Regional culture and adaptive behavior of physicians

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Abstract We examine the possibility that regional differentiation of occupations may shed light on how professional behavior adapts to environmental change. Based on the relative prevalence of occupational categories, we defined five geographic regions within the 48 contiguous United States. 77 psychometric, demographic and cultural metrics that covaried significantly with geographic regions by ANOVA were subjected to principal component analysis (PCA), from which three primary clusters emerged. A panel of judges scored the occupations in these clusters for three primary characteristics: generation of variance (Va), reconciliation of variance with institutional procedures (Re) or implementation of standard institutional practice (Pr). By plotting composites of the clustered elements in a 3-dimensional (Va, Re, Pr) matrix, substantially overlapping regional composites emerged for psychological, cultural and occupational metrics. Based on this putative psychological and cultural differentiation of geographic regions, we asked whether adaptive change in physician—and, by extension, of other professional—behavior might be more strongly correlated with intrinsic (e.g. psychological) or extrinsic (e.g. cultural) factors. Based on significant regional differences in patient behavior and minimal regional differences in physician psychology, we suggest that extrinsic factors may play a more direct role in changing professional behavior than intrinsic factors.

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1 Introduction

Adaptive change in an institution has traditionally been described as the generation of variance followed by institutional adoption and perpetuation. Nevertheless, the mechanisms by which a specialized economic (i.e. occupational) activity adapts to its changing socioeconomic environment are not well understood. Here, we use the geographic distribution of occupational and human capital in the United States to examine adaptive change in the medical profession. Such an approach has the potential to reconcile multiple strands of prior inquiry from macroeconomic theory ([Boschma and Frenken 2006](#)), institutional problem-solving ([Marengo and Dosi 2005](#)), network analysis ([Eagle et al. 2010](#)), resilience theory ([Simmie and Martin's 2010](#)) and socioeconomic studies of human capital ([Storper and Scott 2009](#)).

One way to examine the relationship between occupation and geography is to ask whether different geographic regions contribute differently to processes of variance-generation, adoption of variance and formalized production in an economic context. We consider the hypothesis that: (a) certain psychological signatures are best suited to certain occupations; (b) each region supports an occupational mix that helps define its aggregate psychological and cultural attributes; and (c) the behavior of professionals in each region is influenced by such attributes.

Because the delivery of health care in the United States is influenced by rapidly changing technological and economic pressures, we decided to focus on physicians as an occupational group. Our analysis is intended to serve as a first step toward building testable hypotheses to better understand how physician behavior adapts and changes in response to these pressures over time.

2 Methods

2.1 Data collection

Occupational, cultural and demographic data were obtained from public online sources, unless otherwise noted (Supplementary Table S1). Online data collection from 1,277 anonymous adult participants (cohorts A–C) was described in a previously published psychometric study that also described the validation of the eSAIL inventory ([Mascarenhas et al. 2007](#)). Individuals in these cohorts answered a questionnaire containing demographic questions about age, gender, household income, education, state of residence, profession and mobility. Those data, as well as eSAIL scores, were used in the present analysis. A subset of the 13 eSAIL scales was designed to measure attributes believed to relate to innovation: plasticity/rigidity (IMPROMPTU, DOGMATIC), internal/external locus of control (BOLD, RESPBIAS), optimism/pessimism (POSITIVE, MACH), and abstraction (ABSTRACT) ([Mascarenhas et al. 2007](#)). In the

current work, geographic differences in aggregate psychometric scores for regions and occupations were, in all instances, shown to be independent of age, gender and income. Statewise data were converted to z scores (standard deviations from the national mean). Data are shown as $\pm$ SD. Additional anonymous adult cohorts P, Q and R responded to an advertisement in Craigs List (www.craigslist.org) and answered the eSAIL as well as additional questionnaires. Cohort P respondents ($n = 130$) were divided into two consecutive panels (P1 and P2) of 65 judges representing more than 25 different occupations. Each of these panels scored the Innovation Index independently. Respondents were provided with the following occupational descriptions corresponding to major BLS occupational categories: personnel management, architecture, life sciences research, legal, personal care and service, educational training, community and social services, installation maintenance and repair, transportation, production and manufacturing. Respondents were asked to rate each occupational group with respect to Va (“generates innovation/variance”), Re (“reconciles innovation with institutional constraints”) and Pr (“mainly implements existing protocols”). An average numerical “innovative” rating was then calculated by assigning values of 3, 2 and 1 to Va, Re and Pr, respectively. This is the Innovation Index. Cohort R (primary care) consisted of 93 AMA-listed physicians who consecutively answered the eSAIL and additional questionnaires. Cohort Q ($n = 296$) patients were asked how often they saw their primary care doctor each year and what percentage of those times they asked questions about possible treatment options based on information they had gathered online. Respondents in all cohorts were blind to the overall objectives of this research project.

2.2 Hierarchical clustering

The fraction of the state’s population employed in 22 occupational categories in 48 continental United States (US Bureau of Labor Statistics; www.bls.gov) was used to create a real-valued matrix M of size $n \times m$, where n (rows) is the number of states, m (columns) is the number of occupational categories, and $M(i, j) = x$ meaning that state i employs x % people in occupational category j . The matrix M was hierarchically clustered along both dimensions (namely, states and occupations) in Matlab (version R2009b, The MathWorks, Natick, MA) using correlation distance and average linkage. Other distance metrics (Euclidean, standardized Euclidean, city-block, Mahalanobis, Minkowski, cosine, Spearman correlation, Hamming, Jaccard, and Chebychev distance) and linkage algorithms (single, complete, weighted, centroid, median, and Ward’s linkage) yielded lower cophenetic correlation coefficient (Sokal and Rohlf 1962) for the occupation data. For each linkage, the clustering resulted in two dendrograms: S , grouping states, and J , grouping occupations. Nevada and Wyoming were excluded from analysis because of the over-representation of service jobs in Nevada (24.27% in occupational categories 35-000, 37-000 and 39-000) and the over-representation of mining-related jobs in Wyoming (18.48% in categories 47-000 and 49-000).

2.3 ANOVA analysis

For each of the 48 continental states, 41 cultural/demographic and 9 psychometric metrics were tabulated. These measurements were then aggregated state-wise into the geographical clusters obtained above. To assess which of these metrics were significantly correlated to the 5 geographic clusters obtained above, a linear 5-way analysis of variance (Hogg and Ledolter 1987) was performed in Matlab, and the p -values ($\alpha = 5\%$ confidence interval) recorded. Variables whose p -values were more than 0.05 were discarded from further analysis.

2.4 Principal components analysis

The resulting multivariate matrix N (77 rows of statewide metrics $\times$ 5 geographical clusters) was then subjected to principal components analysis in Matlab, and the loadings and principal component scores recorded. Essentially all the variation in the data was in the first five components (variances of 45.71, 33.46, 10.62, 5.38, and 4.83% respectively). Since almost 80% of the variation in the data was in the first two components, subsequent plots were limited to the first two components.

3 Results

3.1 Occupational clusters define geographic regions

In the contiguous United States, statewide data relating to 22 BLS occupational categories provide a snapshot of economic activity in geographic regions. States were grouped into geographic regions using the fraction of the state's population employed in each occupational category. A matrix M of size $n \times m$ was created, where n is the number of states, m is the number of occupational categories, and $M(i, j) = x$ meaning that state i employs $x\%$ people in occupational category j . The matrix M was hierarchically clustered along both dimensions using correlation distance and average linkage. Results are shown in Fig. 1a. Six primary clusters were identified.

3.2 Significant differences exist in psychometric scores aggregated by region or occupation

Five of six primary geographic clusters identified above were used to aggregate psychometric data from 1,277 individuals who took the eSAIL (Mascarenhas et al. 2007) and 41 publicly available state demographic and cultural metrics (cluster F, representing less than 3% of the US population was omitted for lack of adequate psychometric survey data). A linear 5-way analysis of variance ($\alpha = 5\%$ confidence interval) was performed, and 75 metrics (22 occupational, 16 psychological, 37 cultural-demographic) whose p -values were <0.05 were subjected to further analysis. Significant differences in average psychometric scores were recorded for individual occupations (6 of 6 scales) and geographic regions (4 of 6 scales; Table 1).

Fig. 1 **a** Hierarchical two-dimensional clustering of states versus occupations (scale: z units); **b** dendrogram based on geographic distribution of 75 occupational, psychometric and demographic variables; **c** PCA plot of the data in (**b**); *squares*, *circles* and *open triangles* and *filled inverted triangles* are respectively demographic-cultural, fulfillment, psychometric and occupational metrics; **d** *Va-Re-Pr* plot of regions based on occupation, psychology or culture

3.3 Principal component analysis (PCA) of psychological and cultural metrics yields three primary clusters

The 75 variables selected above were subjected to PCA for a multivariate matrix N (75 rows of statewide metrics $\times$ 5 geographical clusters). Figure 1b, c show, respectively, a dendrogram and PCA plots. The three primary clusters are shown in green, red and blue.

3.4 Scoring clusters for adaptive attributes

We based our next step on three hypothetical assumptions: (a) that adaptive behavior in human practitioners within a profession is partially governed by psychological and/or cultural factors, notwithstanding the possibility that other types of factors, such as infrastructural constraints, may also play a role; we chose to focus on psychology and culture because the role of these two factors on occupational adaptivity is not well understood; (b) regionality of occupations is quite possibly related to aggregate psychological and cultural characteristics for each region, based on the underlying idea that certain cultural and psychological traits may well favor particular occupations; and (c) occupations may inherently differ in the extent to which they demand different attributes of adaptive behavior i.e. some, like life sciences research, may emphasize

Table 1 Psychometric data

Psychometric scale							
	N	1	2	3	4	5	6
(A) Segmented by occupation							
Physicians	536	-0.868 ± 1.211	NS	-0.184 ± 0.978	+0.154 ± 0.927	-0.100 ± 0.816	NS
Creative writers	25	-1.495 ± 0.982	NS	+0.409 ± 0.777	-0.492 ± 0.864	-0.332 ± 0.848	NS
Small business CEOs	46	-1.054 ± 0.985	NS	+0.258 ± 0.838	NS	NS	+0.330 ± 0.992
Salespersons	34	NS	+0.397 ± 0.892	NS	NS	NS	NS
IT professionals	53	NS	NS	NS	NS	NS	NS
Consultants	30	NS	NS	+0.399 ± 1.024	NS	+0.356 ± 0.853	-0.490 ± 1.114
Engineers	27	NS	NS	-0.378 ± 0.951	NS	+0.537 ± 0.677	NS
Librarians	40	NS	-0.312 ± 0.830	NS	NS	-0.515 ± 1.043	NS
Teachers	115	-0.254 ± 0.969	NS	NS	-0.425 ± 1.026	NS	NS
Homemakers	112	+0.454 ± 1.205	-0.299 ± 1.172	-0.207 ± 0.976	NS	-0.326 ± 1.190	+0.251 ± 1.010
(B) Segmented by geographic cluster							
Control (excluding physicians)							
Middle West (MW)	290	NS	-0.143 ± 0.996 ^a	NS	NS	NS	+0.142 ^{ab} ± 0.996
South (S)	144	+0.245 ^{a,b} ± 0.995	-0.175 ^a ± 1.059	NS	NS	-0.107 ^a ± 1.079	+0.327 ^{ab} ± 0.998
West (W)	177	-0.128 ± 0.902	+0.072 ± 0.957	NS	NS	+0.161 ^b ± 0.932	-0.062 ± 0.969
Transitional (T)	413	NS	+0.105 ^b ± 0.951	NS	NS	NS	NS
East (E)	153	-0.161 ± 1.092	-0.095 ± 1.058	NS	NS	-0.146 ^a ± 1.071	-0.123 ± 1.033
Physicians							
Middle West (MW)	123	NS	NS	NS	NS	NS	NS
South (S)	57	-0.650 ^b ± 1.004	NS	NS	NS	NS	+0.277 ^{ab} ± 0.839
West (W)	71	NS	NS	NS	NS	NS	0.000 ± 0.845
Transitional (T)	156	NS	NS	NS	NS	NS	NS
East (E)	103	-1.031 ± 1.187	NS	NS	NS	NS	-0.067 ± 0.823

Data are shown relative to the national average (mean ± SD)

(A) Psychometric variables by occupation: only statistically significant ($p < 0.05$) differences >0.1 SD from the national population mean are shown. (B) Psychometric variables by geographic cluster: Only significant inter-regional differences of >0.2 SD are shown

1 RESPIAS; 2 BOLD; 3 IMPROMPTU; 4 MACH; 5 ABSTRACT; 6 DOGMATIC. NS not significant

^a $p < 0.05$ versus West region

^b $p < 0.05$ versus East region

Table 2 Adaptive attributes of occupations

PCA cluster	<i>Va</i>	<i>Re</i>	<i>Pr</i>	Innovation index
Panel #1 (<i>n</i> = 65)				
Green	80.0 ± 8.7	15.4 ± 6.5	4.6 ± 2.2	2.754 ± 0.109
Red	44.1 ± 2.4*	36.4 ± 4.7	19.5 ± 4.9*	2.246 ± 0.062*
Blue	27.7 ± 14.7*	34.4 ± 8.5	37.9 ± 19.6	1.897 ± 0.334*
Panel #2 (<i>n</i> = 65)				
Green	74.2 ± 7.7	21.9 ± 8.8	3.9 ± 1.1	2.703 ± 0.066
Red	43.8 ± 8.3*	37.5 ± 9.8	18.8 ± 8.7	2.250 ± 0.139*
Blue	27.6 ± 11.0*	31.8 ± 2.4	40.6 ± 12.8*	1.870 ± 0.237*

Occupations in the green, red and blue clusters generated by PCA (Fig. 1c) were scored for *Va*, *Re* and *Pr* characteristics by two independent panels of adults. Innovation Index was calculated from these scores as described in Sect. 2. Mean ± SD are shown. *Va*, *Re* and *Pr* values are the percentages of respondents who selected it as the predominant attribute for the occupations in the cluster (* $p < 0.05$ vs. green cluster)

innovation; other, more production-related activities may focus on the standardization of functions. We postulate three types of adaptive attributes: generation of variance (*Va*, for ‘generating Variance’), reconciliation of variance with institutional practice (*Re*, for Reconciliating variance), and rote propagation of institutional procedures (*Pr*, for Prescriptive). We further operationally define the extent to which each occupation exhibits such attributes as the extent to which they are perceived to do so by an independent panel of random adults. Attributes *Va*, *Re* and *Pr* were scored for each occupation by two independent panels of 65 individuals and Innovation Index was computed as described in Sect. 2. The resulting “attribute” scores for the occupations in the green, red and blue PCA clusters are shown in Table 2. Based on these scores, the green cluster was strongly associated with *Va*; the red cluster with *Re*; and the blue cluster with *Pr*. Supplementary Table S1 shows a complete listing of the 75 variables used in the PCA analysis. A representative subset of each of cluster exhibiting the strongest regional variance (hatched boxes in Fig. 1c) was selected. As detailed in Supplementary Table S1, the *Va* subset, which received the highest Innovation Index score, included patenting, architecture and life sciences research, as well as cultural and demographic features indicating high social diversity and mobility. eSAIL traits believed to be associated with innovative change (BOLD, ABSTRACT) also mapped to this category. In contrast, the *Re* cluster featured institutionalizing functions such as education and community services. The *Pr* cluster was associated with production, maintenance and transportation occupations; higher psychometric scores for scales associated with rigidity (DOGMATIC) and external locus of control (RESPBIAS); and cultural metrics that appear to be associated with orthodoxy and conservative beliefs.

3.5 Average *z* scores for each geographic regional cluster were plotted on a grid of *Va*, *Re*, *Pr* dimensions

Composite *z* values were derived for *Va*, *Re* and *Pr* for each of the five geographic clusters by averaging the values of the metrics included in each hatched box under

each metric type: occupational, psychometric and cultural-demographic. In this way it was possible to quantify regional attributes in three putative dimensions. A three-dimensional plot of five US geographic regions using occupational, psychological or cultural-demographic criteria is shown in Fig. 1d. BLS projections of job growth for 2006–2016 predict job expansion along the *Va* (+2.40%) and *Re* (+7.64%) axes, in contrast to the *Pr* axis, which shows projected job loss (−7.03%). These observations would be consistent with the impact of shortened product cycles increasingly dependent on *Va* and *Re* at the expense of *Pr*.

3.6 Possible influence of intrinsic and extrinsic factors on adaptive change

Based on the tentative association of regional cluster W with generation of variance (*Va*) we asked whether this putative regional association might help us understand how physicians change behavior. Are physicians in this region under different psychological and cultural influences in this region versus those of regional clusters E and S—which appear to be more closely associated with *Re* and *Pr*, respectively, based on Fig. 1d—and, if so, are either of these types of influence more important in changing professional behavior over time?

Based on the data shown in Table 1, the mean psychometric scores of physicians are not significantly different between clusters W and S, except for one scale (DOG-MATIC). On the other hand, the differences between regions for the control population (excepting physicians) are more dramatic (4 of 6 scales). These data suggest that the regional variability in aggregate psychology within a profession is less pronounced than it is for the population at large.

We then explored the possibility that physicians might be influenced to adopt new practices by cultural differences in patient behavior. Cohort R primary care physicians ($n = 93$) were asked about the importance of factors encouraging them to “keep up with the latest clinical studies on new drugs”. On a scale of 1–10 (10 = most important), physicians rated “better able to answer patients’ questions about emerging therapeutic options” significantly higher (mean 7.49 ± 1.53) than either “personal satisfaction from staying informed” or “being the first in your community to implement advances in practice” (6.45 ± 2.18 and 5.69 ± 2.45 respectively; both $p < 0.001$). Patients from W, E and S geographic regions (Cohort Q; $n = 296$) saw their doctors equally often, but patients in the W region were significantly more likely ($16.2 \pm 27.3\%$) than their counterparts in regions E and S (9.4 ± 20.2 and $5.6 \pm 16.6\%$; both $p < 0.03$) to engage their doctors on the subject of treatment options by gathering information online independently. There were no significant differences in age, gender or education between the groups of patients surveyed.

4 Discussion

In this study we have examined the regional distribution of occupations and some underlying psychological and cultural covariates. Our goal was to use a multivariate analysis approach to facilitate a better understanding of how professional behavior adapts to environmental change. A better understanding of the influence of psychology

and culture on adaptive behavior may help improve experimental approaches in a number of related areas.

For instance, in socioeconomic theory, the following question is sometimes posed: Do jobs follow people or do people follow jobs? A number of currently prominent approaches to the study of urbanization respond to this question by privileging the role of individual locational choice in response to amenity values. [Storper and Scott \(2009\)](#) suggest, on the other hand, that spatial patterns of human capital cannot be taken to precede economic development but are instead the consequence of human sorting as an outcome of local productive specialization. In our conceptual frame, the causal order of assembly of interlocking components (occupation, psychology and culture) is not specifically addressed. Nevertheless our data are consistent with Storper and Scott to the extent that our method of analysis is anchored to the means of production (occupation).

In regional planning, [Simmie and Martin's \(2010\)](#) evolutionary approach to urban and regional resilience draws a distinction between neoclassical general equilibrium steady state models and what they describe as 'ecological resilience'. Although their approach is attractive, our data suggests that, at least in the United States, where the roles of different regions may only be fully understood as components of a larger whole, resilience may be a concept of limited applicability when viewed on a local or regional level.

In the field of community development, Eagle and coworkers have shown that the diversity of individuals' relationships in the United Kingdom is strongly correlated with the economic development of communities ([Eagle et al. 2010](#)). We show that metrics of social diversity (such as the prevalence of mixed marriage households, and the percentage of people born outside the state) cluster with innovation, which is quite possibly a rate-limiting variable for economic adaptation. It would be interesting to know whether there is a stronger association of diversity with innovation than with economic development per se.

As the above examples indicate, the data presented here may have relevance to research in a number of related fields. Although more work is needed to develop the present conceptual scheme, it may serve as a rough frame for the construction of more refined models with which to address the influence of psychology and local culture on adaptive behavior within professional practices and, by extension, the economic entities they support.

In this work we attempt to parse the relative influences of psychology and culture upon adaptive behavior within a profession. Our findings suggest a number of avenues for future investigation. For example, it might be interesting to examine whether the individual psychology is less likely to affect behavioral change of practitioners within professions directly than through a more general aggregate effect on regional culture. Despite similar average psychometric scores for physicians across regional clusters in the United States, physician learning and adoption of new treatments may exhibit regional differences because of extrinsic cultural factors such as patient behavior. In this work we do not address the obvious fact that other factors, such as availability of health insurance, competition, or unequal access to information may also play a significant role in physician and patient behavior. Indeed these and other factors almost certainly do. The purpose of this study was to aid further study within which such

questions might be asked with greater precision by unpacking some of the underlying complexity presented by psychological and cultural variables.

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