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Multi-Country Tasks Measures: Beyond US-based Data and a Focus on Migration.

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Multi-Country Tasks Measures: Beyond US-based Data and a Focus on Migration*

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Abstract

The US-based O*NET database is commonly used for multi-country studies on labor markets and migration by assuming invariant *occupation technology*, i.e. the quantitative assignment of tasks to occupations. We claim that the OECD dataset PIAAC (Programme for the International Assessment of Adult Competencies) could provide a valid alternative to obtain country-specific task measures. The US presence in both datasets allows us to compare the consistency of the two data sources along two dimensions. First, we compute the correlation coefficients between aggregate task indexes and they are very high (rarely less than 0.7). Secondly, we use the PIAAC database to replicate the empirical model in Peri and Sparber (2009) on US natives' task upgrading after a migration shock, and the results are strikingly similar to the original O*NET-based estimates. The multi-country variability of PIAAC-based task indexes for European countries are non-negligible; hence, we recommend these PIAAC-based measures for future multi-country analysis.

Keywords: Occupational Network Information (O*NET), Programme for the International Assessment of Adult Competencies (PIAAC), Migration, Task Upgrading.

JEL Classification Codes: J24, C81, F22.

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1 Introduction and Literature References

According to the human capital model (as in Becker, 1964) skills can be intended as a form of investment that can be acquired via education and job training. Indeed, data on education or qualification levels of the adult population ca be obtained from administrative sources or from large surveys and their main advantage is that they are objective and externally determined measures. However, educational attainment has been criticized as a fully reliable measure of job skills because qualifications gained in schools and colleges are only loosely related to the skills actually used in workplaces and, by the same token, to labor productivity. The task framework tries to overcome this latter problem by analyzing directly job skill requirements (Autor et al., 2003). This approach consists of classifying jobs according to their task core requirements, i.e the main activities that workers perform on their workplace.

In a very concise and non-exhaustive way, we identify three main research areas where the task approach has been fully applied. First, the task approach helped explore the causes of job polarization and the link between technological change and the shift in the wage structure. In these studies the primary hypothesis is that workplace computerization and automation lead to the displacement of human labor in tasks that can be described as routine, but does not decrease the demand for complex or nonroutine manual tasks (Autor et al., 2003, 2006, 2008; Spitz-Oener, 2006; Goos and Manning, 2007; Dustmann et al., 2009; Goos et al., 2009).

A second more recent strand considers the effects of international outsourcing on the employment. Antràs et al. (2006), 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.

Finally, the task approach has also been employed in several studies on immigration. Cortes (2008), Peri and Sparber (2009), Ottaviano and Peri (2012), D'Amuri and Peri (2014), and Ottaviano et al. (2018) compare the task assignment of native and migrant workers with similar education, age and experience. They show that the endogenous reaction of natives to migration can be task upgrading in the spirit of comparative advantages. Natives moves towards occupations that require a more intense use of language skills or interactive tasks by leaving to migrants manual tasks.

Most of these studies were on the US economy and could obtain task measures from the Occupational Information Network (O*NET) dataset[1] that provided worker attributes and job characteristics for 974 occupations. Similar detailed datasets were not available outside the US and O*NET has been straightly used to map occupations into quantitative task measures without widespread objections for other countries.

In 2015 the OECD has concluded the second wave of the Programme for the International Assessment of Adult Competencies (PIAAC)[2] and made available the 33-country dataset that contains variables closely comparable to the O*NET descriptors.

The scope of PIAAC is different from O*NET. The PIAAC survey wants to assess the proficiency of adults (16-65) in different skills that are relevant in many social contexts and work situations. O*NET originates as an occupational dataset to assist both employers and individuals respectively in their recruitment, in the design of training programmes, or in career planning. Notwithstanding these different origins, the skill measure technique and methodology to obtain the information from the

[1] https://www.onetcenter.org/database.html

[2] http://www.oecd.org/skills/piaac/

samples is the same for both surveys.

In this paper we pursue the following goals. Initially, we compare the two data sources by focusing on the US economy in two ways. First, we present the correlation between the same task variables coming from the two data sources. Second, we replicate the study by Peri and Sparber (2009) replacing the aggregate task measures obtained by O*NET with the same ones from PIAAC. Our results confirm a very high correlation (rarely below 0.7) between the US task variables coming from O*NET and PIAAC. Moreover, the empirical estimates in the Peri-Spaber study are confirmed in magnitude and in the statistical significance.

As a second goal, we obtain measures of dispersion in task utilization for the European countries participating to the PIAAC study. Inter-country variability in task utilization is non-negligible; hence, we caution future researchers on the plain usage of O*NET for all countries in a one-size-fits-all assumption.

In the remaining of the paper Section 2 we present a broad description of the two datasets with a focus on PIAAC and in Section 3 we compare them by taking advantage of the overlapping data for the US. Section 4 shows the variability of the aggregate task indexes for the European countries when using PIAAC and Section 5 concludes.

2 Sketching the Two Datasets

As mentioned in Section 1, the aims and origins of O*NET and PIAAC are very different. PIAAC is a survey to collect information on how skills are generally used, whereas O*NET serves operationally for recruitment. From a conceptual point of view, in O*NET the unit of analysis is the *occupation* rather than the individual;

by contrast in PIAAC unit of analysis is the *person-job*. We could generally assume that the former presents a better description of the *labor demand*, while the latter is a closer measure to the *labor supply*. As a consequence of a survey on all individuals, in PIAAC we can find characteristics of the unemployed, that are obviously absent in O*NET.

However, the skill measure technique and methodology to obtain the information from the samples is the same for both surveys and is based on the Job Requirement Approach (JRA).[3] We recall the two assumptions of JRA: individuals are as well-informed as to report properly the activities involved in her job and unbiasedly the relative performance. Both PIAAC and O*NET face the same issues for the correct application of the JRA and use similar solutions to obtain reliable information.

In the following Section we report the characteristics of PIAAC as a multi-country study and this represents its most important and original characteristics with respect to the US-based O*NET.

2.1 A Focus on PIAAC

Being an OECD programme, 33 entities participated in PIAAC, comprising 29 OECD member countries, three regional entities from two OECD member countries (England and N. Ireland for UK and Flanders for Belgium) and two partner countries (Cyprus and the Russian Federation).[4]

Units of analysis are the individuals and their competencies, so the PIAAC target population consists of all non-institutionalized adults aged 16-65 who reside in the country at the time of data collection. Adults were to be included regardless

[3] In Appendix A we present the more technical details of the data collection and highlight the similarities.

[4] See Appendix A for the full list of participating countries.

of citizenship, nationality or language and employment status – hence, in PIAAC non-working individuals are also included.

PIAAC questionnaire includes ten groups of questions. They encompass questions about the current job and the work history, the skills used at work, the skills used in everyday life (cognitive skills), questions about the self-perception of one's own skills, and general background questions. The sample stratification allows inference at the country level by different demographic characteristics (e.g. gender and immigration status) and to assess the differences in the task assignments. The multi-country dimension of the survey validates the differences in the occupation technology at the national level, as we present for the European countries participating in PIAAC in Secction 4.

3 Comparing the Datasets: Re-estimating the Effect of Migration with PIAAC (Peri and Sparber, 2009)

The O*NET dataset comes from job incumbents, occupational analysts and occupational experts and is collected for occupations based on the 2010 Standard Occupational Code (SOC).[5] PIAAC uses a slight different nomenclature for skills and tasks, but completely comparable.

In Table 1 we report both PIAAC and O*NET lists of the variables that we decided to aggregate according to the typical analysis of the effects of migration, as

[5]For the public use data, PIAAC uses the ISCO-08 (2 digit) classification instead of SOC-2010 (4 digit). We used the same crosswalk as in Hardy et al. (2018). Details are available from the authors upon requests. See also Goos et al. (2009) for other methods of data crosswalking.

in D'Amuri and Peri (2014).[6]

As a first evidence, we computed correlation coefficients of the variables needed to obtain the aggregate task variables coming from both datasets. In particular, referring to Table 1, we computed the correlation coefficients of the sub-tasks for each of the four aggregate tasks (manual, cognitive, organising and problem solving, interactive). Appendix B reports the very high correlation coefficients that are lower than 0.7 only in three cases out of 14 (significantly different from zero according to traditional tests). The two datasets show also similar internal consistency, i.e. similar correlation among the sub-tasks.

As a further evidence, we used the two datasets to replicate the seminal paper by Peri and Sparber (2009) and compare the estimates.

As a reminder, Peri and Sparber (2009) argue that native and foreign-born workers specialize in different production tasks. A comparative advantage in tasks that require more intensive use of language or communicative skills pertains to natives, whereas migrants show a comparative (although not necessarily absolute) advantage in tasks that require more manual skills. This mechanism explains why migrants have only a modest effect on low-skilled native wage (Ottaviano and Peri, 2012).

To empirically test this hypothesis, Peri and Sparber (2009) combine data from the O*NET dataset with individual data by IPUMS.[7] Then, they regress different task indexes of the native employment on the immigrant share in the US from 1960 to 2000. The regression results – confirmed by the IV implementation – show a negative effect of the immigrant share on the supply of manual tasks by natives and

[6]Following D'Amuri and Peri (2014), for each dataset, we 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.

[7]See https://usa.ipums.org/usa/

Table 1: **Task Types and Variables from O*NET and PIAAC**

Task	Sub-task	O*NET Variables	PIAAC Variables
Manual	Dexterity	Manual dexterity Finger dexterity	Using hands or fingers
	Physical Activities	Stamina	Working physically for long
Cognitive	Writing	Written expression	Writing activities
	Reading	Written comprehension	Reading activities
	Mathematics	Mathematics	Numeracy activities
	Use of PC	Programming	ICT Activities
Organising and Problem Solving	Problem Solving	Complex problem solving	Complex problems
	Planning	Time Management	Planning own activities Planning others activities Organizing own time
Interactive	Teaching	Instructing	Teaching people
	Consulting	Actively looking for ways to help people	Advising people
	Persuading	Persuasion	Influencing people
	Communicating	Speaking	Presentations
	Negotiating	Negotiation	Negotiating with people
	Cooperation	Coordination	Sharing work-related info

Source: Authors' elaboration.

an opposite impact on the supply of communicative tasks.

In Table 2 we replicate the Peri and Sparber (2009) results for the OLS regression analysis using both O*NET and PIAAC for the period 2010-2017.[8] The coefficients obtained with the two dataset are very similar in terms of the direction of the effects and their significance.

As in Peri and Sparber (2009), we also implement the IV analysis. Table 3 shows that the two regressions using PIAAC and O*NET data produce the same results hence confirming the original message of their analysis – during the period 2010-2017, migrants have pushed natives to specialize in language intensive tasks and to supply less manual intensive tasks.

4 Multi-Country Variability: the EU case

Several authors have used the O*NET database to study the effects of migration in EU labor markets – see, for instance, D'Amuri and Peri (2014). Task measures, such as the Task Complexity Index, have been obtained by applying the US-based O*NET values to the European labor market data. The usage of PIAAC in addition or in lieu of O*NET has been recently considered by Hardy et al. (2018) with regards to characteristics of the European labor market in terms of routinization. No other study has taken alternative routes for task measures when analysing the effects of migration in Europe at our knowledge.

In Figure 1 we report our computations of the aggregated task indexes presented in Table 1 and most commonly used in the analysis of the effects of migration. As a

[8]We needed to update the analysis in order to translate the occupation code used in IPUMS with the occupation code used in PIAAC. The very rigorous crosswalk by Hardy et al. (2018) allows the comparison between ISCO-08 and SOC10, but can be used in IPUMS only from 2010 onward.

Table 2: Foreign-Born Workers and the Native Supply of Tasks (OLS)

	(1) Comm./Man.	(2) Comm.	(3) Man.	(4) E. Comm./ E. Man.	(5) E. Comm.	(6) E. Man.
			Using O*NET			
Sh. of Migr.	0.468	0.222	-0.246**	0.344*	0.181	-0.163***
	[0.286]	[0.190]	[0.102]	[0.186]	[0.162]	[0.043]
Obs.	408	408	408	408	408	408
			Using PIAAC			
Sh. of Migr	0.206	0.103	-0.103*	0.255	0.103	-0.151*
	[0.139]	[0.085]	[0.056]	[0.159]	[0.085]	[0.077]
Obs.	408	408	408	408	408	408

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The dependent variable in model (1) is the relative supply of communication over manual tasks by native workers (basic definition). In model (2) it is the supply of communication tasks by native workers (basic definition). In model (3) it is the supply of manual tasks by native workers (basic definition). Models (4), (5) and (6) use an extended definition of the task indexes. The explanatory variable is the foreign-born share of workers with a high school degree or less.

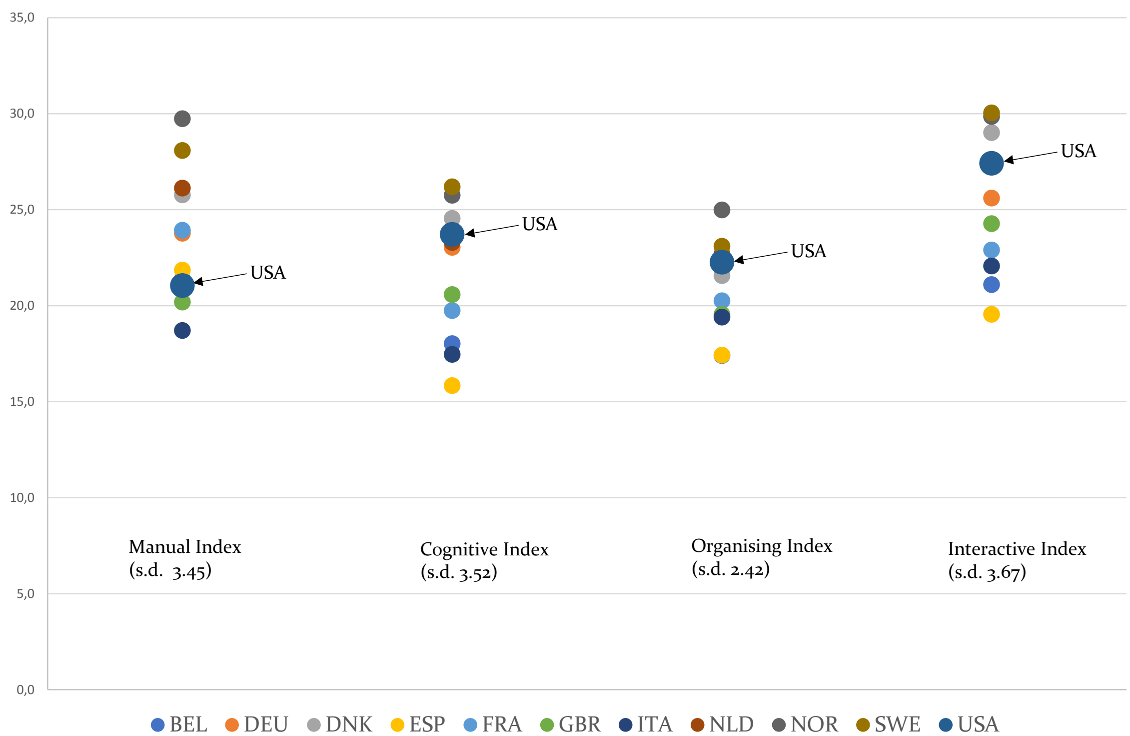
Table 3: Foreign-Born Workers and the Native Supply of Tasks (IV)

	(1) Comm./Man.	(2) Comm.	(3) Man.	(4) E. Comm./ E. Man.	(5) E. Comm.	(6) E. Man.
			Using O*NET			
Sh. of Migr.	1.570**	1.186*	-0.384	1.191***	0.727***	-0.463***
	[0.617]	[0.645]	[0.390]	[0.341]	[0.215]	[0.161]
Obs.	357	357	357	357	357	357
			Using PIAAC			
Sh. of Migr	0.753**	0.456**	-0.297***	0.499***	0.318***	-0.181***
	[0.314]	[0.232]	[0.103]	[0.151]	[0.100]	[0.070]
Obs.	357	357	357	357	357	357

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The dependent variable in model (1) is the relative supply of communication over manual tasks by native workers (basic definition). In model (2) it is the supply of communication tasks by native workers (basic definition). In model (3) it is the supply of manual tasks by native workers (basic definition). Models (4), (5) and (6) use an extended definition of the task indexes. The explanatory variable is the foreign-born share of workers with a high school degree or less.

Figure 1: Task Indexes for European Countries and the US (standard deviation in parenthesis).



Source: Authors' calculations

reference, we report also the same index values for the US that result very different from the index values of the other countries. The standard deviations of the indexes distributions are not negligible.

5 Conclusion

This work presents a comparison between the O*NET and the PIAAC datasets to obtain aggregate task measures at the country level. We have taken advantage of the overlapping information for the US. The comparison has been performed with descriptive statistics and by replicating the study by Peri and Sparber (2009) on the effect of migration in the US. Task variables and constructed indexes with both PIAAC and O*NET for the US are highly correlated and the replication of the study also confirms how the information available in PIAAC is qualitatively and quantitatively comparable with O*NET.

The major advantage of PIAAC is to be a multi-country dataset and therefore to convey more appropriate and country-specific information on aggregate task performance. Indeed, the dispersion of aggregate task indexes for the European countries and the difference with respect to the US data are not negligible (see Figure 1). Future work with a multi-country dimension and considering the task approach should take advantage of the PIAAC dataset instead of using the US-based O*NET to avoid biased results and exploit additional variability.

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TECHNICAL APPENDICES

A Skills assessing in PIAAC and O*NET

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 problem solving in a technology rich environment. 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.[9] 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*, different statistical techniques[10] are used to generate several generic skill indicators from the responses on these items.

Twelve indicators were created (Table 4), five of which refer to information-processing skills (reading, writing, numeracy, ICT skills and problem solving), while 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). According to the purpose of this paper (comparison of the two datasets), we consider only the part of the survey which measures the generic skills through self-reporting. This part, indeed, uses the Job Requirement Approach that ensures a reasonable level of comparability with the US dataset. In particular, in PIAAC a number of skills-use variables are taken directly from questions asked in the background questionnaire using the JRA. Here are some examples of questions:

[9]"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, 2013).

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

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?

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?

Numerical comparisons among 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 4 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.

O*NET 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. It provides a framework that identifies the most important types of information about work and integrates them into a theoretically and empirically sound system (Table 5). Some examples of *descriptors* of skills and job characteristics are the following: qualifications required; practical and technical skills; a wide range of soft skills such as communication skills, stamina etc. A brief description of the main O*NET questionnaires is reported in Table 6 for the four domains of Knowledge, Skills, Abilities and Work activities. Both *Importance* and *Level* of each skill or characteristic are recorded (see Figure 2 for an example).

O*NET and PIAAC classifications use different scales, as O*NET assesses *Importance* of each attribute on any occupation, whereas PIAAC uses the metrics of

Table 4: 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 online 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 coworkers; 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)

Table 5: 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

Table 6: 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 Work Activities	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 (2016) and Tippins and Hilton (2010), p.72, p. 74.

Figure 2: Examples of Questions in PIAAC and ONET

(a) PIAAC 'Cooperating or Collaborating with Co-Workers'

Code	F_Q01a_lead	
Question	In your ^JobLastjob what proportion of your time ^DoDid you usually spend ...	
Code	F_Q01b	
Question	cooperating or collaborating with co-workers?	
Instruction	If the respondent has no co-workers, the answer should be 'none of the time'.	
Responses	01	None of the time
	02	Up to a quarter of the time
	03	Up to half of the time
	04	More than half of the time
	05	All the time
	DK	DK
	RF	RF

Source: http://www.piaac.org/questionnaires.html

(b) O*NET 'Coordinating the Work and Activities of Others'

33. Coordinating the Work and Activities of Others — **Getting members of a group to work together to accomplish tasks.**

A. How <u>important</u> is COORDINATING THE WORK AND ACTIVITIES OF OTHERS to the performance of *your current job*?

Not Important*	Somewhat Important	Important	Very Important	Extremely Important
1	2	3	4	5

* If you marked Not Important, skip LEVEL below and go on to the next activity.

B. What <u>level</u> of COORDINATING THE WORK AND ACTIVITIES OF OTHERS is needed to perform *your current job*?

1	2	3	4	5	6	7
	Exchange information during a shift change		Organize the cleanup crew after a major sporting event			Act as general contractor for building a large industrial complex
						Highest Level

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

Frequency of each task at the workplace. The idea behind the comparison is that if more important tasks also take a longer working time span.

Last fundamental difference to stress is that O*NET survey tasks used at work only for U.S. occupations. PIAAC includes all adults who reside in the country at the time of data collection. The participating countries are: Australia, Austria, Canada, Chile*, Cyprus, Czech Republic, Denmark, England/N. Ireland (UK), Estonia, Finland, Flanders (Belgium), France, Germany, Greece*, Ireland, Israel*, Italy, Jakarta* (Indonesia), Japan, Korea, Lithuania*, Netherlands, New Zealand*, Norway, Poland, Russian Federation, Singapore*, Slovak Republic, Slovenia*, Spain, Sweden, Turkey*, and United States.[11]

B Correlation Analysis to Compare PIAAC and O*NET

In the Tables 7 and 8 we present the correlations between the variables used in the aggregated definitions of (respectively) Manual, Organising and Problem Solving, Cognitive and Interaction-Communication. The coefficients are rarely lower than 0.7 (the simple average is 0.73). We have also included the correlation coefficients between the components of the four indexes in order to check a sort of internal consistency between PIAAC and O*NET, i.e. see whether the correlation among the different components of the two indexes are similar. The difference between correlations of the same components in the two datasets are lower than 0.3 for 13 out of 23 cases.

[11] The star indicates the countries that participated or produced the results only in the second round of the survey.

Table 7: Correlation between O*Net and PIAAC for the US (Manual, Organising, Cognitive)

(a) Manual

Variables	piaac dexterity	onet dexterity	piaac physically
onet dexterity	0.691	1.000	
piaac physically	0.693		1.000
onet physically		0.784	0.878

(b) Organising and Problem Solving

Variables	piaac problem	onet problem	piaac plan
onet problem	0.808	1.000	
piaac plan	0.603		1.000
onet plan		0.835	0.732

(c) Cognitive

Variables	piaac write	onet write	piaac read	onet read	piaac math	onet math	piaac ict
onet write	0.841	1.000					
piaac read	0.880		1.000				
onet read		0.980	0.865	1.000			
piaac math	0.799		0.808		1.000		
onet math		0.763		0.803	0.821	1.000	
piaac ict	0.839		0.893		0.792		1.000
onet ict		0.524		0.574		0.609	0.703

Table 8: Correlation between O*NET and PIAAC (Interaction and Communication)

Variables	piaac teaching	onet teaching	piaac consulting	onet consulting	piaac persuading	onet persuading	piaac speaking	onet speaking	piaac negotiating	onet negotiating	piaac cooperating
onet teaching	0.734	1.000									
piaac consulting	0.840		1.000								
onet consulting		0.595	0.327	1.000							
piaac persuading	0.471		0.461		1.000						
onet persuading		0.640		0.797	0.888	1.000					
piaac speaking	0.694		0.534		0.736		1.000				
onet speaking		0.775		0.831		0.906	0.718	1.000			
piaac negotiating	0.341		0.420		0.883		0.561		1.000		
onet negotiating		0.730		0.782		0.956		0.916	0.895	1.000	
piaac cooperating	0.734		0.792		0.188		0.349		0.071		1.000
onet cooperating		0.824		0.686		0.833		0.837		0.922	0.309

C Occupations with Highest and Lowest Task Indexes in PIAAC and O*NET

Tables 9–12 give the distribution of competencies according to occupational roles for the aggregated tasks. Let's recall that 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 1. Although with different ranks, the same occupations are in the first (or the last) five positions.

Table 9: **Occupations and Manual Intensity Index (MII) in the US**

Occupation	PIIAC 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) in the US

Occupation	**PIIAC 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) in the US

Occupation	PIIAC 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) in the US

Occupation	PIIAC 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.

D Ranking Occupations according to the Task Complexity Index in PIAAC and O*NET

Following Peri and Sparber (2009), we constructed the *Task-Complexity Index (TCI)* as follows:

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

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).

Table 13 reports the computation of the TCI for major occupations by using both PIAAC and O*NET. Although the value of the index may differ, the rank is not that different when considering the two datasets.

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.