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Deviations from cultural consensus about occupations: The duality of occupation meanings and Americans' meaning communities

Aidan Combs[a,b,*], Gabriel Varela[c], Dawn T. Robinson[d], Lynn Smith-Lovin[c], Stephen Vaisey[c]

[a] The Ohio State University, USA
[b] University of Bamberg, Germany
[c] Duke University, USA
[d] University of Georgia, USA

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ABSTRACT

We examine ratings of 642 occupations by a national online sample of U.S respondents in 2019 (Freeland et al., 2020). We analyze the respondents' ratings of occupations on three dimensions of cultural meaning—evaluation (good versus bad), potency (powerful versus powerless), and activity (lively versus quiet). We take deviations of respondents' individual ratings from population evaluation, potency and activity estimates, focusing on deviations from consensus rather than consensus itself. Drawing on Breiger's (1974) work on duality, we examine two projections of the initial rectangular matrix of correlated deviations. Our two projections represent (1) the cultural communities that people form when they differ from consensus in similar ways, and (2) the clusters of occupations that move in similar ways across those subcultures. Correlations among the residuals at the person level are indicators of shared subcultural differences from the mainstream—different ways of meaning-making about what is valuable and worthy about occupational work. At the occupation level, the structure represents schemas for which occupations share common elements and move together when those elements are evaluated differently. We use dyad models to investigate what metrics of occupation similarity predict similarity in deviations from consensus. We find that similarity in affective meaning (evaluation, potency and activity), material requirements, rewards, and work characteristics all predict clustering at the occupation level. Demographic composition of occupations is less important. We find that older respondents, White respondents, and higher income respondents tend to discriminate more between occupations on evaluation and potency. Respondents who are more similar in age have more similar patterns of deviations. However, occupation-level variables are in general much stronger predictors of residual structure than respondent-level variables.

Introduction

Human social organization is predicated on meaning systems and shared participation in those meaning systems (Goldberg and Singell, 2024; Mohr, 1998). Understanding of these systems of meaning—culture, according to Geertz's (1973) classic definition—is therefore crucial for understanding social behavior (Osgood et al., 1957).

Recent extensions of Breiger's (1974) classic work on duality have recognized that meaning systems are fundamentally dual (Mützel and Breiger, 2020; Restrepo Ochoa and Keskintürk, 2025; Shi et al., 2025). Breiger (1974) showed that an initial rectangular matrix can be transformed into two *projections*. One projection represents relations amongst the rows of the data—here, people—and the other relations amongst the columns of the data—here, cultural objects. People are related to one another by common orientations towards cultural objects, and cultural objects are related to one another by their common assessment by people. This approach allows the two different levels of the rectangular matrix of assessments to be viewed as two different systems, operating at different levels but linked by their common connections.

We link this work on duality in culture to work on cultural consensus. Sharedness is a defining aspect of culture and important for realizing intersubjectivity. In a significant advance to the definition and quantitative analysis of culture, Rossi and Berk (1985) argued that to assess consensus is to measure the degree to which the members of a

* Corresponding author at: The Ohio State University, USA.
E-mail address: combs.494@osu.edu (A. Combs).

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designated social group agree with, subscribe to or endorse some statement and hence, by implication, agree with each other. They describe the wide range of phenomena which are more-or-less defined by consensus—values, norms, attitudes and public opinion (Rossi and Berk, 1985). Studies of cultural meaning generally find a large degree of consensus, even with fairly loose definitions of cultural boundaries (Boutyline and Vaisey, 2017; Heise, 2010; Hodge et al., 1964; Romney et al., 1986).

However, this does not mean that all people will report precisely the same thing. Empirically measured meanings occupy distributions, with any one individual providing a response that differs somewhat from the population average. While *doctors* are highly valued in general, some individuals will report neutral-to-negative views and others exceptionally positive ones.

Many approaches to the study of meaning—including most work in the affect control theory tradition (Heise, 2007; Robinson and Smith-Lovin, 2018)—operationalize meaning structures as population averages, discarding individual-level deviations on the assumption that they reflect sociologically uninteresting error or transient deviations created by recent events. Here, we instead examine the possibility that individual-level deviations encode additional structure in meaning systems.

Our analysis takes a relational approach to meaning, centered on an analysis of deviations, informed by Breiger's (1974) work on duality. Focusing on occupational meanings, we analyze two different levels of culture—people who agree with each other on deviations from the cultural norm, and cultural objects (occupational identities) that vary together in those deviations from the cultural norm. We search for subcultures of people who think differently about occupations, as well as occupations that tend to move together because they are connected in a cultural schema about work and worthiness.

Our split focus on *deviation* (vs. consensus) and *duality* (vs. single projection) work together toward uncovering additional structure in meaning. Two individuals who share an unusual opinion (higher or lower than average) can be considered more similar to each other, as members of the same (sub)cultural community. In parallel, two occupational categories that individuals tend to have similarly deviant opinions on—that move together in their minds—can also be considered as linked in some occupational schema. In this way, common patterns of deviation from the cultural pattern might capture unmeasured similarity in both kinds of people in the social structure or in occupational characteristics.

The goals of our analysis are twofold. We use a dataset containing ratings of 642 occupational titles representing all 535 civilian occupational codes in the U.S. census on three dimensions of affective meaning. We use correlations among the differences in ratings as the connections in networks of individuals and occupations. We employ community detection on both the individual and occupation networks to explore their structure and dyad models to determine its predictors, asking which metrics of similarity (1) between occupations and (2) between individuals predict similarities in patterns of residuals.

An affective approach to occupational meaning

Meanings of occupational categories are an important thread in the larger fabric of meaning systems. Occupations are a source not only of material resources but also of esteem. People with occupations seen as prestigious are respected and deferred to, and they enjoy the psychosocial benefits of such treatment (Combs et al., 2023; Freeland and Hoey, 2018; Maloney, 2020). As a result, occupational meanings–including prestige orders (Featherman and Hauser, 1976; Hodge et al., 1964; Lynn and Ellerbach, 2017; Lynn et al., 2024; Valentino, 2020, 2021, 2022) and affective associations (MacKinnon and Langford, 1994; Quinn et al., 2022, 2024)—have long been an area of scholarly interest.

We operationalize cultural meaning using the measurement system used by affect control theorists. Affect control theory places concepts in a three-dimensional space of affective meaning defined by the dimensions of *evaluation* (good vs bad), *potency* (powerful vs weak), and *activity* (active vs inactive).[1] These dimensions have been shown to consistently capture much affective content of concepts across cultures (Osgood, 1962). Affective meanings are used as predictors of interaction (Bergstrand and Jasper, 2018; Clore and Pappas, 2007), emotion (Alhothali and Hoey, 2015; Hitlin and Harkness, 2018; Maloney and Smith-Lovin, 2021), and cultural transmission (Hunzaker, 2016; Jacobs and Quinn, 2022).

More traditional work on occupational meaning uses respondent perceptions of occupational prestige (Lynn and Ellerbach, 2017; Lynn et al., 2024; Valentino, 2020, 2021, 2022). We use affect control theory's multidimensional operationalization rather than unidimensional occupational prestige because recent work has suggested that the three-dimensional measure better captures factors that contribute to perceptions of occupational worth—for instance, the esteem afforded to helping-oriented and relatively poorly-compensated professions like teachers (Combs et al., 2023; Freeland and Hoey, 2018; Maloney, 2020). We think that these occupational features might be especially important in subcultural differences in occupational meaning.

Consensus and deviation

Prior work shows that occupational meanings, like cultural meanings more generally, are generally consensual and largely stable (Boutyline and Vaisey, 2017; Heise, 2010; Hodge et al., 1964; Romney et al., 1986), returning to baseline after even large exogenous shocks like the COVID-19 pandemic (Quinn et al., 2022, 2024). Though the general story is one of consensus, responses do vary on the individual level. There are several possible reasons. A respondent may be part of a subculture or microculture with distinct patterns of meanings (Ambrasat et al., 2014; Ambrasat and von Scheve, 2021; Rogers, 2018, 2019; Valentino, 2021; Zhou, 2005). Alternatively, they might be less well-socialized into their culture's norms (Heise, 2010; Thomas and Heise, 1995). And of course, these deviations might simply reflect measurement error or scale usage (Heise, 2010; Rossi and Berk, 1985).

Work that uses occupational meanings as independent variables usually uses population average values, in no small part because publicly available data sources on occupational meaning–for example, the General Social Survey (GSS) occupational prestige scale (Smith and Son, 2014) and affect control theory meaning dictionaries (Combs, 2023)—generally make available population averages by default. The implicit assumption in this work is that individual-level deviations from population consensus are primarily reflections of error that contribute little, if any, information about cultural meaning (Heise, 2010; Rossi and Berk, 1985).

To understand occupational meaning *structures*, we contend, requires understanding how occupations–and the people who rate them–are related to one another by meaning (Hunzaker and Valentino, 2019; Mohr, 1998). Population averages can capture one sense of relatedness—which occupations lie close to one another in a given meaning space. High-prestige occupations, for example, can be said to be similar to other high-prestige occupations. However, population averages alone cannot capture relatedness on dimensions outside of those directly measured. The duality concept allows us to take a more inductive approach.

We contend that *deviations* from population averages are useful because they can capture similarity in a broader sense, on dimensions that are not measured directly. From the standpoint of occupations, we argue that when two occupations show similar patterns of residuals–-when they move together—it is a signal that they are seen as related in some meaningful way. They share some common element and move

[1] See Robinson and Smith-Lovin (2018) for a recent primer on the theory.

together when that element is evaluated differently. For instance, a *surgeon* and a *home health aide* might not be very close to one another in terms of occupational prestige or structural position. But a respondent who holds medical professions in especially high esteem and sees them both as caring, healing enterprises is likely to rate both categories higher than the cultural average. Deviations, here, can capture similarities (in this case, in institutional membership) that population averages or individual regression analyses cannot.

Existing work has considered the structure that lies in deviations shared by people, rather than occupations. This literature often uses deviations to test for the presence of subcultures with distinct patterns of meaning. It has found some, typically minor, patterned variation along lines of socioeconomic status, geographic region, race, and gender (Ambrasat et al., 2014; Ambrasat and von Scheve, 2021; Dametto et al., 2023; Lynn et al., 2024; Rogers, 2019; Valentino, 2021). However, less work has simultaneously considered how deviations might inform our understandings of structure on the person *and* the occupation projections simultaneously. For this, we must turn to a dual approach.

Duality

We can think of shared deviations from consensus in two ways: as connections between *persons* or between *occupations*. This echoes Breiger's (1974) proposal that a rectangular matrix—in our case, people rating occupations—can be projected as two square matrices that represent relationships between the rows and columns of the initial data. It leaves us with two possible objects of analysis: the *person projection* and the *occupation projection*.

In most cases, dual approaches focus on consensus rather than deviation. The perspective is used as a means to better understand groups of persons underlying survey responses (see a major advance in this approach in Schoon et al., 2024).

Some methods reduce a potentially vast number of responses into analyzable categories. These data reduction techniques are accompanied by an analysis of the kinds of actors that compose each group. Approaches include cluster analysis (Fonseca, 2013; Vanneman, 1977), principal component analysis (PCA) (Pena-López and Sánchez-Santos, 2017) and latent class analysis (LCA) (Bonikowski and DiMaggio, 2016; Feskens et al., 2012; Knight and Brinton, 2017; Lazarsfeld and Henry, 1968; Valentino, 2021). These techniques are also used to match culturally different groups with similar response patterns, using LCA (Kankaraš et al., 2018) and factor analysis (Cudeck and MacCallum, 2007; Jöreskog, 1971; Meredith, 1964). For example, Valentino (2021) utilizes latent class methods to categorize occupational ratings into four categories—four ways that the occupational hierarchy is interpreted—and then describes key demographic and occupational factors associated with each group.

These approaches are effective at grouping cultural objects into categories that allow for further analysis. In this sense, these methods are "dual" in that they aim to determine groups of respondents from the structure of their responses. Both projections of the initial rectangular matrix are often acknowledged. However, these studies are not explicitly concerned with contrasting the *relational* features of each projection. They are typically not concerned with the patterns between cultural objects beyond a confirmation that groups of responses are significantly distinct under some statistical heuristic. This is because the analytical focal point is the respondents and the individual characteristics that explain the underlying heterogeneity in response patterns. With this approach, clusters of responses are only an effective way to reduce and interpret a large number of items, but not the focus of analysis.

In contrast, other scholars take the relationship between cultural objects as the endpoint of their study. This scholarship focuses on patterns among the organizations, behaviors, and beliefs in which individuals are embedded. The field of organizational science provides evidence of structure at the institutional level (McPherson, 1982). It is exemplified by studies of board interlocks (Lamb and Roundy, 2016; Mizruchi, 1996). Following its cultural turn, sociology has seen a growth in techniques that describe the structure of survey items. Relational class analysis (RCA) (Baldassarri and Goldberg, 2014; Goldberg, 2011), belief network analysis (Boutyline and Vaisey, 2017) and correlational class analysis (CCA) (Boutyline, 2017) all provide descriptions of patterns in belief structure.

These studies, in contrast to the previous set, foreground the relationship between columns. The structure of these relationships is a formal representation of the institutional contexts that individuals participate in, or the beliefs they hold about the world. In both approaches, columns are categorized into groups with an analysis of what kinds of respondents fit within each group. In the case of data reduction, the emphasis lies with individuals. In the case of belief and organizational networks, the emphasis lies with column items. Researchers are making use of the dual nature of their data, but do not explicitly develop both projections.

For example, from a bipartite network composed of politicians cosponsoring bills, Fowler (2006) projects connections between politicians to illustrate tensions between members. In contrast, Sokolov and Sokolova (2019) study a bipartite network of readers borrowing similar books, but focuses on the most central books. Both make use of the dual nature of their data, and often refer to both projections. But in either case, the focus of analysis is heavily oriented toward one projection or the other, rather than the duality.

Our study inscribes itself in a third tradition concerned with both projections of the duality. Indeed, Breiger frames his initial proposal as a formalization of Simmel's argument that individuals form social groups, which in turn shape their identity. Although the mechanism connecting one projection to the other may differ—indeed, the way that understandings of occupational categories shape individual identity may be quite complex—we believe that drawing out these connections reveals structure in deviations from consensus. We acknowledge that it is an open question whether or not different views of occupations constitute the material of identity in the classic Simmelian form of the duality argument. We think there is a good case to be made, since the work structure is such a core feature of a modern society. But we explore the duality with the assumption that views of work and occupations might well be a core sense of one's societal values and views.

This approach is found across subjects of study such as social movements (Mohr and Duquenne, 1997), health (Weeden and Cornwell, 2020), segregation (Schaefer et al., 2024), online groups (Lee et al., 2021) and organizational structures (Valeeva, Heemskerk, and Takes, 2020). The study of culture is suited to exploring the dual nature of data (Lizardo, 2024; Light and Moody, 2020; Mark, 2003; Vlegels and Lievens, 2017). For example, Lizardo (2024) applies a new bipartite analysis technique to the Fowler (2006) data, but this time compares both projections—differentiating between a centrist politician and a bipartisan bill, both of which occupy a bridging position. We follow this approach by examining the *person projection* and *occupation projection* of our data.

Research objectives

We construct networks of respondents and occupations, connected by shared deviation from consensus. We apply a community detection algorithm to each network and examine the characteristics of the communities. Finally, we overlay the communities in either projection to understand how they are connected. The alternative hypothesis—consistent with the assumptions of past work—is that residuals may simply reflect measurement error.

We then seek to test the robustness of our claim that similar patterns of residuals indicate underlying similarity. We use dyad models in both the occupation and the person projection. Our dependent variable is correlations in residuals between people (in one projection) and occupations (in the other). Fig. 1 illustrates the calculation of this quantity for both projections of our data. We model the effects of a number of

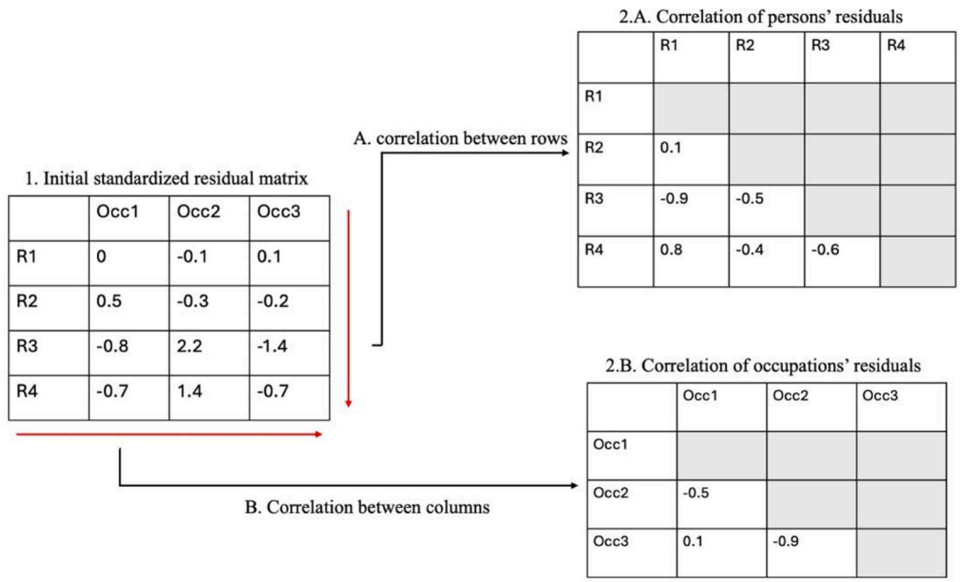

Fig. 1. Dual calculation of person and occupation residual correlations from the respondent x occupation residual matrix.

independent variables related to the degree of similarity or distance between people and occupations on correlations in residuals. If residuals encode information on structure (i.e., they are not merely error) and they reflect underlying pair similarities, we should be able to predict residual correlations using relevant metrics of distance or similarity. We run parallel models on each projection, allowing us to compare the relevant predictors of residual correlation between projections.

Analysis strategy

Our relational research questions lead us to make two analytic choices. First, consistent with our focus on deviations from consensus, we make standardized rating residuals our main object of study. Implicit in this choice lies our operationalization of dissensus, and so also consensus (Rossi and Berk, 1985). Specifically, our method for calculating standardized rating residuals assumes a definition of consensus that allows for respondent-level differences in mean ratings and rating dispersion as well as occupation-level differences in mean ratings. We study respondent-level deviations from population norms net of these factors.

Second, consistent with our relational approach to cultural meaning, we consider the network structures that characterize meaning-based relationships between occupations and between people. Our unit of analysis is therefore not occupations or respondents, but rather occupation-occupation and respondent-respondent ties. Through most of our work, we construct our variables on the level of these dyads.

We proceed as follows. First, we describe our main source of data and our procedure for constructing the dependent variables that we use throughout our analysis. We then present the first step in our analysis: applying community detection algorithms to inductively analyze a network of occupational residual correlations to determine whether residuals indeed encode meaningful information about the structure of occupational meanings. We proceed similarly for the network of respondent residual correlations, describing which demographic characteristics most distinguish each community. We then move to the second step in our analysis, in which we use a dyad model to explore the predictors of meaning residual structure on the occupation side of the duality. We discuss the results of a parallel respondent analysis.

Affective meaning data

Our primary data source is a survey of affective meanings of occupations collected by Freeland and colleagues (2020) between May of 2019 and March of 2020. Here, we report only data collection information relevant to this study. See Quinn et al. (2022) for further detail.

Our analysis sample contains 2276 respondents who passed a series of data quality checks and provided complete, usable sociodemographic information.[2] Freeland and colleagues asked respondents to rate 642 civilian occupational titles,[3] representing all of the 535 civilian occupation codes in the 2010 US Census Occupation Code List, on the three dimensions of affective meaning—evaluation, potency, and activity—used in affect control theory. Respondents were drawn from US Qualtrics panels. They were required to be US citizens. Quota sampling was used to match 2010 US Census marginals for gender, race and ethnicity, educational attainment, and age. See Table 1 for the sociodemographic characteristics of respondents in the analysis sample.

The survey employed a module structure to mitigate respondent fatigue. The occupations were split into 12 modules and each respondent was randomly assigned to rate the occupations in one module. There is no overlap of occupations across modules, meaning that only occupations and respondents within the same module can be compared. One of the modules (Module 1) contained the 20 occupations denoted as "core" occupations in GSS occupational prestige studies (Smith and Son, 2014) plus 10 more chosen to cover all regions of EPA space. 1107 of the respondents in our analysis sample were assigned to Module 1.[4] Between 53 and 57 occupations and between 96 and 126 respondents were assigned to each of the other 11 modules.[5]

[2] See Appendix A in the online supplement for details on data quality checks.

[3] Freeland and colleagues (2020) also included 8 military occupational titles ("sailor in the navy," "soldier," "army private," "tank crew member," "enlisted man in the army," "sergeant," "army corporal," and "army colonel") representing 5 unique 2010 Census codes, for a total of 650 stimuli. However, because additional data sources we used to construct occupation-level independent variables did not provide data for military occupations, we limit our analysis set to civilian occupations.

[4] This module contained a more curated set of occupations and a much larger number of respondents in order to enable a multi-level analysis of occupational deference unrelated to this study.

[5] For module assignments of occupations, see the supporting information of Quinn et al. (2022).

Table 1
Sociodemographic characteristics and employment status for respondents who report and do not report occupations. Proportions are provided in parentheses.

	Respondents with reported occupations	Respondents without reported occupations
Age		
< 35	496 (0.31)	180 (0.27)
35 – 50	434 (0.27)	124 (0.19)
50 – 65	423 (0.26)	223 (0.34)
65 +	261 (0.16)	135 (0.2)
Race/ethnicity		
Asian, Native Hawaiian, or Pacific Islander	75 (0.05)	27 (0.04)
Black	197 (0.12)	89 (0.13)
Hispanic (any race)	361 (0.22)	103 (0.16)
White	887 (0.55)	407 (0.61)
Multiracial	37 (0.02)	18 (0.03)
Other race	57 (0.04)	18 (0.03)
Gender identity		
Woman	975 (0.6)	512 (0.77)
Man	624 (0.39)	146 (0.22)
Nonbinary or other	15 (0.01)	4 (0.01)
Education		
4 year college degree	568 (0.35)	77 (0.12)
Less than 4 year college degree	1046 (0.65)	585 (0.88)
Household income		
$5,000 or less	69 (0.04)	68 (0.1)
$5,001 - $20,000	201 (0.12)	149 (0.23)
$20,001 - $50,000	580 (0.36)	251 (0.38)
$50,001 - $75,000	346 (0.21)	123 (0.19)
$75,001 - $100,000	213 (0.13)	35 (0.05)
$100,001 - $200,000	170 (0.11)	32 (0.05)
$200,001 or more	35 (0.02)	4 (0.01)
Employment status		
Employed full-time	823 (0.51)	13 (0.02)
Employed part-time	336 (0.21)	12 (0.02)
Employed, hours unknown	21 (0.01)	1 (0)
Temporarily unemployed	100 (0.06)	183 (0.28)
Retired or disabled	294 (0.18)	336 (0.51)
Homemaker	9 (0.01)	77 (0.12)
Full time student	29 (0.02)	37 (0.06)
Unemployed, reason unknown	0	3 (0)
Unknown	2 (0)	0
Total	1614	662

Survey procedure

The survey was programmed in Qualtrics XM. Respondents completed it on their own devices. After providing consent, respondents were first asked a series of demographic questions. Their responses determined eligibility based on quota requirements. Those deemed eligible were able to continue in the survey. They were first shown instructions on how to rate an example occupation stimulus on the evaluation, potency, and activity scales. Consistent with established precedent in affect control theory research (Heise, 2007, 2010), respondents provided ratings using continuous sliders, ranging from −4–4. The center, 0, was labeled as "neither/equally" and indicator lines positioned at increments of 1 on either side were labeled with "slightly," "quite," "extremely," and "infinitely." The endpoints were labeled with sets of anchors representing the meaning dimension: "bad/awful" and "good/nice" for evaluation, "powerless/little" and "powerful/big" for potency, and "slow/quiet/inactive" and "fast/loud/active" for activity. Occupational titles—the stimuli—were provided above the scale. The order of occupations was randomized within modules and the order of meaning dimensions was randomized within occupations.

In addition to the affective meaning ratings, respondents were asked to rate the occupational prestige of each occupation using a continuous slider ranging from 1 ("not at all prestigious") to 4 ("has a great deal of prestige"). Respondents completed the prestige section after completing all affective meaning ratings.

We construct our dependent variables, correlations in the residuals of affective meaning ratings, from the ratings in this dataset. Additionally, we use prestige ratings and respondent sociodemographic variables, including respondent age, gender, education, race and ethnicity, household income, and occupation, as independent variables in the second part of our study.

Dependent variable: correlations in residuals of EPA ratings

Our two dependent variables are the correlation in residuals of occupation affective meaning ratings between (a) occupations and (b) respondents. We calculate these quantities for each of the 12 modules separately, then append the results together into one analysis dataset. This calculation is done in four steps.

In order to correct for differences in scale use between respondents, our first step is to standardize ratings within respondent-dimension such that on each dimension, each respondent's mean rating across all occupations in their module is 0 and their rating standard deviation is 1.

Next, we calculate predicted standardized values for each occupation on each of the three dimensions. With standardized ratings as the dependent variable, we use our evaluation, potency and activity ratings data to estimate a multilevel model with no predictors and a random intercept for each occupation-dimension combination. We then use this model to predict population standardized ratings for each occupation-dimension. This approach, unlike calculating simple standardized rating means for each occupation-dimension, allows for partially pooling our estimates, thus improving out-of-sample accuracy.

For each rating, we calculate the residual by subtracting the predicted standardized occupation rating from the observed standardized occupation rating. This results in a rectangular matrix of persons by occupations, with each entry representing a residual—how far that participant's rating on that occupation differed from the general cultural meaning on that dimension.

We then calculate Pearson correlations in residuals between occupations and between people (see Fig. 1). We calculate correlations for each affective meaning dimension separately and also across all three dimensions simultaneously. In order to calculate these correlations for a single dimension, we begin with an $n * m$ matrix of residuals on the specified dimension, where n represents the number of respondents assigned to a given module and m represents the number of occupations in the module. From this data structure, we generate two square correlation matrices: one $m * m$ matrix representing the Pearson correlations between occupations (columns) and one $n * n$ matrix representing the Pearson correlations between respondents (rows).

In order to calculate Pearson correlations across the three dimensions simultaneously, we modify the input matrix. To calculate occupation correlations, we begin with a matrix of dimension $3n * m$. Instead of respondents, rows in this matrix represent respondent-dimensions. Each respondent is represented by three rows: one for their ratings on each of the three dimensions. Similarly, to calculate respondent correlations, we begin with a matrix of dimension $n * 3m$, where each column represents an occupation-dimension combination. As before, an $m * m$ occupation correlation matrix is generated from the column correlations of the $3n * m$ residual matrix, and an $n * n$ respondent correlation matrix is calculated from the row correlations of the $n * 3m$ residual matrix (identically, the column correlations of its transpose).

Residuals encode meaning: a dual community detection approach

Many studies of cultural meaning assume that residuals in affective meaning ratings simply reflect measurement error, rather than information about meaning structures. Therefore, we start with a basic question: is there meaningful structure to be found in rating residuals?

An answer to this question is required in order to proceed to our substantive questions about cultural subcultures of people, and occupational schemas in the culture. To investigate this, we construct completely connected, undirected, weighted networks from the occupation and, separately, person correlation matrices generated for Module 1, which has the largest sample size in our data (n = 1107). We then apply the Spinglass community detection algorithm as implemented in version 2.0.3 of the igraph package (Csardi and Nepusz, 2006; Traag and Bruggeman, 2009) to each of the occupation and person networks. The Spinglass algorithm allows us to perform community detection on the entire weighted network, including negative ties. We investigate structure in the network and communities on each side of the duality, then overlay the occupation and person communities to investigate their interaction.

Residuals encode occupation communities

We start with networks generated from the four occupation correlation matrices (one for each meaning dimension and one across all dimensions simultaneously). The tie weight between two occupations is the value of the Pearson correlation between them. It ranges from −0.31–0.30. We show these networks in Fig. 2, with negative ties omitted from the visualization for interpretability. Colors in these plots indicate communities.

In general, these networks do show community structure. Furthermore, communities contain occupations that seem similar on dimensions found in previous work to organize occupational meaning logics. In the evaluation, potency, and all dimensions networks, occupations roughly organize into three groups. The *Service* group (on the right and in green in the all-dimensions network) contains primarily lower status and lower-income occupations that require less education, such as cashier, bartender, and welder. These occupations are rated relatively low in potency (sample average: 0.3) compared to the other groups (high status = 1.6; high esteem = 2.2). The *High Status* group (on the left and in red in the all-dimensions network) contains primarily higher prestige and higher-income occupations requiring more education, such as lawyer, manager, and legislator. These occupations are rated relatively low in evaluation (sample average: 0.8) relative to the other groups (service = 1.9; high esteem = 2.6), and also relatively low in activity (high status = 0.8; service = 1.2; high esteem = 1.8). The *High Esteem* group (in the middle and in blue in the all-dimensions network) spans the two. It contains “helping” occupations that are highly esteemed but not especially highly paid, like firefighter, paramedic, elementary school teacher, and registered nurse. Most of the occupations in this group relate to health care.

In all but the activity network, these groups are largely stable. However, some occupations on the spatial and conceptual margins of the groups switch memberships between dimensions. In the all-dimensions network and the evaluation network, surgeons and physicians cluster in the high-esteem group with the other healthcare professions. In the potency network, however, they cluster with the high-status group. This may reflect the unique position of these professions as straddling these two groups: surgeons and physicians share a helping orientation, and the esteem that accompanies it, with other healthcare professions, but high income, education, and prestige with the high-status cluster.

On questions of which occupations are worthy or good, the helping orientation may take precedence, leading them to move with the lower-status healthcare occupations. However, on the question of which occupations have power and prestige (as traditionally measured) the metrics that accompany those features might dominate, causing them to instead move with the other high-status occupations.

In contrast to the other networks, the activity network is organized into only two groups. Here, the high esteem cluster dissolves. Physician and surgeon cluster instead with the high-status occupations and the other helping occupations cluster with the service occupations. Because the two clusters share more highly-weighted ties, there is less spatial segregation between the two groups. Together, this suggests less discernable structure in residuals on the activity dimension than the other two, which is consistent with other affect control theory research that finds that activity is a less predictive meaning dimension than evaluation and potency (Robinson and Smith-Lovin 2018). However, there is still enough structure to create two clusters with strong similarities to those on the other dimensions.

If residuals captured nothing more than measurement error, then this analysis would have resulted in random networks, with near-zero tie weights and little patterning. Instead, these networks show clear, meaningful, and consistent structure. Therefore, we proceed to ask questions about how occupations and people move together by considering residuals as the object of study.

Residuals encode respondent communities

In order to describe respondent communities, we now consider the other side of the duality: the respondent-by-respondent residual correlation matrix. For simplicity, we use only the matrix summarizing correlations on all three semantic dimensions. Applying the Spinglass algorithm yields two large communities containing 507 respondents (Group 1) and 588 respondents (Group 2) and one small community containing 12 respondents (Group 3). Because of Group 3’s very small size, we analyze only the differences between Groups 1 and 2.

Fig. 3 shows the distributions of the sociodemographic characteristics of the respondents of the two larger groups (left column) and the characteristics of their occupations (right column). The panels in the left column include only the respondents with necessary occupation or labor force status information: 342 (Group 1) and 397 (Group 2) respondents for job zone and prestige and 506 (Group 1) and 586 (Group 2) respondents for evaluation, potency, and activity. The panels in the left column include the full membership of groups 1 and 2. Statistical significance of the group differences is assessed by estimating a multinomial logit model using all displayed variables to predict assignment to Groups 1, 2, or 3. Variables that are statistically significant predictors of assignment to Group 2 as opposed to Group 1 (reference) are outlined in Fig. 3[6].

The two larger groups, though determined entirely by similarity in residual patterns, are distinct on certain sociodemographic characteristics. Group 1 is younger, has lower household income, and contains proportionally fewer White respondents than Group 2. That there is detectable group structure here suggests to us that residuals encode cultural structure not only among occupations but also among respondents.

Relationship between occupation and respondent communities

We now bring our two parallel analyses of occupation and respondent communities together, taking advantage of the duality between them in order to investigate how the different groups of respondents conceptualize the different groups of occupations. In Fig. 4, we show the average residual rating given by respondents in the three respondent groups of the occupations in the three occupation groups. Groups on both levels are gleaned from the all-dimensions summary matrices, but we show residuals on each semantic dimension separately. As there are only two meaningfully-sized groups and the average standardized residual across the sample is zero by definition, patterns are approximately mirrored between Groups 1 and 2.

6 Respondents without occupations, and so without job zone, prestige, and (for a smaller number) evaluation, potency, and activity data, are listwise-deleted from this model. Statistical significance remains the same for all variables if instead occupation-related variables are treated in a separate model, allowing all respondents to remain in the calculation for the sociodemographic characteristic comparisons.

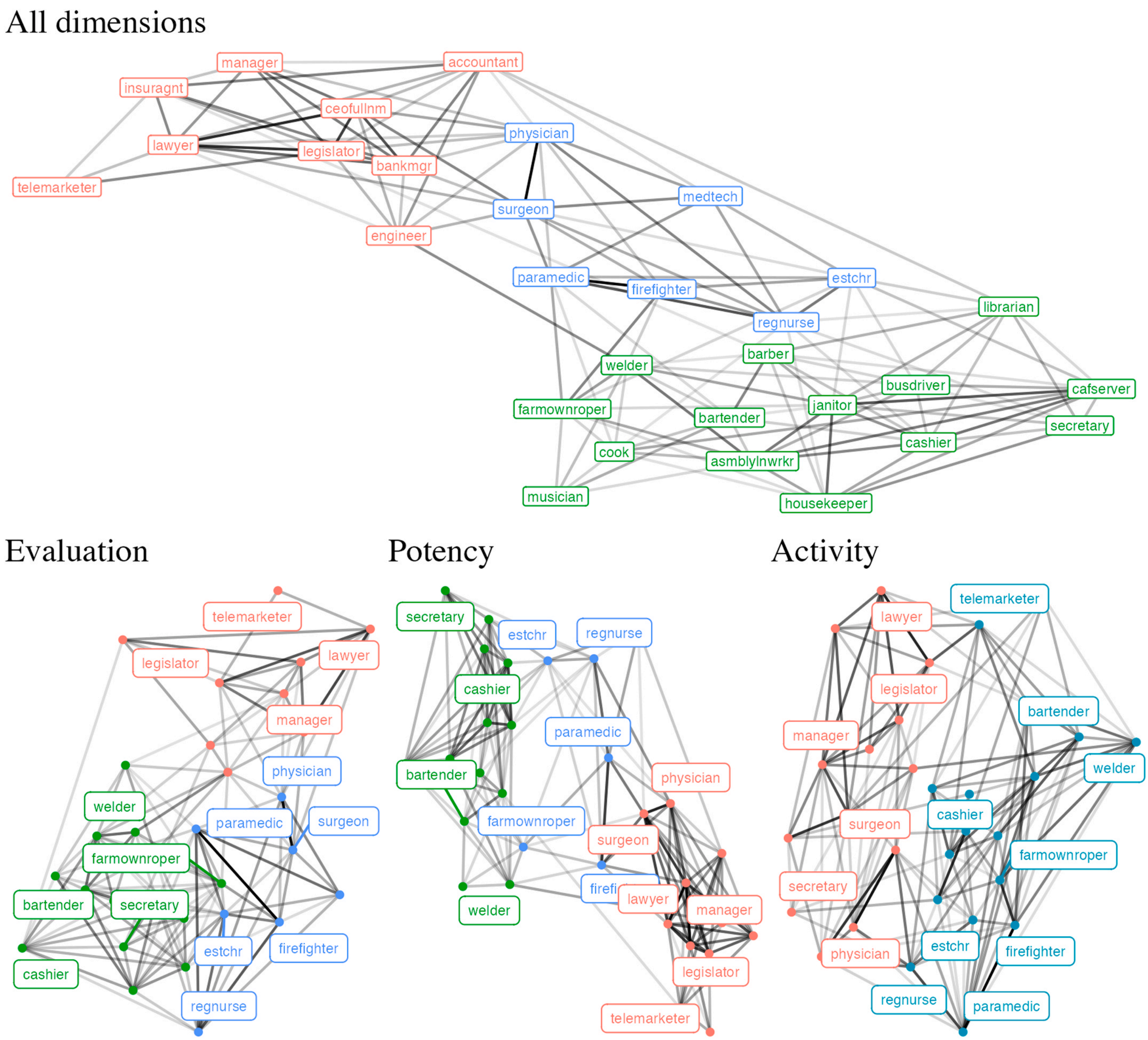

Fig. 2. Network visualization of correlations in affective meaning residuals between occupations in Module 1. Occupations were rated by 1107 respondents. Networks are shown for correlations computed over all dimensions simultaneously (top), evaluation only (bottom left), potency only (bottom center), and activity only (bottom right). Tie weight represents correlation strength. Color denotes community assignment (Spinglass algorithm). Tie weights less than zero are removed from the plot for readability, but all ties are used for community detection. Abbreviation definitions: asmblylnwrkr (assembly line worker), bankmgr (bank manager), cafserver (cafeteria server), ceofullnm (chief executive officer), estchr (elementary school teacher), farmownroper (farm owner and operator), insuragnt (insurance agent), medtech (medical technician), regnurse (registered nurse).

Fig. 4 suggests that the distinction between groups may be in large part one of rating variance. Group 1 —containing respondents that are younger, lower-income, and less likely to be White—appears in many cases to moderate extremes, distinguishing less between occupational groups. They rate the comparatively low-evaluation occupations (the high-status group) higher on evaluation than expected and the higher-evaluation high-esteem and service groups lower on evaluation than expected. They also rate the comparatively low-potency service occupations higher on potency than expected. Adherence to this moderation pattern is not perfect, however. Group 1 under-rates the potency of the high-status occupations to a greater extent than that of the high-esteem occupations, even though the high-esteem occupations are rated higher on potency on average than the high-status occupations (high esteem = 2.2; high status = 1.6 on average across the sample). There are not many substantial group differences on activity. Overall, Group 1 appears to distinguish less between occupational groups on evaluation and potency than Group 2 does, providing ratings that are more similar across them.

Predicting structure across all U.S. occupations

Our examination of the 30 occupations in Module 1 suggests that there is structure in residuals in the occupation projection. Our results suggest that this structure may be organized by characteristics of the occupations, such as their income, educational composition, status, and perceived helping orientation. These factors have been identified in past research as organizers of occupational prestige logics (Lynn and Ellerbach, 2017; Valentino, 2021). Here, we more precisely identify contributors to the structure of occupational meaning dynamics. Using a

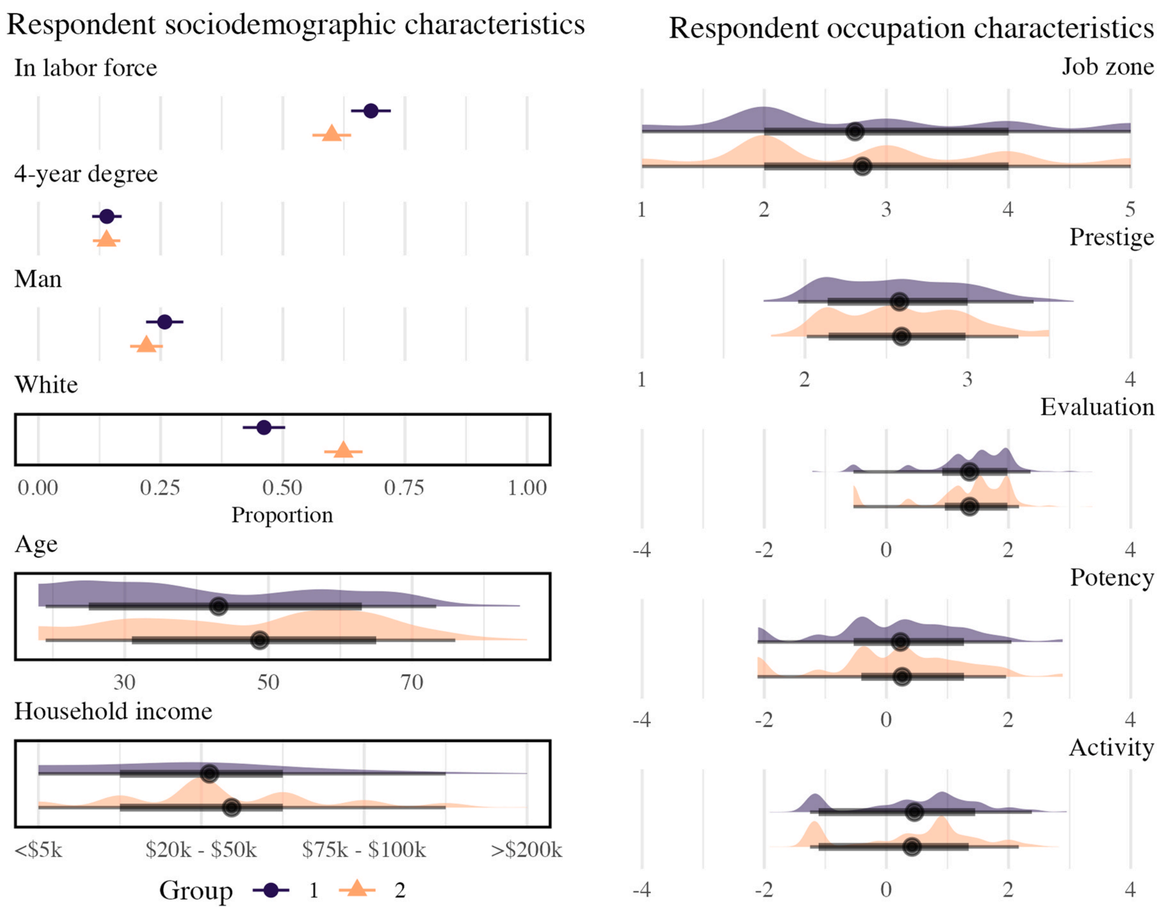

Fig. 3. Descriptive characteristics of respondent Group 1 (507 respondents) and Group 2 (588 respondents). A third group containing 12 respondents is omitted from the plot due to its prohibitively small size. The top four subplots in the left column, representing binary variables, show sample proportions with 95 % confidence intervals. Other subplots, representing ordinal or continuous variables, show sample distributions with points marking the mean, thicker lines marking the middle 66 % of the sample density and thinner lines marking the middle 95 % of the sample density. Panels showing variables that are statistically significant ($p < .05$) predictors of assignment to group 2 as opposed to group 1 in a multinomial logit model including all displayed variables as predictors are outlined.

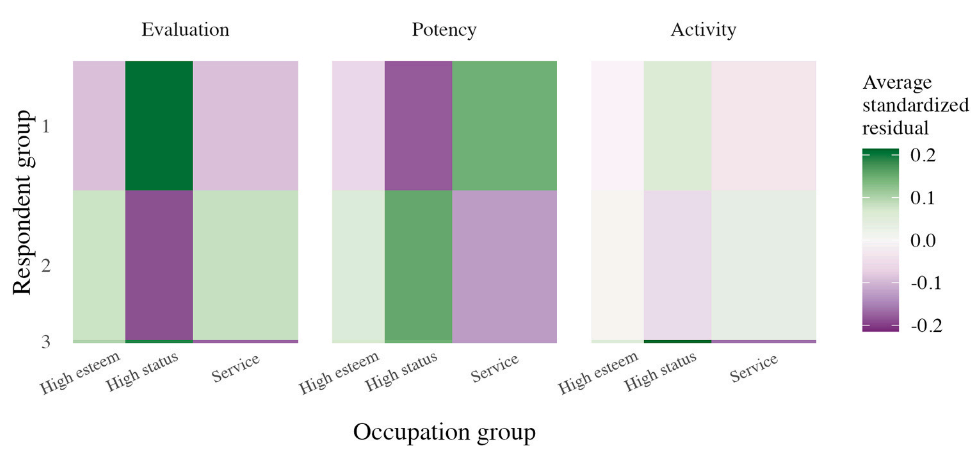

Fig. 4. Average standardized residual ratings of occupation groups by respondent groups. Box sizes are scaled by group size. Groups are determined using the Spinglass algorithm on the relevant correlation matrix projection, across all semantic dimensions simultaneously.

dyad model, we test associations of a number of different metrics of *distance* with correlation strength on the occupation and the person side of the duality.

Dyad modeling has two primary advantages here. First, it allows us to treat data from all modules together—and, therefore, to analyze the entire set of occupation codes used by the U.S. Census, rather than a sample. Second, by analyzing individual ties, it avoids dependence on any particular community detection algorithm and arbitrary cutoffs it employs. The community detection approach we used above allowed us a holistic view of the structure of a small sample of occupations in one oversampled module, and a simple dual extension to consider the interaction between occupation and respondent groups. The dyad model approach used here deepens our understanding of what features of occupations make them move similarly to one another.[7]

Independent variables

To construct additional occupation-level independent variables we use in the following models, we link the affective meaning rating data to publicly available survey data sets that provide more information about occupations. The first of these is the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (Flood et al., 2020), which provides information on the sociodemographic composition of occupations. The second is the Occupational Information Network (O*NET) database, which provides us granular information on the requirements imposed by occupations and the activities workers perform within them.[8]

Our independent variables, like our dependent variables, are constructed on the level of occupation-occupation dyads. We use data from the Quinn et al. affective meaning survey, ASEC, and O*NET to create metrics of *distance* between occupations. Table 2 summarizes the distance metrics we included as independent variables in our models. These are divided into five categories: *affect, Census taxonomy, demographic composition, material rewards and requirements,* and *work and worker characteristics.* For more information on variable construction, see Appendix B in the online supplement.

Control variables

For each continuous distance metric on the occupations and the person side, we control for the average position of the two dyad members on the scale in question. For example, we use the difference in occupational prestige between two occupations as an independent variable and additionally control for the average occupational prestige of the two occupations. This allows us to isolate the effect of distance between occupations from the effect of scale position, which is important as the fact that the scales are bounded makes these correlated by construction. These control variables are all standardized to range from 0 to 1.

Table 2
Summary of independent variables on the occupation side of the dual analysis. All distance metrics are standardized to range between 0 and 1.

Type of distance	Operationalization	Data source
Affect	Cartesian distance in affective meaning space, defined by dimensions of evaluation, potency, and activity.	Freeland et al.
Census taxonomy	Number of levels one would have to travel up in order to reach the most specific grouping two occupations have in common in a merged 2010 Census Bureau/Standard Occupational Classification taxonomy (range: 0–4)	Census Bureau + SOC
Demographic composition		
Gender	Difference in % men	ASEC
Race/ethnicity	Difference in % white	ASEC
Age	Difference in mean age	ASEC
Material rewards and requirements		
Income	Difference in mean income	ASEC
Education	Difference in % workers with BA	ASEC
Job zone	Difference in job zone (required experience, education, and training; 1–5 scale)	O*NET
Prestige	Difference in prestige rating	Quinn et al.
Work and worker characteristics		
Skills, knowledge, and abilities Work interests, styles, and values Work context Work activities	Correlation between occupations on the relevant subset of survey questions, after standardizing individual questions.	O*NET

Models

We use dyad models to investigate the effects of our distance variables on occupational residual meaning structure. Our dependent variables are the strength of residual correlations between occupations (17,159 occupation dyads). All models are linear[9] and run using the stats::lm() function in R. All independent and control variables are standardized to range from 0 to 1 so that effect sizes are comparable. Coefficients can be interpreted as the expected change in dyad residual correlation when an independent variable is changed from its minimum to its maximum, holding all else constant.

Distance predicts occupation residual correlations

Fig. 5 shows estimated coefficients for models predicting affective meaning residual correlations between pairs of occupations. A coefficient table is reported in Appendix D in the online supplement. It is clear that distance between occupations, on several separate metrics, has meaningful effects on affective meaning residuals. The variables predicting correlations calculated across all dimensions simultaneously explain 35 % of the variance in the dependent variable. This model yields a Bayesian Information Criterion (BIC) value that is 7023 points lower than a model with no predictors—a substantial improvement in model fit. 12 of the 13 distance variables have statistically significant effects on correlations calculated across all meaning dimensions simultaneously, and four have effects of magnitude 0.05 or greater—more than half a standard deviation in the dependent variable. Most of the effects—10 of 13—are negative, indicating that occupations that are further apart on these metrics have affective meanings that move together less in cultural space.

Different types of distance are associated with affective meaning residual correlations to different degrees. The effect of affective meaning distance, estimated at −0.19, is nearly three times the magnitude of the next largest coefficient. It stands out as the most important predictor. This indicates that there is a strong correspondence between occupations that sit together in the three-dimensional affective meaning space and those that move together. Occupations that have similar affective meanings (i.e., meanings of worthiness, power and activity) tend to move together.

Occupation-level differences in work and worker characteristics—differences in skills, knowledge, and abilities, interests, values, and styles, work contexts, and work activities—also have consistent, negative effects on affective meaning residual correlations. The same is true for Census taxonomy distance, which is determined primarily by work activities.

Distance between occupations on the last two categories of independent variables—material features (requirements and rewards) and demographics—are less pronounced and less consistent. While greater difference in occupational prestige and average worker education are associated with lower residual correlations, difference in average

[7] One disadvantage of dyad models is that they discard information related to network structure. See Appendix C in the online supplement for discussion of alternative approaches.

[8] For more information, see the documentation available on the O*NET website: https://www.onetcenter.org/dictionary/20.1/excel/

[9] There are negative correlations in these models, making the choice to use a linear model as opposed to transforming the dependent variable in some way non-trivial. See Appendix E in the online supplement for additional analysis that supports this choice.

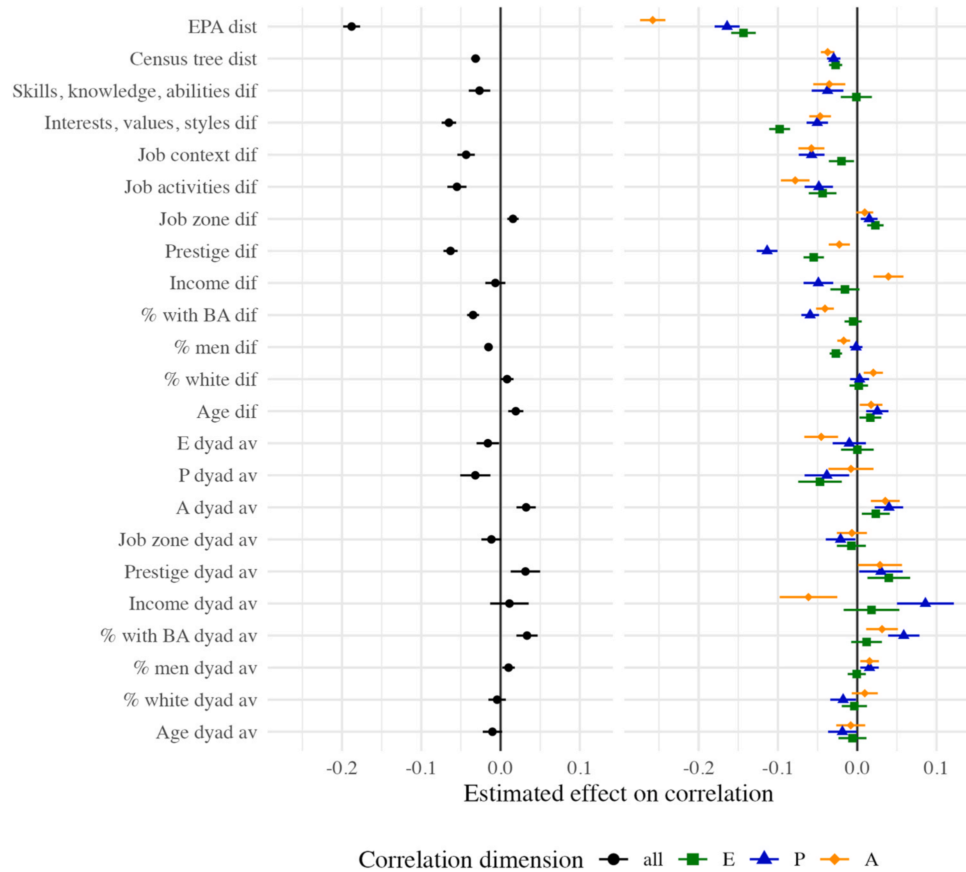

Fig. 5. Effects of distance on affective meaning residual correlation between occupations across all meaning dimensions (left) and on each dimension separately (right). N = 17,159 correlations for all models. Bars represent 95 % confidence intervals. All independent variables are scaled to range from 0 to 1. The range of the dependent variable for the all-dimensions model is −0.33–0.58, with a mean of −0.02 and standard deviation of 0.09.

worker income has no effect, and difference in job zone actually has a small but statistically significant *positive* effect—though, we note that like all coefficients, this is net of all other occupation similarity metrics.

The lack of a strong effect of distance in material rewards and requirements is surprising, as previous work has established that material rewards and requirements play an important role in structuring logics of occupational prestige (Lynn and Ellerbach, 2017; Valentino, 2021). The affective meaning of occupations, as a more general measure of cultural worthiness than prestige (Combs et al., 2023; Freeland and Hoey, 2018), may be more powerful in the cultural domain.

Difference in worker demographic composition—the gender, race, and age distance variables—also show inconsistent effects. This finding supports the idea that these structural features have a less pronounced role in patterning residuals than means (Valentino, 2020, 2022).

While the right panel of Fig. 5 shows that effects are largely similar between meaning dimensions, there are some differences that are consistent with findings from previous work. Namely, occupation-level differences in prestige, income, and education—all indicators of material rewards and requirements—have more of an effect on potency residual correlations than evaluation or activity, indicating that material rewards and requirements play a larger structuring role in potency logics than on the other dimensions. This is consistent with previous work arguing that occupational prestige and its correlates are mainly indicators of power rather than esteem (Combs et al., 2023; Freeland and Hoey, 2018).

Less structure on the person side

We ran parallel dyad models on the person-by-person correlation network, using independent variables representing distance between respondents that paralleled those we used to capture distance between occupations. Variable construction details are located in Appendix B in the online supplement. We estimated two models: one for the subset of respondents with reported occupations, using all independent variables, and a second on the full set of respondents and a more limited set of independent variables that apply to respondents both with and without occupations. As this analysis fulfills a similar purpose as the person-side analysis we performed for Module 1, we provide brief discussion here and full results in Appendix F in the online supplement.

Many of the distance effects in respondent-level dyad models reach statistical significance. All that reach statistical significance are negative, indicating that similar respondents deviate from typical meanings in similar ways. Age difference between respondents is clearly the most important predictor of differences in their residual patterning. Moving from the minimum to the maximum age difference—0 years (two respondents of the same age) to 72 years (one respondent of 18 and another of 90)—is associated with a decrease in residual correlation about a third of a standard deviation in the dependent variable. This is consistent with our results from Module 1 showing that respondent communities differ by age.

In general, however, effect estimates in the respondent-level dyad models are substantially smaller in magnitude than those in occupation-level dyad models. While the respondent-level dyad models do fit better than models without predictors—showing substantial improvements in BIC—they explain very little of the variance in the dependent variable. The model containing all respondents has an adjusted R^2 value of just

0.005.[10] The dyad models show that the structure present on the respondent side of the duality, while detectable, is substantially weaker than that on the occupation side.

Discussion

We have presented a relational, dual approach to the study of occupational meaning structures. We examined an exhaustive dataset on affective meanings of the entire set of civilian occupations recognized by the U.S. Census linked to data on occupational demographic composition and detailed information on the work people do. Our results indicate that individual-level deviations from population consensus in affective meaning—residuals—reflect information about the extent to which occupations move together in respondents' minds.

Our analysis of the occupation and respondent communities created by correlations of their residual ratings in a subset of our data showed clear structure. Residual correlations partition the occupation network into a group of high-status occupations, a group of high-esteem occupations, and a group of service occupations. Overlaying communities created by residual correlations among respondents—communities which are differentiated by respondent race, age, and income—suggests that the source of this structure is that respondents vary in their propensity to distinguish between these occupation groups in their ratings. We note that we standardized participants' responses to account for scale use differences before calculating residuals and eliminated those who provided poor quality data, making it likely, in our view, that these differences in patterns are reflective of a real difference in tendency to differentiate between types of occupations.

Our occupation-level dyad models allowed us to more definitively identify the predictors of occupational structure among all occupations recognized by the U.S. census. We show that occupation residual correlations are associated with many measures of occupational similarity. Consensus affective meaning has the largest effect, indicating that occupations that "sit together" also tend to "move together" in affective meaning. This result shows that residual-based and mean-based conceptions of relational meaning are strongly related. However, the rest of our results show that patterning in residuals is also an independent construct patterned in ways that are distinct from consensus.

The next most important predictors of occupation-level residual correlations are similarities in work-related skills, interests, and activities. Their effects are larger than those of income and education, often identified as dominant predictors of occupational prestige orders (Bukodi et al., 2011; Featherman and Hauser, 1976; Freeland and Hoey, 2018). Variables regarding the things that people actually do at work are only rarely considered in studies of occupational meaning and occupational prestige. Our results suggest they in fact play an important role in delineating occupational schema, and that it may be fruitful to pay them more attention.

Our models on the person side of the projection were less successful at predicting residual correlations. However, we note the fact that there is *any* observable structure in the occupations projection means that different respondents do provide residuals that are patterned both (a) differently from one another and (b) in structured ways. We can draw this conclusion only because our approach is *dual*. Only by looking at the occupation projection can we draw conclusions about the cause of our relatively poor model fit on the person projection. This illustrates the utility of bringing Breiger's (1974) insight to the study of cultural meaning.

In our person-level dyad models, the only variable with which residual correlations have a meaningful association is respondent age difference. This is notable, as we used both standard demographic variables that have been shown to shape meaning ratings—respondent (dis) similarity in gender, race, age, income, and education (Ambrasat et al., 2014; Ambrasat and von Scheve, 2021; Lynn and Ellerbach, 2017; Lynn et al., 2024; Valentino, 2021; Zhou, 2005)—and, in a second model, a slate of variables related to respondents' occupations. There is structure in the residuals of this data set, but on the person side, it is largely unassociated with simple (dis)similarity on commonly-used sociodemographic variables or other features related to respondents' locations in the occupational structure. It is unlikely to be associated with respondent differences in scale use, as we standardize ratings such that all respondents have the same mean and standard deviation before calculating correlations.

There are many possible drivers of structure outside of what we have tested here. We wish to highlight a few as particularly noteworthy avenues for future work. First, we have not tested the effect of respondent region or rural/urban location. Where respondents live determines the composition of the local economies they are exposed to. Living in similar areas may then cause two respondents to see the occupational structure in similar ways—and so to deviate in similar ways from the population consensus (Ambrasat and von Scheve, 2021; Dametto et al., 2023).

We have also not tested the effect of (dis)similarity in respondent political affiliation. Political parties routinely disseminate narratives about the worth, value, and trustworthiness of particular kinds of workers. These narratives may have effects on partisans' views of those occupations. For instance, Democrats trust the higher education system and science, and so also faculty and scientists, to a greater extent than Republicans (Gauchat, 2012; Lee, 2021).

Conclusion

Our study has several implications. First, it shows that individual-level deviations from consensus—residuals—are not merely uninteresting measurement error. Rather, we find that these deviations encode information about the consensual meaning structures that is obscured when scholars focus solely on consensus. Future work would benefit from considering not only how people agree on a particular meaning—using means and medians—but also how people deviate from the norm—using residuals. In other words, scholarship should bring together meanings that "sit together" with those that "move together". The combination of both perspectives, we argue, provides a more complete representation of cultural space.

Second, our study identifies key differences between projections of occupational rating data. By making the comparison of dual projections explicit rather than implicit, we find significant differences in variables that explain variance either projection. This is the case even though both projections emerge from the same source data. This study contributes to calls from cultural and organizational sociology to use both projections of the duality.

Lastly, our study contributes to our understanding of occupational meaning and meaning subcultures. In practice, occupational meaning hierarchies are often treated as consensual. We show how lack of consensus can be viewed as both a feature of respondents (in cultural communities) and occupational schemas (in connections among occupations).Our study highlights a way by which deviation from that consensus can be characterized as a duality, adding to an existing body of scholarship on the ways in which people understand occupational prestige (Lynn and Ellerbach, 2017; Lynn et al., 2024; Valentino, 2021).

CRediT authorship contribution statement

Combs Aidan: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Varela**

[10] We note that part of the difference in effect sizes and R^2 between the occupations and person models is likely because more ratings, on average, are used to create the occupations correlations than the person correlations, meaning we expect them to be less noisy. However, given the magnitude of the differences, we think it is unlikely this is the source of the entire difference. See Appendix G in the online supplement for analysis supporting this conclusion.

Gabriel: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis. **Robinson Dawn T.:** Writing – original draft, Methodology. **Smith-Lovin Lynn:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Vaisey Stephen:** Writing – review & editing, Methodology, Formal analysis, Conceptualization.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.socnet.2025.04.003.

Data and Code Availability

Code used to perform the analysis presented here, as well as public release data files (selected respondent-level information redacted), are available at the following link: https://osf.io/fph9z/.

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