



WORKING PAPERS SERIES
DIPARTIMENTO DI
SCIENZE SOCIALI ED ECONOMICHE
n. 5/2016

**How Workers' Skills Are Used at Work: A
Multi-Country Comparison with PIAAC**

Author/s:

Stefania Borelli

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Stefania Borelli[†]

This Version: May 2016

Abstract

This paper aims to present the comparison between two datasets, O*NET and PIAAC.

Most of the task-based empirical papers in the literature use the O*NET database from the US Department of Labor. This survey assigns values summarizing the importance of several different abilities to each of 812 Occupations (according to the Standard Occupation Classification, SOC). In the literature, the more or less implicit assumption is that the task structure of jobs does not differ by country characteristics (i.e. there is the same task-composition of occupations in Italy and in the United States).

PIAAC (Programme for the International Assessment of Adult Competencies, 2013) is the most comprehensive international survey on adult (aged 16 to 65) skills ever undertaken. Both datasets adopt a Job Requirement Approach (JRA) methodology and so it's possible to make a useful comparison. The comparison between PIAAC and O*NET, using data on the US workers, shows a correlation between variables never less than 0.7 and then to provide evidence of the validity of the first dataset to describe the task content of occupations.

Keywords: job tasks, Occupational Network Information (O*NET), OECD Programme for the International Assessment of Adult Competencies (PIAAC)

JEL Classification Codes: J24, C81.

*I am grateful to Giovanni Peri for his useful comments and suggestions. I also want to thank Paolo Naticchioni and all the participants at the International Economics Reading Group in Sapienza for their help. Usual disclaimer applies.

[†]Department of Economics and Social Sciences, Sapienza University of Rome. Email address: stefania.borelli@uniroma1.it

Introduction

Becker's (1964) Human Capital Model represents the basis for the contemporary analysis of the economic value of skill in the labor market. The principal idea of the Becker framework is that skill can be intended as an investment good that is purchased by education and by job training itself (qualifications). Starting from this idea, the empirical analysis of the labor market use investment measures, such as years of schooling and experience, both as proxies for skill.

Through survey method or where possible through administrative data collection, it's possible measuring the proportions of the adult population who have achieved certain education or qualification levels. The most relevant advantage of this approach is that the measures obtained are objective, externally determined or externally verifiable. Educational measures should also, in principle, be consistent. Objective comparisons across countries are more constrained because for the different educational systems, years of schooling are measures that are more obviously internationally commensurate (Barro and Lee, 1996, 2001).

The most relevant disadvantages of using qualifications or educational attainment as a measure of job skills are, however, well-known. Qualifications gained in schools and colleges are only loose measures of the skills actually used in workplaces, and by the same token of the productivity of workers.

In fact, concretely, empirical analysis of the "return" to education is not directly informative about what skills workers use on the job (but also why these skills are required and how these skill requirements have changed over time).

To supply this conceptual gap, the literature uses a "task framework" to analyze job skill requirements (Autor, Levy and Murnane, 2003): this approach consists of clas-

sifying jobs according to their task core requirements (that are the main activities that workers perform in their work) and then consider the range of skills required to perform these tasks.

The task approach has found application in several branches of recent empirical research. Many recent studies have used the task approach to explore the causes of job polarization and the link between technological change and shift in wage structure. In this strand of work there are Autor et al. (2003), Autor, Katz, and Kearney (2006, 2008), Spitz-Oener (2006), Bartel, Ichniowski, and Shaw (2007), Felstead et al. (2007), Goos and Manning (2007), Smith (2008), Dustmann, Ludsteck, and Schonberg (2009), Antonczyk, DeLeire, and Fitzenberger (2010), Black and Spitz-Oener (2010), Gathmann and Schonberg (2010), Firpo, Fortin, and Lemieux (2011), Goos, Manning, and Salomons (2012). In these studies the primary hypothesis is that work-place computerization leads to the displacement of human labor in tasks that can be described as routine.

The task approach is also employed in several recent studies on immigration. Works by Cortes (2008) and Peri and Sparber (2009), Ottaviano and Peri (2012), D'Amuri and Peri (2012) compare the task assignment of native and migrant workers with similar education.

Many other studies consider the effects of international outsourcing on the employment. Antraès, Garicano, and Rossi-Hansberg (2006) and Grossman and Rossi-Hansberg (2008) develop theoretical models of international offshoring starting with the assumption that routine job tasks are more suitable for offshoring than nonroutine job tasks.

By the empirical point of view, the most appropriate skill measurement is “Job Requirement Approach”. In the JRA, workers are asked to indicate the level of skills

that is required in their current work in several skill domains.

Two assumptions underpin the use of the job requirements approach. First, it is assumed that the individual is a well-informed person to report about the activities involved in his job. Even within quite narrowly categorised occupations, all jobs differ: the assumption is that, normally, the jobholder knows best his work and he can describe the activities and skills involved in his current work. In high-skill jobs this is more likely to be true: workers adapt jobs to their own abilities and tastes. In low-skill jobs, and where the jobholder has been only a short time in post, the assumption might be questioned in some cases. However, on balance it seems reasonable to assume that the individual is generally the best informant about his job. A second assumption is that the individual reports the activities that they perform in an unbiased way. This assumption might also be arguable: individuals might talk up their jobs, to boost their self-esteem. However, it is held that they are less likely to do so when reporting their activities than reporting how good they are in the performance of these activities. To minimise bias the general principle is to ask respondents to report actual behaviour: frequency of use and proportion of time spent on using different skills (rather than often-used alternatives such as the important of these skills for the job).

The job requirement approach is used by both O*NET (US Government's Occupational Information Network) and PIAAC (Programme for the International Assessment of Adult Competencies).

The first database has derived job skill measures for the large majority of US occupations and information are derived by surveys of employees in representative samples of establishments.

PIAAC assesses the proficiency of adults from age 16 onwards in different skills that

are relevant to adults in many social contexts and work situations, and necessary for fully integrating and participating in the labor market, education and training, and social and civic life.

The origin and aims of the O*NET surveys used in the US are very different from those of PIAAC.

O*NET is an occupational database of worker attributes and job characteristics. However, it is remarkable that similar issues and solutions for the analysis of job skills are found in O*NET and PIAAC. One part of O*NET's work has involved surveying employees about the activities involved in their jobs. The same principles have been used in background questionnaire design by PIAAC. In this way, adopting a Job Requirement Approach (JRA) methodology, the two datasets are comparable. However, being a multi-country database, PIAAC could allow to define a "task specialization structure" for each country. The aim of this paper is to compare the US survey O*NET and OECD survey PIAAC and to test the validity of the last survey to measuring the workers' skills.

The remainder of this paper is structured as follows: Section 1 describes the two surveys, Section 2 gives the results of the comparison between the two datasets and Section 3 concludes.

1 Comparison of O*NET and PIAAC Measures of Job Skills Requirements

Although, as highlighting in the Introduction, the aims and origins of O*NET and PIAAC are very different each other, respectively born as an occupational dataset and a survey for collecting information on how skills are used at home, in workplace

and in community, it's evident that it's possible a reasonable comparison between datasets.

1.1 Conceptual Approach and Unit of Analysis

From a conceptual point of view, in O*NET unit of analysis is the occupation rather than the individual; by contrast in PIAAC unit of analysis is the person-job.

This conceptual and analytic difference is originated from the different purpose of the two surveys: “The Survey of Adult Skills (PIAAC) assesses the proficiency of adults from age 16 onwards in literacy, numeracy and problem solving in technology-rich environments. These skills are “key information-processing competencies” that are relevant to adults in many social contexts and work situations, and necessary for fully integrating and participating in the labor market, education and training, and social and civic life. In addition, the survey collects a range of information on the reading- and numeracy-related activities of respondents, the use of information and communication technologies at work and in everyday life, and on a range of generic skills, such as collaborating with others and organising one’s time, required of individuals in their work” (OECD Skills Outlook. First results from the survey on adult skills, 2013).

O*NET is an occupational database of worker attributes and job characteristics that was developed as a replacement for the Dictionary of Occupational Titles. Its objectives are to assist employers and others in their recruitment and in the design of training programmes, and individuals in their career planning.

1.2 Samples and Countries

The Occupational Information Network (O*NET) is a comprehensive system developed by the U.S. Department of Labor that provides information for occupations within the U.S. economy. Then, as mentioned above, O*NET unit of analysis is the occupation.

There were 24¹ national participants in PIAAC, comprising 20 OECD member countries, regional entities from two OECD member countries (UK and Belgium) and two partner countries (Cyprus and the Russian Federation). Although the Russian Federation also participated in PIAAC, its data was not ready for inclusion in the first international report on PIAAC. The tables for England and Northern Ireland are available separately. Unit of analysis are the individual and his competencies, so the PIAAC target population consists of all noninstitutionalized adults between age 16 and 65 (inclusive) who reside in the country (usual place of residency is in the country) at the time of data collection. Adults were to be included regardless of citizenship, nationality or language. The normal territorial unit covered by the survey was that of the country as a whole. The sampling frames used by participating countries were of three broad types: population registers (administrative lists of residents maintained at either national or regional level); master samples (lists of dwelling units or primary sampling units maintained at national level for official surveys); or area frames (a frame of geographic clusters formed by combining adjacent geographic areas, respecting their population sizes and taking into consideration travel distances for interviewers). The minimum sample size required for the Survey

¹Australia, Italy, Austria, Japan, Canada, Republic of Korea, Norway, Cyprus, Poland, Czech Republic, Russian Federation, Denmark, Slovak Republic, Estonia, Spain, Finland, Sweden, Flanders (Belgium), United Kingdom, France, England (UK), Germany, N. Ireland (UK), United States of America

of Adult Skills depended on two variables: the number of cognitive domains assessed and the number of languages in which the assessment was administered. Assuming the assessment was administered in only one language, the minimum sample size required was 5 000 completed cases if all three domains were assessed and 4 500 if only literacy and numeracy were assessed.

The variety of countries in the survey PIAAC (and the inclusion of the United States) makes it possible reasonable and useful comparisons:

- 1) Using data from the two datasets, but considering the same country (USA) it is possible to evaluate the correlation between the O*NET variables and the PIAAC variables. An important correlation will show that the variables measure the same phenomenon.
- 2) Using PIAAC data (for each country) and O*NET data (for the US) it's convenient to verify further the suitability of US data sources for determining qualification requirements in European countries.

1.3 Skills assessed and their scales

In addition to the conventional measures of occupation and educational qualifications, PIAAC includes detailed questions about the frequency with which respondents perform specific tasks in their jobs. Indeed, PIAAC collected a considerable amount of information on the skills possessed and used by adults in addition to the measures of proficiency in literacy, numeracy and PSTRE. Based on this information, the survey measures the use of a wide range of skills, including both information-processing skills, which are also measured in the direct assessment, and generic

skills, for which only self-reported use at work is available.² The survey generates very many items describing generic activities involved in doing the job. The choice of items is informed by theories of skill and the practices of commercial psychology; but to reduce the multiple items to a smaller and more meaningful set of ‘generic skills’, statistical techniques³ are used to generate several generic skill indicators from the responses on these items.

Twelve indicators were created (Table 1), five of which refer to information-processing skills (reading, writing, numeracy, ICT skills and problem solving); the remaining seven correspond to general skills (task discretion, learning at work, influencing skills, co-operative skills, self-organising skills, gross physical skills and dexterity).

The purpose of this paper leads us to consider only the part of the survey which measures the generic skills through self-reported.

This part, indeed, uses the Job Requirement Approach that ensures a reasonable level of comparability with the US dataset⁴.

O*NET has been described as a ‘common language and dynamic system for describ-

²“Although there is some parallel between the skills included in the direct assessment exercise – literacy, numeracy and problem solving in technology-rich environments – and the use of reading, numeracy, problem solving and ICT at work (and at home), there are important differences. The skills use variables are derived by aggregating background questions on tasks carried out at work (or at home). For instance, these questions cover both reading and writing at work but two separate indices are created to maintain, to the extent possible, consistency with the direct assessment module which only tests reading skills in the literacy module. Similarly, the use of problem solving and ICT skills at work are not to be confused with the assessment of proficiency in problem solving in technology-rich environments. Finally, it should be kept in mind that even when there is a parallel between skills use and skills proficiency concepts – notably between reading use and literacy proficiency and between numeracy use and proficiency – there is no correspondence between the questions concerning the tasks performed at work (or at home) and those asked in the direct assessment modules. These issues should be kept in mind when comparing skills proficiency to skills use” (OECD Skills Outlook 2013: First Results from the Survey of Adult Skills, OECD Publishing, 2013).

³For further information on the statistical techniques: Technical Report of the Survey of Adult Skills (PIAAC), Chapter 17: Scaling PIAAC Cognitive Data.

⁴In the Appendix A the use of JRA in both surveys will be discussed in more detail.

Table 1: Indicators of skills use at work in PIAAC Survey

Indicator	Group of tasks
Information-processing skills	
Reading	Reading documents (directions, instructions, letters, memos, e-mails, articles, books, manuals, bills, invoices, diagrams, maps)
Writing	Writing documents (letters, memos, e-mails, articles, reports, forms)
Numeracy	Calculating prices, costs or budgets; use of fractions, decimals or percentages; use of calculators; preparing graphs or tables; algebra or formulas; use of advanced math or statistics (calculus, trigonometry, regressions)
ICT Skills	Using e-mail, Internet, spreadsheets, word processors, programming languages; conducting transactions on line; participating in on-line discussions (conferences, chats)
Other generic skills	
Task discretion	Choosing or changing the sequence of job tasks, the speed of work, working hours; choosing how to do the job
Learning at work	Learning new things from supervisors or co-workers; learning-by-doing; keeping up-to-date with new products or services
Influencing skills	Instructing, teaching or training people; making speeches or presentations; selling products or services; advising people; planning others' activities; persuading or influencing others; negotiating.
Co-operative skills	Co-operating or collaborating with co-workers
Self-organising skills	Organising one's time
Dexterity	Using skill or accuracy with one's hands or fingers
Physical skills	Working physically for a long period

Source: Adapted from “OECD (2013), OECD Skills Outlook 2013: First Results from the Survey of Adult Skills, OECD Publishing”, 2013

Table 2: Summary of O*NET Content Model

Domain	Element description
Worker Characteristics	
Abilities	Enduring attributes of the individual that influence performance
Occupational Interests	Preferences for work environments. Occupational Interest Profiles (OIPs) are compatible with Holland's (1985, 1997) model of personality types and work environments.
Work Values	Global aspects of work composed of specific needs that are important to a person's satisfaction. Occupational Reinforcer Patterns (ORPs) are based on the Theory of Work Adjustment (Dawis - Lofquist, 1984).
Work Styles	Personal characteristics that can affect how well someone performs a job.
Worker Requirements	
Basic Skills	Developed capacities that facilitate learning or the more rapid acquisition of knowledge
Cross-Functional Skills	Developed capacities that facilitate performance of activities that occur across jobs
Knowledge	Organized sets of principles and facts applying in general domains
Education	Prior educational experience required to perform in a job
Experience Requirements	
Experience and Training	If someone were being hired to perform this job, how much of the following would be required?
Basic Skills - Entry Requirement	Entry requirement for developed capacities that facilitate learning or the more rapid acquisition of knowledge
Cross-Functional Skills - Entry Requirement	Entry requirement for developed capacities that facilitate performance of activities that occur across jobs
Licensing	Licenses, certificates, or registrations that are awarded to show that a job holder has gained certain skills. This includes requirements for obtaining these credentials, and the organization or agency requiring their possession.

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Domain	Element description
Occupation Information	
Tasks	Occupation-Specific Tasks
Tools and Technology	Machines, equipment, tools, software, and information technology workers may use for optimal functioning in a high performance workplace.
Workforce Characteristics	
Labor Market Information	Current labor force characteristics of occupations.
Occupational Outlook	Future labor force characteristics of occupations.
Occupational Requirements	
Generalized Work Activities	Work activities that are common across a very large number of occupations. They are performed in almost all job families and industries.
Intermediate Work Activities	Work activities that are common across many occupations. They are performed in many job families and industries.
Detailed Work Activities	Specific work activities that are performed across a small to moderate number of occupations within a job family.
Organizational Context	Characteristics of the organization that influence how people do their work.
Work Context	Physical and social factors that influence the nature of work.

Source: Adapted from O*NET Content Model, for further information: <http://www.onetcenter.org/content.html>

ing the world of work for both the public and private sectors’. It is a comprehensive system for collecting, organising and disseminating information on occupational and worker requirements, based around the notion of competency, with emphasis on skills transferability. The O*NET surveys measure a larger number (239 different dimensions or ‘descriptors’ of skills and job characteristics) of activities and attributes than are found in the PIAAC.

The O*NET framework is composed by eight subgroups of variables: background, abilities, education and training, skills, knowledge, work styles, work context and generalised work activities. The Content Model is the conceptual foundation of O*NET. The Content Model provides a framework that identifies the most important types of information about work and integrates them into a theoretically and empirically sound system (Table 2). In total, 239 different dimensions or ‘descriptors’ of skills and job characteristics including: qualifications required; practical and technical skills; a wide range of soft skills such as communication skills, stamina etc; as well as details of the tasks involved in the job (Table 3) and for the four domains of Knowledge, Skills, Abilities and Work activities, both the ‘Importance’ and ‘Level’ of each skill or characteristic being measured is recorded (see Figure 1).

Also in PIAAC a number of skills-use variables are taken directly from questions asked in the background questionnaire using the JRA. For example:

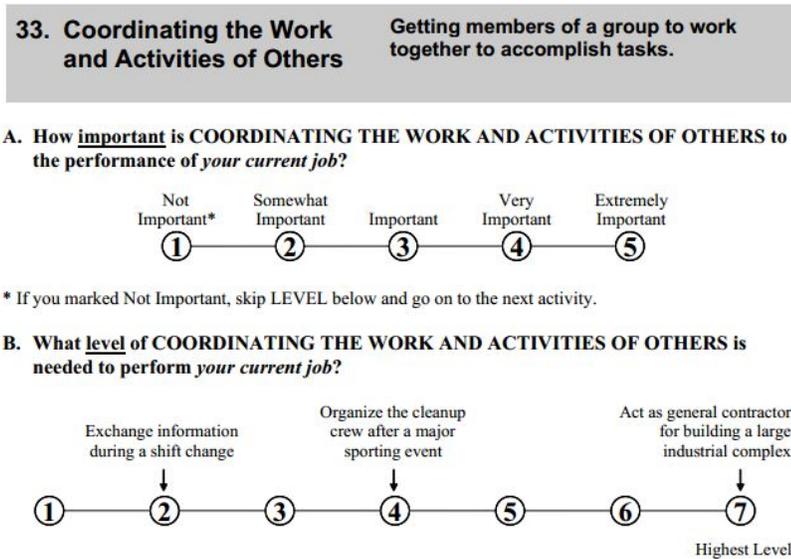
1. Problem-solving skills: How often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution?
2. Co-operative skills: What proportion of your time do you usually spend co-operating or collaborating with co-workers?

Table 3: Description of Main O*NET Questionnaires

Survey instrument	Main content	Information recorded
Education and training	required education, related work experience, training (5 items or descriptors)	Levels
Knowledge	various specific functional and academic areas (e.g., physics, marketing, design, clerical, food production, construction) (33 items or descriptors)	Importance and Levels
Skills	reading, writing, math, science, critical thinking, learning, resource management, communication, social relations, technology (35 items or descriptors)	Importance and Levels
Abilities	writing, math, general cognitive abilities, perceptual, sensory-motor, dexterity, physical coordination, speed, strength (52 items or descriptors)	Importance and Levels
Generalized Activities	Work various activities (e.g., information processing, making decisions, thinking creatively, inspecting equipment, scheduling work)(41 items or descriptors)	Importance and Levels
Work context	working conditions (e.g., public speaking, teamwork, conflict resolution, working outdoors, physical strains, exposure to heat, noise, and chemicals, job autonomy)(57 items or descriptors)	Levels
Work style	personal characteristics (e.g., leadership, persistence, cooperation, adaptability)(16 items or descriptors)	Importance and Levels

Source: Handel (2010), p.15, and Tippins and Hilton (2010), p.72, p.74

Figure 1: O*NET ‘Coordinating the Work and Activities of Others’



Source: <http://www.onetcenter.org/questionnaires.html>

3. Self-organising skills: How often does your job usually involve organising your own time?
4. Physical skills: How often does your job usually involve working physically for a long period?
5. Dexterity: How often does your job usually involve using skill or accuracy with your hands or fingers?

For these skills-use variables numerical comparisons between the use of different skills are possible: a value of 0 indicates that the skill is never used; a value of 1 indicates that it is used less than once a month; a value of 2 indicates that it is used less than once a week but at least once a month; a value of 3 indicates that it is used at least once a week but not every day; and a value of 4 indicates that it is used

every day. All other variables described in Table 1 have been derived based on more than one question from the background questionnaire using IRT (Item Response Theory). These variables have been transformed so that they have a mean of 2 and a standard deviation of 1 across the pooled sample of all participating countries, thus allowing meaningful comparisons across countries.

Although the O*NET and PIAAC classifications seem to use different scales, in this paper the comparison will concern only the “Importance” scale from O*NET and the “Frequency” scale from PIAAC. The idea behind the comparison is that if a skill is essential for the performance of their job, then it will take a long working time.

2 O*NET vs PIAAC: analysis of similarities and differences

2.1 Matching SOC to ISCO

O*NET data comes from job incumbents, occupational analysts and occupational experts and is collected for 812 occupations which are based on the 2000 Standard Occupational Code (SOC). Following Goos et al. (2011), I manually converted the 2000 Standard Occupational Code (SOC 4 digit) used in the O*NET data to ISCO-08 codes (2 digit) used in the PIAAC. Correspondence tables exist only between the six-digit SOC 2010 and 4-digit ISCO-08, so I collapsed the occupations in major groups at 2 digit, using different occupational weights derived from US data which reflect the situation in the US economy.

Table 4: Skill Types and Variables from O*NET and PIAAC

Type of skill	Sub-type of skill	O*NET Variables	PIAAC Variables
Manual Skills	Dexterity	Manual Dexterity Finger Dexterity	Using hands or fingers
	Physical Activities	Performing general physical activities	Working physically for long
Cognitive Skills	Writing	Writing	Index of use of writing skills
	Reading	Reading	Index of use of reading skills
	Mathematics	Mathematics	Index of use of numeracy skills
	Use of PC	Interacting with computer	Index of use of ICT skills
	Learning Activities	Learning Strategies	Index of readiness to learn
Organising and Problem Solving Skills	Problem Solving	Complex Problem Solving	Complex Problems
	Planning	Organising, Planning, and Prioritizing Work	Planning Own Activities Planning Others Activities Organizing Own Time
Interactive Skills	Selling	Selling or Influencing Others	Selling
	Teaching	Training and Teaching Others	Teaching People
	Consulting	Provide Consultation and Advice to Others	Advising People
	Persuading	Persuasion	Influencing People
	Communicating	Establishing and Maintaining Interpersonal Relationships	Presentations
	Negotiating Planning	Negotiation Organising, Planning, and Prioritizing Work	Negotiating with People Planning Others Activities
	Cooperation	Interpreting info for others	Sharing Work-related Info

2.2 Assigning Job Skills and Abilities to Occupations

There are also differences in skill's nomenclature but it may be argued that some nomenclature differences do not matter very much, as long as the meaning is clear. I use only a subset of the O*NET and PIAAC abilities datasets: Table 4 (previous page) provides a list of the variables used.

Following Peri and Sparber (2009), for each dataset, I merge task-specific value (score between 0 and 4 in PIAAC, 1 and 5 in O*NET) with individual US workers in the 2009 Census, re-scaling each value so that it equals the percentile score in that year. This gives a standardized measure of the relative importance of a given skill among US workers. Then, a task with a score of 6 for some skill indicates that only 6 percent of workers in the United States in 2009 were supplying that skill less intensively.

2.3 Correlations between O*NET and PIAAC Variables: the US case

For each group of variables in Table 4, I calculate a score as described in the previous paragraph and correlation analysis was used to test the degree of similarity between both PIAAC and O*NET.

Table 5 presents the correlations between the variables of the two datasets considering the Manual Skills; Table 6 presents the correlations concerning the Organising and Problem Solving Skills.

Table 7 presents the results concerning the Cognitive Skills and finally the Table

Table 5: Manual Skills: Correlation between O*Net and PIAAC Datasets

Variables	onet dexterity	piaac dexterity	onet physically	piaac physically
onet dexterity	1.000			
piaac dexterity	0.741	1.000		
onet physically	0.833	0.700	1.000	
piaac physically	0.778	0.729	0.933	1.000

Table 6: Organising and Problem Solving Skills: Correlation between O*Net and PIAAC Datasets

Variables	onet complex pr.	piaac complex pr.	onet planning	piaac planning
onet complex pr.	1.000			
piaac complex pr.	0.840	1.000		
onet planning	0.834	0.69	1.000	
piaac planning	0.706	0.586	0.736	1.000

8 presents the correlations concerning the Interactive and Communicative Skills. These correlation coefficients are high in general, they range from 0.678 to 0.945.

The results of the analysis suggest that both datasets confer a score of similar value on the competencies possessed by the workers. Although in PIAAC the target population consists of all adults between age 16 and 65 and then the analysis is at person-level (not occupation-level), it has a predictive power of the “Task Complexity” at occupation-level.

Table 9-13 give the distribution of competencies according to occupational roles. In particular, Table 9 shows the scores of the five occupations with the lowest and highest Manual Intensity Index, according to PIIAC and O*NET. Table 10 shows the scores for the Cognitive Intensity Index; Table 11 shows the results for the Organising and Problem Solving Intensity Index and Table 12 shows the score for the Interactive Intensity Index. For each occupation, the score is equal to the percentile along the distribution of skill intensities. For instance, a score of 5 in “Manual Intensity Index” for “Business and administration professionals” indicates that 5% of all workers in US in 2009 were using the manual skills less intensively than “Business and administration professionals”. Each index is constructed as a mean of the competencies scores, where, for each index, the competencies/variables are given in Table 4.

Although with different rank in many cases, the same occupations are in the first (or the last) positions.

Table 13 gives the distribution of the Task Complexity Index of each occupation. Following Peri and Sparber (2009), this index is constructed as:

$$TCI = \ln \left[\frac{CII + III + OII}{MII} \right]$$

Table 7: Cognitive Skills: Correlation between O*Net and PIAAC Datasets

Variables	onet writing	piaac writwork	onet reading	piaac readwork	onet int pc	piaac ictwork	onet math	piaac numwork	onet learning	piaac readytolearn
onet writing	1.000									
piaac writwork	0.850	1.000								
onet reading	0.977	0.831	1.000							
piaac readwork	0.896	0.924	0.893	1.000						
onet int pc	0.835	0.680	0.852	0.741	1.000					
piaac ictwork	0.817	0.814	0.835	0.880	0.834	1.000				
onet math	0.712	0.619	0.724	0.712	0.694	0.696	1.000			
piaac numwork	0.597	0.571	0.639	0.618	0.567	0.666	0.847	1.000		
onet learning	0.849	0.747	0.816	0.816	0.568	0.613	0.654	0.494	1.000	
piaac readytolearn	0.856	0.782	0.873	0.870	0.727	0.834	0.608	0.527	0.825	1.000

Table 8: Interactive and Communicative Skills: Correlation between O*Net and PIAAC Datasets

Variables	onet selling	piaac selling	onet teaching	piaac teaching	onet consulting	piaac advising	onet persuasion	piaac influencing	onet presentation	piaac presentation	onet negotiating	piaac negotiating
onet selling	1.000											
piaac selling	0.767	1.000										
onet teaching	0.379	0.173	1.000									
piaac teaching	0.501	0.158	0.741	1.000								
onet consulting	0.674	0.277	0.624	0.654	1.000							
piaac advising	0.614	0.221	0.464	0.789	0.626	1.000						
onet persuasion	0.776	0.425	0.517	0.690	0.749	0.768	1.000					
piaac influencing	0.742	0.495	0.551	0.717	0.677	0.748	0.905	1.000				
onet presentation	0.605	0.225	0.392	0.542	0.693	0.592	0.872	0.791	1.000			
piaac presentation	0.502	0.157	0.657	0.766	0.684	0.600	0.750	0.806	0.718	1.000		
onet negotiating	0.792	0.450	0.487	0.695	0.763	0.748	0.972	0.879	0.868	0.737	1.000	
piaac negotiating	0.803	0.565	0.407	0.632	0.641	0.794	0.871	0.891	0.729	0.642	0.883	1.000

where CII, III, OII and MII are respectively the Cognitive intensity Index, the Interactive Intensity Index, the Organising and Problem Solving Index and the Manual Intensity Index. The TCI is standardized between 0 and 100 (the occupation with the lowest Task Complexity Index has score 0 and the occupation with the highest Task Complexity Index has score 100).

Also in this case, there is a good match between the scores.

Table 9: Occupations and Manual Intensity Index (MII): US case

Occupation	PIAAC MII	Occupation	O*NET MII
Five Occupations with Lowest Manual Intensity Index			
Business and administration professionals	1	Business and administration professionals	5
Administrative and commercial managers	9	Administrative and commercial managers	7
Chief executives, senior officials and legislators	17	Production and specialised services managers	12
Science and engineering professionals	18	Teaching professionals	16
Production and specialised services managers	37	General and keyboard clerks	18
Five Occupations with Highest Manual Intensity Index			
Labourers in mining, construction, manufacturing and transport	87	Labourers in mining, construction, manufacturing and transport	83
Building and related trades workers, excluding electricians	89	Building and related trades workers, excluding electricians	84
Stationary plant and machine operators	90	Metal, machinery and related trades workers	88
Handicraft and printing workers	93	Assemblers	93
Market-oriented skilled forestry, fishery and hunting workers	95	Electrical and electronic trades workers	95

Author's calculation on PIAAC and O*NET and 2009 US Census.

Table 10: Occupations and Cognitive Intensity Index (CII): US case

Occupation	PIAAC CII	Occupation	O*NET CII
Five Occupations with Lowest Cognitive Intensity Index			
Market-oriented skilled forestry, fishery and hunting workers	0	Cleaners and helpers	0
Cleaners and helpers	20	Agricultural, forestry and fishery labourers	18
Assemblers	24	Personal service workers	30
Agricultural, forestry and fishery labourers	25	Market-oriented skilled forestry, fishery and hunting workers	32
Labourers in mining, construction, manufacturing and transport	28	Labourers in mining, construction, manufacturing and transport	34
Five Occupations with Highest Cognitive Intensity Index			
Business and administration professionals	84	Business and administration professionals	80
Science and engineering professionals	85	Administrative and commercial managers	82
Production and specialised services manager	91	Teaching professionals	83
Chief executives, senior officials and legislators	94	Science and engineering professionals	84
Administrative and commercial managers	96	Production and specialised services managers	86

Author's calculation on PIAAC and O*NET and 2009 US Census.

Table 11: Occupations and Organising-Problem Solving Intensity Index (OII): US case

Occupation	PIAAC OII	Occupation	O*NET OII
Five Occupations with Lowest Organising-Problem Solving Intensity Index			
Assemblers	4	Cleaners and helpers	0
Cleaners and helpers	10	Sales workers	29
Agricultural, forestry and fishery labourers	13	Personal service workers	31
Labourers in mining, construction, manufacturing and transport	20	Drivers and mobile plant operators	34
Drivers and mobile plant operators	25	Stationary plant and machine operators	37
Five Occupations with Highest Organising-Problem Solving Intensity Index			
Science and engineering associate professionals	77	Science and engineering professionals	87
Teaching professionals	82	Administrative and commercial managers	87
Administrative and commercial managers	84	Business and administration professionals	88
Production and specialised services managers	88	Health professionals	91
Chief executives, senior officials and legislators	91	Production and specialised services managers	99

Author's calculation on PIAAC and O*NET and 2009 US Census.

Table 12: Occupations and Interactive Intensity Index (III): US case

Occupation	PIAAC III	Occupation	O*NET III
Five Occupations with Lowest Interactive Intensity Index			
Assemblers	4	Cleaners and helpers	0
Cleaners and helpers	13	Handicraft and printing workers	25
Agricultural, forestry and fishery labourers	22	Assemblers	25
Handicraft and printing workers	28	Agricultural, forestry and fishery labourers	26
Market-oriented skilled forestry, fishery and hunting workers	30	Stationary plant and machine operators	29
Five Occupations with Highest Interactive Intensity Index			
Customer services clerks	70	Teaching professionals	66
Production and specialised services managers	71	Health professionals	77
Administrative and commercial managers	73	Administrative and commercial managers	79
Sales workers	75	Production and specialised services managers	79
Chief executives, senior officials and legislator	89	Chief executives, senior officials and legislator	82

Author's calculation on PIAAC and O*NET and 2009 US Census.

2.4 Correlations between O*NET and PIAAC Variables: the EU case

Several recent works have used O*NET abilities survey even when object of the study was the EU labor market. Is it appropriate to use US data, such as the O*NET, to calculate a Task Complexity Index for European countries? Are results obtained for the O*NET database in the US similar to those that would be obtained in Europe? Are O*NET questions perceived in the same way by workers in the US

Table 13: The Task Complexity Index (TCI) of each occupation: PIAAC and O*NET, US labor market.

Occupation	PIAAC TCI	Rank	O*NET TCI	Rank
Chief executives	65	4	72	6
Administrative man.	74	3	95	2
Production man.	50	7	85	3
Hospitality man.	37	13	45	14
Science and eng. prof.	52	6	67	8
Health prof.	33	18	47	12
Teaching prof.	49	8	75	5
Business and adm.prof.	100	1	100	1
Information prof.	62	5	70	7
Legal, social and cultural prof.	77	2	85	4
Science and eng.associate prof.	34	17	42	17
Health associate prof.	29	19	36	20
Business and adm. associate prof.	46	9	67	9
Legal ass. prof.	34	16	44	16
Information and communications techn.	37	12	45	15
General and keyboard clerks	35	14	63	10
Customer services clerks	40	10	60	11
Numerical and material recording clerks	39	11	47	13
Other clerical support work.	24	24	33	21
Personal service work.	20	27	21	30
Sales work.	27	21	36	19
Personal care work.	27	20	41	18
Protective services work.	34	15	26	24
Market-oriented skilled agricultural work.	25	23	31	22
Market-oriented skilled forestry work.	10	34	22	29
Building and related trades work.	18	28	25	25
Metal work.	24	25	20	33
Handicraft and printing work.	17	31	25	27
Electrical work.	26	22	26	23
Food processing work.	21	26	25	26
Stationary plant and machine op.	17	29	20	32
Assemblers	0	38	17	35
Drivers and mobile plant op.	17	30	20	31
Cleaners and helpers	3	37	0	38
Agricultural lab.	10	35	17	36
Labourers in mining	11	33	19	34
Food preparation ass.	4	36	13	37
Refuse workers and other el. work.	16	32	23	28

Author's calculation on PIAAC and O*NET and 2009 US Census.

ad in Europe?

Remembering that PIAAC was conducted in the US as well, its data may also serve to verify further the suitability of US data sources for determining qualification requirements in European countries. Remembering, furthermore, that the results of both surveys can be compared with O*NET data at the ISCO 2-digit, also in this case correlation analysis was used to test the degree of similarity between both PIAAC survey and the O*NET one (Table 14, next page).

Correlations are in average quite high (mostly around 0.7) but in some cases significantly lower than the correlations reported on Tables 5-8.

While correlations are quite high for Manual Skills and Cognitive Skills (all correlations are greater than 0.7 with some exceptions for Dexterity and Learning activities), for Organizing and Problem Solving there are conflicting results: if correlation for Problem Solving are very high (around 0.9) for Planning they are lower than 0.7 in almost all countries.

For Interactive Skills the correlations are quite high for variables as Persuading and Negotiating (around 0.9), they are high (around 0.7) for Planning Others, Communicating and Selling and, finally, they are significantly lower for Teaching, Consulting and Cooperating.

In particular for some countries, as Germany, Denmark, France and Netherlands, linear correlation for Teaching between European and US data across occupations is not so different from correlation between PIAAC and O*NET US data.

These low correlations may potentially restrict the validity of the analyses, however correlations are generally so high that it appears methodologically valid to use US data for European countries. In particular, the mean of linear correlations results quite high (between 0.753 and 0.796) for Belgium, Germany, Denmark, France, UK,

Netherlands and Sweden.

Although the use of US data for constructing task-composition of occupations for European countries has been justified by a correlation analysis, this approach does not allow for country-level and (eventually) over time differences across the EU.

Table 14: Correlation between O*NET variables (US labor market) and PIAAC variables (European labor markets)

Variables	BEL	CZE	DEU	DNK	ESP	FRA	UK	ITA	NLD	NOR	POL	SVK	SWE
Manual Skills													
Dexterity	0.766	0.687	0.758	0.749	0.815	0.816	0.682	0.692	0.77	0.753	0.671	0.425	0.759
Physical	0.871	0.848	0.864	0.873	0.897	0.909	0.878	0.801	0.894	0.814	0.852	0.835	0.894
Cognitive Skills													
Writing	0.863	0.835	0.814	0.796	0.777	0.822	0.821	0.81	0.831	0.688	0.753	0.839	0.8
Reading	0.907	0.876	0.901	0.915	0.93	0.896	0.928	0.907	0.903	0.784	0.913	0.928	0.874
Math	0.817	0.775	0.766	0.851	0.699	0.829	0.798	0.821	0.811	0.809	0.832	0.833	0.849
Use of PC	0.802	0.815	0.796	0.711	0.697	0.823	0.797	0.833	0.798	0.808	0.782	0.726	0.701
Learning Activities	0.721	0.621	0.783	0.656	0.578	0.785	0.694	0.612	0.714	0.473	0.671	0.741	0.578
Organising and Problem Solving Skills													
Problem Solving	0.876	0.843	0.876	0.881	0.747	0.867	0.826	0.858	0.874	0.781	0.853	0.848	0.89
Planning	0.662	0.675	0.68	0.605	0.586	0.702	0.714	0.594	0.772	0.654	0.72	0.716	0.684
Interactive Skills													
Teaching	0.536	0.534	0.737	0.735	0.591	0.759	0.694	0.561	0.721	0.575	0.666	0.639	0.749
Consulting	0.621	0.535	0.573	0.627	0.56	0.57	0.565	0.6	0.687	0.567	0.536	0.565	0.606
Planning Others	0.692	0.714	0.687	0.645	0.638	0.716	0.76	0.726	0.78	0.578	0.741	0.708	0.655
Communicating	0.741	0.666	0.738	0.782	0.693	0.691	0.769	0.64	0.774	0.717	0.61	0.717	0.776
Persuading	0.946	0.887	0.895	0.89	0.849	0.872	0.852	0.855	0.919	0.816	0.889	0.805	0.874
Negotiating	0.897	0.818	0.906	0.866	0.825	0.879	0.837	0.853	0.92	0.796	0.906	0.852	0.892
Cooperating	0.581	0.32	0.45	0.626	0.41	0.573	0.498	0.278	0.543	0.427	0.387	0.233	0.426
Selling	0.804	0.703	0.645	0.738	0.782	0.559	0.685	0.665	0.82	0.568	0.71	0.745	0.713
Min	0.536	0.32	0.45	0.605	0.41	0.559	0.498	0.278	0.543	0.427	0.387	0.233	0.426
Max	0.946	0.887	0.906	0.915	0.93	0.909	0.928	0.907	0.92	0.816	0.913	0.928	0.894
Avg	0.771	0.715	0.757	0.762	0.710	0.769	0.753	0.712	0.796	0.683	0.735	0.715	0.748

3 Conclusion

This work presents a comparison between two datasets, O*NET and PIAAC, through a correlation analysis. The aim of the comparison is to test if the results obtained for measuring workers' skill by PIAAC are consistent respect to the largely used US dataset O*NET. This comparison is possible since both datasets using the job requirement approach. The analysis involves a subset of the O*NET and PIAAC tasks grouped into manual, cognitive, organising-problem solving and interactive. In the first step I proceeded to compare O*NET and PIAAC using data on US workers: the analysis confirms that the two datasets are both useful to measuring workers' competencies. In the second step I compared O*NET and PIAAC using data on, respectively, US and European workers: the correlations are in general higher for Cognitive Skills and they are all on average higher for some countries than others. This suggests that PIAAC allows a more precise and usable international comparison of skills structures: the size of the PIAAC database, with more than 100 000 respondents in employment, ensures a rich source of information about country differences (around 5 000 cases in each country and all sectors and occupations for a given country).

Two national surveys based on O*NET questionnaires, "Indagine sulle professioni" in Italy and "Kvalifikace 2008" in the Czech Republic, have been concluded in recent years. Also the comparison between these national surveys and O*NET at the ISCO 2-digit confirms that the validity of the US surveys to construct a task structure specialization for considered European labor markets.

However, the main advantage of using the international survey PIAAC is that it allows to highlight the country-level and eventually over time differences across the

European countries. Further, for explaining the difference at country-level and at industry-level, it's possible and useful to include country-level variables from other sources such as R&D expenditure and innovation policies to improve the reliability of task-approach analysis (even for small countries, for example, using methods such as those from small-area statistics).

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