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Contents	
List of Tables and Figures	iii
Abstract	iv
1. Introduction	1
2. Existing Definitions of "Middle-Skill" Occupations	2
2.1. Approach Based on Required Education, On-the-Job Training, and Work Experience	3
2.2. Approach Based on a Range of Median Occupational Wages	4
2.3. Approach Based on a Skills Index Summarizing Job Tasks Data	5
2.4. Hint of Proposed New Index	6
3. Data Sources	6
4. Toward a New Empirical Definition of Skilled Non-College Occupations	7
5. Methodology	. 11
5.1. Constructing the Skills Index	. 11
5.2. Educational Attainment Typically Required for Entry	. 14
5.3. Linking Datasets	. 16
6. Skilled Non-College Occupations: Definition and Main Empirical Findings	. 17
6.1. New Empirical Definition of Skilled Non-College Occupations	. 17
6.2. Exploratory Analysis	. 20
7. Summary and Conclusions	. 32
References	. 35
Appendix	. 38

## List of Tables and Figures

Table 1. Three Approaches to the Identification of "Middle-Skill" Jobs	6
Table 2. The O*NET Knowledge Dimension: Areas and Domains	9
Table 3. The O*NET Skills Dimension: Areas and Domains	10
Table 4. Time Intervals in the O*NET Experience and Training Dimensions	11
Table 5. Descriptive Statistics of the O*NET Summary Scores	12
Table 6. Kendall Correlation Matrix of the K, S, T, and E Scores	13
Figure 1. Density Estimate of the KSTE Index for All Occupations	18
Figure 2. Density Estimate of the KSTE Index for Skilled Occupations	18
Figure 3. Density Estimate of the KSTE Index for Non-College Occupations	19
Figure 4. Density Estimate of the KSTE Index for Skilled Non-College Occupations	19
Figure 5. Density Estimates of the KSTE Index for Skilled College and Skilled Non-	
College Occupations	19
Figure 6. Top 10 Largest Major Occupations	21
Figure 7. Top 10 Largest NAICS Sectors	23
Figure 8. Educational Attainment Typically Required for Entry in SNCOs	25
Figure 9. Estimated Educational Attainment of Workers in SNCOs	25
Figure 10. Density Estimates of Mean Hourly Wages of SNCOs and All Occupations	27
Figure 13. Median Hourly Wages and KSTE Scores across SNCOs	30
Figure 14. Median Hourly Wages and KSTE Scores across SNCOs: Top Five SNCOs	
by Wage Quartile	31
Table A1. Skilled Non-College Occupations and Associated KSTE Scores	38
Table A2. Employment in Largest Detailed Occupations by Major Occupations (in	
thousands of jobs)	41
Table A3. Employment in Largest NAICS Industries, by NAICS (in thousands of	
jobs)	42
Table A4. Employment in Largest Detailed Occupations, by NAICS Sectors (in	
thousands of jobs)	43

#### Abstract

This paper presents a new approach to the identification of relatively skilled occupations that do not typically require a bachelor's degree for entry. I call this group of occupations Skilled Non-College Occupations (SNCOs). The proposed approach relies heavily on a new skills index based on data from the Occupational Information Network (O\*NET) sponsored by the U.S. Department of Labor. In contrast with studies that estimate that employment in so-called middle-skill jobs in the U.S. represents one third to nearly a half of total employment, this study estimates that the combined employment of SNCOs accounted for 16.2% of all jobs in 2016. Exploratory analysis shows that SNCOs (a) represent only one in five jobs that do not require a 4-year college degree for entry; (b) encompass a wide variety of occupations and industries, even though they are highly concentrated in a relatively small number of them; (c) usually pay above-average wages; (d) show a quite low correlation between wages and the skills scores; and (e) include a significant proportion of workers who are potentially underemployed in terms of their level of educational attainment.

Keywords: occupations, skills, educational attainment, employment, wages, middle-skill jobs.

#### Matías D. Scaglione

#### 1. Introduction

In the 2000s, a consensus started to emerge in the scholarly literature around the empirical observation that job creation in the U.S. has been following a pattern of "polarization" between "good" and "bad" jobs since the 1980s. Although this polarization in job creation was identified in the late 1980s and early 1990s in the seminal work of Harrison and Bluestone (1988, 1990), and received some attention by sociologists in the 1990s and early 2000s (see Massey & Hirst, 1998; Morris, Bernhardt, & Handcock, 1994; Wright & Dwyer, 2003), it was not until the mid-2000s that the problem started to attract significant academic and public attention with the work of David Autor and colleagues (Autor, Katz, & Kearney, 2006; Autor, 2010, 2015; Autor & Dorn, 2012). The empirical observation of a polarization in job creation or job opportunities, which leads to a polarization of the wage and skills distributions if sustained over time, is mostly based on observations of changes in the wage distribution and in levels of employment across different categories of educational attainment.

According to this body of research, "job polarization" arises when most jobs created are relatively low paying and low skill, filled by individuals with relatively low educational attainment, or relatively high paying and high skill, filled by individuals holding bachelor's degrees or more. This view's proponents complete the pattern once they bring into the picture the so-called "middle-skill" jobs, which stand between the two poles of "low-skill" and "high-skill" jobs and have been expanding at a much lower rate compared to either extreme. These middle-skill jobs usually pay higher wages compared to the large mass of low-skill jobs and typically attract individuals with less than a bachelor's degree. A main implication of the low creation rate of middle-skill jobs is that opportunities for individuals without 4-year college degrees to work relatively "good," middle-wage jobs have been declining in the U.S. since the 1980s. Based on the observation that the demand for college graduates outpaces the supply, dominant policy recommendations derived from the job polarization approach are primarily focused on expanding the mass of college-educated workers (Autor, 2010; Goldin & Katz, 2008).

However, some scholars, business consultants, and leaders of nonprofit organizations challenge the notion of job polarization that dominates the academic literature on the relationships among education, skills, wages, and employment. In this view, the main problem with middle-skill jobs is not their relative decline, as observed in the job polarization story, but that their supply is significantly larger than the supply of specialized middle-skilled workers.<sup>1</sup> Middle-skill jobs in 2015 accounted for 53% of all jobs in the U.S. and 43% of workers were "trained to the middle-skill level," widely cited estimates from the National Skills Coalition (2017) suggest. This "skills gap," the argument goes, can be remedied mostly by expanding

<sup>&</sup>lt;sup>1</sup> Proponents of a "skills gap" in middle-skill jobs in the U.S. include National Skills Coalition (2017); Burrowes, Young, Restuccia, Fuller, and Raman (2014); Tyszko, Sheets, and Fuller (2014); and Kochan, Finegold, and Osterman (2012).

specific vocational education and training programs that can help applicants secure relatively good, middle-wage jobs without holding bachelor's degrees, thus simultaneously contributing to reduce wage inequality and increase the potential growth of the national economy (Kochan, Finegold, & Osterman, 2012, pp. 3–4). A general expansion in the number of job applicants with 4-year college degrees, as prescribed by proponents of the job polarization observation, will not contribute, by itself, to reduce the alleged skills gap in middle-skill jobs.

This controversy is not based on different theories attempting to explain a well-defined empirical phenomenon, but on contested empirical observations supposedly based on the same object of study (i.e., middle-skill jobs). The problem gets more complicated, however, once we realize that different authors refer to different things when they use the expression "middle-skill jobs," not only between approaches but often within the same general approach. Studies on job polarization tend to neglect middle-skill jobs, concentrating their analytical attention on the socalled high- and low-skill jobs and typically defining middle-skill jobs loosely as middle-wage jobs. On the other hand, more systematic studies of middle-skill jobs have been so far unable to come up with a rigorous unified definition, offering a wide range of employment estimates that reveal important methodological differences. Empirical definitions of middle-skill jobs have decisive implications for our understanding of labor market dynamics, which in turn may inform major public policies affecting large sectors of the population.

This paper presents a new approach to the identification relatively skilled occupations that do not typically require a bachelor's degree for entry. I call this group of jobs "Skilled Non-College Occupations." The rest of the paper is divided into six sections. Section 2 assesses definitions of middle-skill occupations, focusing on three approaches to identify middle-skill occupations. Section 3 briefly describes the main datasets this study employs. Section 4's overview describes the main components of the proposed new skills index that underlies the new definition of skilled non-college jobs. Section 5 presents this new approach, detailing the construction of the new skills index, justifying the chosen measure of the typical education required for entry, and describing how the different datasets are linked. Section 6 describes the main empirical findings of the study, starting with the most general results of an analysis using the new definition of skilled non-college occupations, and then provides select findings from a general exploratory analysis focused on occupations, economic sectors, educational attainment, and the relationship between wages and the new skills index. Section 7's summary and conclusions include recommendations for future research.

#### 2. Existing Definitions of "Middle-Skill" Occupations

Middle-skill occupations are usually defined as those occupations that demand medium to relatively high skills but require less than a 4-year university degree for entry. Empirical attempts to identify this group of occupations for the U.S. generally find no major methodological hurdles with the educational requirement component, but they all face the problem of approaching the notion of "skills" empirically, through observable measures, and then defining some rule to identify the skill levels assumed to be associated with middle-skill occupations. This section discusses three alternatives for identifying middle-skill occupations empirically in the U.S. The

first and most widely cited method employs levels of *required education*, *on-the-job training*, and *work experience*. The second method approaches middle-skill occupations through a definition of a range of median occupational *wages*. Finally, the third method defines "skilled technical" occupations by employing a skills index based on the technical knowledge workers must have to perform specific tasks. This last alternative is the most rigorous method and offers the basis for my own approach.

#### 2.1. Approach Based on Required Education, On-the-Job Training, and Work Experience

The National Skills Coalition (2017) provides the most widely cited employment estimates of middle-skill jobs in the U.S. (see, for instance, Leins, 2017; Sappenfield, 2017; Selingo, 2018). The coalition bases its method on a schema proposed by Holzer and Lerman (2007), in which middle-skill jobs are those that "generally require some significant education and training beyond high school but less than a bachelor's degree" (Holzer & Lerman, 2007, p. 8). Holzer and Lerman use the 22 *major* occupations (the most aggregated occupational grouping) in the Standard Occupational Classification system that federal agencies use to classify workers for collecting, calculating, or disseminating data. They assign a low-, middle-, and high-skill level to each of the 22 major occupations based on the *average* educational attainment and/or training of the *detailed* occupations (the most disaggregated occupational grouping, with 819 items) within each major occupation.<sup>2</sup>

The National Skills Coalition method refines Holzer and Lerman's system by using a better source of educational attainment, training, and experience data, published by the Bureau of Labor Statistics in 2010, and by employing a more precise definition of "middle skill" occupations at the detailed aggregation level. In the coalition's definition, a detailed middle-skill occupation requires more than a high school diploma and less than a bachelor's degree, or a high school diploma and one of the following: apprenticeship, long-term on-the-job training, moderate term on-the-job training, and work experience.<sup>3</sup> Middle-skill occupations are then estimated at the most aggregated level of major occupations. The resulting middle-skill major occupations are Healthcare Support; Protective Support; Sales and Related; Office and Administrative Support; Construction and Extraction; Installation, Maintenance, and Repair; Production; and Transportation and Material Moving.

A problematic feature of the National Skills Coalition method is that it sacrifices precision when it moves from the detailed to the major level of occupational aggregation, leading to potentially significant distortions in the employment estimates of the different skill levels. Let us imagine a major occupational group with five detailed occupations, each with 10 workers. Let us assume that three of the detailed occupations are defined as middle skill, while one remaining occupation is defined as low skill and the other high skill. According to the coalition method, this

<sup>&</sup>lt;sup>2</sup> For definitions of middle-skill occupations that use educational attainment of workers, instead of the typical

education required for entry, see, for instance, Autor, Katz, and Kearney (2006), and Modestino (2010, 2015).

<sup>&</sup>lt;sup>3</sup> Low-skill occupations require less than a high school diploma or a high school diploma and no work experience and less than a month of on-the-job training. High-skill occupations require a bachelor's degree or more education.

major occupation would be defined as middle-skill, even though it contains 40% of workers who are not employed in middle-skill detailed occupations.

The method proposed by the National Skills Coalition yields an estimated share of middleskills occupations of 53% of all jobs in 2015. In contrast, a study by the U.S. Congress Joint Economic Committee (Heinrich, 2018) uses the definition of "middle-skill" occupations at the level of *detailed* occupations proposed by the National Skills Coalition (Heinrich, 2018, p. 13) and retains the detailed occupations to compute employment estimates. It finds an employment share of middle-skill detailed occupations of nearly *one-third* of all jobs in the U.S. in 2016. The difference of nearly 20 percentage points between the two estimates shows the distorting effect of estimating occupational employment shares at the highest level of aggregation (major occupations), when attributes are defined at the lowest level of aggregation (detailed occupations).

#### 2.2. Approach Based on a Range of Median Occupational Wages

Harry Holzer proposes a different approach in a 2015 study for the Brookings Institution. Departing from the method that he proposed with Lerman in 2007 to identify middle-skill jobs, Holzer now concentrates on the occupational wage distribution and defines "middle-wage occupations" as detailed occupations with median hourly wages between 75% and 150% of the overall median hourly wage (Holzer, 2015, p. 2).<sup>4</sup> Even though Holzer claims that "middle-wage" and "middle-skill" jobs are "not always identical" (Holzer, 2015, p. 1), he nonetheless treats "middle-wage" jobs as a valid approximation for middle-skill jobs throughout the report (see especially note 2 on page 3). The employment share of these middle-wage jobs was 37% of all jobs in 2013, significantly below the National Skills Coalition estimate of 53% and closer to the 33% computed in the study prepared for the U.S. Congress Joint Economic Committee (Heinrich, 2018, p. 2).

Holzer's methodological approach has two main problems. He briefly discusses the first in his 2015 report. Wages are not good indicators or predictors of educational attainment, which is typically regarded as a proxy of skills in mainstream labor economics. Put simply, differences in educational attainment or in any potential empirical proxy of skills cannot explain wage differences, even after considering them across demographic groups, industries, and geographic regions. For instance, relatively skilled or "middle-skilled" occupations can report very different wages, even within the same industry: In 2016, Emergency Medical Technicians and Paramedics reported a relatively low median wage of \$15.70, while Diagnostic Medical Sonographers showed a very high median wage of \$33.50.

The second problem in Holzer's method is that it is not obvious why the range of 75% to 150% of the overall median wage, or any wage range for that matter, can be considered the "middle" of the occupational wage distribution. In 2016, for instance, that range of occupational median hourly wages, from \$13 to \$26 an hour, contained 40% of all jobs, from the 31<sup>st</sup> through the 72<sup>nd</sup> percentile. That 40% employment share is close to the employment share of 39% that

<sup>&</sup>lt;sup>4</sup> For an alternative definition of middle-skill jobs using wages, see Autor (2010).

Holzer obtains for 2000, the base year in his 2015 analysis. An alternative would be to divide the wage distribution into thirds, in which case the middle third would be defined by hourly median wages 77% to 133% of the overall median in 2016. This exercise, however, tells us nothing about the size of this new "middle-wage" group of workers other than it represents by definition one third of all jobs. Assuming that this group is defined for a base year, measurements of the share of employment in different years using the base-year wage range would provide some useful information on employment change within that specific range of wages. However, not all the occupations in that wage range would be "middle wage," since the shape of the wage distribution changes over time, implying that the base-year wage range does not necessarily coincide with the wage range defining middle-wage occupations in a non-base year (i.e., ranges of wages associated with specific ranges of employment percentiles change over time). Wages, therefore, are not a good measurement to identify with precision so-called middle-skill occupations, or occupations in the "middle" of the job market.

#### 2.3. Approach Based on a Skills Index Summarizing Job Tasks Data

Jonathan Rothwell proposes the most rigorous approach to the identification of middle-skill jobs in a 2015 study prepared for the U.S. National Academies of Sciences, Engineering and Medicine. Instead of using primarily educational attainment, training, experience, or wages, Rothwell focuses on the knowledge required to perform specific tasks for detailed occupations using data from the Occupational Information Network (O\*NET) program, sponsored by the U.S. Department of Labor. The O\*NET database contains rich and complex surveys that describe work and worker characteristics across detailed occupations. Rothwell proposes an index using a subset of the O\*NET knowledge requirements survey to "measure technical knowledge or skill" (Rothwell, 2015, p. 6). He confines his analysis to detailed occupations that require a high degree of technical knowledge (i.e., a knowledge score above a threshold he defines) and do not require a bachelor's degree for entry. The combined employment of these "skilled technical" occupations represented 12% of the total U.S. workforce in 2014.

Rothwell's approach offers two main analytical advantages. The most important is that the selection of "skilled technical occupations" is based on empirical measures of work or task requirements of detailed occupations. O\*NET's empirical measures of work requirements are not without flaws or limitation (see Handel, 2016), but they represent an improvement over attempts to approach the required average knowledge and skills with measures like educational attainment or wages. The focus switches from education and wages to the specific knowledge and skills required to perform specific tasks in different occupations. The second analytical advantage, which is derived from the first one, is that these numerical summary scores of knowledge and/or skills can be treated as continuous variables, thus allowing for a more accurate selection of groups of occupations based on the distance of their respective scores relative to a definite threshold and for the computation of distances between occupational scores themselves.

Rothwell's approach has two important limitations. The first is the focus on "technical work," which leaves out many occupations that require above-average levels of strictly nontechnical knowledge, skills, on-the-job training, and work experience but do not typically

require a bachelor's degree for entry, like first-line supervisors of retail sales workers. The second limitation, which is a consequence of the first, is the exclusive use of the O\*NET *knowledge* requirements in the construction of Rothwell's index that measures "technical knowledge or skill," thus excluding potentially relevant measures like the O\*NET *skill* requirements. Rothwell defends this methodological decision by claiming, in the case of skills, that the O\*NET skill requirements do not lend themselves "to any straightforward way of categorizing which skills apply to skilled technical workers and which do not" (Rothwell, 2015, p. 7). Table 1 summarizes the three approaches discussed in this section.

	11		
	National Skills Coalition (2014)	Holzer (2015)	Rothwell (2015)
Method	Middle-skill occupations are <i>major</i> occupations with the majority of workers in middle-skill detailed occupations that require associate's degree, postsecondary non-degree award, some college but no degree, or high school degree and one of the following: apprenticeship, moderate- or long-term on-the-job training, or work experience.	Middle-wage occupations are <i>detailed occupations</i> with median hourly wages of 75% to 150% of the median hourly wage.	Skilled technical occupations are <i>detailed occupations</i> that (a) require high level of knowledge in a technical domain; and (b) do not require a bachelor's degree for entry
Datasets	Occupational Employment Statistics and U.S. Bureau of Labor Statistics employment projections	Occupational Employment Statistics	O*NET, Occupational Employment Statistics, U.S. Bureau of Labor Statistics employment projections
Estimates	53% in 2015	37% in 2013	12% in 2014

#### Table 1. Three Approaches to the Identification of "Middle-Skill" Jobs

#### 2.4. Hint of Proposed New Index

This paper provides a new method to identify occupations that are relatively skilled but do not typically require a bachelor's degree for entry. The method draws on Rothwell's use of O\*NET work requirements to measure knowledge and skills. I include the key skills requirements and consider all knowledge and skills dimensions. I also follow the National Skills Coalition's procedure of incorporating on-the-job training and work experience as additional measures of knowledge and skills, but use O\*NET instead of employment projections data. In brief, the new method proposes a "skills" index that includes occupational measures of knowledge, skills, training, and experience based on O\*NET data. The following three sections describe the data used in this paper, explain why a new approach to the identification of so-called middle-skill jobs is necessary, and present the new method.

#### 3. Data Sources

The data for this study come from three sources: the O\*NET dataset, the Occupational Employment Statistics dataset, and the Bureau of Labor Statistics Employment Projections program dataset. The O\*NET dataset comprises surveys that include, among others, measures of different job requirements, like the specific set of skills required to perform a specific job, by detailed occupations. This study uses version 21.3 of the O\*NET database, employing measures

from the Knowledge, Skills, and Education, Training, and Experience surveys.<sup>5</sup> Job incumbents report all used O\*NET data, except for the skills information that job analysts impute. Sections 4 and 5 of this paper describe the main features of the O\*NET surveys this study employs. The Occupational Employment Statistics dataset include data on employment and wages by detailed occupations and industries at the national, state, and metropolitan levels. Occupational Employment Statistics collects data at the establishment level and provides the most accurate publicly available measures of occupational employment and wages in the U.S. Lastly, the federal employment projections data provide a measure of educational attainment that detailed occupations typically require for entry. Although O\*NET provides a measure of required education by occupation, subsection 5.2 discusses why the employment projections data offer are a superior measure of required education. All the different elements from each dataset are finally consolidated in a single dataset, as explained in subsection 5.3.

#### 4. Toward a New Empirical Definition of Skilled Non-College Occupations

My proposed definition of skilled non-college occupations is inspired by the empirical approach Rothwell (2015) proposed in his definition for skilled technical work. It follows Rothwell's general method of (a) computing an index of "skills" for detailed occupations using O\*NET data, (b) setting a lower bound of the "skills" index that defines the "skilled" occupations (i.e., all detailed occupations with a "skills" score above the index's lower threshold are considered "skilled"), and (c) selecting the occupations that typically require less than a bachelor's degree for entry. However, my definition of skilled non-college occupations departs quite significantly from Rothwell's in that it includes all kind of workers, as opposed to Rothwell's focus on technical workers. Also, my definition employs a skills index that incorporates four O\*NET-based dimensions: *Knowledge*, *Skills*, *Training*, and *Experience*, in contrast with Rothwell's reliance on a single O\*NET-based measure of "technical knowledge." The main analytical motivation behind the new index is to approximate empirically the multidimensional and elusive nature of the notion of skills (Attewell, 1990). Historically, such attempts at the national level have been impaired by theoretical preferences or by limitations of datasets. The most common practice in empirical studies using U.S. nationally representative samples, especially in labor economics, has been to approach the observable dimensions of skills using proxies like educational attainment or wages (see, for instance, Juhn, 1999; Katz & Murphy, 1992).

However, since the late 1970s, some social scientists started using more direct measures of skill requirements and other job characteristics from the Dictionary of Occupation Titles (see Spenner, 1979, 1983; Rumberger, 1981; Howell & Wolff, 1991). Due to methodological problems and high maintenance costs (Handel, 2016, p. 158), the U.S. Department of Labor replaced the dictionary with the first complete version of O\*NET in June 2008 (Handel, 2016, p. 158). Despite offering the possibility to improve the empirical study of job requirements and work activities by detailed occupations, researchers seldom use the data to study U.S. work and labor markets, perhaps due to a "daunting" size that "requires attention in selecting variables"

<sup>&</sup>lt;sup>5</sup> Version 21.3 of the O\*NET database is available at https://www.onetcenter.org/db\_releases.html.

(Handel, 2016, p. 172). In the case of Rothwell's pioneering studies using O\*NET data to study science, technology, engineering, and mathematics occupations (Rothwell, 2013) and skilled technical work (Rothwell, 2015), the problem of variable selection in O\*NET is a minor one, since those studies focus on knowledge, more specifically on science, technology, engineering, and mathematics or technical knowledge. They only consider other O\*NET dimensions, like skills or abilities, as inadequate complementary measures of the central knowledge dimension. In our case, however, the selection of O\*NET variables is not trivial, since centrality is assigned not to any individual dimension, but to a *set of dimensions* that are assumed to be the best candidates to empirically approach the concept of skills using this dataset.

By "skilled non-college occupations" I mean jobs that require the employee to possess certain work capacities and competencies without holding at least a 4-year college degree. To identify these capacities and competencies, I chose O\*NET's Knowledge, Skills, Training, and Experience dimensions because they refer to individual work capacities and competencies that can be developed through formal education and formal or informal training. The first two dimensions, Knowledge and Skills, are obvious candidates and have joint methodological primacy within the set, because they can be assumed to be *essential and complementary* in the construction of the skills index. They are essential because they are the most direct and precise proxies of skills in the O\*NET dataset—and for that matter in any publicly available U.S. official dataset. They are also complementary because they attempt to address the distinction between *theoretical knowledge* and *experiential knowledge*. This distinction not only applies to the cases where a person employs acquired theoretical knowledge (e.g., knowledge of mathematics) at work (e.g., the use of mathematics to solve specific work-related problems), but to specific instances of experiential knowledge or skills proper that cannot be directly linked to codified theoretical principles (e.g., critical thinking, persuasion, complex problem solving).

In O\*NET, Skills and Knowledge, along with Education, are considered "Worker Requirements" that "represent developed or acquired attributes of an individual that may be related to work performance" (National Center for O\*NET Development, 2017, p. 8). The Knowledge dimension refers to "[o]rganized sets of principles and facts applying in general domains" (National Center for O\*NET Development, 2017, p. 9). It includes 10 areas and 33 domains (e.g., "Computers and Electronics" domain within the "Engineering and Technology" area). Table 2 shows the Knowledge dimension's areas and domains.

Business and Management
1. Administration and Management; 2. Clerical; 3. Economics and Accounting; 4. Sales
and Marketing; 5. Customer and Personal Service; 6. Personnel and Human Resources
Manufacturing and Production
7. Production and Processing; 8. Food Production
Engineering and Technology
9. Computers and Electronics; 10. Engineering and Technology; 11. Design; 12. Building
and Construction; 13. Mechanical
Mathematics and Science
14. Mathematics; 15. Physics; 16. Chemistry; 17. Biology; 18. Psychology; 19. Sociology
and Anthropology; 20. Geography
Health Services
21. Medicine and Dentistry; 22. Therapy and Counseling
Education and Training
23. Education and Training
Arts and Humanities
24. English Language; 25. Foreign Language; 26. Fine Arts; 27. History and Archeology;
28. Philosophy and Theology
Law and Public Safety
29. Public Safety and Security; 30. Law and Government
Communications
31. Telecommunications; 32. Communications and Media
Transportation
33. Transportation
Source: National Center for O*NET Development (2017)

Table 2. The O\*NET Knowledge Dimension: Areas and Domains

The Skills dimension is divided into two subdimensions. Basic Skills "facilitate the acquisition of new knowledge" (National Center for O\*NET Development, 2017, p. 8), like reading comprehension and critical thinking. Cross-Functional Skills include the "[d]eveloped capacities that facilitate performance of activities that occur across jobs," (National Center for O\*NET Development, 2017, p. 8) like complex problem solving, persuasion, or a technical skill like programming. Skills include 7 areas with 35 domains (e.g., "Service Orientation" skills domain within the "Social Skills" area). Table 3 shows the areas and domains of the O\*NET Skills dimension.

	Content
asic kills	1. Reading Comprehension; 2. Active Listening; 3. Writing; 4. Speaking; 5. Mathematics;
	6. Science
n N	Process
	7. Critical Thinking; 8. Active Learning; 9. Learning Strategies; 10. Monitoring
	Social Skills
	11. Social Perceptiveness; 12. Coordination; 13. Persuasion; 14. Negotiation; 15.
s	Instructing; 16. Service Orientation
kill	Complex Problem Solving Skills
S	17. Complex Problem Solving
nal	Technical Skills
tio	18. Operations Analysis; 19. Technology Design; 20. Equipment Selection; 21. Installation;
nc	22. Programming; 23. Operation Monitoring; 24. Operation and Control; 25. Equipment
Ψ	Maintenance; 26. Troubleshooting; 27. Repairing; 28. Quality Control Analysis
-SS	System Skills
L.	29. Judgment and Decision Making; 30. Systems Analysis; 31. Systems Evaluation
0	Resource Management Skills
	32. Time Management; 33. Management of Financial Resources; 34. Management of
	Material Resources; 35. Management of Personnel Resources

 Table 3. The O\*NET Skills Dimension: Areas and Domains

*Source: National Center for O\*NET Development (2017)* 

The last two dimensions, Training and Experience, are secondary measures in skills index that are assumed to be *complementary* with each other and with the Knowledge and Skills dimensions. They are secondary measures because they provide a less precise and more indirect proxy of skills, only reporting distributions across intervals of time of required training and experience by occupation. Training and Experience are assumed to be complementary with each other and with Knowledge and Skills because they individually refer to different unobservable processes of skills development. In O\*NET, Experience and Training are classified as "Experience Requirements" that are "related to previous work activities and explicitly linked to certain types of work activities" (National Center for O\*NET Development, 2017, p. 14). The Experience dimension refers to the "[a]mount of related work experience required to get hired" (National Center for O\*NET Development, 2017, p. 14). It includes 11 categories of time intervals, ranging from no work experience to more than 10 years of related work experience. Training consists of two subdimensions: On-Site or In-Plant Training (On-Site Training for short), referring to organized on-site instruction, and On-the-Job Training, denoting the amount of job training required to perform the job. These subdimensions include 9 categories of time intervals, many of which coincide with the Experience intervals, ranging from no on-site training or no on-the-job training or a short demonstration, to more than 10 years of on-site training or on-the-job training. Table 4 shows the different time intervals of the Experience and Training dimensions.

Experience	<b>On-Site Training</b>	<b>On-the-Job Training</b>
1. None <sup>*</sup>		
2. Less than a month <sup><math>\dagger</math></sup>	<i>.</i>	
3. 1–3 months	(same interval	(s)
4. 3–6 months		/
5. 6 months–1 year		
6. 1–2 years		
7. 2–4 years		
8. 4–6 years		
9. 6–8 years	8. 4–10 years	(same intervals)
10. 8–10 years	9. Over 10 years	
11. Over 10 years		ч

 Table 4. Time Intervals in the O\*NET Experience and Training Dimensions

\* "None or short demonstration" in the case of On-the-Job Training.

<sup>†</sup> "Anything beyond short demonstration, up to and including 1 month" in the case of On-the-Job Training.

Source: National Center for O\*NET Development (2017)

All four O\*NET dimensions described above are assumed to individually approach the concept of skills empirically, to some extent. A crucial aspect of this study is the additional assumption that a *composite index*, including all or some of the chosen dimensions and assigning them weights that are proportional to their assumed empirical and conceptual importance, will better approach empirically the *multidimensional* concept of skills than an index based on a single dimension. The next steps are (a) to decide whether it makes empirical sense to include all the chosen dimensions or to discard some; and (b) to devise weights for each resulting dimension that can be justified on conceptual and empirical grounds. The final configuration of the skills index is the result of empirical tests based on simple conceptual observations, not on an a priori construction. The technical steps involved in the construction of the index and other methodological procedures are discussed in the next section.

#### 5. Methodology

Skilled non-college occupations are jobs that require employees to possess certain work capacities and competencies without holding at least a 4-year college degree. My proposed definition relies heavily on a new skills index and depends, more conventionally, on a standard categorization of the occupations that typically require less than a 4-year college degree for entry. This section describes the construction of the skills index, discusses some important methodological aspects of the chosen classification of occupations by required educational attainment, and explains how different datasets are linked to produce employment and wage estimates.

#### 5.1. Constructing the Skills Index

Given the critical importance of the proposed definition of skilled non-college occupations, in this section I detail three methodological steps in the construction of the new skills index:

(1) computation of normalized summary scores of the O\*NET Knowledge, Skills, Experience, and Training dimensions;

- (2) evaluation of correlations between the summary scores and final selection of the summary scores, or components, to include in the final index; and
- (3) assignment of weights to each component and final assemblage of the composite skills index.

**5.1.1. Summary scores.** The computation of summary scores is straightforward for Knowledge and Skills. Each domain in these two dimensions has two scales: average Importance (from 1 to 5), which refers to the degree of importance of a domain, and average Level (from 0 to 7), which refers to the degree to which a domain is required or needed to perform a job. The new index employs the Level scale because it captures *absolute relevance* of domains across occupations, not their *relative importance* within occupations. Thus, I compute the average Knowledge and Skills scores using the scores of the Level scale across all the Knowledge and Skills dimensions and then normalize the result by dividing it by the mean score for all the detailed occupations.

In the case of Training and Experience, the computation of summary scores is somewhat more complex. Rather than Importance or Level scales, their scores come from the frequency distributions of respondents across the time intervals presented in Table 4. The proposed summary scores for these dimensions attempt to address the distributions of respondents across intervals of related work experience and training time. To this end, midpoints were calculated for each closed interval, and a maximum value of 15 years was set for the maximum open-ended interval of "Over 10 years." The summary score by occupation is a sum of the midpoint values weighted by the frequency of respondents in the Experience dimension, and the On-Site Training and On-the-Job Training subdimensions. The two training subdimensions are then averaged to form a single Training score. The Experience and Training scores are normalized following the procedure applied to the Knowledge and Skills summary scores. Table 5 shows descriptive statistics of the new summary scores, which I call the K, S, T and E scores.

Tuble 5. Descrip	nic Statistic	s of the O		J Deores
	K	S	Т	Ε
Minimum	0.19	0.35	0.04	0.01
1 <sup>st</sup> Quartile	0.79	0.86	0.43	0.46
Median	1.00	1.01	0.75	0.86
3 <sup>rd</sup> Quartile	1.19	1.15	1.32	1.40
Maximum	1.84	1.67	7.40	3.98
$3^{rd} - 1^{st}$ Quartiles	0.40	0.29	0.89	0.94

Tuble 5. Descriptive Studistics of the O Till'I Summary Scores	T	ab	le	5.	D	escriptive	<b>Statistics</b>	of	the	<b>O*NET</b>	<b>Summary</b>	Scores
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Each score is normalized so that the mean equals 1.00. *Source: own calculations based on O\*NET data.* 

**5.1.2. Correlations.** The next step is to evaluate the correlation of the summary scores with each other. Descriptive statistics in Table 5 show that the T and E summary scores are clearly skewed distributions, with medians of 0.75 and 0.86 significantly below the means of 1.00 and relatively high interquartile ranges, but they are not conclusive about the potential skewness of the K and S scores. Two widely used normality tests (the Anderson-Darling and Shapiro-Wilks test) were run to assess the distribution of the scores, and all of them failed the tests with 95% confidence. The skewness of all the summary scores and the non-linear relationship between them indicate that the standard Pearson correlation coefficient, which assumes normality and a

linear relationship among variables, should be replaced by correlation coefficients that do not assume normality or linearity, like the Spearman or Kendall coefficients. The Kendall coefficient is preferred here due to its statistical advantages relative to the Spearman coefficient (see Kendall & Gibbons, 1990).

Table 6 presents the Kendall correlation coefficients for the summary scores. The pair K-S shows the strongest relationship, with a correlation coefficient of 0.55. The relationship, however, is not strong in absolute terms, confirming the thesis of potential complementarity advanced in Section 4 (i.e., a mild or relatively weak relationship between summary scores supports the thesis that they are potentially complementary). This is observed in all the pairs of scores, which means in principle that all scores are potentially complementary and should be included in the skill index. On the other hand, very strong relationships (e.g., above 0.8) mean in this context that scores are potentially redundant.

of the K, S, T, and E Scores				
	K	S	Т	
K	1.00			
S	0.55	1.00		
Т	0.30	0.31	1.00	
Ε	0.41	0.43	0.44	

Table 6. Kendall Correlation Matrix of the K, S, T, and E Scores

Source: own calculations based on O\*NET data.

**5.1.3. Weights.** The last step assigns weights to the scores and assembles the final skills index. It is clear from Section 4 that the Knowledge and Skills dimensions should have higher weights than Training and Experience. Knowledge and Skills are much more direct and precise empirical proxies of skills than Training and Experience, and thus require a more prominent presence in the index. Training, in turn, is more directly tied to the target occupation than Experience, which refers to experience that may have been accumulated in related occupations, thus justifying a higher weight for Training relative to Experience.

The new skills index is simply a weighted sum of the summary scores, defined by the formula

$$KSTE_i = \sum w_j Q_{ij}$$

where *KSTE* denotes the skills index, *w* the weight of the summary score, *Q* the summary score, and *i* and *j* index the occupations and the summary scores, respectively. The skills index is then normalized by dividing it by the overall average skills index, like in normalization of the summary scores. Several configurations of the KSTE index with different weights were tested, following simple proposed rules for the weights of scores and for the selection of the final configuration. The rule for weights stipulates that weights for the K and S scores must be equal and individually *at least three times larger* than the weight of the T score. The weight for the T score, in turn, must be larger, but *less than twice* as large than the weight of 2.5 percentage points (e.g., from 0.10 to 0.125) to avoid unnecessary granularity, and all the score weights in each configuration must add to 1.0. The second rule stipulates that the final configuration of the

KSTE score is the configuration that meets the first rule and shows the *lowest correlation* with the corresponding configuration of a score based just on the Knowledge, Skills, and Training dimensions.<sup>6</sup> This rule aims at maximizing the role of Experience, given the constraint of the weights rule. The chosen final configuration of the KSTE index consists of weights of 0.4 for the K and S scores, respectively, 0.125 for the T score and 0.075 for the E score.<sup>7</sup>

An important finding of the test of different KSTE configurations is that they yield alternate rankings of occupations, which can result in quite varied groups of occupations when they are defined relative to a threshold, like the mean of the KSTE scores. For instance, compared to the unweighted KSTE configuration, the chosen weighted KSTE configuration yields a group of occupations with above-average KSTE indexes that is 11% larger in terms of the number of occupations and 12% larger in terms of employment. Of course, these differences get smaller as the weights get closer, as with the competing KSTE configurations that meet the weights rule or between a weighted KSTE configuration and its corresponding KST configuration. For instance, relative to its corresponding KST index, the final KSTE configuration yields a group of occupations with above-average KSTE scores that are only 2% larger both in terms of the number of occupations and in terms of employment. The much higher weights assigned to the K and S scores, along with the fact that the distributions of K and S are more compact relative to the distributions of T and E (see Table 5), ensures *relatively narrow differences among* competing KSTE configurations. Ultimately, an important function of this procedure is to let the weighted T and E scores define the relative position of some occupations whose KS score are fairly close to some KS threshold. Assuming this threshold is the mean, occupations with quite low or quite high KS measures will not be significantly affected by the T and E scores, while occupations with KS measures that are fairly close to the average KS score can be significantly affected by the T and E scores.

#### 5.2. Educational Attainment Typically Required for Entry

There are two main official sources of required educational attainment by occupation. One is O\*NET itself, which includes a Required Education dimension that reports the distribution of respondents across 12 levels of educational attainment categories, by detailed O\*NET occupational codes.<sup>8</sup> The O\*NET database indicates, for instance, that 66% of the sampled incumbents in the Registered Nurses occupation report an associate's degree as the required level of education. This source of required education by detailed occupational codes is the most

<sup>&</sup>lt;sup>6</sup> This KST configuration has the same weights as the KSTE index for the K and S scores and a residual weight for the T score. For example, a KST index with weights of 0.4 for K and S, respectively, and 0.2 for T corresponds with a KSTE index with weights of 0.4 for K and S, respectively, and 0.15 for T and 0.05 for E.

<sup>&</sup>lt;sup>7</sup> Two KSTE configurations met the weights rule. The other configuration consisted of weights of 0.425 for K and S, respectively, 0.1 for T and 0.05 for E. The chosen configuration shows a Kendall correlation coefficient of 0.90 with the corresponding KST configuration, versus 0.93 for the discarded KSTE configuration.

<sup>&</sup>lt;sup>8</sup> The O\*NET education categories are (1) Less than a High School Diploma; (2) High School Diploma or Equivalent; (3) Post-Secondary Certificate; (4) Some College; (5) Associate's Degree; (6) Bachelor's Degree; (7) Post-Baccalaureate Certificate; (8) Master's Degree; (9) Post-Master's Certificate; (10) First Professional Degree; (11) Doctoral Degree; (12) Post-Doctoral Training.

widely used reference in recent studies (see, for instance, Abel & Deitz, 2016; Rothwell, 2015; Fogg & Harrington, 2011).

The other source of required educational attainment by occupation is from the Employment Projections program (EPP) at the U.S. Bureau of Labor Statistics.<sup>9</sup> The EPP assigns educational attainment categories to detailed occupations based on analyses of quantitative information from the American Community Survey and O\*NET, and qualitative information from interviews of persons who are "knowledgeable about education and training requirements for the occupations," including "employers, workers in the occupation, training experts, and representatives of professional and trade associations and unions, among others" (Sommers & Morisi, 2012, p. 17). The bureau introduced these educational categories in the 2010-2020 employment projections, issued in 2012, with new on-the-job training and related work experience dimensions. According to the bureau, the fairly new EPP educational, training and experience dimensions represent, together, "the typical path to enter an occupation and become competent performing it" (Sommers & Morisi, 2012, p. 14).<sup>10</sup>

In the new skills index I use the EPP required educational attainment data by detailed occupation. The quality of these EPP data is superior to the similar O\*NET data for three reasons. First, the EPP data result from mixed-method analyses that includes O\*NET data as an input. Second, small sample sizes limit O\*NET data for some occupations (Sommers & Morisi, 2012, p. 17). Third, the EPP data can be almost directly linked to the Occupational Employment Statistics (OES) dataset (see the next subsection), unlike the O\*NET data, which need to be linked to the OES dataset through a crosswalk and a weighting procedure, resulting in a less accurate measure of required education at the OES occupational level.

I assigned EPP data on education required for entry to all occupations, except for the important case of Registered Nurses. Until the 2014-2024 employment projections released in 2016, the EPP reported that the detailed occupation Registered Nurses typically required an associate's degree for entry. The program upgraded this educational requirement to a bachelor's degree in 2016, but I reversed the decision based on the fact that almost all states in the U.S. require the minimum of an associate's degree to qualify for registered nurse status (see *Nurse Journal*, 2017). This solution is similar to Rothwell's proposal to downgrade the level of required education for Registered Nurses using O\*NET data, from bachelor's degree to associate's degree (Rothwell, 2015, p. 8). The main difference is that Rothwell changed a weighted average that resulted from the crosswalk between O\*NET and OES occupations,

<sup>&</sup>lt;sup>9</sup> The EPP education categories are (1) Less than High School; (2) High School Diploma or Equivalent; (3) Some College, No Degree; (3) Postsecondary Nondegree Award; (4) Associate's Degree; (5) Bachelor's Degree; (6) Master's Degree; (7) Doctoral or Professional Degree.

<sup>&</sup>lt;sup>10</sup> A third, widely cited approach to required education is proposed by Anthony Carnevale and colleagues at the Center on Education and the Workforce, at Georgetown University. They propose that the maximum level of educational attainment reported by job incumbents in household surveys reflects the level of educational attainment required by their specific jobs. For example, retail salespersons with bachelor's degrees are deemed to be employed in college jobs, even though the EPP indicates that the retail salespersons occupation does not require formal education credentials. See Harrington and Sum (2010a) for a critique of this approach, Carnevale, Smith, and Strohl (2010) for the center response to that critique, and Harrington and Sum (2010b) for a response to that response.

whereas I am modifying a Bureau of Labor Statistics data point for one of the most populous detailed occupations.

#### 5.3. Linking Datasets

For the empirical analysis in Section 6, I created a single dataset that combines the 2016 values of (a) OES estimates of occupational employment and wages, at the national, state, and metropolitan levels, and broken down by industry at the national level; (b) O\*NET-based occupational K, S, T, and E summary scores and the final KSTE index; and (c) EPP education level typically required for entry by occupation and EPP projected employment by occupation. The final dataset may be regarded as an extension of the OES dataset, preserving its complex structure, and adding O\*NET and EPP data. The incorporation of EPP data is straightforward, since both occupational schemes are virtually identical.<sup>11</sup>

The addition of O\*NET data is more complex, presenting two separate obstacles. First, the O\*NET occupational system is an expanded version of the occupational system used in OES, where some *single* OES occupations correspond with *many* O\*NET occupations, as detailed by the official crosswalk offered by the O\*NET Resource Center.<sup>12</sup> This situation implies that, for some occupations, more than one O\*NET value, like the corresponding KSTE score, needs to be collapsed into a single value for the corresponding single OES occupation. In our case, the different O\*NET-based values were incorporated by taking a simple average across the several O\*NET occupations associated with a single OES occupation (I used a simple average since it is not possible to weight O\*NET-based values in the O\*NET occupational scheme). For example, the O\*NET-based values proceeding from five occupations, namely "Registered Nurses," "Acute Care Nurses," "Advanced Practice Psychiatric Nurses," "Critical Care Nurses," and "Clinical Nurse Specialists."

The second obstacle is that O\*NET does not offer values for 50 OES detailed occupations, the bulk of which are generic detailed occupations with "All Other" in their titles, like "Drafters, All Other." The solution here was to use the OES dataset with the O\*NET existing values already incorporated and assign to each missing occupation the weighted average of the O\*NET-based values of its "family" of occupations, using the OES U.S. estimates of employment by occupation as weights. The family of occupations is defined here by the minor occupational group, identified by the three first digits of the Standard Occupational Classification (SOC) code. For instance, in the case of "Drafters, All Other" (SOC code 17-3019), from the minor occupational group "Drafters, Engineering Technicians, and Mapping Technicians" (SOC minor

<sup>&</sup>lt;sup>11</sup> Three 2016 OES occupations lack 2016 EPP data: "Teachers and Instructors, All Other, Except Substitute Teachers" (SOC code 25-3097), "Substitute Teachers" (SOC code 25-3098), and "Fishers and Related Fishing Workers" (SOC code 45-3011). The first two OES occupations were recoded to SOC 25-3099, "Teachers and instructors, all other," but kept their original OES titles and values. The third occupation was recoded to SOC 45-3000, "Fishing and Hunting Workers," also keeping its original OES title and values. This occupation lacks EPP education, experience and training data; values of "No formal educational credential," "None" and "Moderate-term on-the-job-training," respectively, were imputed manually.

<sup>&</sup>lt;sup>12</sup> The crosswalk employed to link OES and O\*NET data is the "O\*NET-SOC 2010 occupations to 2010 SOC occupations crosswalk" available online at https://www.onetcenter.org/crosswalks.html

code 17-3), the imputed values are averages of the O\*NET values of three non-generic detailed occupations in the minor group, namely "Architectural and Civil Drafters," "Electrical and Electronics Drafters," and "Mechanical Drafters."

The last important procedure in the final dataset was the re-normalization of O\*NET-based scores and indexes (other indexes besides the final weighted KSTE index were included for analytical purposes). Even though the scores and indexes were normalized in the O\*NET dataset to better evaluate the selection of scores and alternative indexes, that normalization is lost in the translation of O\*NET occupational codes into OES occupational codes and needs to be recalculated. The new normalization follows the same procedure employed in the O\*NET dataset, dividing the occupational score by the *simple* average of each score. The decision to use a simple instead of a weighted average as the reference measure rests on the premise that normalized measures are meant to capture attributes of occupations, in and of themselves, irrespective of the distribution of employment across them.

#### 6. Skilled Non-College Occupations: Definition and Main Empirical Findings

This section presents the main empirical findings of the study, starting with the most general empirical results stemming from the new definition of Skilled Non-College Occupations (SNCOs), and then following with a selection of findings from a general exploratory analysis focused on occupations, economic sectors, educational attainment, and the relationship between wages and the new KSTE score.

#### 6.1. New Empirical Definition of Skilled Non-College Occupations

The proposed definition of SNCOs is based on a *relative* measure of skills. An occupation is said to be "skilled" if its KSTE score is above a definite threshold, with the expression "skilled" being a shorthand for "relatively more skilled." Occupations with KSTE values below the threshold, however, cannot be said to be "unskilled," since all jobs require skills, irrespective of how they are approached empirically, and should be considered "relatively less skilled" occupations, always in terms of their KSTE values, of course. Figures 1 and 2 below illustrate the selection of a skilled group based on a specific threshold. Figure 1 shows the unweighted density estimates of the KSTE index for all occupations and the dotted line plots the threshold above which the occupations are said to be "skilled." The threshold here is the mean KSTE score, which equals 1.00 in the normalized KSTE score. Figure 2 shows the resulting density estimate of the group of relatively more skilled occupations, displaying a much more skewed distribution of KSTE values, as expected.



Source: own calculations based on OES, O\*NET, and EPP data.

The "non-college" component also deserves explanation. "Non-college" refers here to the levels of educational attainment that are below a 4-year college degree, following a wellestablished convention in labor economics (see, for instance, Abel & Deitz, 2016). A clear shortcoming of this convention is that it leaves out levels of college educational attainment below the 4-year college degree, like some college-no degree and associate's degree in the OES categories of educational attainment. However, the main objective here is to analytically separate two broad labor market categories: college vs. non-college, meaning markets that do or do not require 4-year college degrees. Each of these categories involve significantly different labor market characteristics like wages, employment growth, and unemployment rate. *In terms of these labor market categories*, occupations that require some college but no degree or require only an associate's degree, have much more in common with occupations that do not require any college than they do with occupations requiring a bachelor's degree or more. Again, the term "non-college" is an analytically convenient shorthand for "less than a bachelor's degree" and does not imply that some subbaccalaureate categories cannot be regarded as "college" categories in other contexts.

The only element that remains for a definition of SNCOs is the KSTE score above which an occupation can be said to relatively skilled. I set his threshold at the average KSTE score for all occupations, based on (a) the fact that the mean and median KSTE values for all occupations is virtually identical; and (b) the notion than a simple above-average criterion is preferable in terms of simplicity and clarity over a criterion based on a multiple of the average, like in Rothwell (2015). Thus, a SNCO is defined more precisely as an occupation that meets the following two criteria:

- 1. its KSTE score is above the average KSTE score (this is the "skilled" component); and
- 2. it typically requires less than a bachelor's degree for entry (this is the "non-college" component).

Figure 3 plots the unweighted density estimates of the KSTE index for non-college occupations. The density of the "skilled" occupations is represented by the area to the right of the vertical line, at the average KSTE value for all occupations, which equals 1.00 by construction. Figure 4 shows the density estimate of the KSTE index for SNCOs, depicting the expected

skewed distribution, with a relatively high concentration of values in the 1.00–1.25 range. This concentration of values toward the lower end of the distribution is higher in SNCOs relative to skilled college occupations, as shown in Figure 5, below, which plots the overlay density estimates of the KSTE index for SNCOs and skilled college occupations.



Source: own calculations based on OES, O\*NET, and EPP data.

In 2016, the U.S. had about 22.7 million jobs in SNCOs, accounting for 16.2% of all the jobs reported by OES. SNCOs are represented by 179 out of 819 detailed occupations. Table A1 in the appendix lists all the SNCOs and their corresponding KSTE values.





Source: own calculations based on OES, O\*NET, and EPP data.

A comparison between SNCOs and skilled college occupations offers an opportunity to assess the relative importance of skilled jobs in each group of occupations. In 2016, jobs in SNCOs accounted for 21% of all jobs in non-college occupations, which means that about only *one in five jobs in non-college occupations belongs to a skilled occupation*, always according to the new definition. In contrast, jobs in *skilled college occupations* (i.e., those with above-average KSTE and that typically require a bachelor's degree or more for entry) accounted for 80% of all jobs in college occupations. This means that *four in five jobs in college occupations belong to relatively skilled occupations*. Not surprisingly, these findings suggest that the chances of an individual without a bachelor's degree to get a job in a relatively skilled occupation are *much lower* than the chances of an individual with a bachelor's degree or more to get a job in a

relatively skilled occupation. However, the lower chances of the individual without a bachelor's are worsened by the fact that a significant proportion of jobs in SNCOs are held by individuals with bachelor's degree or more. The next section presents other important findings from a general exploratory analysis of SNCOs.

#### **6.2. Exploratory Analysis**

The following subsections offer a detailed description of SNCOs across occupations, economic sectors, and different levels of educational attainment, and they explore the relationship between wages and the KSTE index.

**6.2.1. Major occupations.** This subsection explores SNCOs across major occupations, the most aggregated group of occupations provided by the Standard Occupational Classification system. Out of 20 available major occupations with detailed SNCOs, the top 10 largest major occupations account for 92.1% of all employment in SNCOs, with the top five major occupations alone accounting for 70.0% of all employment in SNCOs. I will only focus here on the top five largest major occupations. The single largest major occupation is Installation, Maintenance, and Repair, with 21.0% of all SNCOs employment, a relatively high mean KSTE score of 1.21 (68<sup>th</sup> percentile in detailed SNCOs), and a relatively low mean hourly wage of \$23.10 (28<sup>th</sup> percentile in detailed SNCOs). This major occupation is in turn led by the detailed occupation Maintenance and Repair Workers, General, accounting for 27.9% of total employment in the major occupation. Table A2 in the appendix lists the detailed occupations that account for roughly 80% of the total SNCO employment in each major occupation.

The second largest major occupation is Healthcare Practitioners and Technical, with nearly 15.8% of total employment, a mean KSTE score of 1.13 (43<sup>rd</sup> percentile in detailed SNCOs), and a very high mean hourly wage of \$32.40 (78<sup>th</sup> percentile in detailed SNCOs), surpassed only by Management (not shown in Figure 6), with a mean hourly wage of \$33.90. This major occupational group is decisively shaped by the detailed occupation Registered Nurses, the single largest detailed occupation across all major occupational groups. With 2.86 million members in 2016, Registered Nurses represents 12.6% of all SNCO employment and nearly 80% of the total employment in the Healthcare Practitioners and Technical. The defining importance of the Registered Nurses occupation in terms of employment is observed in the virtual coincidence of the mean KSTE score of the major occupation, pulled by the relatively high wage of Registered Nurses (\$34.70).

Major Occupation	Employment Share	Mean KSTE	Mean Hourly Wage
Installation, Maintenance, and Repair	21.0	1.21	23.1
Healthcare Practitioners and Technical	15.8	1.13	32.4
Construction and Extraction	14.4	1.31	26.1
Sales and Related	10.7	1.06	27.1
Production	8.0	1.18	25.1
Office and Administrative Support	6.7	1.13	27.4
Protective Service	6.0	1.20	30.3
Computer and Mathematical	4.1	1.08	28.3
Architecture and Engineering	2.8	1.18	28.1
Transportation and Material Moving	2.6	1.15	29.5

#### Figure 6. Top 10 Largest Major Occupations

Source: own calculations based on OES, O\*NET and EPP data. Employment share in %. Mean hourly wage in 2016\$.

The third largest major occupation is Construction and Extraction, with 14.4% of all SNCO employment, the highest KSTE score across all available major occupations, with a level of 1.31 (85<sup>th</sup> percentile in detailed SNCOs), and a mean hourly wage of \$26.10 (45<sup>th</sup> percentile in detailed SNCOs). In terms of employment, the detailed occupations of Carpenters and Electricians lead this major group, with 20.7% and 18.6% of total employment in Construction and Extraction, respectively. These detailed occupations are followed by First-Line Supervisors of Construction and Extraction Workers (16.4% of the major group's total employment), and Plumbers, Pipefitters, and Steamfitters (12.6%), with the four largest occupations accounting for nearly 68% of the major occupation's total employment.

The fourth largest major occupation is Sales and Related, with 10.7% of all SNCO employment, one of the lowest KSTE scores (1.06, 22<sup>nd</sup> percentile in SNCOs) in all available major occupations, on par with Community and Social Service (1.03), and a mean hourly wage of \$27.10 (49<sup>th</sup> percentile in SNCOs). Of the four detailed occupations in this major group, two of them represent 88% of the major occupation's total employment. The largest detailed occupation in this group is First-Line Supervisors of Retail Sales Workers, accounting for 48.9% of the group's total employment. The second largest detailed occupation is the generic Sales Representative, Services, All Other, with 39.1% of the group's total employment.

Last, the fifth largest major occupation is Production, with 8.0% of all SNCO employment, an average mean KSTE value of 1.18 (61<sup>st</sup> percentile in SNCOs), and a mean hourly wage of \$25.10 (40<sup>th</sup> percentile in SNCOs). Employment in the group is highly concentrated in the two largest detailed occupations, First-Line Supervisors of Production, and Operating Workers and Machinists, which represent 33.7% and 21.6% of the major occupation's total employment, respectively, thus accounting jointly for nearly 55% of Production's total employment. The remaining detailed occupations in the group are much smaller in size, including occupations like Computer-Controlled Machine Tool Operators, Metal and Plastic (8.1% of the major occupation's total employment), Water and Wastewater Treatment Plant and System Operators (6.4%), and Chemical Equipment Operators and Tenders (4.1%).

**6.2.2. Sectors.** This subsection explores SNCOs across sectors defined by the North American Industry Classification System (NAICS), the most aggregated level of industrial classification the system provides. Of the 20 sectors that include detailed SNCOs, the 10 largest encompass 82% of all SNCO employment, with the top five sectors alone accounting for 62.4%. As in the previous subsection, I concentrate here on the top five largest sectors. The largest sector is Health Care and Social Assistance, with 16.1% of all employment in SNCOs, a KSTE score of 1.13 (43rd percentile in detailed SNCOs), and a mean hourly wage of \$31.50 (75th percentile in detailed SNCOs), the second highest mean hourly wage across sectors after Utilities (\$35). Employment in this sector is highly concentrated in a single NAICS industry ("industry," hereafter), General Medical and Surgical Hospitals, with 57.2% of the sector's SNCO employment. Table A3 in the appendix lists the industries, ordered from top to bottom in terms of employment, whose accumulated employment accounts for roughly 80% of the corresponding sector's employment. Not surprisingly, the detailed occupation Registered Nurses represents nearly 70% of the employment in Health Care and Social Assistance. Table A4 in the appendix shows the detailed occupations, ordered from top to bottom in terms of employment, whose accumulated employment accounts for roughly 80% of the corresponding sector's employment.

The second largest sector is Construction, with 14.1% of all SNCO employment, a relatively high KSTE value of 1.30 (84<sup>th</sup> percentile in detailed SNCOs), and a mean hourly wage of \$25.70 (44<sup>th</sup> percentile in detailed SNCOs). Employment in this sector is highly concentrated in a single industry, Building Equipment Contractors, representing more than 42% of the sector's all-SNCO employment. Other sizable industries in this sector include Building Finishing Contractors (13.7% of all SNCO employment in the sector), Foundation, Structure, and Building Exterior Contractors (11.3%), and Residential Building Construction (10.8%). The detailed SNCOs in the Construction sectors are not highly concentrated in terms of employment, with Carpenters and Electricians accounting for 17.9% and 14.5% of the sector's all SNCO employment, respectively, followed by First-Line Supervisors of Construction and Extraction Workers (12.9%) and Plumbers, Pipefitters, and Steamfitters (10.6%).

The third largest sector is Federal, State, and Local Government, excluding schools and hospitals, with 11.6% of all SNCO employment, a KSTE score of 1.20 (65<sup>th</sup> percentile in detailed SNCOs), and a fairly high mean hourly wage of \$29.50 (65<sup>th</sup> percentile in detailed SNCOs). Industries in this sector only distinguish among the local, state, and federal levels of government. Local Government is by far the largest public employer, with nearly 70% of all SNCO employment in the public sector, followed by the Federal Executive Branch (16.8%) and State Government (13.2%). Employment across detailed SNCOs in the public sector is moderately concentrated in Police and Sheriff's Patrol Officers, with 24.1% of the sector's SNCO employment, and Firefighters, with 11.4%.

Sector	Employment Share	Mean KSTE	Mean Hourly Wage
Health Care and Social Assistance	16.1	1.13	31.5
Construction	14.1	1.30	25.7
Federal, State, and Local Government*	11.6	1.20	29.5
Manufacturing	11.1	1.18	25.2
Retail Trade	9.4	1.10	21.4
Professional, Scientific, and Technical Serv.	4.8	1.13	29.7
Administrative and Support	4.5	1.14	24.6
Wholesale Trade	3.5	1.17	27.5
Transportation and Warehousing	3.4	1.19	29.6
Other Services**	3.2	1.17	22.4

#### Figure 7. Top 10 Largest NAICS Sectors

\*Excluding state and local schools and hospitals. \*\*Except Public Administration. Source: own calculations based on OES, O\*NET, and EPP data. Employment share in %. Mean hourly wage in 2016\$.

The fourth largest sector is Manufacturing, with 11.1% of all SNCO employment, a KSTE score of 1.18 (61<sup>st</sup> percentile in detailed SNCOs), and a mean hourly wage of \$25.20 (40<sup>th</sup> percentile in detailed SNCOs). Employment is highly distributed across industries in Manufacturing, due in part to the more detailed disaggregation of this sector (no other sector has as many industries as the Manufacturing sector). The low concentration of employment by industry in Manufacturing is illustrated by fact that the top five industries in terms of employment, listed in Table A3 in the appendix, concentrate a quarter of all SNCO employment in Manufacturing(compared, for instance, to 83% in Health Care and Social Assistance, 87% in Construction, and 53% in Retail Trade). SNCO employment by detailed occupation is moderately concentrated, with the top five largest occupations accounting for 51% of the sector's all SNCO employment. This group of occupations is led by First-Line Supervisors of Production and Operating Workers (17.8%) and Machinists (12.8%).

Last, the fifth largest sector is Retail Trade, with 9.4% of all SNCO employment, a relatively low KSTE score of 1.10 (37<sup>th</sup> percentile in detailed SNCOs), and a relatively low mean hourly wage of \$21.40 (24<sup>th</sup> percentile in detailed SNCOs). Industries in this sector are somewhat concentrated, with the top five industries (see Table A3 in the appendix) accounting for 53% of the sector's all SNCO employment. This group of industries is led by Automobile Dealers (16.6%), Other General Merchandise Stores (12%), and Grocery Stores (10.6%). Employment across detailed occupations is highly concentrated in this sector, with only four detailed occupations (see Table A4 in the appendix) representing around 80% of the sector's SNCO employment. The single largest occupation, First-Line Supervisor of Retail Sales Workers, accounts for a little more than half of the sector's total SNCO employment.

**6.2.3. Educational attainment.** This section discusses and compares the employment shares across two definitions of educational attainment. In one definition, the one employed so far in this study, educational attainment is seen as a typical requirement for entry into an occupation. In the second definition, educational attainment refers to the estimated educational attainment of workers. An occupation can be said to typically require a certain level of education, but the

educational attainment of individual workers can differ from that average or typical level of required education.

Let us first concentrate on the educational attainment typically required for entry (Figure 8). A high school diploma or equivalent is by far the most frequent educational level typically required for entry in SNCOs, with the total employment of detailed SNCOs that typically require a high school diploma or equivalent representing almost *two-thirds* of all SNCO employment. Top detailed occupations in this category include First-Line Supervisors of Office and Administrative Support Workers (9.7% of all employment in SNCOs requiring high school for entry), Maintenance and Repair Workers, General (9.0%), First-Line Supervisors of Retail Sales Workers (8%), Sales Representatives, Services, All Other (6.4%), and Carpenters (4.6%).

The second most frequent level of educational attainment typically required for entry is the associate's degree, represented in nearly a *fifth* of all SNCO employment. Not surprisingly, this category is dominated by Registered Nurses, with nearly 65% of all employment in SNCOs typically requiring an associate's degree for entry. The effect of the decision to downgrade the EPP educational requirement from bachelor's to associate's degree is significant in terms of SNCO employment: It increases the employment size of this category by 185%, from 1.5 million to 4.4 million workers. Other large occupations in this category include Computer Network Support Specialists (4.3%), Electrical and Electronics Engineering Technicians (3.1%), Web Developers (2.9%), Respiratory Therapists (2.9%), and Architectural and Civil Drafters (2.2.%).

A third important category of required education is postsecondary nondegree award, with nearly 2.2 million workers or 9.6% of all SNCO employment. The employment level is particularly relevant in this case, since this category would have been the second largest category after high school had I not decided to include Registered Nurses under the associate's degree. Postsecondary nondegree awards are certificates or other awards, but not degrees, awarded by educational institutions after students complete formal postsecondary schooling. They do not include certification issued by a professional organization or certifying body. SNCO employment in this educational category is highly concentrated in five out of 20 detailed occupations, namely Automotive Service Technicians and Mechanics (29.7% of all SNCO employment in the postsecondary nondegree award category), Firefighters (14.5%), Heating, Air Conditioning, and Refrigeration Mechanics and Installers (13.5%), Emergency Medical Technicians and Paramedics (11.2%), and Telecommunications Equipment Installers and Repairers, Except Line Installers (10.5%).

The remaining categories of typically required education for entry are less than high school and some college, no degree, with 2.9% and 2.7% of all SNCO employment, respectively. Employment in this category is highly concentrated in few eminently physical or manual skilled occupations: Painters, Construction, and Maintenance (33.3% of all employment in SNCOs typically requiring less than a high school degree for entry), Roofers (17.8%), Drywall and Ceiling Tile Installers (14.3%), and Service Unit Operators, Oil, Gas, and Mining (6.6%). The concentration of employment is extreme in the case of some college, no degree, where a single occupation, Computer User Support Specialists, concentrates more than 99% of all employment in SNCOs typically requiring some college, no degree.



### Figure 9. Estimated Educational Attainment of Workers in SNCOs



LHS: Less than high school; PNA: postsecondary nondegree award (only in Figure 8); SC: some college, no degree; AD: associate's degree; BD: bachelor's degree; MD: master's degree. The estimates of educational attainment of workers result from applying the 2014 and 2015 American Community Survey employment shares by educational attainment for workers 25 years and older to the OES employment levels.

Source: own calculations based on OES, O\*NET, and EPP data.

Let us now focus on the estimated educational attainment of workers in SNCOs (Figure 9). High school is barely the single largest category, with an estimate of 26% of all SNCO employment, followed closely by some college, with 24.5% of all SNCO employment, and by bachelor's degree, with 21.4%. Employment in the high school category is not highly concentrated, with the largest 10 detailed occupations accounting for an estimate of roughly 48% of all SNCO employment of workers that report a high school diploma or equivalent as their maximum level of educational attainment. This relatively low concentration of employment, compared with the typically required education I just discussed, is observed in some categories of workers' educational attainment, where each detailed occupation encompasses more than one education category (e.g., the detailed occupation Maintenance and Repair Workers, General reports 40.5% of its employment in the high school category, 27.1% in some college, 14.0% in less than high school, 10.5% in associate degree, and 1% in bachelor's degree). The largest detailed occupations in the high school category include Maintenance and Repair Workers, General (9.1% of SNCO employment in the category), First-Line Supervisors of Retail Sales Workers (5.9%), First-Line Supervisors of Office and Administrative Support Workers (5.4%), Automotive Service Technicians and Mechanics (4.9%), and Carpenters (4.8%).

The second largest category, formed by workers with some college but no degree, shows a somewhat more even distribution of employment than the high school category (the 10 largest occupations represent 43% of all SNCO employment) and share with the high school category many of the occupations at the top of the employment hierarchy. The largest three detailed occupations, for instance, include the same largest occupations than in the high school category, but in different order. Prominent occupations in this category include Sales Representatives, Services, All Other and Police and Sheriff's Patrol Officers, each representing about 4% of all SNCO employment in the category, and Computer User Support Specialists and Registered Nurses, each with roughly 3%.

The bachelor's degree and associate's degree categories are both defined by the salient role of the Registered Nurses occupation. In each of these categories, Registered Nurses represent nearly 30% of all the SNCO employment in each category. A closer look at the employment levels reveals that the estimated number of Registered Nurses holding bachelor's degrees (1.37 million workers) is much larger than the estimated number of Registered Nurses with associate's degrees (nearly 968,600 workers). This difference of more than 40% between the two employment levels has two implications. The first is methodological: the different employment levels supports, in principle, the Bureau of Labor Statistics decision to adjudicate a bachelor's degree as the typically required education for entry into the Registered Nurses occupation. However, my methodological decision was based, again, on the fact that almost all states in the U.S. still require an associate's degree for licensing. This decision was deliberately inclusive and may be revised in the near future, since the typical education required for entry into the Registered Nurses occupation may be in a process of transitional upgrading.

The second implication is that the sheer volume of Registered Nurses with bachelor's degrees significantly increases the proportion of workers with bachelor's degree in SNCOs. This proportion increases from 17.6% of all SNCO employment when the Registered Nurses occupation is excluded when the Registered Nurses occupation is included. This measurement is critical in this study, because the presence of workers with educational credentials above an associate's degree may indicate overqualification or underemployment of college graduates. The Registered Nurses occupation does not offer a good example to explore the possibility of overqualification, due to the methodological issues discussed above. The occupation with the second largest number of workers with bachelor's degrees, Sales Representatives, Services, All Other, with 8.3% of all SNCO employment of workers with bachelor's degrees, offers a better case to illustrate overqualification. According to the EPP, the Sales Representatives, Services, All Other occupation typically requires a high school diploma or equivalent. The distribution of educational attainment of workers in this occupation, however, indicates that 24.2% of workers have high school diplomas as their maximum level of educational attainment, while 42.4% hold bachelor's degrees. Overall, nearly 60% of services sales representatives are educated above the level typically required for entry. This fact alone suggests the presence of a significant share of overqualified workers in this occupation. Other SNCOs with large proportions of workers with bachelor's degrees across all SNCOs also show sizable shares of workers with bachelor's degrees or more within themselves, like First-Line Supervisors of Office and Administrative Support Workers (7.7% of all SNCO employment of workers with bachelor's degrees), with an estimate of more than 46% of its workers holding bachelor's degrees or more, or First-Line Supervisors of Retail Sales Workers (5.3% of all SNCO employment of workers with a bachelor's degree), with an estimate of 36% of its workers with at least a bachelor's degree. Again, these relatively high shares of workers with 4-year university degrees working in occupations that typically do not require that much formal education suggests the presence of overqualified individuals. A rigorous evaluation of the overqualification thesis is beyond the scope of this paper and deserves separate study.

**6.2.4. Detailed SNCOs: Wages and KSTE Scores.** This subsection briefly describes some central facts related to the wages of SNCOs and the relationship between wages and KSTE scores in SNCOs. Let us concentrate first on the distribution of wages. A comparison of the distribution of mean hourly wages in SNCOs versus the distribution of mean hourly wages of all detailed occupations, non-college occupations, and skilled occupations (see Figures 10, 11, and 12) clearly shows that the distribution of mean hourly wages in SNCOs is more symmetrical or less skewed than the distributions of mean hourly wages in the comparison occupational groups. This simply means that the distribution of mean hourly wages of all detailed occupations, non-college occupations, or skilled occupations.

A comparison of the ranges of mean hourly wages where the distributions are denser provides important information to assess the shape and range of the distribution of mean hourly wages of SNCOs versus different occupational groups. As is directly observable in Figure 10, the much more compact distribution of mean hourly wages in SNCOs is denser between the low \$20s and the mid \$30s, in 2016 dollars, whereas the more frequent values for all occupations is significantly below that range. The location and shape of the distribution of wages of SNCOs suggests a higher average wage for SNCOs compared to the average wage for all occupations. In effect, the weighted average of the mean hourly wages of SNCOs is \$27.20, 14% higher than the weighted average of the mean hourly wages for all occupations, which stands at \$23.90.





Source: own calculations based on OES, O\*NET, and EPP data.

Comparisons with the skilled and non-college groups of occupations offer an additional analytical advantage. In the case of a comparison between the wage distributions of SNCOs and all non-college occupations, the exercise shows the effect of the "skilled" component on the shape and range of the distribution of occupational wages. As shown in Figure 11, the more frequent mean hourly wages in SNCOs are higher than the more frequent mean hourly wages in non-college occupations. In effect, the weighted average of the mean hourly wages of SNCOs is \$27, 50% higher than the weighted average of the mean hourly wages of non-college occupations of \$18. Put simply, the relatively more egalitarian or compact distribution of wages

in SNCOs has a higher average wage vis-a-vis the average wage of the relatively more unequal distribution of wages in non-college occupations.



Source: own calculations based on OES, O\*NET and EPP data.

Like in the previous comparison with non-college occupations, the comparison between the wage distributions of SNCOs and all skilled occupations shows the impact of the "non-college" component on the shape and range of the distribution of occupational wages. The visual comparison is also quite clear in this case. Even though the more frequent values of mean hourly wages between both distributions overlap, as shown in Figure 12, the significant mass of employment with wages above the mid \$30s in skilled occupations easily pulls, as it were, the average occupational wage in this group above the corresponding average occupational wage in SNCOs. In effect, the weighted average of the mean hourly wages of skilled occupations is \$37, almost 40% higher than the same measure of wages in SNCOs. Thus, the relatively more dispersed or unequal distribution of occupational wages in skilled occupations commands a higher average wage in comparison with the average wage of the more egalitarian distribution of wages in SNCOs.

An important observation on the range of wages in SNCOs is the share of employment in occupations with median occupational hourly wages below the overall median occupational hourly wage. This measure provides a general approximation to the overall quality of the jobs in this occupational group in terms of occupational wages. In 2016, the employment of occupations with a median hourly wage below the overall median hourly wage of \$17.80 represented 8.6% of all SNCO employment. Exactly 80% of the employment in this subset of SNCOs is concentrated in two occupations: Maintenance and Repair Workers, General, with an employment share of 68% and a median hourly wage just below the overall median hourly wage, and Emergency Medical Technicians and Paramedics, with an employment share of 12% and a median hourly wage is higher than the corresponding employment share of skilled occupations, at 4.6%, but is significantly lower than the same employment share in non-college occupations, which stands at an impressive 66.5%.

It follows, then, that the likelihood of an occupation reporting a median hourly wage below the overall median hourly wage increases (decreases) dramatically if the occupation is a noncollege (skilled) occupation. This rule is patently illustrated in the case of skilled occupations (which, it is worth remembering, include both college and non-college occupations), where 86% of the employment of skilled occupations with median hourly wages below the overall median hourly wage are non-college occupations. Thus, the relatively low employment share of SNCOs with median wages below the overall median wage shows how the above average KSTE scores weed out most low paying non-college occupations, exposing the unsurprising positive relationship between occupational hourly wages and the KSTE scores.

The relationship between occupational hourly wages and the KSTE scores is effectively positive, but the contrast between a highly skewed distribution of the KSTE index for SNCOs (Figure 4) and a much more symmetrical distribution of the mean hourly wages of SNCOs (Figure 10) already suggests a relatively low correlation between both variables. Figure 13 plots the relationship between mean hourly wages and the KSTE index for SNCOs, with the size of the bubbles being proportional to the occupation's employment level, also suggests a positive but not highly strong correlation between both variables. A Kendall rank correlation coefficient of 0.2 confirms this relatively low correlation, challenging, in principle, widely held views based on the human capital approach, which equates more knowledge, skills, training and/or experience with proportionally higher hourly wages. It can admittedly be argued that a simple correlation cannot address the relationship between wages and a proxy of skills when the phenomenon of wage determination is affected by important variables like age, gender, race, educational attainment, industry, geography, and union membership status.<sup>13</sup> A short answer to this potential criticism is that occupational wages and the KSTE scores are summary measures that already include, as it were, the effects of important "independent" variables like age, gender, race, education, etc. The mean or median hourly wages of any detailed occupation are in theory summary measures determined by the weighted intervention of different hourly wages by those important "independent" variables. In practice, this relationship is limited by data quality, which is high in the case of the OES dataset. Applying the same logic to the KSTE index, we can conclude that a relatively low correlation between occupational wages and KSTE scores suggests an effectively low correlation among both variables, mediated by the effects of important variables like age, gender, race, industry, etc. In general, simple averages are more complex than commonly assumed.

Figure 13 helps illuminate the nature of the general relationship between wages and the KSTE scores by showing all SNCOs (except for two very small ones with KSTE scores above 1.8 in order to improve the graphical representation of the SNCOs). The 10 largest SNCOS are highlighted and identified. The combined employment of these 10, or nearly 6% of all SNCOs, represents 48.3% of all SNCO employment. The largest 10 occupations show a wide dispersion of median hourly wages from \$17.80 for Maintenance and Repair Workers, General, and \$32.90 for Registered Nurses, concentrated mostly within a relatively narrow range of the KSTE index, from the 1.03 of Sales Representatives, Services, All Other, to the 1.13 of First-Line Supervisors of Office and Administrative Support Workers, and Registered Nurses. This high concentration

<sup>&</sup>lt;sup>13</sup> Other important processes affecting the determination of wages are the balance between the supply of and demand for labor at the occupational level (i.e., a shortage or excess of workers in a specific occupation) and practices of "social closure" in some occupations, especially professional. Variables attempting to capture these phenomena are not readily available in public datasets and are not typically included in studies of wage determination.

of occupational employment in a relatively narrow range of the KSTE values is also observed across all SNCOs, with 80% of all SNCO employment concentrated in occupations with a KSTE score below 1.2.



Figure 13. Median Hourly Wages and KSTE Scores across SNCOs

Source: own calculations based on OES, O\*NET, and EPP data. FLS is First-Line Supervisors.

The largest 10 SNCOs include a rich variety of occupations, without the predominance of manufacturing or technical occupations typically associated with middle-skill jobs. A comparison of two occupations in this group illustrates the varied nature of the SNCOs. Registered Nurses is by far the largest occupation, with 12.6% of all SNCO employment, a very high median hourly wage of \$32.90 (73rd percentile) and a KSET measure of 1.13 (45th percentile). Electricians is the 10th largest occupation, with 2.7% of all SNCO employment, a median hourly wage of \$25.40 (35<sup>th</sup> percentile), and a very high KSTE value of 1.52 (96<sup>th</sup> percentile). Some of the differences between both occupations conform to a stereotype of the differences between occupations in the service sector, especially in rapidly expanding and polarized "care work" (Dwyer, 2013), and those in the production or industrial sector. The female-dominated Registered Nurses occupation is highly dynamic in terms of employment growth, with an average annual growth rate of 1.7% in 2006-2016. The male-dominated Electricians occupation is highly cyclical in terms of employment and has still not reached the prerecession employment level of 2008, showing an average annual growth rate of 0.1% in 2006-2016. Electricians earn, on average, a median hourly wage that is 23% lower than the median hourly wage of Registered Nurses, but they are required to have much more on-the-job and onsite training and more work experience than Registered Nurses (T scores of 3.49 and 0.46, respectively; and E scores of 1.94 and 0.9, respectively). This requirement is essentially why the KSTE score of Electricians is much higher than the KSTE measure of Registered Nurses, since

the KS measure of Registered Nurses is somewhat higher than the KS value for Electricians (1.25 vs. 1.17).



Source: own calculations based on OES, O\*NET, and EPP data.

The variation of median hourly wages and KSTE scores across SNCOs can be further explored in Figure 14, which plots the five largest occupations in each quartile of median hourly wages. The employment in these 20 occupations represents 67% of all SNCO employment. Again, the relatively high concentration of employment across SNCOs justifies the analytical focus on a relatively small number of big occupations. Even though a detailed discussion of Figure 14 will not be pursued in this paper, suffice it to say that this exercise only amplifies the level of detail of the mix of occupations by median hourly wages and KSTE index. More specifically, Figure 14 allows for a quick characterization of the different wage quartiles in terms of their dominant or largest occupations. For instance, the fourth quartile is dominated by Registered Nurses, with a little more than 50% of the combined SNCO employment in the quartile, and by three first-line supervisor occupations, with a combined employment that represents 22% of the quartile's SNCO employment. The mixes of dominant occupations in the remaining quartiles should be self-evident in Figure 14's employment shares of each occupation in the quartile's SNCO employment (between parentheses, in percentages).

#### 7. Summary and Conclusions

This paper has presented a new methodological approach to identify occupations in the U.S. that require medium to relatively high skills but that do not typically require a bachelor's degree for entry. I call this group of occupations Skilled Non-College Occupations (SNCOs). Existing approaches to empirically isolate this group of occupations, commonly known as "middle-skill" occupations, offer different methods that in some cases lead to significantly different estimates of middle-skill occupations. Following the spirit of Rothwell (2015), the new approach relies heavily on a new skills index based on the knowledge, skills, training, and work experience required to perform a job at the detailed occupational level, using O\*NET data. Thus, the new method provides a rigorous definition of SNCOs to improve the measurement of skills through a new composite index of skills based on O\*NET data.

In contrast to studies that estimate that the employment of so-called middle-skill occupations in the U.S. represent one third to nearly half of total employment, this study estimates that the combined employment of SNCOs accounted for 16.2% of all jobs in 2016. A general exploratory analysis in Section 6 yields six important findings:

- 1. In non-college occupations (i.e., those typically requiring less than a bachelor's degree), *one in five jobs* belongs to a relatively skilled occupation. In contrast, for college occupations (i.e., those typically requiring a bachelor's degree or more), *four in five jobs* belong to a relatively skilled occupation. This extremely large difference in the likelihood of getting into a relatively skilled occupation with or without a bachelor's degree should be a warning sign for advocates of career paths associated with middle-skill jobs.
- 2. The exploratory analysis across occupations and industries reveals a composition of SNCOs that defies stereotypes of middle-skill jobs. Skilled care workers and technicians in the health care sector and skilled production workers in manufacturing are part of the group, as expected. Other occupations like first-line supervisors of administrative support workers, police officers, and sales representatives in the service sector add new layers of complexity to the notion of middle-skill jobs.
- 3. Employment in SNCOs is concentrated in a relatively small number of detailed occupations, led in size by Registered Nurses. For instance, nearly half of all jobs in SNCOs is concentrated in the top 10 detailed SNCOs, out of 179 detailed SNCOs. This high concentration of employment across occupations, which is also observable across industries, suggests that studies that focus on specific occupations, possibly also within

specific industries, may shed more light on the nature and dynamics of SNCOs and the different educational and career paths associated with them.

- 4. The correlation between median occupational wages and the KSTE scores is quite low, challenging in principle the central tenets of human capital theory, where "learning," represented in this case by the average knowledge, skills, training, and work experience required in each detailed occupation, is supposed to keep pace with "earnings" (Brown, Cheung, & Lauder, 2015, p. 213). The relationship between skills and wages needs to be explored further in studies that incorporate the KSTE index or similar skills indexes in conventional multivariate analysis of wage determination.
- 5. The SNCO wage distribution is much more symmetrical and more compact or egalitarian than the wage distributions of all occupations, skilled occupations, and non-college occupations. Mean hourly wages of SNCOs are more frequent between the low \$20s and the mid \$30s, or between a lower bound that stands somewhat below and an upper bound that stands well above the overall mean hourly wage of \$24 in 2016. The distribution of KSTE values across SNCOs is much more skewed than the wage distribution, with most values concentrated toward the lower end of the distribution. The observed low correlation between occupational wages and the KSTE scores is then explained by the important differences in the shapes of their distributions.
- 6. There is a clear mismatch between the aggregated levels of educational attainment typically required by SNCOs and the aggregated levels of educational attainment of workers in SNCOs. While more than *two-thirds* of jobs require a high-school degree or less, an estimate of *two-thirds* of the workers in SNCOs report levels of educational attainment above a high school diploma. The aggregated excess of education effectively attained by workers relative to the education occupations require suggests that a significant proportion of workers in SNCOs are *overqualified* or *underemployed* in terms of educational attainment. This result is consistent with findings in recent research on the relationships among education, skills, and employment in the U.S. (see Abel & Deitz, 2016; Beaudry, Green, & Sand, 2015; Cappelli, 2015; Fogg & Harrington, 2011).

Summing up, SNCOs in the U.S. represent a much smaller mass of employment compared to existing definitions of middle-skills jobs. More specifically, SNCOs (a) represent only one in five jobs that do not require a 4-year college degree for entry; (b) encompass a wide variety of occupations and industries, even though the jobs are highly concentrated in a relatively small number of occupations and industries; (c) usually pay above-average wages; (d) show a quite low correlation between wages and skills; and (e) include a significant proportion of workers who are potentially underemployed in terms of educational attainment.

This paper leaves some important questions unaddressed. These questions refer to the demographics of workers in SNCOs, the dynamics of SNCOs over time, and the variation in the dynamics and composition of SNCOs across subnational geographic areas. What is the composition of SNCOs in terms of age, sex, race, and ethnicity, and how has it changed over time? Have SNCOs expanded or contracted over the last decades, especially since the Great Recession? Are SNCOs expected to expand or contract in official employment projections? In

terms of employment, which SNCOs have expanded or contracted, and which ones are projected to grow or decline? Do the relative size and composition of SNCOs vary significantly across states and metropolitan areas? Answers to these important questions, based on the method proposed in this paper, should offer a more accurate understanding of the nature and dynamics of SNCOs in the U.S.

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### Appendix

### Table A1. Skilled Non-College Occupations and Associated KSTE Scores

Code	Title	KSTE
33-2022	Forest Fire Inspectors and Prevention Specialists	2.18
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	1.90
47-4021	Elevator Installers and Repairers	1.78
49-1011	First-Line Supervisors of Mechanics, Installers, and Repairers	1.75
33-1021	First-Line Supervisors of Fire Fighting and Prevention Workers	1.71
53-5031	Ship Engineers	1.53
19-4091	Environmental Science and Protection Technicians, Including Health	1.52
47-2111	Electricians	1.52
17-3021	Aerospace Engineering and Operations Technicians	1.51
47-1011	First-Line Supervisors of Construction Trades and Extraction Workers	1.51
33-2021	Fire Inspectors and Investigators	1.48
33-1012	First-Line Supervisors of Police and Detectives	1.45
53-5021	Captains, Mates, and Pilots of Water Vessels	1.44
49-9021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	1.43
33-1099	First-Line Supervisors of Protective Service Workers, All Other	1.42
49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment	1.42
49-9044	Millwrights	1.39
11-9013	Farmers, Ranchers, and Other Agricultural Managers	1.39
45-1011	First-Line Supervisors of Farming, Fishing, and Forestry Workers	1.38
51-8012	Power Distributors and Dispatchers	1.36
47-2152	Plumbers, Pipefitters, and Steamfitters	1.35
51-1011	First-Line Supervisors of Production and Operating Workers	1.33
47-5012	Rotary Drill Operators, Oil and Gas	1.33
27-2021	Athletes and Sports Competitors	1.33
33-2011	Firefighters	1.32
49-9051	Electrical Power-Line Installers and Repairers	1.32
27-2032	Choreographers	1.32
17-3029	Engineering Technicians, Except Drafters, All Other	1.31
39-4031	Morticians, Undertakers, and Funeral Directors	1.30
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists	1.29
51-4111	Tool and Die Makers	1.29
51-8031	Water and Wastewater Treatment Plant and System Operators	1.28

Code	Title	KSTE
47-2181	Roofers	1.28
49-9099	Installation, Maintenance, and Repair Workers, All Other	1.27
11-9141	Property, Real Estate, and Community Association Managers	1.27
33-9021	Private Detectives and Investigators	1.26
53-7071	Gas Compressor and Gas Pumping Station Operators	1.26
19-4093	Forest and Conservation Technicians	1.25
17-3024	Electro-Mechanical Technicians	1.25
35-1011	Chefs and Head Cooks	1.25
49-2021	Radio, Cellular, and Tower Equipment Installers and Repairers	1.25
51-8011	Nuclear Power Reactor Operators	1.25
49-2091	Avionics Technicians	1.25
47-2211	Sheet Metal Workers	1.24
11-9131	Postmasters and Mail Superintendents	1.24
51-9081	Dental Laboratory Technicians	1.24
11-3071	Transportation, Storage, and Distribution Managers	1.24
17-3026	Industrial Engineering Technicians	1.23
11-9071	Gaming Managers	1.23
29-9012	Occupational Health and Safety Technicians	1.23
47-2171	Reinforcing Iron and Rebar Workers	1.22
51-8013	Power Plant Operators	1.22
53-5022	Motorboat Operators	1.21
17-3027	Mechanical Engineering Technicians	1.21
47-2141	Painters, Construction and Maintenance	1.21
45-2021	Animal Breeders	1.21
51-9082	Medical Appliance Technicians	1.21
53-2021	Air Traffic Controllers	1.21
49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers	1.21
27-2099	Entertainers and Performers, Sports and Related Workers, All Other	1.21
53-2012	Commercial Pilots	1.21
29-2081	Opticians, Dispensing	1.20
29-2041	Emergency Medical Technicians and Paramedics	1.20
51-9011	Chemical Equipment Operators and Tenders	1.20

Code	Title	KSTE
49-9062	Medical Equipment Repairers	1.19
29-9099	Healthcare Practitioners and Technical Workers, All Other	1.19
17-3025	Environmental Engineering Technicians	1.19
47-4011	Construction and Building Inspectors	1.19
11-9061	Funeral Service Managers	1.18
47-2022	Stonemasons	1.18
53-6051	Transportation Inspectors	1.18
53-1031	First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators	1.18
49-9041	Industrial Machinery Mechanics	1.18
51-4012	Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic	1.17
17-3019	Drafters, All Other	1.17
53-7011	Conveyor Operators and Tenders	1.16
17-3022	Civil Engineering Technicians	1.16
51-8099	Plant and System Operators, All Other	1.16
49-3011	Aircraft Mechanics and Service Technicians	1.16
15-1152	Computer Network Support Specialists	1.16
27-4012	Broadcast Technicians	1.16
47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters	1.16
53-6041	Traffic Technicians	1.16
49-3091	Bicycle Repairers	1.15
29-1124	Radiation Therapists	1.15
47-2041	Carpet Installers	1.15
51-7032	Patternmakers, Wood	1.15
17-3011	Architectural and Civil Drafters	1.15
51-4062	Patternmakers, Metal and Plastic	1.15
39-4011	Embalmers	1.14
19-4051	Nuclear Technicians	1.14
49-9043	Maintenance Workers, Machinery	1.14
17-3023	Electrical and Electronics Engineering Technicians	1.14
41-1012	First-Line Supervisors of Non-Retail Sales Workers	1.14
47-2021	Brickmasons and Blockmasons	1.14
33-3021	Detectives and Criminal Investigators	1.14
47-2151	Pipelayers	1.14
47-2132	Insulation Workers, Mechanical	1.14

Code	Title	KSTE
43-1011	First-Line Supervisors of Office and Administrative Support Workers	1.13
29-1141	Registered Nurses	1.13
49-3051	Motorboat Mechanics and Service Technicians	1.13
51-4061	Model Makers, Metal and Plastic	1.13
51-6092	Fabric and Apparel Patternmakers	1.13
37-1012	First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	1.13
19-4041	Geological and Petroleum Technicians	1.13
11-9081	Lodging Managers	1.13
49-9069	Precision Instrument and Equipment Repairers, All Other	1.12
47-2081	Drywall and Ceiling Tile Installers	1.12
47-2031	Carpenters	1.12
41-9021	Real Estate Brokers	1.11
17-3013	Mechanical Drafters	1.11
29-2099	Health Technologists and Technicians, All Other	1.10
11-9051	Food Service Managers	1.10
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door	1.10
49-3042	Mobile Heavy Equipment Mechanics, Except Engines	1.10
45-4011	Forest and Conservation Workers	1.10
53-2022	Airfield Operations Specialists	1.09
49-9092	Commercial Divers	1.09
49-9081	Wind Turbine Service Technicians	1.09
49-9097	Signal and Track Switch Repairers	1.09
29-2092	Hearing Aid Specialists	1.09
19-4099	Life, Physical, and Social Science Technicians, All Other	1.08
29-2054	Respiratory Therapy Technicians	1.08
43-9031	Desktop Publishers	1.08
49-2097	Electronic Home Entertainment Equipment Installers and Repairers	1.08
53-1011	Aircraft Cargo Handling Supervisors	1.08
39-2011	Animal Trainers	1.08
49-9063	Musical Instrument Repairers and Tuners	1.08
13-1031	Claims Adjusters, Examiners, and Investigators	1.08
49-9095	Manufactured Building and Mobile Home Installers	1.07
27-1012	Craft Artists	1.07
47-4099	Construction and Related Workers, All Other	1.07

Code	Title	KSTE
27-4021	Photographers	1.07
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers	1.07
51-8092	Gas Plant Operators	1.07
49-3041	Farm Equipment Mechanics and Service Technicians	1.07
15-1151	Computer User Support Specialists	1.06
49-9071	Maintenance and Repair Workers, General	1.06
49-9061	Camera and Photographic Equipment Repairers	1.06
51-8091	Chemical Plant and System Operators	1.06
49-9094	Locksmiths and Safe Repairers	1.06
15-1134	Web Developers	1.06
47-4041	Hazardous Materials Removal Workers	1.06
41-1011	First-Line Supervisors of Retail Sales Workers	1.06
47-5013	Service Unit Operators, Oil, Gas, and Mining	1.05
51-4192	Layout Workers, Metal and Plastic	1.05
27-4014	Sound Engineering Technicians	1.05
19-4011	Agricultural and Food Science Technicians	1.05
29-1126	Respiratory Therapists	1.05
49-3023	Automotive Service Technicians and Mechanics	1.05
49-2098	Security and Fire Alarm Systems Installers	1.05
47-2142	Paperhangers	1.05
17-3012	Electrical and Electronics Drafters	1.05
27-3099	Media and Communication Workers, All Other	1.05
49-9096	Riggers	1.05
45-3000	Fishers and Related Fishing Workers	1.04
49-9052	Telecommunications Line Installers and Repairers	1.04
29-2033	Nuclear Medicine Technologists	1.04
49-2096	Electronic Equipment Installers and Repairers, Motor Vehicles	1.04
33-3052	Transit and Railroad Police	1.04
33-3051	Police and Sheriff's Patrol Officers	1.04
21-1094	Community Health Workers	1.03
47-2011	Boilermakers	1.03
41-3099	Sales Representatives, Services, All Other	1.03
51-9071	Jewelers and Precious Stone and Metal Workers	1.03
23-2093	Title Examiners, Abstractors, and Searchers	1.03

Code	Title	KSTE
29-2032	Diagnostic Medical Sonographers	1.02
51-4011	Computer-Controlled Machine Tool Operators, Metal and Plastic	1.02
27-4099	Media and Communication Equipment Workers, All Other	1.01
43-3061	Procurement Clerks	1.01
53-1021	First-Line Supervisors of Helpers, Laborers, and Material Movers, Hand	1.01
47-2072	Pile-Driver Operators	1.01
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	1.01
51-2011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	1.01
49-2092	Electric Motor, Power Tool, and Related Repairers	1.01
27-2042	Musicians and Singers	1.01
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	1.01
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic	1.01
51-4041	Machinists	1.00

# Table A2. Employment in Largest Detailed Occupations by Major Occupations (in thousands of jobs)The combined employment of the largest detailed occupations account for roughly 80% of the corresponding major occupation's employment.

42

1. Installation, Maintenance, and Repair Occupations	-
Maintenance and Repair Workers, General	1,332
Automotive Service Technicians and Mechanics	647
First-Line Supervisors of Mechanics, Installers, and Repairers	453
Industrial Machinery Mechanics	334
Heating, Air Conditioning, and Refrigeration Mechanics and Inst.	295
Bus and Truck Mechanics and Diesel Engine Specialists	254
Telecommunications Equipment Ins. and Rep., Exc. Line Inst.	228
Installation, Maintenance, and Repair Workers, All Other	146
Aircraft Mechanics and Service Technicians	129
2. Healthcare Practitioners and Technical Occupations	
Registered Nurses	2,857
3. Construction and Extraction Occupations	
Carpenters	677
Electricians	607
First-Line Supervisors of Constr. Trades and Extr. Workers	538
Plumbers, Pipefitters, and Steamfitters	412
Painters, Construction and Maintenance	217
Sheet Metal Workers	134
4. Sales and Related Occupations	
First-Line Supervisors of Retail Sales Workers	1,194
Sales Representatives, Services, All Other	954

#### **5. Production Occupations**

First-Line Supervisors of Production and Operating Workers
Machinists
Computer-Controlled Machine Tool Operators, Metal and Plastic
Water and Wastewater Treatment Plant and System Operators
Chemical Equipment Operators and Tenders

Tool and Die Makers

Aircraft Structure, Surfaces, Rigging, and Systems Assemblers

6. Office and Administrative Support Occupations	
First-Line Supervisors of O&A Support Workers	1,443
7. Protective Services Occupations	
Police and Sheriff's Patrol Officers	658
Firefighters	316
Detectives and Criminal Investigators	105
8. Computer and Mathematical Occupations	
Computer User Support Specialists	603
Computer Network Support Specialists	189
9. Architecture and Engineering Occupations	
Electrical and Electronics Engineering Technicians	135
Architectural and Civil Drafters	97
Engineering Technicians, Except Drafters, All Other	74
Civil Engineering Technicians	72
Mechanical Drafters	64
Industrial Engineering Technicians	63
10. Transportation and Material Moving Occupations	
First-Line Supervisors of Transp. and MatMov. M&V Ops.	203
First-Line Supervisors of Helpers, Laborers, and Material Movs.	184
Commercial Pilots	39
Captains, Mates, and Pilots of Water Vessels	37
Other Occupations	
Claims Adjusters, Examiners, and Investigators	274
First-Line Supervisors of Non-Retail Sales Workers	253
Emergency Medical Technicians and Paramedics	245
Food Service Managers	201
Property, Real Estate, and Community Association Managers	180

 Table A3. Employment in Largest NAICS Industries, by NAICS (in thousands of jobs)

 The combined employment of the largest NAICS industries account for roughly 80% of the corresponding NAICS sector's employment.

1. Health Care and Social Assistance		7. Administrative and Support Services	
General Medical and Surgical Hospitals	2,081	Employment Services	327
Offices of Physicians	328	Services to Buildings and Dwellings	198
Nursing Care Facilities (Skilled Nursing Facilities)	209	Investigation and Security Services	126
Outpatient Care Centers	206	Business Support Services	102
2. Construction		Office Administrative Services	58
Building Equipment Contractors	1,353	8. Wholesale Trade	
Building Finishing Contractors	437	Machinery, Equipment, and Supplies Merchant Wholesalers	179
Foundation, Structure, and Building Exterior Contractors	362	Professional and Commercial Equipment and Supplies Wholesalers	99
Residential Building Construction	344	Wholesale Electronic Markets and Agents and Brokers	89
3. Federal, State and Local Government		Motor Vehicle and Motor Vehicle Parts and Supplies Wholesalers	64
Local Government	1,838	Grocery and Related Product Merchant Wholesalers	59
Federal Executive Branch	442	Other top industries**	149
4. Manufacturing		9. Transportation and Warehousing	
Machine Shops; Turned Product; and Screw, Nut, and Bolt Mfg.	174	General Freight Trucking	99
Aerospace Product and Parts Manufacturing	150	Warehousing and Storage	98
Motor Vehicle Parts Manufacturing	125	Support Activities for Air Transportation	79
Plastics Product Manufacturing	97	Postal Service	58
Medical Equipment and Supplies Manufacturing	79	Scheduled Air Transportation	57
Other top industries*	1,354	Other top industries*	190
5. Retail Trade		10. Other Services	
Other General Merchandise Stores	250	Automotive Repair and Maintenance	336
Grocery Stores	222	Commercial and Industrial Machinery and Equipment (except Autom	111
Electronics and Appliance Stores	146	Business, Professional, Labor, Political, and Similar Organizations	49
Building Material and Supplies Dealers	142	Death Care Services	48
Other industries*	463	Electronic and Precision Equipment Repair and Maintenance	41
6. Professional, Scientific and Technical Services			
Architectural, Engineering, and Related Services	304		
Computer Systems Design and Related Services	303		
Management, Scientific, and Technical Consulting Services	160		
Other Professional, Scientific, and Technical Services	71		

#### Table A4. Employment in Largest Detailed Occupations, by NAICS Sectors (in thousands of jobs)

The combined employment of the largest detailed occupations account for roughly 80% of the corresponding NAICS sector's employment.

1. Health Care and Social Assistance	
Registered Nurses	2,511
First-Line Supervisors of Office and A&S Workers	217
Emergency Medical Technicians and Paramedics	168
2. Construction	
Carpenters	575
Electricians	465
First-Line Supervisors of Constr. Trades and Extr. Workers	414
Plumbers, Pipefitters, and Steamfitters	341
Heating, Air Conditioning, and Refrigeration Mech.and Inst.	216
Other top occupations*	548
3. Federal, State and Local Government	
Police and Sheriff's Patrol Officers	633
Firefighters	301
Maintenance and Repair Workers, General	154
Registered Nurses	148
Detectives and Criminal Investigators	104
Other top occupations*	745
4. Manufacturing	
First-Line Supervisors of Production and Operating Workers	449
Machinists	323
Maintenance and Repair Workers, General	188
Industrial Machinery Mechanics	187
Computer-Controlled Machine Tool Operators, Metal and Plastic	142
Other top occupations*	732
5. Retail Trade	
First-Line Supervisors of Retail Sales Workers	1,085
Automotive Service Technicians and Mechanics	328
First-Line Supervisors of Office and A&S Workers	191

Sales Representatives, Services, All Other

111

6. Professional, Scientific and Technical Services	
Computer User Support Specialists	174
Sales Representatives, Services, All Other	170
First-Line Supervisors of Office and A&S Workers	96
Other top occupations*	417
7. Administrative and Support Services	
Sales Representatives, Services, All Other	148
First-Line Supervisors of Office and Adm. Support Workers	97
First-Line Supervisors of Landscaping and Lawn Serv. Workers	64
Other top occupations*	516
8. Wholesale Trade	
First-Line Supervisors of Non-Retail Sales Workers	84
First-Line Supervisors of Office and Admin. Support Workers	81
Maintenance and Repair Workers, General	46
Other top occupations*	421
9. Transportation and Warehousing	
First-Line Supervisors of Transportation and Mach. and Vehicle Op.	84
Bus and Truck Mechanics and Diesel Engine Specialists	79
Aircraft Mechanics and Service Technicians	78
Other top occupations*	365
10. Other Services	
Automotive Service Technicians and Mechanics	231
First-Line Supervisors of Mechanics, Installers, and Repairers	55
Maintenance and Repair Workers, General	50
Other top occupations*	245