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## Abstract

This paper examines differences in the skill content of work throughout the United States, ranging from densely populated city centers to isolated and sparsely populated rural areas. To do so, we classify detailed geographic areas into categories along the entire urban-rural hierarchy. An occupation-based cluster analysis is then used to measure the types of skills available in the regional workforce, which allows for a broader measure of human capital than is captured by conventional measures. We find that the occupation clusters most prevalent in urban areas—scientists, engineers, and executives—are characterized by high levels of social and resource-management skills, as well as the ability to generate ideas and solve complex problems. By contrast, the occupation clusters that are most prevalent in rural areas—machinists, makers, and laborers—are among the lowest in terms of required skills. These differences in the skill content of work shed light on the pattern of earnings observed across the urban-rural hierarchy.

Key words: human capital, skills, occupations, urban-rural, earnings

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# I. INTRODUCTION

Human capital refers to the knowledge and skills people use to produce goods and services. Increasingly, it has been identified as a key ingredient to the success and vitality of U.S. regions, particularly as the economy has shifted away from manufacturing and goods distribution toward a greater emphasis on the production of high knowledge and idea-intensive services. Indeed, regions with higher levels of human capital tend to be more innovative, have greater amounts of economic activity, and faster economic growth; and workers in these places are more productive and earn higher wages (Abel and Gabe, 2011; Carlino, Chaterjee, and Hunt, 2007; Moretti, 2004; Glaeser, Scheinkman, and Shleifer, 1995; and Rauch, 1993).

While the importance of human capital to regional economies has gained wide recognition among urban economists and regional scientists, a limitation of much of the existing research is that human capital is measured simply as the share of a region's workforce with a college degree. While this conventional measure of human capital has been linked to a number of measures of regional vitality, a growing body of research demonstrates that formal education provides an incomplete picture of the knowledge and skills possessed by workers (Florida, Mellander, Stolarick, and Ross, 2011; Abel and Gabe, 2011; Bacolod, Blum, and Strange, 2009; Florida, Mellander, and Stolarick, 2008; Ingram and Neumann, 2006). At best, this conventional measure captures differences in the "vertical differentiation" of human capital (i.e., the amount of skill people possess), but says nothing about the "horizontal differentiation" of human capital (i.e., the specific types of skill people possess) (Bacolod, Blum and Strange, 2009).

Given this significant limitation, recent research has focused on developing broader measures of human capital to provide a more complete picture of the knowledge and skills available in regions. However, with a focus on understanding the sources of urban agglomeration economies, this research has tended to characterize differences in knowledge and skills among metropolitan areas (Bacolod, Blum, and Strange, 2010; Scott, 2009). Separately, other researchers have studied the types of work occurring in rural areas (McGranahan and Wojan, 2007; Wojan, 2000). As a result, we currently lack a unified analysis documenting the spatial distribution of skills across the entire urban-rural hierarchy.

We attempt to fill this gap by examining differences in the skill content of work throughout the United States, ranging from densely populated city centers to isolated and sparsely populated rural areas. In doing so, we tackle two significant measurement challenges. First, while there is no universally accepted definition of urban and rural areas, we can use information on population density and remoteness to classify detailed geographic areas, PUMA regions, into categories that are representative of points along the urban-rural continuum. Second, unlike the attainment of a college degree, the types of skills embodied in people are not directly observable. Therefore, we utilize an approach that allows us to infer the types of skills available in the regional workforce using data on the skill requirements of occupations. The urban-rural continuum combined with information on the occupations present in U.S. regions allows us to characterize differences in the skill content of work across the urban-rural hierarchy. We demonstrate that differences in the skill content of work help explain the pattern of earnings observed across the urban-rural hierarchy.

## II. U.S. URBAN-RURAL HIERARCHY

The first step of our analysis requires characterizing the urban-rural hierarchy across the United States. To do this, we take the same general approach employed in other urban-rural classification systems such as the USDA's Urban Influence and Beale Codes, which assign all U.S. counties to a category along a continuum. In our analysis, use of the existing codes is not possible because the occupation-level data required for the workforce skills analysis is available at the PUMA (Public Use Microdata Area) level. PUMAs are defined by the U.S. Census Bureau to be contiguous geographic areas (within the same state) with a population of approximately 100,000 people. They are smaller than counties in urban and other well-settled areas, while they may consist of multiple counties in areas with very low populations. Thus, using PUMAs also reveals a more finely grained spatial definition in populated areas than would be available using counties. Because we are interested in the skills that are used "on the job" and recognizing that people often commute across regional boundaries, we use "place of work" PUMAs in the analysis.

Two factors are used to characterize PUMAs along the urban-rural continuum: proximity to a central city and population density. "Central city" is a specific designation that the Census Bureau assigns to the largest place in a metropolitan area according to official Office of Management and Budget standards. Any PUMA that is at least 90 percent contained within a central city is designated as completely urban (coded as a "1" along the urban-rural continuum). For the remaining PUMAs, two values are calculated. The first is the distance between the centroid of that PUMA and the centroid of the closest central city. The second is the PUMA's population density (i.e., total population divided by area in square kilometers). Once these values are calculated for all PUMAs, the quartiles for each are determined. Then, based on the two factors (distance and density) for each PUMA not characterized as a central city, the urban-rural category is assigned according to Figure 1.

As can been seen in Figure 1, those PUMAs that are the closest to a central city (within 13.8km) and have the highest density (over 290 people/km$^2$) are assigned a value of “2” (recall that a category value of “1” is assigned to PUMAs in a central city) while those that are the furthest from a central city (over 59km) and have the lowest density (under 22.2 people/km$^2$) are assigned a value of “10.” Very low density PUMAs with close proximity to a central city receive a value of “5” along with very high density PUMAs that are in the quartile of those furthest from a central city. Table 1 shows the complete categorization, number of PUMAs, and share of total PUMAs in each category for the entire urban-rural continuum.

We define as “Rural Outposts” those PUMAs with the greatest distances to a central city (i.e., most remote) and the lowest population densities (i.e., sparsest populations). In our analysis, we arrive at 204 “place-of-work” PUMAs (about 17 percent of the areas considered) that would be considered rural outposts. They are the second largest share of PUMAs. The greatest share (18.2 percent) is “Urban” PUMAs (coded as a “3”) which are those with the highest population density and in the second closest quartile or the closest quartile with the second highest density. Figure 2 shows the assignments across the entire urban-rural continuum for the entire United States, noting that many of the most urban areas have small geographic areas relative to the entire country and are not readily visible on the map.

## III. SKILLS-BASED OCCUPATION CLUSTERS

In recent years, there has been growing interest in occupation-based approaches to regional economic analysis (see, e.g., Currid and Stolarick, 2010; Gabe, 2009; Scott, 2009; Florida, Mellander, and Stolarick, 2008; Markusen, 2004; Feser, 2003). Here, the emphasis has shifted away from industries and what people make in their jobs (e.g., textiles) to occupations and the types of knowledge and skills (e.g., creativity) required to thrive in a person's chosen profession. An industry-based approach counts all textile workers the same, whether their job entails loading a machine, maintaining the plant's IT network, or charting the firm's financial future. By contrast, an occupation-based approach views these workers (e.g., production, information technology, and financial executives) as quite distinct. As a result, focusing on occupations allows us to develop new measures of workforce skills.

To do so, we use occupation-level information from the U.S. Department of Labor's Occupational Information Network (O*NET).[1] The O*NET system contains data collected via interviews of incumbent workers and input from professional occupational analysts about job-related skill requirements pertinent to the 35 areas shown in Table 2. A wide range of workforce skills are included, which are grouped into the broad categories of content, process, social, complex problem solving, technical, system, and resource management skills.[2]

The O*NET system provides information on two dimensions of these workforce skills: the importance of each skill to the performance of a job and level of skill required

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[1] O*NET is discussed in detail by Peterson et al (2001) and Feser (2003).

[2] Content and process skills are grouped under the heading of basic skills in the O*NET skills hierarchy, while the other five broad types of skills are considered to be cross-functional skills.

to perform a job. The scale used in the O*NET system to rate the importance of workforce skills ranges from 1 to 5, where a score of 1 is "not important" and a score of 5 is "extremely important." If a skill is viewed as at least "somewhat important" (a score of 2 or higher), the respondent is asked to rate the level of skill required for the job. This scale ranges from 1 to 7, and different anchors are provided for each knowledge area. For example, the technical skill "Operation and Control" has as anchors an importance rating of 2 for "adjust the settings on a copy machine to make reduced size photocopies," a rating of 4 for "adjust the speed of assembly line equipment based on the type of product being assembled," and a rating of 6 to indicate a skill level equivalent to "control aircraft approach and landing at a large airport during a busy period."

To form our clusters, we matched occupational categories between the O*NET system and the U.S. Census American Community Survey (ACS). We started with information on the skill requirements (i.e., importance and level) for 854 detailed occupations available in the O*NET system. When necessary, we combined more than one of these detailed "O*NET occupations" into a single aggregate occupational category available in the ACS data using existing hierarchical relationships. This matching process resulted in 444 distinct occupations for which a match existed between O*NET and the ACS data set.[3] After making these sorts of adjustments, we calculated a skills index score that is the product of the importance and level of skill required for a job.[4]

Similar to the analysis conducted by Feser (2003) and Gabe and Abel (2011), we used Ward's (1963) hierarchical clustering method to assign occupations into groups with

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[3] Because the O*NET occupations are provided at a more detailed point in the Standard Occupational Classification (SOC) hierarchy, information from virtually all of the 854 detailed O*NET occupations is actually used in our analysis.

[4] Feser (2003) and Abel and Gabe (2011) used a similar approach, which in our application places a greater emphasis on high skill requirements that are relevant to a given occupation.

similar skill requirements to reduce the set of 444 occupations to a more manageable number.[5] This method starts by identifying the two most similar occupations and joins them into a cluster, and then—in subsequent iterations—combines other occupations with similar skill requirements into new clusters or adds occupations to existing clusters. Choosing the exact number of clusters to maintain is somewhat subjective, depending on the intended use of the information. In our analysis, we found that 11 clusters provided a manageable number of occupational categories for the subsequent analysis, as well as occupational groupings with reasonably similar skill requirements.

Table 3 provides a descriptive title for each of the 11 clusters based on our assessment of the mean index values for the skill in each cluster. The first cluster, which we termed “Engineers” due to the high levels of complex problem solving, system, process and content skills that are required, includes occupations such as chemical engineers, computer programmers, and database administrators (shown in Table 4). The cluster that we labeled as “Executives,” made up of occupations such as chief executives, financial managers and lawyers, has an overall skills profile that falls only slightly below that of Engineers, with particularly high requirements in the dimensions of social, resource management, system, and process skills. As shown in Table 4, the largest cluster in terms of the proportion of the U.S. workforce is “Servers,” which includes occupations such as salesperson, dental assistant, and receptionist. This cluster has relatively modest skill requirements, particularly in the areas of technical skills and resource management skills. Likewise, the cluster of “Laborers,” which includes occupations such as dishwashers, taxi drivers and laundry workers, has very low requirements in almost all of

5 This approach forms clusters by minimizing the sum of the squared differences among occupations in the 35 dimensions of skill. Feser (2003) provides a detailed account of how to construct occupational clusters using the O*NET data.

the dimensions of skill. Importantly, these skill clusters generally cut across the major Standard Occupational Classification (SOC) categories, suggesting that our skills-based clusters provide a different way of looking at occupational groups beyond the categorization scheme typically used for reporting data.

In addition, the earnings of workers in these skills-based occupation clusters vary in a meaningful way. Figure 3 is a scatter plot showing the relationship between average U.S. earnings in the cluster, using data from the 2005-09 5-year sample of the U.S. Census Bureau's American Community Survey, and its average skills index value (shown in Table 3). The scatter plot reveals a strong association between skills and earnings—a finding uncovered in numerous academic studies.[6] For example, the average annual earnings of individuals in the Executives skills-based cluster exceed the wages and salaries of those in the Laborers cluster by about $50,000. The top three clusters in terms of the average skills index shown in Table 3 have average annual earnings of over $65,000.

## IV. SKILLS ACROSS THE URBAN-RURAL HIERARCHY

The final step of our analysis involves using the clusters we developed to characterize the skills profile of areas across the U.S. urban-rural hierarchy. The figures shown in Table 5 are location quotients that are measured as the cluster's average percentage of workforce employment in the PUMAs in each category of the urban-rural hierarchy divided by the share of the total U.S. workforce in the same skills-based cluster. Values greater than 1.0 indicate that the skills-based cluster is over-represented in

[6] Two recent studies on this topic are by Florida, Mellander, Stolarick, and Ross (2011) and Abel and Gabe (2011).

that particular category, while values less than 1.0 suggest that the cluster is under-represented in that category compared to the United States as a whole.

These figures reveal some interesting patterns in the skills that are used across the urban-rural hierarchy. Perhaps most striking, the most urbanized areas of the United States—City Centers—tend to specialize in the skills-based clusters of Scientists, Technicians, Engineers, and Executives. These are among the most highly skilled clusters (ranked third, fifth, first, and second, respectively, out of the 11 clusters), and include occupations where the ability to think, generate ideas, and solve problems is important. As a result, it is not surprising that these clusters score particularly high in the dimensions of complex problem solving, process, and social skills. Moreover, the types of activities undertaken by people working in these clusters are those that are most likely to benefit from advantages of physical proximity provided by dense urban environments, such as enhanced information exchange and idea generation facilitated by face-to-face contact (Storper and Venebles, 2004). The fact that the location quotients for these skills-based clusters drop sharply between the Central City (Code 1) and City Ring (Code 2), and then tend to gradually decline through the remaining portion of the urban-rural hierarchy underscores the importance of a dense urban environment for the people working in these clusters, and is consistent with evidence of the rapid attenuation of knowledge spillovers (Rosenthal and Strange, 2008).

By contrast, the most rural areas—encompassing the Semi-Rural, Rural Fringe, Rural, and Rural Outpost categories—tend to specialize in the skills-based clusters of Machinists and Makers, which include “hands-on” occupations in the construction trades, production and assembly, and maintenance and repair, and to a lesser extent in the skills-based cluster of Laborers. These clusters are characterized by relatively low skills requirements (ranked seventh, ninth, and last, respectively, out of the 11 clusters), with particularly low index values in the dimensions of social and content skills. It is particularly interesting to note the absence of social skills—e.g., coordination, persuasion, and negotiation—in the most rural areas, which are places where extensive interaction and face-to-face contact are hindered by the obstacles of isolation and distance. Perhaps not surprisingly, we also see that rural areas tend to be under-represented in the clusters with the highest skills requirements, such as Engineers, Executives, Scientists, and Analysts. This means that the percentages of the rural workforce in these clusters are well below the corresponding national averages and even further below their urban counterparts.

Our analysis also shows that some types of workforce skills do not tend to cluster geographically. In particular, the skills-based clusters of Managers, Servers, and Assistants have location quotients that do not diverge much from 1.0 throughout the entire urban-rural hierarchy. This means that the types of skills captured by these clusters are largely ubiquitous throughout the United States. This is because people working in the occupations that comprise these clusters—sales managers, funeral directors, receptionists, home care aides, and teaching assistants—tend to interact with the general public, and thus are widely distributed across the United States (Gabe and Abel, 2011).

Our results show the skills-based clusters that are over-represented in urban areas (e.g., Scientists, Technicians, Engineers and Executives) and more rural places (e.g., Machinists, Makers and Laborers) differ markedly in terms of the overall skills requirements and—most strikingly—the importance of skills that benefit from close physical proximity (e.g., social and complex problem solving skills). The importance of dense urban environments to the sharing of ideas and knowledge among individuals utilizing high complex problem solving and social skills is further demonstrated in Figure 4. It shows the average earnings, once again using figures from the 2005-09 5-year American Community Survey of the U.S. Census Bureau, for each of the skills-based clusters across the urban-rural hierarchy.

Now we see that the returns to skill differ considerably between urban and rural areas. The skills-based cluster of Executives, which requires very high social and complex problem solving skills, has the highest average annual earnings in the most urban areas (e.g., City Centers and City Rings)—with wages and salaries about $10,000 higher than those earned in the other high-skilled clusters of Engineers and Scientists. This substantial earnings premium for Executives in urban areas reflects the high return in cities, enhanced by close physical proximity, to problem solving skills and social skills such as coordination, negotiation, and persuasion (Florida, Mellander, Stolarick, and Ross, 2011). No such earnings premium exists for Executives in rural areas. The average annual earnings of Executives are similar (and in some cases lower) than the wages and salaries earned by Engineers and Scientists in the Semi-Rural, Rural Fringe, Rural, and Rural Outpost regions. In areas without dense work environments, Executives are no more productive than the other high-skilled occupational clusters.

A least-squares trend line fit using earnings data for the Executives skills-based cluster shows a $3,303 reduction in annual average wages for each step along the urban-rural continuum. The clusters of Engineers ($2,051 reduction), Analysts ($2,022 reduction) and Scientists ($1,981 reduction) have the next steepest declines in average annual earnings for each rung along the continuum. These four clusters have the highest requirements in the dimensions of complex problem solving, process, content, and (along with Managers) social skills. The skills-based clusters with the lowest reductions in average annual wages and salaries for each category along the urban-rural continuum—Makers ($485 reduction), Laborers ($528 reduction) and Machinists ($596 reduction)—are also those that are the most over-represented in rural areas. These clusters, which require very little in the way of social, content, and complex problem solving skills, do not exhibit substantially enhanced earnings—a reflection of productivity—associated with population density or proximity to an urban center.

## V. CONCLUSIONS

Important differences in the skill content of work exist across the urban-rural hierarchy in the United States. The most urban areas tend to specialize in the skills-based clusters of Scientists, Technicians, Engineers and Executives. These clusters are characterized by high levels of skill required in the dimensions of complex problem solving, process, content and (with the exception of the cluster of Technicians) social and resource management skills. In particular, the dimensions of social and complex problem solving skills are apt to benefit from the flows of ideas and knowledge that are facilitated by dense urban environments (Florida, Mellander, Stolarick, and Ross, 2011). The clusters that are over-represented in rural areas—namely, Machinists, Makers and Laborers—are among the lowest in terms of required skills, with notably low levels of social, content, and complex problem solving skills.

An extension to our main analysis examined differences in average cluster earnings across the urban-rural hierarchy. Here, we also find evidence supporting the idea that skills, especially those encompassed in Executives, Scientists, and Engineers, are highly valued in urban areas. For example, the cluster of Executives is characterized by substantially higher earnings in urban areas, where social and complex problem solving skills are particularly valuable, than in rural places. On the other hand, the clusters of Machinists, Makers, and Laborers, which tend to be over-represented in rural areas, have a relatively flat earnings trajectory when moving across the urban-rural hierarchy. Individuals in these low-skilled occupational clusters do not benefit much from the enhanced flow of information and ideas facilitated by dense urban areas.

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Table 1. Urban-Rural Continuum Categories

| Category | Number of PUMAs | % of PUMAs | Designation | Description (Distance and Density) |
|---|---|---|---|---|
| 1 | 114 | 9.4% | City Center | >90% in Central City |
| 2 | 126 | 10.4% | City Ring | <13.8 KM and >290 Pop/KM$^2$ |
| 3 | 221 | 18.2% | Urban | Close and Dense |
| 4 | 69 | 5.7% | Urban Fringe | Close or Dense |
| 5 | 95 | 7.8% | Semi-Urban | Close, Dense, or Moderate |
| 6 | 125 | 10.3% | Suburban | Accessible and Moderate |
| 7 | 24 | 2.0% | Semi-Rural | Isolated or Sparse |
| 8 | 119 | 9.8% | Rural Fringe | Far and Low-Density |
| 9 | 115 | 9.5% | Rural | Isolated and Sparse |
| 10 | 204 | 16.8% | Rural Outpost | >59KM and <22.2 Pop/KM$^2$ |

Table 2. Workforce Skills

| Basic Skills | Cross-Functional Skills | | |
|---|---|---|---|
| *Content* | *Social Skills* | *Technical Skills* | *System Skills* |
| Reading Comprehension | Social Perceptiveness | Operations Analysis | Judgment and Decision Making |
| Active Listening | Coordination | Technology Design | Systems Analysis |
| Writing | Persuasion | Equipment Selection | Systems Evaluation |
| Speaking | Negotiation | Installation | |
| Mathematics | Instructing | Programming | *Resource Management Skills* |
| Science | Service Orientation | Operation Monitoring | Time Management |
| | | Operation and Control | Mgmt. of Financial Resources |
| *Process* | *Complex Problem Solving Skills* | Equipment Maintenance | Mgmt. of Material Resources |
| Critical Thinking | Complex Problem Solving | Troubleshooting | Mgmt. of Personnel Resources |
| Active Learning | | Repairing | |
| Learning Strategies | | Quality Control Analysis | |
| Monitoring | | | |

Source: U.S. Department of Labor, Occupational Information Network (O*NET).

Table 3. Skills-based Occupation Clusters

| Cluster | Average Skills Index | Content | Process | Social Skills | Complex Problem Solving Skills | Technical Skills | System Skills | Resource Management Skills |
|---|---|---|---|---|---|---|---|---|
| Engineers | 0.70 | 0.85 | 0.85 | 0.50 | 1.00 | 0.65 | 0.95 | 0.53 |
| Executives | 0.69 | 0.76 | 1.00 | 1.00 | 0.92 | 0.16 | 1.00 | 1.00 |
| Scientists | 0.59 | 0.91 | 0.87 | 0.68 | 0.89 | 0.21 | 0.85 | 0.48 |
| Managers | 0.48 | 0.48 | 0.58 | 0.66 | 0.53 | 0.22 | 0.55 | 0.74 |
| Technicians | 0.43 | 0.52 | 0.54 | 0.35 | 0.56 | 0.41 | 0.49 | 0.26 |
| Analysts | 0.42 | 0.66 | 0.65 | 0.63 | 0.60 | 0.06 | 0.59 | 0.36 |
| Machinists | 0.40 | 0.20 | 0.33 | 0.17 | 0.40 | 0.78 | 0.33 | 0.17 |
| Servers | 0.25 | 0.41 | 0.39 | 0.44 | 0.31 | 0.06 | 0.27 | 0.14 |
| Makers | 0.19 | 0.06 | 0.13 | 0.05 | 0.16 | 0.43 | 0.09 | 0.06 |
| Assistants | 0.12 | 0.22 | 0.18 | 0.24 | 0.10 | 0.02 | 0.08 | 0.02 |
| Laborers | 0.05 | 0.00 | 0.00 | 0.02 | 0.00 | 0.15 | 0.00 | 0.01 |

Notes: The average skills index values are based on the 35 specific skills shown in Table 1. Values for the other skills categories (e.g., content, social, system) are based on the specific skills that fall under the broad category.

Table 4. Percentage of U.S. Workforce by Skills-Based Occupation Cluster

| Cluster | Total Occupations | % of U.S. Workforce | Representative Occupations |
|---|---|---|---|
| Engineers | 22 | 3.6% | Chemical engineer, computer programmer, database administrator |
| Executives | 24 | 8.3% | Chief executives, financial managers, education administrators, lawyers |
| Scientists | 42 | 8.1% | Biologists, psychologists, economists, physicians and surgeons |
| Managers | 21 | 7.8% | Funeral directors, transportation managers, purchasing agents, sales managers |
| Technicians | 29 | 2.5% | Chemical technician, drafter, clinical lab technologist, explosives worker |
| Analysts | 39 | 11.5% | Budget analyst, market researcher, cost estimator, technical writer |
| Machinists | 56 | 5.2% | Aircraft mechanic, electrician, security system installer |
| Servers | 56 | 17.7% | Salesperson, dental assistant, receptionist, payroll clerk, cargo agent |
| Makers | 71 | 12.9% | Carpenter, tool and die maker, engine assembler, machine feeder |
| Assistants | 42 | 10.0% | Baggage porter, teacher assistant, counter clerk, home care aide |
| Laborers | 42 | 12.3% | Dishwasher, roofer, taxi driver, laundry worker |

Source: 2005-09 5-year sample of the U.S. Census Bureau American Community Survey.

Table 5. Skills across the Urban-Rural Hierarchy

| | Urban-Rural Continuum Categories | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Engineers | 1.12 | 0.98 | 0.83 | 0.89 | 0.78 | 0.76 | 0.72 | 0.68 | 0.62 | 0.68 |
| Executives | 1.07 | 0.99 | 0.92 | 0.92 | 0.90 | 0.87 | 0.86 | 0.88 | 0.86 | 0.84 |
| Scientists | 1.34 | 1.00 | 0.93 | 0.95 | 1.01 | 0.91 | 0.85 | 0.94 | 0.88 | 0.90 |
| Managers | 0.87 | 1.01 | 1.03 | 1.05 | 1.02 | 1.04 | 1.06 | 1.03 | 1.05 | 1.03 |
| Technicians | 1.14 | 0.92 | 0.91 | 0.98 | 0.94 | 0.93 | 0.89 | 0.94 | 0.91 | 0.92 |
| Analysts | 1.03 | 1.02 | 0.95 | 0.95 | 0.92 | 0.91 | 0.90 | 0.89 | 0.90 | 0.87 |
| Machinists | 0.83 | 0.95 | 1.07 | 1.08 | 1.10 | 1.18 | 1.24 | 1.20 | 1.24 | 1.19 |
| Servers | 1.05 | 1.00 | 0.99 | 1.00 | 0.99 | 0.98 | 0.96 | 0.98 | 0.97 | 0.96 |
| Makers | 0.80 | 0.98 | 1.09 | 1.06 | 1.08 | 1.17 | 1.22 | 1.18 | 1.22 | 1.16 |
| Assistants | 1.00 | 1.03 | 1.03 | 1.01 | 1.04 | 1.02 | 1.02 | 1.02 | 1.02 | 1.00 |
| Laborers | 0.93 | 1.02 | 1.05 | 1.03 | 1.06 | 1.06 | 1.06 | 1.05 | 1.07 | 1.04 |

Source: 2005-09 5-year sample of the U.S. Census Bureau American Community Survey.

Figure 1. Grid Used to Assign PUMAs to Urban-Rural Continuum Categories

| Density | | | | |
|---|---|---|---|---|
| Low (Q1) | 5 | 7 | 9 | 10 |
| Q2 | 4 | 6 | 8 | 9 |
| Q3 | 3 | 5 | 6 | 7 |
| High (Q4) | 2 | 3 | 4 | 5 |
| 1= central city | Close (Q1) | Q2 | Q3 | Far (Q4) |
| | Distance to central city | | | |

Figure 2. Urban-Rural Hierarchy across the United States

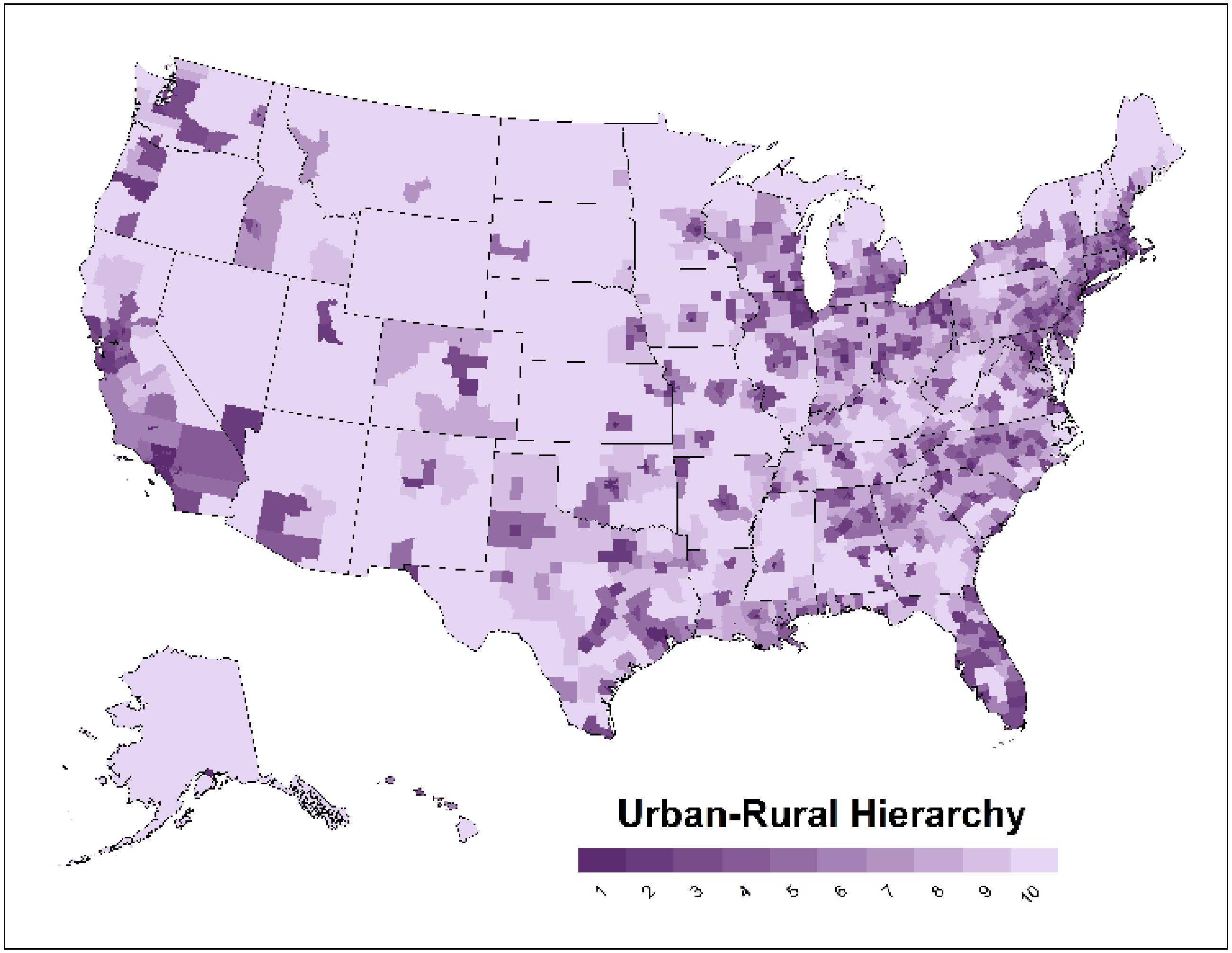

Figure 3. Skills and Earnings across Occupation Clusters

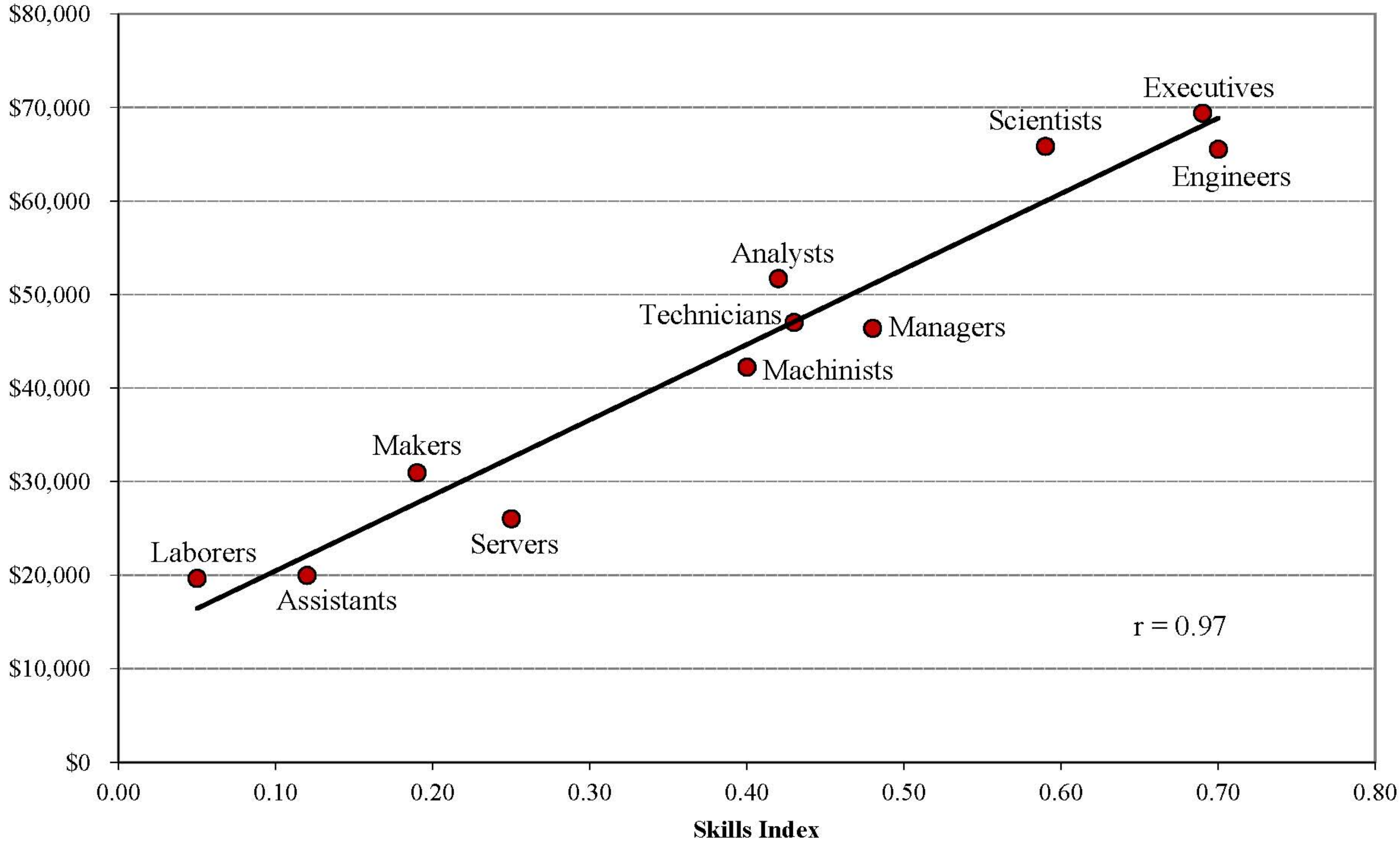

Figure 4. Average Cluster Earnings across the Urban-Rural Hierarchy