) | –.014 (.034) |
| Upper | –.501** (.194) | –.350 (.212) | .231 (.124) | .122 (.079) |
| Age | | | | |
| 18 to 29 years | –.120 (.091) | –.085 (.096) | .160** (.052) | .144*** (.040) |
| 55+ years | .212* (.092) | .141 (.097) | .042 (.051) | .112** (.041) |
| GSS Subset (9 Dummies) | Yes | Yes | Yes | Yes |
| Constant | 6.085*** (.128) | 1.966*** (.143) | 1.692*** (.077) | 1.488*** (.061) |
| Observations | 988 | 988 | 988 | 988 |
| R-squared | 9% | 12% | 14% | 14% |

Note: Robust standard errors are in parentheses. In these analyses, HIGH training time is defined with respect to the 90th percentile of the TRAIN distribution. The reference category for *subjective class* is middle class. The reference category for *degree* is bachelor's or a more advanced degree, and the reference group for *age* is 30 to 54 years. Respondents who placed all occupations into one rung or who rated fewer than 100 occupations were not included in this analysis; the results, however, are substantively the same if all respondents are included.

* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed tests).

occupational attributes and the extent to which eliteness on these attributes is a basis for pile sort organization.

Figure 8 depicts the mean ratio associated with training time—for three status groups—across various thresholds of what constitutes

a HIGH training-time occupation. For example, in panel a of Figure 8, “75” on the x -axis corresponds to the ratio measure when a HIGH training-time occupation is defined as above the 75th percentile of the training-time distribution. Note that because the ratio would

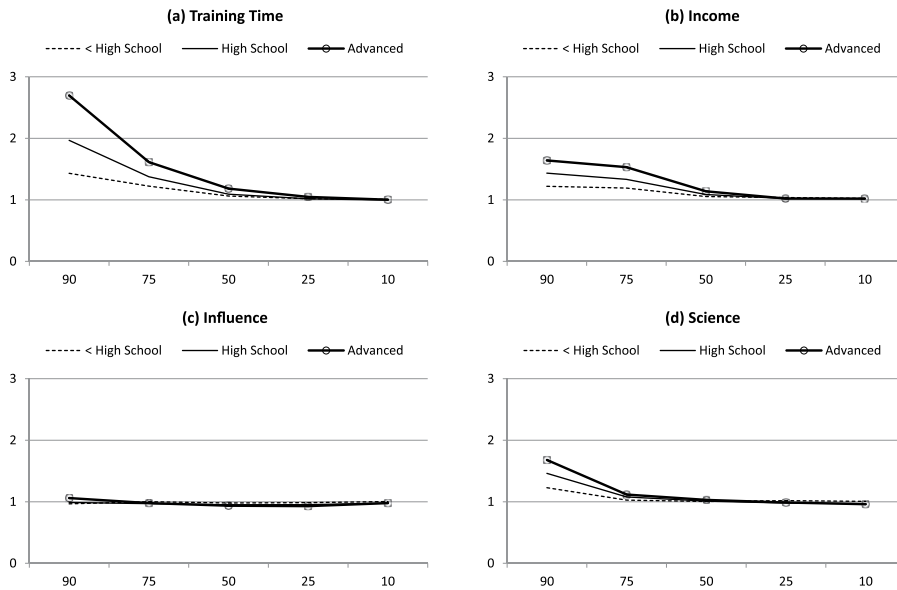


Figure 8. Overall Boundary Sharpness by Occupational Attribute

be undefined for respondents without any between-category pairings (the denominator would be 0), we calculate the ratio after adding a constant of .01 to the between-category density scores.

First, for all degree groups, panel a in Figure 8 clearly suggests that an occupation's training time is a salient attribute in terms of how respondents categorize occupations. For any reasonable definition of what constitutes HIGH training time, we see that respondents are more likely to group HIGH occupations together in one category than they are to mix HIGH and LOW occupations together; regardless of the respondent's degree level, the ratio is greater than one when HIGH is defined with respect to the 50th percentile or higher of the TRAIN distribution.

Panels b, c, and d, of Figure 8 summarize the ratio for three additional occupational characteristics studied by Zhou (2005) (for details, see England and Kilbourne 1988). MMEANYR is the "mean annual earnings of men in the experienced civilian labor force who worked" full-time and year-round in an occupation (England and Kilbourne 1988:6). SCINPREF is the percentage of workers in an occupation who have "a preference for

activities of a scientific or technical nature" (England and Kilbourne 1988:17). INFLU refers to the percentage of workers in an occupation where the worker is in "a position to motivate, convince, or negotiate" (England and Kilbourne 1988:199). Comparing panel a to its counterparts b through d, the training time of an occupation appears to be a particularly salient organizing principle in terms of how boundaries are drawn. Occupational income (MMEANYR), salience in science (SCINPREF), and authority (INFLU), for example, are all correlated with TRAIN at a moderate level (respectively, $r = .64$, $r = .41$, $r = .43$), but none give rise to a boundary as sharp as that observed for training time.

DISCUSSION

Occupational prestige scores have become a stock measure in the sociologist's arsenal (Nakao and Treas 1994), despite unanswered questions related to the nature of occupational beliefs at the individual level (see Coxon and Jones 1978; Goldthorpe and Hope 1972; Zhou 2005). We argue that although there is nothing technically incorrect about occupational prestige scores, it is also entirely

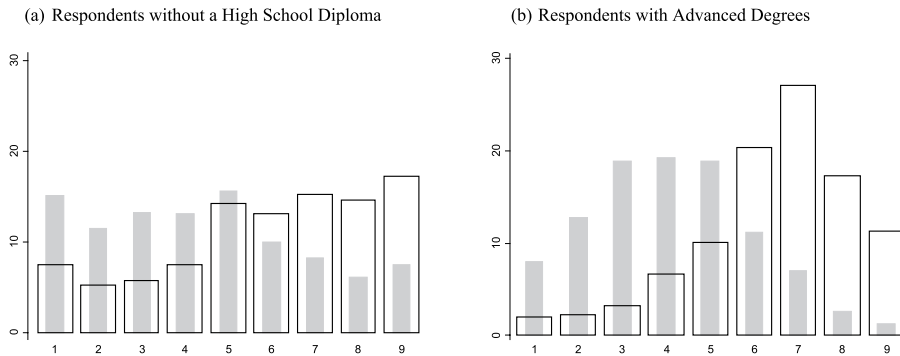


Figure 9. Comparing Pile Sort Outcomes for Respondents with Lowest versus Highest Degree Status

Note: The y-axis corresponds to the percentage of occupations placed in each rung. The white bars indicate the distribution of HIGH occupations; the gray bars indicate the placement of LOW occupations. HIGH is defined with respect to the 90th percentile of the training-time distribution. Panel a represents the aggregated pile sort for all respondents in all 10 subsets with less than a high school diploma. Panel b represents all respondents with advanced degrees.

possible that the aggregate “averages out” meaningful types of variation in individuals’ belief systems. In the present study, we took a new approach to old data: we examined the *entire* classification system as the outcome of interest and identified new questions to be examined with a sociological lens. Goldberg (2011:1398) notes that a major challenge for sociology is to operationally define the “symbolic building blocks [of culture] that are replicated, albeit unsystematically, across individuals.” Our study attempts to do just this with a cultural construct that is central to the study of stratification.

In our exploration of pile sort dissimilarity (Analysis 1), we find that high-status individuals exhibit more compatibility in their definition of the occupational landscape than do lower-status individuals. We then show that consensus materializes, in part, because higher-educated individuals are more likely to segregate occupations on the basis of training time (Analysis 2), with education-intensive occupations placed higher on the prestige ladder relative to all other occupations (Analysis 3). Figure 9 helps summarize these findings by showing the aggregated pile sort distribution for HIGH and LOW occupations for respondents with an advanced degree ($n = 71$) and respondents with less than a high school diploma ($n = 235$).

The white bars in Figure 9 represent the distribution of HIGH occupations and the gray bars the LOW occupations, defined with respect to the 90th percentile of training time. The defining feature of pile sort 9b relative to 9a is the distinction that emerges between training-intensive occupations and all other occupations. Although far from being a perfectly pure category, it is clear that respondents with advanced degrees are more likely to group HIGH occupations in the top rungs of the ladder, separated from the LOW occupations that tend to be concentrated in lower rungs of the ladder. For the less educated respondents in 9a, the distribution of HIGH occupations is also left-skewed as in 9b, but the overall divide between HIGH and LOW is much fuzzier. In 9a, there is simply more within-HIGH and within-LOW variability relative to between HIGH and LOW.

These results meaningfully improve our understanding of how individuals make sense of the occupational landscape, but our study only scratches the surface of what can be learned by taking entire classification systems as the object of analysis. Moving forward, we suggest that scholars tackle a number of important questions that were outside the scope of this study. First, what is the role of other macro-level status characteristics (e.g., sex, race, and subjective class identification)

in terms of how occupational hierarchy is perceived?¹⁹ For example, in Model 2 of Table 2, why do women (relative to men) tend to polarize the means of HIGH and LOW training-time occupations? Similarly, it is unclear why respondents who identify as upper class (controlling for education, sex, race, and age) downgrade the prestige of training-intensive occupations relative to respondents who identify with the middle class. Perhaps individuals who see themselves as inhabiting the uppermost class view the vast majority of occupations in the GSS module as regular or common occupations, which they might view as a step below a truly elite group of roles (e.g., philanthropist).

Second, this study focused on unpacking the role of training requirements in how pile sorts are organized, but other types of logics remain to be explored. We suggest that future research examine the possibility of multiple or cross-cutting symbolic boundaries more generally. As a first step, our analysis focused on one of the simplest scenarios: the possibility of a single boundary (tied to a single attribute) that divides occupations into two categories (HIGH and LOW). Our supplemental analysis suggests that training-time eliteness is a stronger organizing principle than at least some other occupational characteristics (income, salience in science, and authority characteristics), but other occupational attributes may be far more important than training time. Future research should also go beyond the standard dictionary of occupational attributes to think about more abstract ways in which value might be construed. For example, do some individuals conceptualize the desirability or prestige of an occupation according to the concreteness of the labor performed (e.g., "I fixed a road today") versus, say, the morality of the occupation's broader purpose?

Third, drawing on Harding (2007), future research should aim to unpack the heterogeneity in mental maps observed among less educated individuals. To be clear, our study does not suggest that individuals with less education do not possess systematic frameworks for organizing the occupational landscape. Rather, our results merely tell us that

individuals with less education (relative to those with more) are less unified in *how* they map occupations, and that training time is less salient as an organizing principle compared to respondents with more education.

Indeed, a key task for future research is figuring out what best explains the pile sort behavior of individuals with less education. For example, to what extent is heterogeneity more pronounced because lower-status individuals are more likely to report first-order evaluations, whereas higher-status individuals report third-order evaluations, which are likely more consensual? What role does occupational literacy play with respect to heterogeneity in views? As noted in Part B of the online supplement, education was a major predictor of the number of occupations respondents left unranked. In light of this, one wonders whether individuals with lower levels of education who did sort many cards were more likely to sort in a random fashion.²⁰

Moreover, to what extent is there more pile sort heterogeneity among the less educated because the group is fragmented with respect to multiple (competing) logics, such as in Harding's (2007) case? Or, are our results showing that individuals with less education simply have less organized belief systems (see Boutyline and Vaisey forthcoming; Converse 1964; Zaller 1990)? If this is the case, then it is not about yellow and blue lenses giving rise to a green average, but rather green plus noise creating a greenish average.²¹ So far, all we know is that the greater dyadic distance we observe among individuals with less education can be linked to some extent, but certainly not fully, to heterogeneity in the mean and spread of their pile sort distributions (see Figure 6).

In terms of the broader implications of this work, we suggest that future research examine whether penalties accrue to individuals who attempt to navigate the occupational environment using a map that does not align with the shared ideology of individuals in positions of power. For example, in light of Rivera's (2012, 2015) recent work on the importance of cultural fit in hiring, and Lizardo's (2006) work on cultural consumption and network tie formation, one wonders about

the extent to which abstract frames pertaining to the *definition* of social phenomena can also constitute a form of cultural incompatibility or incongruence. Culture is typically operationalized with respect to specific forms (e.g., “Do you attend operas and symphonies?”), from which two individuals can be characterized as aligned in their cultural preferences if they consume or prefer the same forms of culture (e.g., “We both like attending operas.”). This type of equivalence is clearly one basis for commonality and interpersonal attraction, but we speculate that another important form of alignment is rooted in the extent to which individuals share mental maps of various cultural and social spaces.

Finally, understanding how perceptions of the entire occupational landscape shape selection into occupations (or the identification of aspirational occupations) could help advance a long-standing sociological interest in processes related to social reproduction (MacLeod 2008; Willis 1981). As Young (2006:11) argues in *The Minds of Marginalized Black Men*:

Beliefs . . . are not deducible from behavior, but rather help to create the cultural fabric that informs and encourages such action. In other words, the way people think about the processes of social and personal mobility inform us about how they choose to act with respect to future prospects and possibilities.

Building on this line of thinking, to what extent do views of the occupational hierarchy influence how individuals conceptualize whether certain occupations are (in)appropriate for themselves and for others?

To this point, it becomes apparent from Figure 9 that our characterization of social mobility should be contingent on how occupations are relationally construed. We speculate that the concept of “moving up” might be qualitatively different for respondents who are aligned with the mapping on the left versus the right. To an individual with the type of gradational map we see on the left, aspiring to move from one rung to another over one generation could be interpreted as a significant amount of social mobility. For an individual

who uses the lens on the right, meaningful mobility is likely defined in terms of crossing the divide between education-intensive and non-intensive occupations.

Therein lies the problem with using average prestige ratings to define the occupational hierarchy; the average summarizes all ratings but may or may not be applicable to any actual rater. This is not the type of problem, however, that needs to be solved in a technical sense. We believe there is little to be gained by debating whether aggregate prestige ratings are right or wrong, but instead much to be learned by examining the valuation processes on which that construct is built. In this application, we find that our observation of aggregate consensus across time and space (the Treiman constant) masks meaningful variation in how certain groups map occupations.

Acknowledgments

We are indebted to Sarah Bruch, Rebecca Durkee, Elizabeth Felix, Jennifer Glanville, John Levi Martin, Michael Lovaglia, Flint Neidenthal, Olga Novoselova, Michael Sauder, Austin Van Loon, and Jessica Welburn for their insights and suggestions at various stages of the project. We also wish to thank participants of the Inequality Seminar at the University of Iowa and the Organizational Behavior and Theory seminar at Carnegie Mellon’s Tepper School of Business.

Notes

1. One aspect of these data that remains unclear is if individuals approach the pile sort task from a first-order perspective (what do *I* think about the ranks of these occupations?) or a third-order perspective (what do most others think about the ranks of these occupations?). We reflect on this issue more in the Discussion, but we generally suspect it is some combination of both. See Goldthorpe and Hope (1972) for more discussion on what evaluators are actually thinking when they are asked to rate the prestige of occupations.
2. For example, the correlation between the prestige rankings of 29 occupations in 1925 and 1963 is .94 in the United States, .98 in Japan, and .94 in the Netherlands (Treiman 1977:74). Moreover, in the United States as well as in other industrialized and non-industrialized countries, correlations of rankings between ethnic groups and sexes are extremely high. In the United States, for instance, women’s and men’s rankings are highly correlated ($r = .98$) (Treiman 1977:67).

3. RC28 is the Research Committee on Social Stratification associated with the International Sociological Association.
4. For instance, farmers give lower scores on average to all occupations compared to non-farm laborers; women rank ministers substantially higher than do men; men assign more prestige to factory owners than do women; and respondents with less than an 8th-grade education give higher prestige scores to craft and unskilled occupations than do individuals with more education (Reiss 1961:162–195).
5. For example, in geography and spatial mapping, see Groumpos (2010) on “fuzzy cognitive maps” and Golledge and Stimson (1997) on “wayfinding.” In cognitive psychology, see Tversky and colleagues (Tversky 1981; Tversky and Schiano 1989) on “cognitive reference frames.” With regard to social environments and networks, see Neal and Neal (2013) on “social cognitive mapping” and Casciaro and colleagues (Casciaro 1998; Casciaro, Carley, and Krackhardt 1999) on “cognitive social structures.” In organizations, see Porac and colleagues (Porac and Thomas 1990, 1994; Porac, Thomas, and Baden-Fuller 1989; Porac et al. 1995) on “mental maps.” In sociology more broadly, see Morning (2011) on racial “conceptualization” as well as the large literature on logics (McPherson and Sauder 2013; Meyer and Hammerschmid 2006; Thornton and Ocasio 1999, 2008) and symbolic boundaries (Bail 2008; Lamont 1992; Lamont and Molnar 2002).
6. A classic example of this dynamic comes from Whyte’s (1943) study of bowling performances among the Norton Street Gang, where actors with low social status tended to underperform relative to their actual bowling ability in the presence of higher-status group members. In more recent applications, researchers have documented, for example, the link between an actor’s status and self-assessments of ability (Correll 2001, 2004; Correll and Ridgeway 2003) as well as the link between an actor’s status and the likelihood of engaging in conformist behaviors (Phillips, Turco, and Zuckerman 2013; Phillips and Zuckerman 2001).
7. In practice, the occupation-level means shown in panel 1b are typically converted into a 100-point scale (see Nakao and Treas 1994:7–8).
8. For further discussion on how education affects ideological content, see Bobo and Licari (1989), Bourdieu and Passeron (1990), Brody (1994), Weil (1985), and Zhou (2005).
9. The question also arises as to whether training requirements is a salient basis for classifying occupations *relative* to other occupational attributes. We address this point in the online supplement (<http://asr.sagepub.com/supplemental>) as well as in the Discussion.
10. Data are available at [http://www.icpsr.umich.edu/icpsrweb/ICPSR/series/28/studies/9593?archive=](http://www.icpsr.umich.edu/icpsrweb/ICPSR/series/28/studies/9593?archive=ICPSR&sortBy=7)ICPSR&sortBy=7. The occupational prestige module was administered once again in the 2012 GSS. However, according to GSS administrators, no date has been scheduled for the release of the raw ratings.
11. Of the 740 occupational cards included in the prestige module, 15 were not actual occupational titles but instead referred to occupations of persons connected to the respondent (e.g., “the occupation of my spouse” and “the occupation of my father when I was growing up”). We did not analyze rankings associated with these cards in this study.
12. See Part B of the online supplement for an analysis of the number of occupations respondents ranked.
13. Similar to Zhou (2005), we found 22 occupational titles in the GSS prestige module, such as “panhandler,” “retiree,” and “prostitute,” that did not clearly fit into the 1980 census categories, and we dropped them from the analysis.
14. The TRAIN time variable is highly correlated ($r = .72$) with a composite index of the four occupational attributes used in Zhou’s (2005) analysis. To characterize an occupation’s proximity to “nature and reason,” Zhou studied SCINPREF (“Salience in Knowledge/Science”) and FIF (“Salience in Creativity”). To characterize an occupation’s authority position, he focused on DCP (“Salience in Authority”) and INFLU (“Salience in Influence”).
15. In the analyses that follow, we tested other measures of spread, such as the coefficient of variation, the coefficient of quartile dispersion, and the Herfindhal index of concentration and—in this application—found them to yield the same substantive results. We use the standard deviation because of the intuitive appeal of the interpretation in this context; for example, a standard deviation of three versus one indicates that for a given set of occupations, respondents placed occupations, on average, about three rungs versus only one rung away from the mean of the set.
16. Using the Pearson correlation to measure within-group consensus leads us to the same substantive conclusion.
17. The results are substantively the same when using a fractional logit model or using an OLS model of logged between-group density.
18. Also, in supplementary analyses, we tested whether an actor’s degree status affects how occupations are mapped, because education status affects the tangible reality in which the actor is embedded. We found, however, that the effects of education remain substantively the same even after controlling for factors such as the respondent’s income, her “big class” position, objective job characteristics of her current occupation (e.g., physical hazards), and subjective job satisfaction. More generally, the effects of educational status reported in Analyses 2 and 3 are robust to controlling for differences in a variety of background characteristics, including

- general happiness, marital status, urbanicity, and political views.
19. In a similar vein, it would be useful to unpack important nuances related to educational status. Because of data limitations, we treated educational experience crudely, insofar as we divided the sample by degree type (e.g., high school, two-year degree, four-year degree) even though these broad categories have substantial variation. For example, two individuals with four-year college degrees could have had vastly different institutional experiences (e.g., one majored in biomedical engineering and the other in social work; one attended an elite private university and the other a recently established for-profit institution).
 20. A separate but equally important issue related to the survey instrument pertains to respondents' rule-following attitudes. What if individuals with more education simply felt more comfortable not using every category, whereas respondents with less education felt compelled to make gradational distinctions (i.e., to sort cards into all nine boxes)?
 21. We thank a reviewer for pointing this out.

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