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OCCUPATION ANALYSIS FOR THE GREATER CLEVELAND AREA

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EXECUTIVE SUMMARY

Occupation is an important aspect of regional economy; it has been forgotten, however, in most studies of regional economies. We developed a set of benchmark occupation clusters that share similar knowledge and skills and examined the Cleveland metropolitan area based on the derived occupation clusters. The following are major findings:

• In terms of the knowledge intensity of its metropolitan labor force, Cleveland ranks 41st out of 337 metropolitan areas in the U.S. (top 15%). It is the most highly ranked metropolitan area in Ohio.

• Seven out of 20 occupation clusters in the Cleveland metro area has seen some growth between 1999 and 2003. In particular, Cleveland grew faster than the nation as well as Ohio in the financial and legal personnel cluster.

• Doctors, biomedical scientists, and technicians are relatively more concentrated in the Cleveland area than in any other metro area in Ohio. However, the distribution is skewed toward medical practitioners. Research-oriented occupations in biomedical science are seriously underrepresented in the region. The lack of research-oriented biomedical professionals can become an obstacle for efforts to build strength in the biotech industry.

• Almost all occupations in the computer scientists and related specialists cluster are significantly underrepresented in the Cleveland area. Efforts to continue the development of IT-related industries in the region will face significant challenge and require additional workers with the right skills.

• Engineers, technicians, and architects are relatively well represented in the Cleveland area. In particular, the number of highly skilled engineers in the region is higher than the national average.

• Cleveland's work force can satisfy labor needs in traditional manufacturing sectors, such as rubber and miscellaneous plastic products, fabricated metal products, petroleum refining, and primary metal, as well as emerging service sectors related to finance and insurance services.

• Key occupation clusters with the best match between supply and demand of occupations in manufacturing industries are skilled laborer and machine operators, supervisors and management personnel, and engineers, technicians, and architects. Key occupation clusters with the best match between supply and demand of occupations in service industries are supervisors and management personnel, clerical workers, and sales, marketing, and

advertisement personnel. In the finance and insurance-related sectors, the financial and legal personnel cluster is particularly important.

- Key occupations for manufacturing sectors are well represented in the Cleveland area. However, because there is also a high demand for well-trained workers, the region is likely to face a shortfall of skilled manufacturing workers for future growth.

- The distribution of key occupations for service sectors in the Cleveland area roughly follows the national averages except for finance and legal personnel. The growth of the finance and insurance-related sectors in the region and the strong presence of finance and legal personnel suggest potential for the future growth of these industries in the Cleveland area.

INTRODUCTION

Industry has been a dominant focus in most regional economic analyses over the last several decades because of Isard's (1960) early work on industrial analysis and the popularity of the economic base theory. Many regional analysis techniques, such as location quotients, shift-shares, and input-output analysis, were developed to examine local industrial structure, industry cycles, and industrial linkages. For most traditional economic development scholars and professionals, therefore, regional economic analysis involves examining industrial strengths and weaknesses and developing strategies to replace declining industries and build regional competitiveness. Many state and local governments established industry task forces and launched strategic plans to improve the business environment and to develop specific target industries that could create new jobs and eventually boost the overall economic performance of a region. The development of the steel industry in Chicago and the polymer industry in Akron provide examples of this kind of development.

This trend is changing now that researchers have begun paying attention to occupations as well as industries. Recently, regional competitiveness has become increasingly dependent upon local knowledge bases and worker quality. Old style industry-targeting strategies accompanied by huge benefit packages for firms (e.g., tax incentives) have now proven to be futile (Greenstone & Moreti, 2003; McGuire, 2003) because firms tend to focus more on the quality of the local labor force in their location decisions. Thus, examining regional economies from a different angle, such as occupations, can provide important insights for regional development. For instance, although the automobile and chemical industries produce completely different products, software engineers in the two sectors often perform similar tasks and thereby are interchangeable. Because workers who perform similar tasks can easily move between industries with minimal retraining, strategies focusing solely on industries are likely to overlook occupation-based opportunities across industries.

A regional economy indeed has two dimensions, industry and occupation. In fact, the failure of many previous industry-targeting strategies can be attributed to the lack of understanding of a two-dimensional regional economy. Policy approaches based on one-dimensional thinking (i.e., industry-based strategies) for a two-dimensional regional economy are likely to fail. For this reason, policymakers need to pay as much attention to the functions that local workers perform as to the output that they produce.

This study investigates Cleveland's metropolitan economy from an occupation perspective. The economic characteristics and prospects of the region are examined in terms of the types of jobs that local workers perform. The findings from this study are summarized in the following four sections. Section 2 describes the benchmark approach for regional analysis and presents a set of occupation clusters. Section 3 examines the Cleveland metropolitan area based on the benchmark occupation clusters derived in section 2 and illustrates the geographic distribution of occupations in the region. Section 4 examines three knowledge-intensive occupation groups in the region. Session 5 suggests effective industry-targeting strategies based on the analysis of current occupational mix in Cleveland. The appendices contain clustering methods, definitions, and other detailed supplementary data.

KNOWLEDGE-BASED BENCHMARK APPROACH FOR REGIONAL ANALYSIS

The primary database used in this study is the Bureau of Labor Statistics' 2001 Occupational Employment Survey (OES). The OES database has employment and wage information for almost 700 occupation categories at different geographical levels, including metropolitan area, state, and nation. Although the database provides rich information on occupational mixes at different geographic scales, its size and complexity make it difficult to utilize for regional analysis. Besides, workers often move from one occupation to another with little effort needed for retraining. In other words, many occupations share core knowledge and skills and are thereby interchangeable. This study creates benchmark occupation groups according to their knowledge requirements to foster more meaningful analysis at a manageable level. Subsequent regional analysis is conducted based on derived benchmark occupation clusters.

To create benchmark occupation clusters, a new database, the Occupational Information Network (ONET), is introduced. ONET (version 5.1 published in 2003) is a comprehensive database of worker attributes and characteristics. It describes over 900 occupations in terms of 33 knowledge variables.[1] Occupation categories in the OES and ONET databases are roughly comparable. When ONET has more detailed occupation categories, however, they are aggregated so that all ONET occupations match the OES occupations. ONET occupation categories are then grouped into 20 occupation clusters based on their knowledge requirements. Since ONET was originally developed based on a nationwide survey of occupations and their knowledge requirements, benchmark clusters can be used as a national-level reference in regional analysis. Appendix A provides detailed technical information on how benchmark occupation clusters are derived.

Table 1 shows 20 benchmark occupation clusters, their mean knowledge intensity, and the number of U.S. total employment. [2] In terms of size, clerical workers and semi-skilled laborer and service workers make up the two largest occupation groups and represent 22 and 17 percent of the total U.S. employment, respectively. The most knowledge-intensive

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[1] See Feser (2003) for more detailed discussion of the ONET database.
[2] The knowledge intensity of occupation clusters is measured based on Feser and Koo (2001). In the following formula, S_i is the mean knowledge intensity for occupation cluster i, K_{ij} is the knowledge requirement j for occupation cluster i, and n_i is the number of occupations in occupation cluster i:

$$S_i = \frac{\sum_j (K_{ij})^2}{n_i}$$

occupation clusters are social scientists (118.6); engineers, technicians, and architects (99.2); doctors, biomedical scientists, and technicians (78.2); computer scientists and related specialists (68.0); and healthcare specialists (64.9). Appendix B shows the importance of 33 knowledge variables for each occupation cluster. An effective regional analysis could be conducted by examining the unique knowledge characteristics of occupational clusters and regional labor force endowments.

Table 1 Benchmark Occupation Clusters and Knowledge Intensity

Occupation Cluster	Knowledge Intensity	US Emp (2003)
Social scientists	118.6	312,530
Engineers, technicians, and architects	99.2	2,537,580
Doctors, biomedical scientists, and technicians	78.2	1,550,920
Computer scientists and related specialists	68.0	2,684,440
Healthcare specialists	64.9	9,514,430
Earth scientists	63.3	205,370
Supervisors and management personnel	59.5	10,206,780
Special educators and teachers	58.1	6,676,230
Sales, marketing, and advertisement personnel	54.3	6,146,480
Farming and agricultural workers	46.9	465,280
Financial and legal personnel	44.7	3,551,750
Law enforcement workers	37.6	2,979,860
Clerical workers	29.2	26,648,240
Artists and performers	28.2	979,880
Specialized mechanics, repairs, and technicians	24.8	5,401,960
Transportation ad mining workers	22.8	4,986,180
Skilled laborer and machine operators	18.6	7,383,360
Construction workers	15.0	3,753,650
Food preparation workers	14.6	3,212,350
Semi skilled laborer and service workers	11.6	20,919,480

Source: OES, ONET, and Author's Calculation

METROPOLITAN KNOWLEDGE INDEX

The knowledge intensities of occupations can provide meaningful information about the quality of the regional labor force and the readiness of the regional economy for the 21st century. Regions and states with a high concentration of relatively knowledge-intensive occupation groups are in a better position to identify and nurture more knowledge-intensive industries. In other words, the quality of the regional labor force, when measured by occupation mixes and their knowledge intensities, can indicate the region's potential in the knowledge economy. This study derives the metropolitan knowledge index based on benchmark occupation clusters.[3]

Table 2 lists the top 45 metropolitan areas in the country in terms of labor force quality. Regions with higher knowledge intensity scores are the location of jobs that demand relatively more knowledge and skills. As expected, so-called high-tech regions, such as San Jose, Boston, Washington, and Raleigh-Durham, appear at the top of the list. Relatively small regions that are not often considered technologically advanced, such as Stamford (CT), Huntsville (AL), and McAllen (TX), are also at the top 45 list. The Cleveland-Lorain-Elyria metropolitan area has the highest knowledge intensity score in Ohio, and it ranks only 41st out of 337 metropolitan areas in the U.S. This implies that Ohio's overall labor quality is in the top 15 percent of all metropolitan areas in the U.S.

To examine the quality of Cleveland's regional labor force in more detail, we compare Cleveland with two of the most knowledge-intensive metro areas (Boston and Raleigh-Durham) and two peer metro areas (Columbus and Cincinnati) in Table 3. As expected, Boston and Raleigh-Durham have strong concentrations of knowledge-intensive occupations. For instance, the location quotients of doctors, biomedical scientists, and technicians in the two cities are 1.31 and 1.92, respectively. Those of computer scientists and related specialists are 1.98 and 2.13, and those of engineers, technicians, and architects are 1.40 and 1.17, respectively.

[3] The metropolitan knowledge index is estimated with the following formula where M_k is the metropolitan knowledge index of metro area k, S_i is the mean knowledge intensity for occupation cluster i, E_{ik} is the employment share of occupation cluster i in metro area k, and n_k is the number of occupation clusters present in metro area k: $M_k = \frac{\sum_i S_i E_{ik}}{n_k}$

Table 2: Metropolitan Knowledge Index

Rank	Metropolitan Area	Total Emp (2003)	Knowledge Index
1	San Jose, CA PMSA	877,640	37.56
2	Boston, MA-NH PMSA	1,920,950	36.72
3	Washington, DC-MD-VA-WV PMSA	2,694,130	36.71
4	Raleigh-Durham-Chapel Hill, NC MSA	663,250	36.38
5	Stamford-Norwalk, CT PMSA	200,220	35.79
6	Hartford, CT MSA	597,390	35.77
7	Baltimore, MD PMSA	1,223,090	35.71
8	Philadelphia, PA-NJ PMSA	2,340,250	35.50
9	Austin-San Marcos, TX MSA	651,670	35.17
10	Pittsburgh, PA MSA	1,077,020	34.92
11	Albany-Schenectady-Troy, NY MSA	444,360	34.82
12	Huntsville, AL MSA	177,930	34.77
13	Houston, TX PMSA	2,057,880	34.76
14	Rochester, NY MSA	511,350	34.72
15	McAllen-Edinburg-Mission, TX MSA	176,900	34.67
16	Dallas, TX PMSA	1,890,340	34.60
17	Newark, NJ PMSA	967,580	34.45
18	St. Louis, MO-IL MSA	1,274,720	34.34
19	Middlesex-Somerset-Hunterdon, NJ PMSA	624,420	34.33
20	Nassau-Suffolk, NY PMSA	1,195,460	34.31
21	Bridgeport, CT PMSA	184,890	34.21
22	Lawrence, MA-NH PMSA	154,430	34.18
23	Monmouth-Ocean, NJ PMSA	396,610	34.15
24	Atlanta, GA MSA	2,124,780	34.11
25	Worcester, MA-CT PMSA	228,570	34.09
26	Lowell, MA-NH PMSA	124,290	34.09
27	Richmond-Petersburg, VA MSA	541,950	34.08
28	Denver, CO PMSA	1,136,190	34.07
29	Oklahoma City, OK MSA	522,870	34.04
30	New Haven-Meriden, CT PMSA	253,710	34.02
31	Providence-Fall River-Warwick, RI-MA MSA	520,890	33.96
32	Minneapolis-St. Paul, MN-WI MSA	1,686,210	33.96
33	Seattle-Bellevue-Everett, WA PMSA	1,298,550	33.91
34	Madison, WI MSA	280,530	33.90
35	Sacramento, CA PMSA	747,270	33.85
36	Oakland, CA PMSA	1,017,080	33.84
37	Milwaukee-Waukesha, WI PMSA	817,420	33.84
38	Kansas City, MO-KS MSA	930,340	33.84
39	Bergen-Passaic, NJ PMSA	638,670	33.77
40	Boulder-Longmont, CO PMSA	154,950	33.73
41	Cleveland-Lorain-Elyria, OH PMSA	1,087,940	33.72
42	Jackson, MS MSA	210,050	33.67
43	Portland, ME MSA	154,880	33.67
44	Dayton-Springfield, OH MSA	450,210	33.63
45	Phoenix-Mesa, AZ MSA	1,596,920	33.61

Source: OES, ONET, and Author’s Calculation

Table 3: Occupation Cluster Mix in Selected Metropolitan Areas*

Occupation Cluster	Boston	Raleigh-Durham	Cleveland	Columbus	Cincinnati
Financial and legal personnel	1.54	0.95	1.15	1.02	0.89
Social scientists	1.60	2.22	0.54	0.73	0.77
Artists and performers	1.38	0.88	0.87	0.84	0.80
Doctors, biomedical scientists, and technicians	1.31	1.92	0.98	0.84	0.78
Transportation ad mining workers	0.61	0.66	0.79	0.96	1.01
Computer scientists and related specialists	1.98	2.13	0.74	1.29	1.00
Supervisors and management personnel	1.14	1.07	0.94	1.02	1.02
Specialized mechanics, repairs, and technicians	0.82	0.87	0.90	0.86	0.98
Semi skilled laborer and service workers	0.92	0.81	0.96	1.05	1.00
Clerical workers	0.98	0.97	1.00	1.03	0.96
Skilled laborer and machine operators	0.73	0.72	1.40	0.89	1.14
Healthcare specialists	1.08	0.94	1.10	0.93	1.02
Construction workers	0.68	0.90	0.82	0.78	0.79
Special educators and teachers	0.96	0.92	0.88	0.73	0.77
Sales, marketing, and advertisement personnel	1.15	1.07	1.11	0.99	1.07
Food preparation workers	0.83	0.88	0.97	0.97	0.92
Law enforcement workers	0.98	0.85	1.02	0.92	0.91
Engineers, technicians, and architects	1.40	1.17	0.94	0.93	0.96
Farming and agricultural workers	0.34	0.53	0.20	0.31	0.30
Earth scientists	0.56	1.69	0.38	0.56	0.43

Source: OES and Author's Calculation

* Values are LQs of occupation clusters (2003).

In contrast, all three Ohio cities have quite generic occupation mixes overall, similar to those of the nation (i.e., their location quotients are close to 1 for most occupation clusters). Cleveland has a slight edge over the other two peer cities in financial and legal personnel (LQ=1.15), skilled laborer and machine operators (LQ=1.40), healthcare specialists (LQ=1.10), and sales, marketing, and advertisement personnel (LQ=1.11). Surprisingly, despite having a strong healthcare industry, Cleveland does not have a particularly concentrated cluster of doctors, biomedical scientists, and technicians when compared to the nation (LQ=0.98). Given that it is the most critical occupation group for developing the biotech industry on which Cleveland has set its sights, a lower than expected concentration of doctors, biomedical scientists, and technicians cluster can limit the region's strategy of developing the biotech industry.

OCCUPATION CLUSTERS IN THE CLEVELAND METROPOLITAN AREA

CLUSTER TRENDS

Occupation clusters depict an important aspect of the regional economy, i.e., local labor force. An analysis of regional occupation distributions can provide policy makers with useful insights regarding the economic structure of a region. In particular, changes of occupation distributions can describe potential structural shifts that a region has gone through. To examine changes of occupational structure in the Cleveland area, occupation cluster employment trends between 1999 and 2003 in US, state, and Cleveland are compared in Table 4. The examination of occupation trends at different geographical levels shows national as well as regional economic forces that shape the characteristics of the regional economy. In the Cleveland metropolitan area, only seven out of 20 occupation clusters experienced some growth during this period. The most significant drivers of growth are service related occupation clusters, such as food preparation workers (31.3%), sales, marketing, and advertisement personnel (6.9%), healthcare specialists (6.0%), and financial and legal personnel (5.6%). These, with an exception of food preparation workers, are relatively well-paid occupations that may shape the future of Cleveland. In particular, financial and legal personnel outpaced the nation as well as the state in terms of its growth rate.

On the other hand, there have been significant employment declines in a wide range of occupation groups. Most noticeable losses are found in manufacturing related clusters. For instance, the skilled laborer and machine operators cluster lost some 24 percent of its employment during the 1994-2003 period. Note that Cleveland's doctors, biomedical scientists, and technicians cluster declined by 4.7 percent during this period whereas the national cluster grew by over eight percent. In combination with the lackluster growth of the healthcare specialists cluster, this implies some serious challenges to growing healthcare-related industries in the Cleveland area. Occupation trends in Table 4 suggest that the growth in healthcare-related industries in Cleveland is driven by low- to mid-level occupations. Job growth in more knowledge-intensive occupations (e.g., doctors and biomedical scientists), which is potentially related to the development of the biotech industry in the future, is not observed. The region also suffered a significant loss in other knowledge-intensive and high-paying occupation clusters such as computer scientists and related specialists and engineers, technicians, and architects. Over 20 percent of its workforce in both clusters was lost between 1999 and 2003. Given the importance of these occupations for the development of knowledge-based industries in the new economy, Cleveland's economic future may be stifled.

Table 4: Occupation Cluster Trend 1999-2003

Occupation Cluster	Cleveland MSA Employment (2003)	% Change in Employment, 1999-2003 US	State	Cleveland MSA
Financial and legal personnel	34,627	4.2%	3.0%	5.6%
Social scientists	1,519	14.5%	19.7%	-5.8%
Artists and performers	8,148	2.6%	3.2%	17.3%
Doctors, biomedical scientists, and technicians	12,964	8.5%	4.1%	-4.7%
Transportation ad mining workers	33,677	-1.2%	-10.5%	-19.1%
Computer scientists and related specialists	16,860	10.1%	-3.4%	-22.9%
Supervisors and management personnel	81,881	-3.4%	-12.4%	-13.3%
Specialized mechanics, repairs, and technicians	41,415	1.6%	-3.5%	-1.0%
Semi skilled laborer and service workers	171,224	2.5%	-0.9%	1.3%
Clerical workers	227,939	4.0%	1.5%	-1.9%
Skilled laborer and machine operators	89,273	-15.2%	-15.7%	-25.0%
Healthcare specialists	89,126	9.1%	4.7%	6.0%
Construction workers	26,456	3.8%	-9.9%	-14.3%
Special educators and teachers	49,690	7.4%	10.6%	5.4%
Sales, marketing, and advertisement personnel	58,190	0.9%	8.5%	6.9%
Food preparation workers	26,565	-1.7%	7.8%	31.3%
Law enforcement workers	25,833	0.9%	-6.5%	-2.0%
Engineers, technicians, and architects	20,399	-0.4%	-9.3%	-34.0%
Farming and agricultural workers	823	5.1%	33.7%	-19.4%
Earth scientists	730	19.2%	-15.3%	-41.8%

Source: OES and Author's Calculation

KNOWLEDGE-INTENSIVE OCCUPATION CLUSTERS[4]

As mentioned earlier, knowledge and its spillovers are the most important elements in the development process, particularly in the new economy.[5] In particular, since knowledge is tacit and its movement depends on knowledge workers, human capital can serve as an intermediate agent in the knowledge spillover process. The accumulation of human capital can generate positive externalities since new skills acquired by each worker can be shared or can spill over to others in the same location, eventually making the entire labor pool more productive. In addition, firms' location decisions are often more influenced by the availability of high-quality labor force than by state and local policies, such as tax incentives and relocation

[4] Detailed tables of other occupation clusters are available upon requests.
[5] A knowledge production function approach developed by Griliches (1979) and applied later by Jaffe (1989) and Anselin et al. (1997) suggests that human capital is a crucial input factor for knowledge production activities.

subsidies. Therefore, the economic success of a region in the new economy hinges on whether its economy has the right mix of workers to produce and disseminate new knowledge.

A promising but rarely applied approach to regional analysis involves examining regional occupation mixes to determine a region's human capital and potential growth. In particular, a close look at knowledge-intensive occupations can provide rich information about a region's economic adaptability and prospects in the new economy. To evaluate the current position and future potential of the Cleveland economy, this study focuses on the three most knowledge-intensive occupation clusters: doctors, biomedical scientists, and technicians; computer scientists and related specialists; and engineers, technicians, and architects. Each occupation cluster is evaluated based on its detailed occupations and core knowledge requirements. Geographic distributions of these occupations are also presented.

Doctors, Biomedical Scientists, and Technicians Cluster

The doctors, biomedical scientists, and technicians cluster consists of 29 occupations and is one of the most knowledge-intensive occupation groups. Some of the occupations require more extensive knowledge than others. Appendix B shows that the doctors, biomedical scientists, and technicians cluster relies on four distinct but related knowledge fields: biology, chemistry, medicine and dentistry, and mathematics. These knowledge variables define the characteristics of this cluster. Occupations included in this cluster share these knowledge bases although their requirement levels may vary by occupation.

Table 5 illustrates the concentration levels of the 29 cluster member occupations in the Cleveland area. Physicians in many different specialties are overrepresented in Cleveland; the location quotient of general practitioners is as high as 1.70. Given the strength of Cleveland's healthcare industry, this is not surprising. However, this occupation cluster has a lower than expected concentration level (LQ=0.98) because of the dearth of related professions other than doctors in the region. For instance, professionals who are more likely to be involved in biomedical research activities, such as medical scientists (LQ=0.12), environmental scientists and specialists (LQ=0.21), biological science postsecondary teachers (LQ=0.27), microbiologists (LQ=0.33), health specialist postsecondary teachers (LQ=0.39), and biological technicians (LQ=0.47), are seriously underrepresented in the Cleveland area. Other potentially important professions, such as epidemiologists, biochemists and biophysicists, and agricultural science teachers, have only a negligible presence (that is why LQ can not be estimated). In addition, many of these underrepresented occupations in Cleveland have experienced a significant decrease between1999 and 2003, whereas the national trend shows substantial gains in most occupations potentially because a strong performance of biotech-related sectors. In other words, the presence of a strong healthcare industry accounts for a high concentration of physicians, but the region lacks other research-oriented biomedical professionals. Such an unbalanced distribution of occupations explains the lower-than-expected level of overall concentration of the doctors, biomedical scientists, and technicians cluster and may hamper the region's future development of the biotech industry.

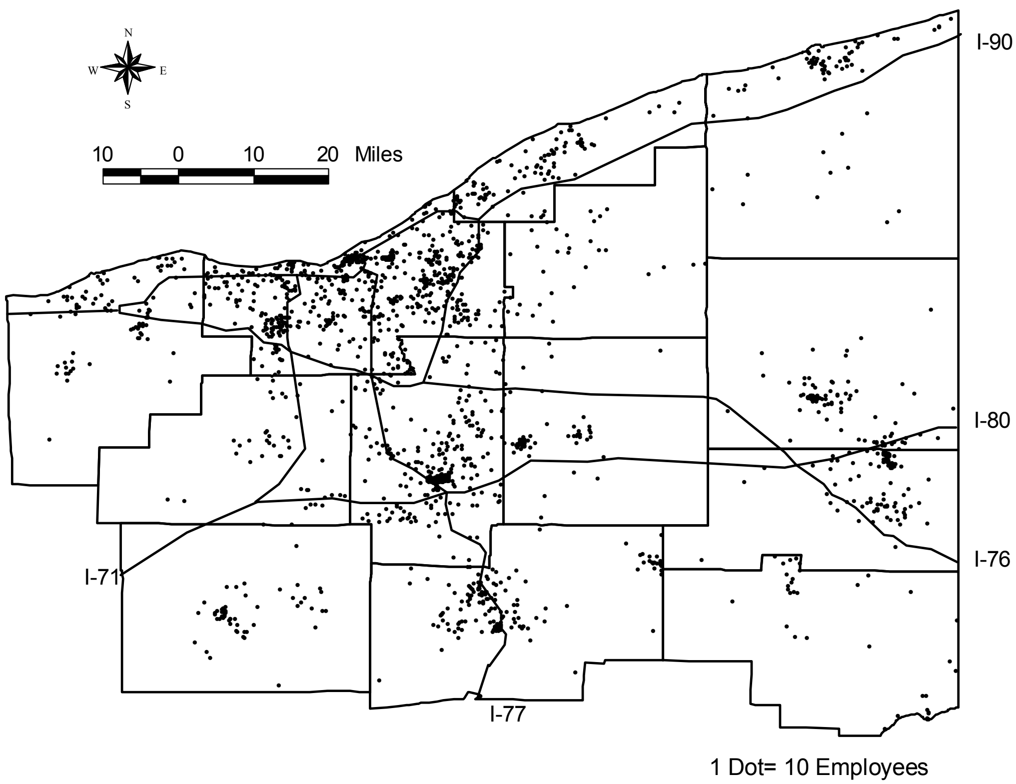
Table 5: Occupations in the Doctors, Biomedical Scientists, and Technicians Cluster

Occupation	LQ 2003	% Change in Employment 1999 - 2003 Cleveland	US
Pediatricians, General	1.7	44.4	42.1
Internists, General	1.5	25.5	2.9
Chemical Technicians	1.5	12.9	-18.7
Physician Assistants	1.4	130.0	5.8
Chemists	1.3	-27.4	11.9
Medical and Clinical Laboratory Technicians	1.3	-24.6	2.9
Medical and Clinical Laboratory Technologists	1.2	42.1	0.8
Biomedical Engineers	1.2	-12.5	8.2
Obstetricians and Gynecologists	1.2	*	2.1
Family and General Practitioners	1.1	*	-16.7
Chiropractors	1.1	*	75.1
Dentists	1.1	26.1	40.0
Anesthesiologists	1.1	*	-8.2
Surgeons	1.1	-7.5	2.6
Podiatrists	1.1	*	74.5
Pharmacists	1.1	-1.9	-5.0
Materials Scientists	1.0	*	-9.6
Veterinarians	0.7	-50.9	11.8
Biological Technicians	0.5	-27.3	25.2
Health Specialties Teachers, Postsecondary	0.4	31.8	22.2
Microbiologists	0.3	*	-9.7
Biological Science Teachers, Postsecondary	0.3	-7.7	53.2
Environmental Scientists and Specialists, Including Health	0.2	-73.2	15.0
Medical Scientists, Except Epidemiologists	0.1	*	186.9
Biochemists and Biophysicists	*	*	22.2
Zoologists and Wildlife Biologists	*	*	15.8
Epidemiologists	*	*	66.1
Agricultural Sciences Teachers, Postsecondary	*	*	37.7
Forestry and Conservation Science Teachers, Postsecondary	*	*	45.4

Source: OES, ONET, and Author's Calculation; * Not enough information for estimation

Figure 1 shows the geographic distribution of doctors, medical scientists, and technicians in Northeast Ohio. Geocoded establishment data for 13 Northeast Ohio counties were purchased from Dun and Bradstreet, and the number of employees was distributed according to the state's occupation staffing patterns. The estimated occupation distributions by firm were aggregated at the census tract level and were overlapped with county boundaries in Northeast Ohio. Therefore, the map covers a larger area than the Cleveland metropolitan area.

Figure 1: Distribution of Doctors, Biomedical Scientists, and Technicians Cluster



Source: Dun and Bradstreet DMI File

Computer Scientists and Related Specialists Cluster

The computer scientists and related specialists cluster includes 11 occupations and is defined by two very distinct knowledge fields: computers and electronics and mathematics (see Appendix B). When compared to other occupation groups, the knowledge requirements for this cluster are more narrowly defined and have significant depth. Occupations that require in-depth specialized knowledge bases often pose a significant challenge for economic development professionals because unique knowledge requirements make it difficult for existing workers to transition to other occupations through retraining programs. Therefore, developing a sizable local pool of workers qualified for such occupations is costly and time-consuming.

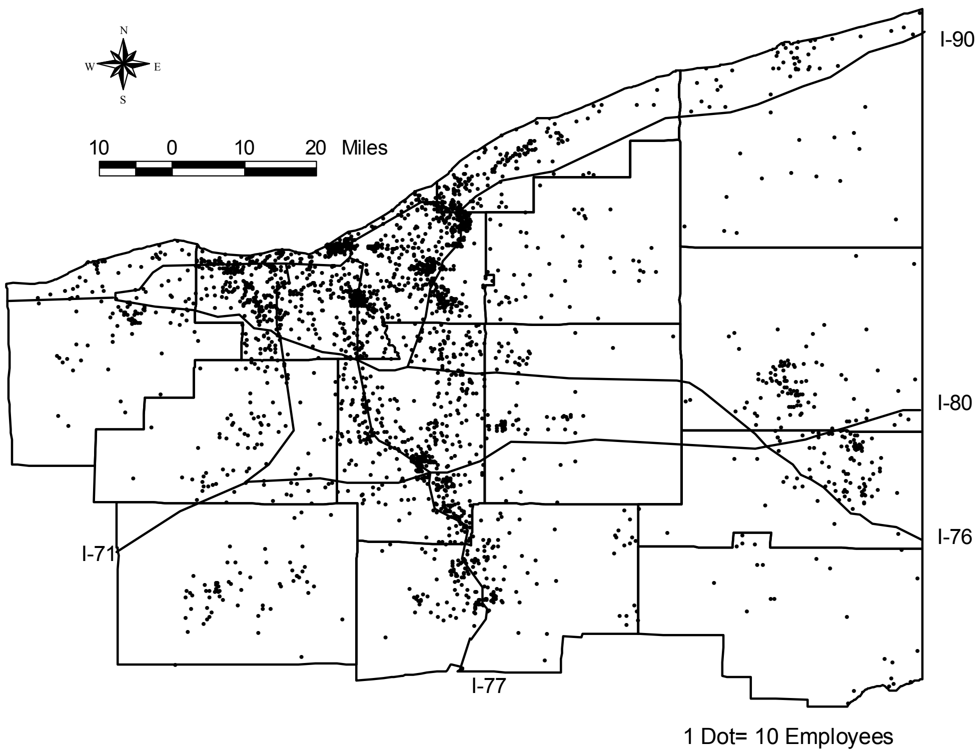
Table 6 shows that Cleveland significantly lacks professionals in the computer scientists and related specialists cluster. Nine out of eleven occupations are underrepresented (i.e., the location quotients are less than 1). Database administrators (LQ=1.35) and network and computer systems administrator (LQ=1.14) are the only occupations with a significant presence in the Cleveland area. However, the knowledge intensity of database administrators is among the lowest in the cluster. Concentration levels of other more knowledge-intensive occupations, such as computer hardware engineers (LQ=0.21), computer software engineers, systems software (LQ=0.36), computer and information scientists (LQ=0.41), and computer software engineers, applications (LQ=0.67) are far below the national averages. In addition, Cleveland has lost a significant share of these more knowledge-intensive occupations between 1999 and 2003, whereas the national trend shows substantial gains in those occupations during the same period. The extent of the underrepresentation of this occupation cluster in the Cleveland area is such that any future attempt to develop strategic industries that demand high-quality computer specialists is likely to be seriously undermined. Figure 2 shows the geographic distribution of computer scientists and related specialists in Northeast Ohio.

Table 6: Occupations in the Computer Scientists and Related Specialists Cluster

Occupation	LQ (2003)	% Change in Employment 1999 - 2003 Cleveland	US
Database Administrators	1.4	-11.1	-11.7
Network and Computer Systems Administrators	1.1	-31.4	-18.3
Computer Programmers	0.9	72.3	36.4
Computer Systems Analysts	0.7	-49.8	36.7
Computer Support Specialists	0.7	-29.4	4.4
Computer Software Engineers, Applications	0.7	-41.0	10.9
Computer Science Teachers, Postsecondary	0.6	-14.7	-0.6
Network Systems and Data Communications Analysts	0.5	30.5	16.3
Computer and Information Scientists, Research	0.4	6.6	50.5
Computer Software Engineers, Systems Software	0.4	*	20.1
Computer Hardware Engineers	0.2	-24.9	12.1

Source: OES, ONET, and Author's Calculation; * Not enough information for estimation

Figure 2: Distribution of Computer Scientists and Related Specialists Cluster



Source: Dun and Bradstreet DMI File

Engineers, Technicians, and Architects Cluster

The engineers, technicians, and architects cluster is the second most knowledge-intensive group and consists of 35 occupations. Compared to the previous two occupation groups, this cluster requires relatively broader knowledge bases. Four knowledge fields, engineering and technology, design, mathematics, and physics, define the cluster. Such broad knowledge requirements can pose a challenge for regions because training workers for these occupations can be costly as well as time-consuming.

Table 7 presents the concentration levels of the 35 cluster member occupations in the Cleveland area. Almost all of them have lost employment in Cleveland between 1999 and 2003, whereas many of them have experienced employment increases nationally during the same period. The most noticeable characteristic of this cluster is its concentration patterns. Cleveland has a strong presence of relatively more knowledge-intensive occupations. For instance, chemical engineers (LQ=1.45), mechanical engineers (LQ=1.30), material engineers (LQ=1.22), and industrial engineers (LQ=1.19) are all more concentrated than the national averages. This is probably due to the historically strong presence of the manufacturing sector.

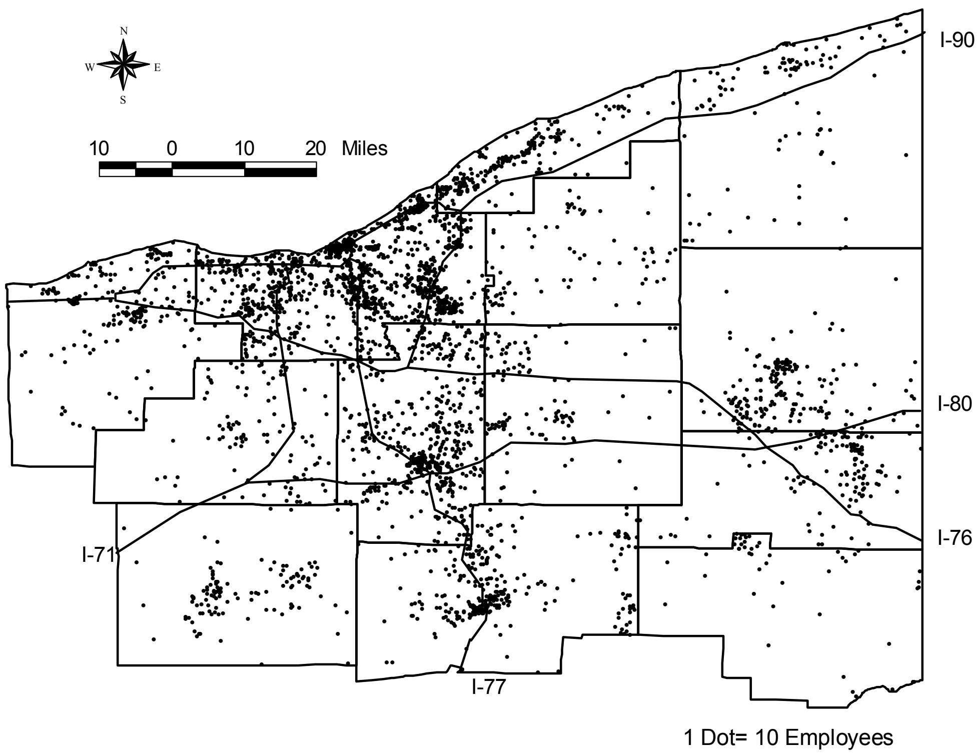
The table, however, also shows that mid-range knowledge occupations (i.e., technicians and drafters) are underrepresented. These occupation distribution patterns are in contrast to the popular belief that the region lacks workers in more knowledge-intensive occupations. In addition, from an economic development policy perspective, such a pattern poses a relatively less serious challenge because training technicians and drafters, if necessary, costs less than training engineers. Figure 3 shows the geographic distribution of engineers, technicians, and architects in Northeast Ohio.

Table 7: Occupations in the Engineers, Technicians, and Architects Cluster

Occupation	LQ (2003)	% Change in Employment 1999 - 2003	
		Cleveland	US
Mechanical Engineering Technicians	1.47	-30.8	-12.3
Chemical Engineers	1.45	-4.8	13.5
Mechanical Engineers	1.30	-29.1	2.4
Mechanical Drafters	1.27	-53.5	12.2
Materials Engineers	1.22	-35.1	6.4
Electricians	1.20	-17.0	-4.6
Industrial Engineers	1.19	-40.5	0.6
Electrical Engineers	0.98	-47.0	-2.1
Industrial Engineering Technicians	0.97	-5.4	24.3
Architects, Except Landscape and Naval	0.92	-13.4	28.1
Landscape Architects	0.92	-7.9	36.3
Architectural and Civil Drafters	0.92	-39.5	5.4
Engineering Managers	0.92	-56.2	-21.5
Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	0.90	15.0	-26.1
Statisticians	0.77	33.3	25.7
Civil Engineering Technicians	0.72	-12.7	-1.1
Electrical and Electronics Drafters	0.70	-53.5	-15.5
Physicists	0.69	2.3	20.4
Aerospace Engineers	0.65	*	-1.5
Environmental Engineering Technicians	0.53	60.0	-5.4
Physics Teachers, Postsecondary	0.50	-16.7	5.7
Civil Engineers	0.48	-54.1	-1.3
Chemistry Teachers, Postsecondary	0.48	-46.8	-4.3
Environmental Engineers	0.47	-41.9	-11.6
Electronics Engineers, Except Computer	0.42	-29.0	28.5
Urban and Regional Planners	0.34	-67.9	7.1
Mathematicians	*	*	-28.4
Marine Engineers and Naval Architects	*	*	11.5
Mining and Geological Engineers, Including Mining Safety Engineers	*	*	-33.9
Nuclear Engineers	*	*	67.1
Petroleum Engineers	*	*	20.6
Architecture Teachers, Postsecondary	*	*	41.3
Engineering Teachers, Postsecondary	*	*	11.7

Source: OES, ONET, and Author's Calculation; * Not enough information for estimation

Figure 3: Distribution of Engineers, Technicians, and Architects Cluster



Source: Dun and Bradstreet DMI File

OCCUPATION-BASED INDUSTRY TARGETING

Traditional industry-targeting strategies usually focus on existing employment concentrations in a region or on the latest trendy industries without any serious consideration of the region's capacity to attract, nurture, and develop certain industries. When trying to develop knowledge-intensive high-tech industries, however, state and local governments need to pay more attention to their endowments, i.e., their capabilities to build strength locally in such industries. The most important regional asset when developing specialization in a certain sector is labor force. Whether a region has the right mix of workers is a critical question in many firms' location decisions. This section analyzes the Cleveland economy based on a new approach for industry targeting. By studying occupation and industry information together, economic development professionals can make better-informed policy decisions.

MATCHING REGIONAL OCCUPATION MIX (SUPPLY) AND INDUSTRY LABOR NEEDS (DEMAND)

To examine how well Cleveland's labor force fits different industries, the region's occupation mix should be compared with industry labor needs. If Cleveland has an occupation mix that closely matches the labor needs of a certain industry, the region may indeed be well prepared to attract, nurture, and develop that industry. To implement this strategy, we used the location quotients (LQ) of the 20 occupation clusters in the Cleveland metro area to measure the supply of labor force and knowledge-intensity weighted industry staffing patterns as demand for labor needs. Knowledge-intensity weighted industry labor needs are obtained by multiplying industry labor needs (i.e., shares of occupation cluster employment for a certain industry derived from the national staffing pattern matrix) and knowledge intensity. Cleveland's occupation mix aggregates employment across all industries by occupation cluster, whereas industry labor needs cover occupation cluster distributions by industry.

We introduced the Spearman correlation as a goodness-of-fit measure between the region's occupation mix and industry labor needs. This measure correlates the relative importance of occupation clusters for a certain industry with the relative strengths of local occupation clusters measured by location quotients. High correlation coefficients therefore imply that the regional occupation mix is close to industry labor needs. In other words, the measure can provide valuable information as to whether the region has the right mix of workers to develop a certain type of industry. Tables 8 and 9 list the top 10 best-fit manufacturing and service industries for Cleveland's labor endowments. In manufacturing, the occupation mix of the Cleveland economy bears a strong resemblance to the labor requirements for traditionally strong industries in the Cleveland metro area, such as rubber and miscellaneous plastic products (LQ=1.40), fabricated metal products (LQ=2.41), petroleum refining (LQ=1.23), and primary metal (LQ=2.77). In services, the finance and insurance service-related sectors top the list.

Table 8: Top 10 Best-Fit Manufacturing Industries

SIC	Industry	LQ	Correlation
30	Rubber and Miscellaneous Plastics Products	1.40	0.62
34	Fabricated Metal Products, Except Machinery and Transportation Equipment	2.41	0.60
26	Paper and Allied Products	0.98	0.58
29	Petroleum Refining and Related Industries	1.23	0.58
38	Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks	1.03	0.58
33	Primary Metal Industries	2.77	0.56
39	Miscellaneous Manufacturing Industries	0.97	0.55
28	Chemicals and Allied Products	1.83	0.54
36	Electronic and Other Electrical Equipment and Components, Except Computer Equipment	0.87	0.54
37	Transportation Equipment	1.11	0.54

Source: ES202 and Author's Calculation

Table 9: Top 10 Best-Fit Service Industries

SIC	Industry	LQ	Correlation
63	Insurance Carriers	1.11	0.62
64	Insurance Agents, Brokers, and Service	0.72	0.60
61	Non-Depository Credit Institutions	1.04	0.55
65	Real Estate	0.91	0.54
73	Business Services	0.79	0.54
62	Security and Commodity Brokers, Dealers, Exchanges, and Services	0.62	0.53
67	Holding and Other Investment Offices	1.00	0.46
76	Miscellaneous Repair Services	0.88	0.46
80	Health Services	1.15	0.45
60	Depository Institutions	1.18	0.44

Source: ES202 and Author's Calculation

A comparison of manufacturing and service sectors in Tables 8 and 9 reveals an interesting pattern. Most best-fit manufacturing sectors are already highly concentrated in the region, whereas best-fit service sectors seem to be emerging now. None of the best-fit service sectors are as strongly concentrated as many of the best-fit manufacturing sectors. This implies that having the right mix of labor force to develop such manufacturing industries might reflect current industrial concentrations in Cleveland rather than indicate future development potential. An already strong presence of many best-fit manufacturing sectors can in fact place a limit on further growth because of the limited availability of workers with the right knowledge and skills. On the other hand, although the presence of best-fit service sectors is not as strong as best-fit manufacturing sectors, relatively high correlations between industry needs and local labor pools suggest that there is more potential for further future growth in finance and insurance-related sectors.

Table 10 and 11 illustrate staffing patterns of best-fit manufacturing and service sectors in more detail. For instance, the staffing patterns of the 10 best-fit manufacturing industries in Table 10 are highly skewed. Some 30 to 50 percent of workers are skilled laborers and machine operators. However, this occupation cluster accounts for only 8.77 percent of Cleveland's labor pool. Even if the location quotient for the cluster shows that skilled laborers and machine operators are highly concentrated in the Cleveland area, the competition for skilled workers can be significant because of the substantial demands of the above-mentioned manufacturing industries. This point is well illustrated in Cleveland Fair Share LQs. Cleveland Fair Share LQs compares total occupation group employment and hypothetical occupation group employment that is estimated under an assumption that industries in the region follow the national staffing patterns. Therefore, when Fair Share LQ>1, Cleveland has more people in that occupation group than what is expected given the region's industry structure. For instance, Cleveland Fair Share LQ for the skilled laborers and machine operators cluster is 1.02. Although the cluster is highly concentrated in the Cleveland area, the supply and the expected demand are roughly balanced. On the other hand, Cleveland Fair Share LQs for the doctors, biomedical scientists, and technicians and computer scientists and related specialists clusters, which are critical for biotech and IT related industries, are only 0.90 and 0.74 respectively. That is, Cleveland has lower than expected such knowledge-intensive workers given its industry mix, strongly implying that the region's industry structure focuses more on the lower-end side (i.e., less knowledge-intensive) than the national average.

Table 10: Staffing Patterns of Top 10 Best-Fit Manufacturing Industries

Occupation Cluster	SIC 30	SIC 34	SIC 26	SIC 29	SIC 38	SIC 33	SIC 39	SIC 28	SIC 36	SIC 37	Cleveland LQ	Cleveland Fair Share LQ
Financial and legal personnel	1.3	1.7	1.4	4.2	3.8	1.3	1.9	2.4	2.6	2.4	1.11	1.04
Social scientists	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.76	1.10
Artists and performers	0.1	0.1	0.1	0.0	0.5	0.0	1.0	0.1	0.3	0.6	0.72	0.82
Doctors, biomedical scientists, and technicians	0.4	0.1	0.3	2.6	1.0	0.5	0.1	9.3	0.1	0.1	0.89	0.90
Transportation and mining workers	2.8	2.7	5.1	6.8	0.4	4.7	1.3	2.6	1.0	1.9	0.80	1.03
Computer scientists and related specialists	0.5	0.6	0.6	2.7	5.3	0.7	1.0	1.7	5.2	2.0	0.74	0.74
Supervisors and management personnel	9.7	9.8	9.0	11.8	8.8	9.7	9.9	11.4	8.2	7.2	0.94	0.94
Specialized mechanics, repairs, and technicians	4.7	3.9	7.0	7.5	3.4	8.2	2.2	7.5	4.0	7.6	0.87	0.98
Semi skilled laborer and service workers	10.5	5.7	9.1	3.5	4.9	7.7	15.9	5.6	3.9	4.2	0.95	1.02
Clerical workers	7.0	8.5	7.2	8.1	10.6	6.3	12.8	9.5	8.2	5.9	0.98	0.99
Skilled laborer and machine operators	50.9	51.2	46.4	27.4	33.1	45.3	34.5	32.6	44.4	35.5	1.42	1.02
Healthcare specialists	0.1	0.1	0.1	0.4	0.4	0.1	0.1	0.4	0.2	0.3	1.08	0.96
Construction workers	0.2	3.0	0.1	0.8	0.3	0.7	1.9	0.1	0.3	2.0	0.76	0.98
Special educators and teachers	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.88	1.03
Sales, marketing, and advertisement personnel	2.2	3.0	3.1	3.2	5.0	1.7	5.8	3.9	3.7	1.8	1.06	1.03
Food preparation workers	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.84	1.03
Law enforcement and safety workers	0.1	0.2	0.2	0.9	0.3	0.4	0.2	0.9	0.2	0.6	1.10	1.59
Engineers, technicians, and architects	2.8	3.9	2.7	5.4	12.5	4.3	2.3	4.5	9.4	9.7	1.02	0.98
Farming and agricultural workers	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.20	0.37
Earth scientists	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.66	1.21

Source: OES, ONET, and Author's Calculation
Figures represent percentages of occupation groups in each industry.

Table 11: Staffing Patterns of Top 10 Best-Fit Service Industries

Occupation Cluster	SIC 63	SIC 64	SIC 61	SIC 65	SIC 73	SIC 62	SIC 67	SIC 76	SIC 80	SIC 60	Cleveland LQ	Cleveland Fair Share LQ
Financial and legal personnel	11.2	6.3	24.6	4.4	1.5	18.5	16.0	0.9	0.6	15.0	1.11	1.04
Social scientists	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.76	1.10
Artists and performers	0.1	0.0	0.0	0.1	1.1	0.3	0.5	0.1	0.0	0.0	0.72	0.82
Doctors, biomedical scientists, and technicians	0.1	0.0	0.0	0.0	0.1	0.0	0.2	0.0	6.6	0.0	0.89	0.90
Transportation and mining workers	0.0	0.0	0.1	0.4	1.8	0.1	0.6	2.1	0.2	0.0	0.80	1.03
Computer scientists and related specialists	6.7	2.2	3.3	0.4	11.3	5.4	5.6	0.3	0.5	3.4	0.74	0.74
Supervisors and management personnel	9.7	9.4	10.7	17.2	6.6	9.3	16.6	10.3	3.7	11.8	0.94	0.94
Specialized mechanics, repairs, and technicians	0.3	0.1	0.2	13.1	1.7	0.1	1.8	35.3	0.7	0.2	0.87	0.98
Semi skilled laborer and service workers	11.0	15.3	12.9	18.3	22.9	5.7	7.0	6.9	7.0	8.9	0.95	1.02
Clerical workers	38.5	38.1	33.9	24.9	18.6	27.1	27.5	15.8	18.9	50.7	0.98	0.99
Skilled laborer and machine operators	0.1	0.0	0.0	0.2	5.2	0.1	0.2	10.9	0.5	0.0	1.42	1.02
Healthcare specialists	2.2	0.7	0.6	0.8	2.7	0.4	1.0	0.0	51.4	0.4	1.08	0.96
Construction workers	0.0	0.0	0.0	1.8	1.2	0.0	0.1	3.7	0.1	0.0	0.76	0.98
Special educators and teachers	0.0	0.0	0.0	0.3	0.1	0.0	0.3	0.0	1.0	0.0	0.88	1.03
Sales, marketing, and advertisement personnel	9.7	23.5	7.7	10.1	6.9	26.5	8.2	3.2	0.2	4.0	1.06	1.03
Food preparation workers	0.0	0.0	0.0	0.7	0.3	0.0	0.1	0.0	1.9	0.0	0.84	1.03
Law enforcement and safety workers	0.5	0.3	0.3	2.4	7.0	0.6	0.5	0.2	0.5	0.6	1.10	1.59
Engineers, technicians, and architects	0.3	0.1	0.0	0.3	0.9	0.1	0.7	1.2	0.1	0.0	1.02	0.98
Farming and agricultural workers	0.0	0.0	0.0	0.1	0.1	0.0	0.2	0.0	0.3	0.0	0.20	0.37
Earth scientists	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.66	1.21

Source: OES, ONET, and Author's Calculation
Figures represent percentages of occupation groups in each industry.

Identifying Key Occupations

Occupation-based analysis can help policymakers determine the key occupations for certain industries. Key occupations are defined as those that are critical to the development and expansion of an industry because, first, they require a high level of knowledge and skills to perform essential functions (these occupations are therefore not easily replaceable) and second, the industry demands a significant number of workers in those occupations. Therefore, knowledge intensity and the size of occupations determine how critical they are to the development and expansion of a certain industry. To implement this idea, we developed the key occupation index.[6] Occupation clusters with higher values are more important to the development and expansion of a certain target industry.

Table 12 shows the key occupation indexes for the top 10 best-fit manufacturing industries. All top 10 manufacturing industries share almost identical key occupation groups. The skilled laborers and machine operators cluster makes up one of the most important occupation groups in the top 10 manufacturing industry targets. Supervisors and management personnel and engineers, technicians, and architects clusters are also critical to those industries. All three occupation clusters are relatively well-represented in the Cleveland area (see Cleveland LQs). In particular, the skilled laborer and machine operators cluster is highly concentrated in the region (LQ=1.42). Given the strong presence of the manufacturing sector in the Cleveland area, this finding is hardly surprising.

Significant concentrations in several manufacturing industries that demand very similar worker skills can indicate a challenge for Cleveland's future. The strong presence of key occupations for those traditionally strong manufacturing industries in Cleveland may not be enough to satisfy increasing future demand for skilled workers. Since firms will compete for the same talents, unless there is a significant growth in those occupation groups, the region is likely to face a shortfall of workers with necessary skills for those industries during economic upturns. On the other hand, the region is prone to hit hard during economic downturns because of high concentration of manufacturing industries that have quite similar labor use patterns.

Two relatively more knowledge-intensive industries, chemical and allied products (SIC 28) and electronic and other electrical equipment and components (SIC 36), demand high numbers of doctors, medical scientists, and technicians and computer scientists and related

[6] Occupation index is estimated with the following formula, where V_{mi} is the key occupation index of the occupation cluster *m* for industry *i*, C_{mi} is the employment share of the occupation cluster *m* in industry *i*, and K_i is the knowledge intensity of industry *I*: $V_{mi} = C_{mi} \times K_i$

specialists. As presented in the previous section, both occupation clusters are underrepresented in the Cleveland area. This is the case even after taking into account the region's Industry structure. Cleveland Fair Share LQs for the doctors, medical scientists, and technicians and computer scientists and related specialists clusters are 0.90 and 0.74 respectively. In other words, industries in Cleveland hire disproportionately smaller shares of these occupation groups compared to national averages. Given their high knowledge intensities, relatively low Fair Share LQs also imply that the Cleveland economy lacks knowledge-intensive functions considerably.

An in-depth analysis of detailed occupations in the doctors, biomedical scientists, and technicians cluster in the previous section provides some circumstantial evidence for this point. Although there is a relatively strong presence of medical practitioners in the region, research-related professionals such as microbiologists and medical scientists are seriously underrepresented. The analysis also showed that virtually all occupations in the computer scientists and related specialists cluster are underrepresented in the Cleveland area. Therefore, unless significant efforts are made to develop a critical mass of those key occupation groups, the development of the chemical and allied products (SIC 28), electronic and other electrical equipment and components (SIC36), or any other industries that rely heavily on those relatively knowledge-intensive occupations will likely face serious limitations because of the lack of local labor force with right skills.

Table 13 shows key occupation indices for the top 10 best-fit service industries and their share of occupation and concentration in the Cleveland metropolitan area. In the service sector, supervisors and management personnel, clerical workers, and sales, marketing, and advertisement personnel clusters are in high demand among a wide range of industries. In addition, the financial and legal personnel cluster is particularly important in the finance and insurance service-related sectors, and doctors, biomedical scientists, and technicians and healthcare specialists clusters are critical for the health service industry. Cleveland has above average levels of concentration in the financial and legal personnel and sales, marketing, and advertisement personnel groups. The emerging status of many finance and insurance service-related industries and the relatively strong presence of financial and legal personnel in the Cleveland area suggest that there will be more room for future growth in those industries. However, the region needs to pay constant attention to educating and retraining workers in those key occupations to satisfy increasing demand from emerging finance and insurance service-related sectors.

Table 12: Key Occupations for Top 10 Best-Fit Manufacturing Industries

Occupation Cluster	SIC 30	SIC 34	SIC 26	SIC 29	SIC 38	SIC 33	SIC 39	SIC 28	SIC 36	SIC 37	Cleveland LQ	Cleveland Fair Share LQ
Financial and legal personnel	58.6	75.1	60.3	188.2	169.0	59.5	86.3	108.2	114.4	106.4	1.11	1.04
Social scientists	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.76	1.10
Artists and performers	2.3	2.3	1.7	0.0	12.7	0.8	29.0	1.7	8.2	16.6	0.72	0.82
Doctors, biomedical scientists, and technicians	27.4	6.3	26.6	199.4	74.3	38.3	7.0	726.5	9.4	7.8	0.89	0.90
Transportation and mining workers	63.8	60.4	117.0	155.7	9.8	107.2	29.4	59.1	21.9	42.2	0.80	1.03
Computer scientists and related specialists	34.7	38.8	42.8	185.0	361.1	44.2	70.0	115.6	352.2	132.6	0.74	0.74
Supervisors and management personnel	577.2	584.3	533.7	701.5	524.8	577.2	589.6	675.9	489.1	430.8	0.94	0.94
Specialized mechanics, repairs, and technicians	116.1	96.2	173.8	187.0	85.1	202.4	54.1	185.3	99.9	188.0	0.87	0.98
Semi skilled laborer and service workers	122.0	66.2	105.3	40.4	57.2	89.4	184.1	65.0	45.0	49.0	0.95	1.02
Clerical workers	204.4	246.7	209.1	237.1	308.4	183.7	372.3	278.6	239.4	173.2	0.98	0.99
Skilled laborer and machine operators	947.5	952.9	863.4	509.5	616.2	843.0	642.3	606.7	826.6	660.7	1.42	1.02
Healthcare specialists	6.5	4.5	9.1	28.6	24.7	5.8	3.9	27.3	13.6	18.8	1.08	0.96
Construction workers	3.6	44.6	1.4	12.5	4.4	10.1	29.1	1.8	3.9	30.3	0.76	0.98
Special educators and teachers	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.2	0.0	0.0	0.88	1.03
Sales, marketing, and advertisement personnel	120.0	161.8	169.4	172.1	271.5	94.5	315.5	213.9	202.0	96.7	1.06	1.03
Food preparation workers	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0	0.0	0.84	1.03
Law enforcement and safety workers	4.5	7.9	7.9	35.0	12.0	13.2	6.4	33.1	6.0	21.8	1.10	1.59
Engineers, technicians, and architects	273.8	386.9	266.8	530.7	1237.0	429.5	226.2	450.4	928.5	958.3	1.02	0.98
Farming and agricultural workers	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.8	0.5	0.0	0.20	0.37
Earth scientists	0.0	0.6	0.6	13.3	0.0	0.0	0.0	0.6	0.0	0.0	0.66	1.21

Source: OES, ONET, and Author's Calculation
Figures represent relative importance of occupation groups to each industry.

Table 13: Key Occupations for Top 10 Best-Fit Service Industries

Occupation Cluster	SIC 63	SIC 64	SIC 61	SIC 65	SIC 73	SIC 62	SIC 67	SIC 76	SIC 80	SIC 60	Cleveland LQ	Cleveland Fair Share LQ
Financial and legal personnel	502.0	282.5	1101.0	195.8	66.2	826.5	716.5	39.3	27.3	670.1	1.11	1.04
Social scientists	0.0	0.0	0.0	0.0	7.1	0.0	8.3	0.0	0.0	0.0	0.76	1.10
Artists and performers	2.3	0.6	1.1	1.4	29.9	8.7	14.9	2.5	0.0	0.6	0.72	0.82
Doctors, biomedical scientists, and technicians	10.9	0.8	0.0	0.0	4.7	0.0	13.3	0.0	513.0	0.0	0.89	0.90
Transportation and mining workers	0.7	0.2	2.1	9.6	42.0	1.6	13.0	47.0	4.6	0.5	0.80	1.03
Computer scientists and related specialists	456.3	148.2	221.0	23.8	768.4	363.8	381.5	21.1	36.0	229.2	0.74	0.74
Supervisors and management personnel	578.9	556.9	635.5	1024.0	392.7	555.7	985.3	613.4	217.2	702.1	0.94	0.94
Specialized mechanics, repairs, and technicians	6.2	3.0	4.0	323.6	43.2	2.7	44.1	874.2	17.4	4.5	0.87	0.98
Semi skilled laborer and service workers	127.8	177.2	149.1	211.8	265.8	65.7	81.4	79.9	81.0	102.8	0.95	1.02
Clerical workers	1124.0	1113.0	989.3	726.8	543.4	790.7	802.7	461.1	551.9	1481.0	0.98	0.99
Skilled laborer and machine operators	2.4	0.6	0.7	4.1	96.3	0.9	3.9	202.0	8.7	0.0	1.42	1.02
Healthcare specialists	142.1	48.0	38.3	49.3	175.2	22.7	67.5	1.3	3339.0	25.3	1.08	0.96
Construction workers	0.3	0.2	0.2	27.2	18.5	0.0		55.1	0.8	0.0	0.76	0.98
Special educators and teachers	1.2	0.0	0.0	14.5	7.0	0.6	19.2	0.0	60.4	0.0	0.88	1.03
Sales, marketing, and advertisement personnel	525.1	1274.0	415.4	546.3	375.2	1441.0	444.7	172.1	11.9	214.5	1.06	1.03
Food preparation workers	0.0	0.0	0.0	10.1	4.7	0.0	1.6	0.3	27.9	0.0	0.84	1.03
Law enforcement and safety workers	19.2	10.5	12.8	89.5	264.3	23.7	16.9	8.3	18.4	20.7	1.10	1.59
Engineers, technicians, and architects	24.8	12.9	4.0	31.7	89.3	6.0	69.4	123.0	6.0	4.0	1.02	0.98
Farming and agricultural workers	0.0	0.0	0.0	2.3	4.7	0.5	10.3	0.0	11.7	0.0	0.20	0.37
Earth scientists	0.6	0.0	0.0	1.9	3.2	0.0	1.9	0.0	0.0	0.0	0.66	1.21

Source: OES, ONET, and Author's Calculation
Figures represent relative importance of occupation groups to each industry.

APPENDICES

A and B

APPENDIX A. DERIVATION OF BENCHMARK OCCUPATION CLUSTERS

The procedure for deriving benchmark occupation clusters proceeds as follows.[7] First, we match occupation categories in the OES and ONET databases. Occupations in these databases are roughly comparable, but when ONET has more detailed occupation categories than OES, they are aggregated so that all ONET occupations match the OES occupations. This step is necessary because occupation clusters derived from ONET are used to examine geographic distribution patterns of occupations based on the OES data. On the other hand, a total of 48 OES occupations do not have comparable ONET occupations. Those unmatched OES occupations are dropped at the statistical clustering stage. They are, however, added back later to potentially related occupation clusters based on our judgment.

The adjusted ONET database prepared for the statistical clustering step has 33 knowledge variables for 661 occupations. Each cell represents the importance of those 33 types of knowledge to the performance of tasks in a certain occupation. We then apply common data reduction techniques to knowledge variables and occupation categories in the ONET database. A principal component factor analysis is conducted to reduce the number of knowledge variables and thereby obtain more interpretable occupation cluster definitions. Derived principal components of knowledge variables are rotated using a varimax solution for better interpretation of the results. Knowledge factors with loadings of at least 0.5 are used for the interpretation of each factor. A total of 13 knowledge factors are extracted, depending upon eigenvalues and interpretability. Table A.1 shows derived knowledge factors from the ONET knowledge database.

We then conduct a statistical cluster analysis to group occupations based on 13 derived knowledge factors. Ward's (1963) agglomerative hierarchical cluster algorithm is applied to 661 occupations with 13 knowledge factors.[8] This step yields a set of benchmark occupation clusters that draw on the same set of knowledge requirements. The most difficult task in a statistical cluster analysis is determining how many clusters need to be extracted. A large number of clusters are more representative but may lack simplicity. On the other hand, if the number of derived clusters is too small, comprehensiveness may be sacrificed. One of the most common criteria is an R-square that represents the proportion of variance accounted for by

[7] This procedure relies heavily on Feser (2003).
[8] A cluster analysis is conducted based on 13 knowledge factors instead of 33 knowledge variables because a large number of dimensions for clustering (e.g., 33 knowledge variables) can dilute the unique characteristics of occupations groups. In fact, the comparison of results based on 13 knowledge factors and 33 knowledge variables shows that the former produce more intuitive and interpretable results.

clusters. The examination of R-squares at each level of cluster hierarchy reveals that the statistical clustering procedure may stop at around 17-21 clusters. After careful review of the five sets of results, a total of 20 occupation clusters are retained based on their interpretability. Table 1 lists the final set of occupation clusters and their knowledge intensities.

Table A1: Knowledge Factors

Knowledge Factor	Knowledge Variable
Factor 1	Engineering and technology, Design, Building and construction, Mechanical, Mathematics, Physics
Factor 2	Sociology and anthropology, Education and training, History and archeology
Factor 3	Chemistry, Biology, Medicine and dentistry
Factor 4	Customer and personal service, Psychology, Therapy and counseling, Philosophy and theology
Factor 5	Administration and management, Economics and accounting, Personnel and human resources
Factor 6	Clerical
Factor 7	Sales and marketing, Communications and media
Factor 8	English language, Foreign language
Factor 9	Public safety and security, Law and government
Factor 10	Geography, Transportation
Factor 11	Computer and electronics, Telecommunication
Factor 12	Production and processing, Food production
Factor 13	Fine arts

APPENDIX B. OCCUPATION CLUSTERS AND KNOWLEDGE REQUIREMENTS

Table B1: Occupation Clusters and Knowledge Requirements

Occupation Cluster	Administration_and_Management	Clerical	Economics_and_Accounting	Sales_and_Marketing	Customer_and_Personal_Service	Personnel_and_Human_Resources	Production_and_Processing	Food_Production	Computers_and_Electronics	Engineering_and_Technology	Design	Building_and_Construction	Mechanical	Mathematics	Physics	Chemistry	Biology	Psychology	Sociology_and_Anthropology	Geography	Medicine_and_Dentistry	Therapy_and_Counseling	Education_and_Training	English_Language	Foreign_Language	Fine_Arts	History_and_Archeology	Philosophy_and_Theology	Public_Safety_and_Security	Law_and_Government	Telecommunications	Communications_and_Media	Transportation	Knowledge Intensity
Financial and legal personnel	9.5	7.7	16.1	2.1	3.4	4.0	1.2	0.2	7.3	0.6	0.4	0.4	0.6	16.3	0.2	0.1	0.2	2.9	2.0	1.7	0.2	1.3	4.0	11.6	0.3	0.2	1.1	0.9	2.0	12.3	2.1	4.1	0.9	44.7
Social scientists	9.1	7.9	12.0	0.7	1.7	3.7	0.2	0.0	6.7	0.3	0.2	0.1	0.1	15.9	0.4	0.6	1.6	18.1	24.7	8.0	0.7	6.8	23.9	20.5	1.2	0.5	22.8	5.9	0.3	9.5	1.5	9.7	0.4	118.6
Artists and performers	4.1	2.6	1.3	3.4	2.7	1.7	2.0	0.2	4.5	2.0	5.6	1.5	1.8	5.5	1.5	0.9	0.6	2.4	2.0	1.2	0.4	0.6	5.1	9.2	0.4	13.2	0.8	0.5	0.7	0.8	3.1	9.4	0.8	28.2
Doctors, biomedical scientists, and technicians	7.5	5.1	1.2	0.7	3.5	3.0	1.1	1.0	5.9	3.9	1.0	0.5	2.0	15.8	5.9	17.7	22.4	6.7	1.6	0.9	16.6	7.4	9.7	12.8	0.6	0.0	0.4	0.6	2.9	3.1	1.5	4.2	0.8	78.2
Transportation and mining workers	2.5	2.5	0.7	0.4	2.2	1.2	1.8	0.1	2.3	5.6	0.9	2.8	12.3	5.4	5.1	1.9	1.2	1.1	0.6	5.2	0.6	0.3	2.3	4.3	0.3	0.1	0.2	0.2	6.4	2.6	2.9	1.9	9.2	22.8
Computer scientists and related specialists	9.0	7.5	3.6	2.4	6.1	1.8	1.1	0.1	29.5	8.1	6.9	0.2	2.9	18.6	1.8	0.4	0.3	2.7	1.1	0.7	0.3	0.8	13.0	11.9	0.2	0.3	0.5	0.6	4.1	1.6	7.1	5.6	0.5	68.0
Supervisors and management personnel	19.8	6.3	10.0	5.8	8.8	14.3	5.2	1.2	4.2	2.4	1.8	2.2	3.5	12.0	1.5	1.9	1.1	7.1	2.5	1.8	0.5	1.9	12.0	10.2	0.6	0.5	0.5	1.0	4.0	5.5	2.0	4.6	2.7	59.5
Specialized mechanics, repairs, and technicians	1.0	2.0	0.7	0.8	2.0	0.3	2.3	0.0	6.9	7.9	4.4	5.2	16.7	6.6	4.3	2.2	0.3	0.6	0.4	1.1	0.4	0.3	1.2	3.8	0.3	0.5	0.4	0.2	3.3	1.3	3.4	1.8	1.8	24.8
Semi skilled laborer and service workers	2.1	2.7	1.1	2.2	5.9	1.0	2.0	0.4	1.8	1.8	1.2	1.0	4.0	5.4	1.3	2.3	2.1	1.9	0.8	1.1	1.2	1.0	1.9	4.3	0.3	0.9	0.1	0.2	2.1	1.4	1.2	1.7	1.4	11.6
Clerical workers	4.1	15.9	5.1	2.7	9.1	2.1	1.3	0.2	7.9	0.4	0.3	0.2	0.8	9.2	0.4	0.5	0.2	1.9	1.1	2.6	0.9	0.6	2.3	9.0	0.9	0.2	0.5	0.4	2.0	3.4	3.1	3.8	2.9	29.2
Skilled laborer and machine operators	0.7	2.5	0.2	0.2	0.4	0.4	9.5	0.2	3.8	5.8	3.9	2.0	11.9	9.0	4.2	3.1	0.2	0.4	0.3	0.3	0.5	0.2	0.8	3.5	0.2	0.3	0.1	0.2	1.9	0.6	0.8	1.1	0.7	18.6
Healthcare specialists	6.0	7.7	2.2	2.2	16.1	4.2	1.8	0.6	6.4	2.4	1.1	0.7	3.0	8.7	3.2	5.4	7.4	15.1	5.1	1.2	12.1	14.9	11.2	11.1	1.3	0.5	0.8	3.4	5.0	4.3	2.2	4.1	2.0	64.9
Construction workers	0.8	0.8	0.2	0.2	1.2	0.3	2.2	0.0	0.9	4.7	4.8	12.9	7.9	7.4	2.8	1.7	0.2	0.3	0.2	1.1	0.2	0.2	0.7	2.4	0.1	0.8	0.2	0.1	2.3	0.8	0.7	0.7	1.1	15.0
Special educators and teachers	7.4	6.5	1.8	0.7	6.8	2.2	0.2	0.2	4.9	0.8	0.6	0.2	0.9	10.2	1.7	2.0	3.5	8.6	4.3	2.5	4.3	9.4	23.5	17.3	4.7	1.9	2.6	2.2	2.5	2.3	1.6	5.6	0.7	58.1
Sales, marketing, and advertisement personnel	8.6	6.7	7.8	19.9	11.5	3.4	4.5	0.6	7.8	3.0	4.6	1.2	2.2	11.9	1.0	0.7	0.4	5.2	2.6	3.7	0.3	0.9	6.3	11.0	1.0	3.1	0.8	0.9	1.9	4.2	3.0	9.4	2.9	54.3
Food preparation workers	3.5	2.8	1.4	1.2	5.1	1.5	4.3	6.3	0.9	1.3	0.6	0.8	3.5	6.5	1.6	3.3	5.9	0.9	0.8	1.4	0.9	0.3	2.2	3.9	0.3	0.5	0.6	0.7	3.9	3.3	0.9	1.4	0.8	14.6
Law enforcement and safety workers	4.1	4.2	1.2	0.6	4.0	2.5	2.1	0.2	5.1	4.1	2.2	1.8	3.8	8.8	4.1	5.5	1.9	5.2	2.9	3.3	3.0	2.8	4.2	8.6	0.9	0.3	0.6	1.0	16.5	10.0	3.8	3.9	5.4	37.6
Engineers, technicians, and architects	11.6	4.8	4.8	2.3	3.8	3.3	7.4	0.1	12.2	21.9	19.4	8.2	7.9	23.0	14.1	6.2	1.8	2.7	1.2	3.1	0.3	0.7	7.9	12.6	0.3	0.8	1.2	0.6	6.1	4.4	3.2	4.7	1.9	99.2
Farming and agricultural workers	6.8	3.6	4.1	3.7	3.0	2.7	8.6	14.7	3.1	4.6	2.7	2.6	5.6	10.1	2.9	6.8	9.9	2.3	1.7	2.0	2.5	1.8	5.6	7.9	0.7	0.4	0.6	1.0	2.8	3.3	1.7	4.6	3.1	46.9
Earth scientists	4.8	2.9	1.7	0.5	0.7	1.2	1.1	0.2	7.9	7.9	8.4	0.7	3.4	22.2	17.3	5.1	4.0	1.4	3.9	19.3	0.4	0.3	3.9	8.2	0.7	0.6	4.5	0.4	1.7	2.2	2.8	6.0	1.7	63.3

Source: ONET Knowledge Database and Author's Calculation (Grey scale indicates critical knowledge variables for each occupation cluster)

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