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

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Abstract

We claim that the OECD dataset PIAAC (Programme for the International Assessment of Adult Competencies) could provide a valid alternative to the US-based O*NET database in order to obtain country-specific task measures. The US presence in PIAAC allows to compare the two datasets by computing the same task indexes twice. We find that correlation coefficients between aggregate task indexes are very high (rarely less than 0.7). Focusing on European countries, we recommend the PIAAC-based task measures for future domestic and multi-country analysis (e.g. on the effects of migration in the labor markets) since task indexes appear very different among European economies.

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1 Introduction and Literature References

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., 2008; Spitz-Oener, 2006; Goos and Manning, 2007; Dustmann 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. Peri and Sparber (2009), 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 analyzed the US economy and could obtain task measures from the Occupational Information Network (O*NET) dataset.[1] Similar detailed datasets were not available outside the US and O*NET has been straightly used to map occupations into quantitative task measures 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. Notwithstanding the different origins of the two datasets, the skill measure technique and methodology to obtain the information from the samples is the same for both surveys.

A comprehensive review of studies that employed data from PIAAC is provided by Martin (2018). Accordingly, only Henseke and Green (2017) exploited the task approach for a cross-country analysis on the skill use at the work place.

In this paper we show that PIAAC data are more appropriate for international comparisons since they convey country-specific information similar to O*NET, but not based only on the US economy. Exploiting the US presence in PIAAC (and clearly in O*NET), we computed various correlation measures between the same task aggregate variables from the two data sources and highlighted how correlation is very high. Finally, by focusing on the European economies, we note that the variability of the PIAAC-based task indexes is high; hence, we caution future researchers on the plain usage of O*NET in a one-size-fits-all assumption.

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

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

2 Sketching the Two Datasets

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 by the individual in many contexts (home, workplace, community), 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 the unit of analysis is the *person-job* for the employed individuals. Being a survey on *all* individuals, PIAAC provides data also for the unemployed and on their performance in their last job. This information is absent in O*NET.

Notwithstanding these differences, the skill-measure technique and methodology to obtain the information from the samples is the same for both surveys and relies on the Job Requirement Approach (JRA) — the JRA is based on the assumption that individuals are so well-informed to report properly and unbiasedly both: (*i*) the activities involved in their jobs, (*ii*) the relative performance.[3]

As an OECD programme, PIAAC involved 33 entities including 29 OECD member countries, three regions-states from two OECD member countries (England and N. Ireland for UK and Flanders for Belgium) and two partner countries (Cyprus and the Russian Federation).

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 of citizenship, nationality or language and employment status. In terms of occupation characteristics, PIAAC uses the International Standard Classification of Occupation (ISCO08) — issued by the International Labor Office (ILO) — while O*NET is based on the 2018 Standard Occupational Classification (SOC10) — provided by the US Bureau of Labor Statistics. The latter encompasses 974 occupational titles, much more than the 436 units classified by the ILO. Nonetheless, SOC classification is adopted only for US datasets and specific cross-walks are needed in order to match O*NET with data for other countries. Therefore, another advantage of using the PIAAC data rather than O*NET for countries other than the US is that no data cross-walks are needed.

PIAAC questionnaire includes ten groups of questions. They encompass 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 especially at the sectoral level. The multi-country dimension of the survey validates the differences in the occupation technology at the national level (see Section 4 below) and suggests its usage for both domestic analyses and cross-country comparisons. The sample size ranges between 4,500 and 5,000 individuals depending on the sections of the questionnaires that were activated country by country.

[3] In an Appendix available from the authors as supplemental material we report more technical details of the data collection.

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

Task	Sub-task	O*NET Variables	PIAAC Variables
Manual	Dexterity	Manual dexterity	Using hands or fingers
		Finger dexterity	
	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.

3 Comparing the Two Datasets

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 in Peri and Sparber (2009) or D'Amuri and Peri (2014).[4] A standardized measure of the relative importance of a given skill is obtained for US workers. We recall the metrics: a task with a score of 6 indicates that only 6 percent of workers in the United States were supplying that skill less intensively.

In Table 2 we present the correlations between the variables used in the aggregated definitions of *Manual*, *Organising and Problem Solving*, *Cognitive* and *Interaction-Communication* defined in Table 1. It is worth clarifying that the two datasets are compared at the occupation level, i.e. average intensity measures are computed across workers in the same occupation. The coefficients are rarely lower than 0.7 (with only two exceptions). We have also included the correlation coefficients between the components of the four indexes. This allows us to check whether the internal consistency of the aggregate indexes is similar in PIAAC and O*NET, i.e. see whether the correlation among the different components of the two indexes are the same. The difference between correlations of the same components in the two datasets are lower than 0.3 for 13 out of 23 cases.[5]

[4]Following Peri and Sparber (2009) and 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, re-scaling each value so that it equals the percentile score in that year. A replication of the econometric model in Peri and Sparber (2009) with PIAAC instead of O*NET is available from the authors upon request. The results are stikingly similar.

[5]In an Appendix available from the authors as supplemental material we report more evidence on the high correlation between the two datasets, e.g. rank correlations of task indexes by occupation. Another comparison is based on the replication of the study by Peri and Sparber (2009) with PIAAC instead of the O*NET dataset. The results are still available in the Appendix.

Table 2: Correlation between O*Net and PIAAC for the US (Manual, Organising, Cognitive, Interaction and Communication)

(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

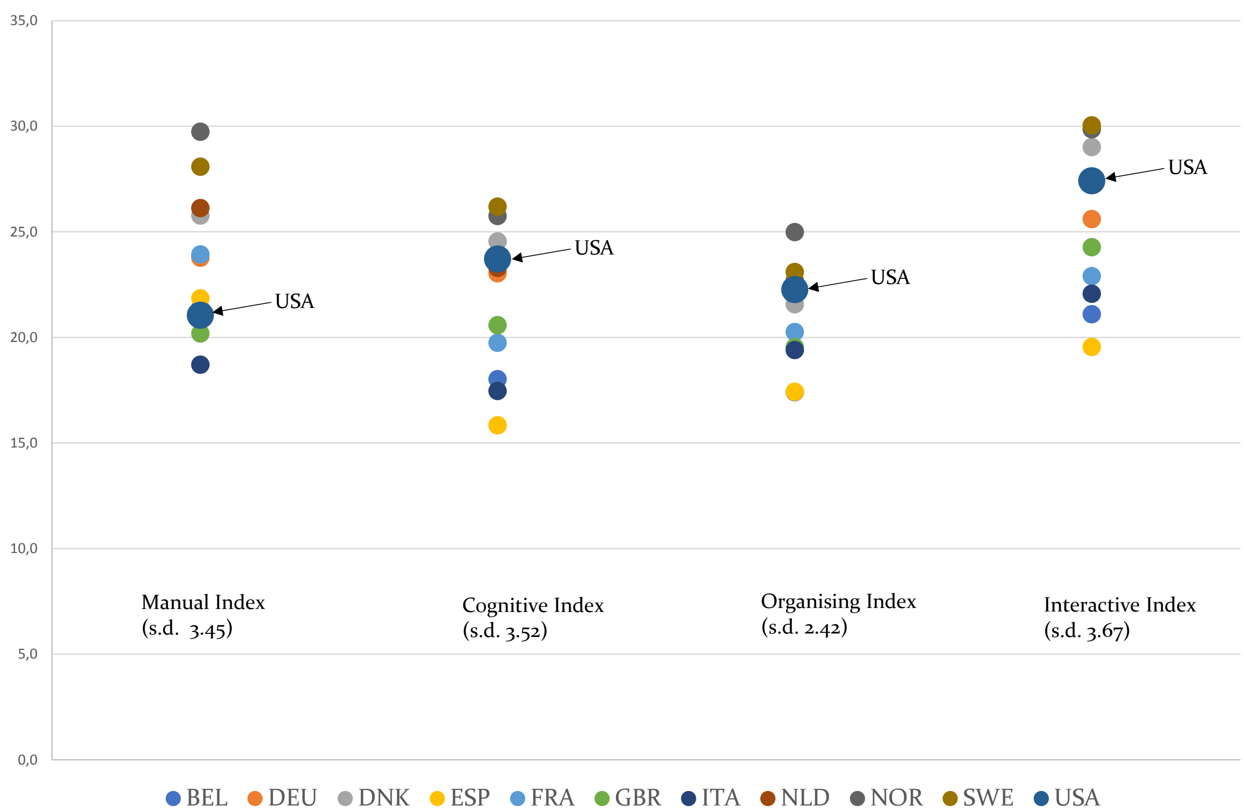
(d) Interaction and Communication

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

4 Country-Specific Variability from PIAAC in Europe

Some authors have used the task approach to study the economic effects of migration on Europe, but used O*NET as the reference for the occupational technology — see for instance D'Amuri and Peri (2014). We claim that these studies lack country-specific characteristics of the occupational technology by applying the US-tailored O*NET to other countries.

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



Source: Authors' calculations

Indeed, Figure 1 reports our PIAAC-based computations of the task indexes of Table 1 for major European countries — Belgium (BEL), Denmark (DNK), France (FRA), Germany (DEU), Great Britain (GBR), Italy (ITA), Netherlands (NLD), Norway (NOR), Spain (ESP), Sweden (SWE). These indexes range from 1 to 100 and mirror the distribution of task intensity at the country level based on occupations as reported by individual workers. These same indexes have been used in studies on the impact of migration, but they were computed with O*NET and so without any variation. Therefore, if the one-size-fits-all assumption that justifies the usage of O*NET for all countries were correct, we should expect all dots in Figure 1 computed with PIAAC to collapse onto the US value (apart from negligible measurement errors). Instead, Figure 1 shows that there is a significant dispersion with coefficients of variation ranging between 12 and 16 per cent when we allow country variability.

Some recent studies have used the country-specific information on task in PIAAC. For instance, Hardy et al. (2018) employ PIAAC (in addition or in lieu of O*NET) to investigate the characteristics of the European labor markets and the effect of routinization.

5 Future Work

Task variables and constructed indexes with both PIAAC and O*NET for the US are highly correlated confirming how the information available in PIAAC is qualitatively and quantitatively comparable with O*NET. But 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. For instance, the dispersion of aggregate task indexes for the European countries (and the difference with respect to the US) are not negligible (see Figure 1). Future work using the task approach for either domestic analysis or with a multi-country dimension 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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