Developing a Task-based Approach for the Measurement of Human Resources in Knowledge-based Capital

Mariagrazia Squicciarini (OECD)

Marie Le Mouel (DIW Berlin, Germany)

Paper Prepared for the IARIW 33rd General Conference

Rotterdam, the Netherlands, August 24-30, 2014

Session 4A

Time: Tuesday, August 26, Afternoon

DEVELOPING A TASK-BASED APPROACH FOR THE MEASUREMENT OF HUMAN RESOURCES IN KNOWLEDGE-BASED CAPITAL

Mariagrazia Squicciarini (OECD) and Marie Le Mouel (DIW Berlin)

ABSTRACT

Research on the role of Knowledge-Based Capital (KBC) as a key driver of firm performance, especially as a complementary and enabling asset for other investments, has burgeoned in recent years and has contributed to making significant progress in the measurement of resources devoted by firms to KBC. The expenditure based approach of Corrado, Hulten and Sichel (2005, 2009, hereafter CHS) has been widely adopted across OECD countries. Such an approach relies on the economics and management literature, where knowledge assets can be seen as embedded in a firm's employees.

The present paper seeks to quantify the human resources devoted to KBC by looking at the task content of occupations. To do so, it builds on previous work by the authors that uses the Occupational Information Network (O*NET) data from the United States Department of Labor to estimate organisation capital. The methodoly is here extended in two directions. Firstly, the same database is used to identify workers who contribute to the creation and accumulation of four KBC asset types: Organisational Capital, Research and Development, Computerised Information and Design. Results suggest that there is a large overlap between these assets, as they tend to be associated with similar workers. Secondly, the OECD database from the Programme for the International Assessment of Adult Competencies (PIAAC) is used to test whether the results derived using the ONET databse can be generalised to a set of OECD countries. Results suggest that occupational categories seem to be associated with the performance of distinct tasks at the international level.

Keywords: Knowledge-based capital, organisational capital, embeddedness, tasks, Occupational Network Information (O*NET), OECD Programme for the International Assessment of Adult Competencies (PIAAC).

* *We are in debt to Carol Corrado, Cecilia Jona-Lasinio, Mary O'Mahony, Kyoji Fukao, Tsutomu Miyagawa, and Matilde Mas for their extremely valuable comments and suggestions. We are also very grateful to the participants in the "OECD Expert Meeting on the Measurement of Intangible Assets" and of the "OECD-INDICSER Meeting on Estimating Intangible Capital at the Sector Level" for helpful discussion. The support and advice of Alessandra Colecchia, Colin Webb, Andrea de Panizza and Fernando Galindo Rueda is also gratefully acknowledged. All errors remain our own.*

DEVELOPING A TASK-BASED APPROACH FOR THE MEASUREMENT OF HUMAN RESOURCES IN KNOWLEDGE-BASED CAPITAL

Introduction

Knowledge-based capital (KBC) is extremely important for firms, industries and countries as it has been shown to be positively related to measures of economic performance and competitiveness (see e.g. Edquist, 2011, and Dal Borgo et al., 2013, for recent evidence). It consists of (firm-specific) assets lacking of physical substance whose main value stems from their knowledge content and lasting nature. Knowledge is often tacit in nature, is mainly embodied in people. Hence, the generation and accumulation of KBC in firms is strongly linked to companies' investment in human capital.

The OECD has developed a methodology which exploits information about the tasks that employees perform on the job - rather than relying on their occupational title, as done previously in the literature - and has applied it to estimate investment in organisational capital. Based on this experimental methodology, data on wages have been used to estimate own-account investment in organisational capital (OC), both at the industry and country level (Squicciarini and Le Mouel, 2012).

Follow up analysis (Squicciarini and Le Mouel, forthcoming) further refined the task-based methodology by including information on the skills and knowledge base of workers – especially their educational background. It did so motivated by the large body of literature suggesting the importance of human capital capabilities, in terms of skills and education, for the accomplishment of the relevant tasks on the job. This refinement was labelled as "TaSK", to underline that the performance of a number of **Ta**sks, as well as the endowment of workers in terms of **S**kills and **K**nowledge to perform these tasks effectively, all contribute to the generation and accumulation of KBC.

The current paper discusses how the TaSK approach can be used to define and measure not only OC, but also other assets identified by Corrado, Hulten and Sichel (henceforth CHS, 2009), especially computerised information (CI), design, and research and development (R&D). These knowledge based assets play a key role in the functioning of firms - especially OC and CI - , and as inputs in innovation processes – R&D and design in particular. In addition, they have been shown to be extremely complementary in nature. On the one hand, firms appear to be able to maximise the benefits from their investments in CI if these are accompanied by matching investments in organisational capabilities and in human capital (see e.g. Breshnahan, Brynjolffson and Hitt, 2002; and Aral and Weill, 2007). On the other hand, R&D and design investments appear to be highly related and jointly affect a firm's innovative performance (e.g. Santamaria et al, 2009). Recent evidence also suggests that firms often rely on the full spectrum of Intellectual Property Rights (IPR) instruments at their disposal (the so called "IP bundle") to protect the results of their innovative activities (see e.g. the forthcoming STI Scoreboard 2013).

The novel TaSK-based methodology relies on detailed survey data relating to the tasks that employees perform on the jobs, and the skills and knowledge areas they are endowed with. While available data, which at present relate to the United States only, allow for a comprehensive description of the profiles of the workforce contributing to the generation and accumulation of OC, CI, R&D and design, they nevertheless do not allow for a definition of the TaSK profiles of other important KBC types as branding and training. Our experimental work suggests that the majority of KBC-related employees contribute to the generation and accumulation of more than one type of asset. Some assets, especially CI, appear to be extremely "complementary", as workers contributing to the generation of this KBC asset type are almost always contributing to the generation and accumulation of other assets as well.

In addition to expanding the set of assets to which this task-based methodology can be applied, the present paper also tests the extent to which this methodology can be applied across countries. Using the recent OECD data from the Programme for the International Assessment of Adult Competencies (PIAAC), the analysis is replicated on task-related survey data covering 17 countries, of which the United States. Comparative results show that a general picture emerges across countries concerning the performance of certain tasks by occupational category.

The remainder of this document spells out the TaSK-based methodology devised for the definition and measurement of OC, CI, R&D and design. It briefly discusses the literature this experimental approach relies upon and the way in which the TaSK approach has been operationalised and used to estimate employment figures for 15 OECD countries. We currently present only employment related figures and to not seek to quantify the percentage of earnings, i.e. salaries, corresponding to investment in these assets. Valuing investments in these intangible assets is beyond the scope of this paper as it requires further methodological advances and data collection, e.g. related to employees' time use and earnings by occupations.

A TaSK-based approach to the definition of KBC assets

OC, CI, R&D and design have been at the centre of a wide array of studies – in e.g. management, organisation science, economics, innovation studies – aiming to define and measure these KBC, and to assess their economic relevance and strategic importance. Although extremely helpful for a better understanding of the way KBC assets are generated and of the role they play for the competitiveness of firms and countries, these contributions nevertheless rely on diverse methodologies and data sources and generally address punctual issues. This makes it difficult to look at the array of KBC assets and their interactions, and to generalise results or compare them.

The TaSK experimental approach to defining and measuring OC, CI, R&D and design combines a focus on human capital with an expenditure-based approach. On the one hand, the literature suggests that firms' knowledge-based assets reside in its human capital, and are generated by the workforce accomplishing specific sets of task within the firm. In this respect, jobs can be seen as "building blocks" arising out of the bundle of tasks that employees perform under different administrative titles (see e.g. Cohen, 2013). Moreover, it is argued that human capital should be looked at as a multi-level resource (Ployhart and Moliterno, 2011) emerging out of characteristics as individuals' knowledge base, skills and abilities, as these are linked to individual-level outcomes. A broad literature further underlines the positive relationship existing between performance on the job and workforce endowment in terms of education, abilities and skills that are relevant to the tasks to be accomplished (see, e.g., Kaplan et al., 2012; Ng and Feldman, 2009).

On the other hand, when it comes to measuring investment in KBC formation, one of the most used methods is the expenditure-based approach. In the case of human capital-related assets, this corresponds to quantifying the resources devoted to the generation of KBC assets on the basis of the cost (i.e. the remuneration) of the workers contributing to its formation. Examples are CHS approach to measuring OC, whereby it is assumed that own-account investment in OC corresponds to 20% of managers' time and proxied by a corresponding fraction of managers' earnings.

In what follows we describe the way the experimental TaSK approach is operationalised to define and measure OC, CI, R&D and design, rather than surveying in depth the relevant literature or the many definitions that exists for each of the KBC types considered. A thorough discussion in that respect can be found in Squicciarini and Le Mouel (2012) in relation to organisational capital. Carrying out the same exercise with respect to the other KBC types considered remains beyond the scope of the present paper, for two main reasons. Being human capital-based, the TaSK approach is able to identify the workforce contributing to the generation and accumulation of these KBC, and doing so it accommodates many of the definitions that have been proposed by the literature.

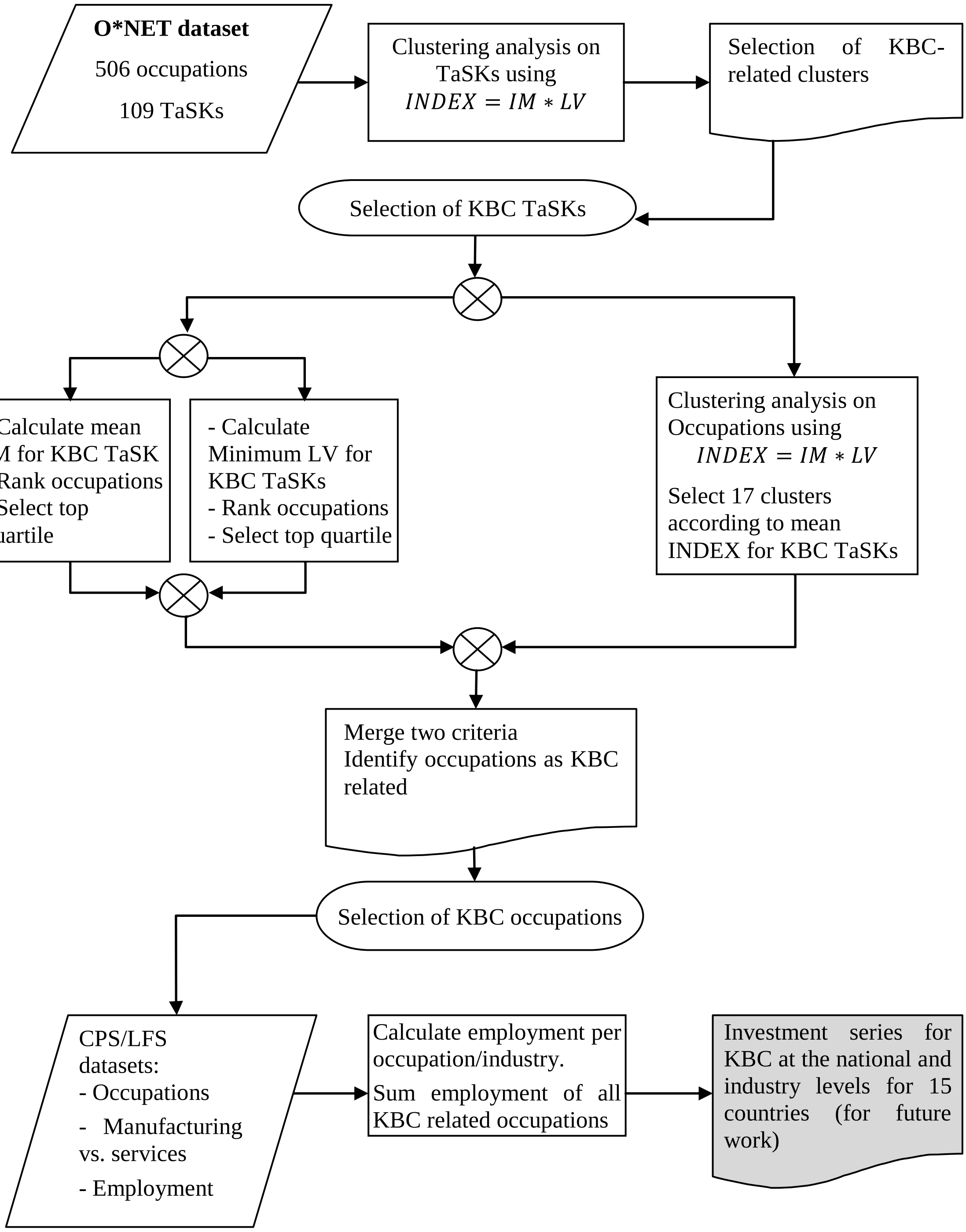
Operationalising the TaSK-based approach to measuring human resources related to KBC

We implement a three-step approach to identifying and quantifying the human resources devoted to a number of knowledge-based assets. We first define the sets of tasks, skills and knowledge areas (i.e. the TaSKs) corresponding to the performance of activities related to different knowledge-based assets considered. We then select those occupations that show a high content of these sets of activities. We finally use occupation-specific employment figures to estimate the share of the workforce contributing to the OC, CI, R&D and design for 15 countries. Figure 1 provides a summary flow chart of this methodology, which is described in more details below, and highlights the different datasets exploited, each containing a specific set of information.

The data used in the first part of the analysis are gathered from the Occupational Information Network (O*Net, or ONET) database, a project on occupational information sponsored by the US Department of Labor. This dataset contains a wealth of survey-based information about: workers' main characteristics and requirements; experience and occupational requirements; workforce characteristics; as well as occupation-specific information. The ONET dataset has been extensively used in the analysis about the effect of technological change on the task content of occupations, and in particular to determine the tradability and the offshorability of tasks and occupations (*e.g.* Jensen and Kletzer, 2010; Ritter, 2009; Goos, Manning and Salomons, 2010; and Lanz, Miroudot and Nordas, 2011). It has also been used to study the effect of technological change on wages and the demand for skills (*e.g.* Autor and Handel, 2009; and Crinó, 2009) and wage distribution (Firpo, Fortin and Lemieux, 2011), as well as to identify patterns of regional and urban concentration of occupations (Feser, 2003; and Scott and Mantegna, 2009).

The version of the ONET database used here covers, as of April 2013, 903 occupations and follows the US SOC 2010 classification. The "occupational requirements" category is the main source of information we rely upon, as it contains elements defined in such a way as to be comparable across all occupations. These consist of 41 tasks that employees perform on the job, as well as 35 Skills and 33 Knowledge areas that the workforce relies upon to perform their tasks. The list of these 109 elements, with their code and full description, can be seen in Table 1 (displaying the results of the cluster-based selection of KBC-related tasks, skills and knowledge areas. See below.). Information is collected through employees' surveys or interviews with occupational experts. These are asked to rank on a Likert scale ranging between 1 ("not important") and 5 ("extremely important") the "Importance" of a particular task, skill or knowledge area in their day to day job, and on a scale of 1 (lowest level) to 7 (highest level) its "Level", i.e. the extent to which they perform or use certain tasks, skills or knowledge in their daily job. Two variables, i.e. Importance and Level, are thus associated with each occupation-activity pair.

Figure 1. Flow chart of the TaSK-based methodology



Source: Authors' own compilation.

Legend: The index ("*INDEX*") corresponds to the un-weighted product of the IMportance ("*IM*") and LEvel ("*LE*") scores.

Identifying the tasks related to KBC assets

The first step of the analysis requires identifying the tasks, skills and knowledge areas associated with different knowledge-based assets. As already mentioned, we rely on the CHS classification of KBC and focus on four particular assets commonly associated with firm performance, innovation and productivity: computerised information, R&D, design and organisational capital. Using an approach similar to that of Lanz, Miroudot and Nordas (2011) and of Squicciarini and Le Mouel (2012), we perform hierarchical clustering analysis in order to separate the 109 activities into coherent clusters. Using the description of the activities in each cluster, we then identify the clusters that are associated with one of the four KBC assets. Our clustering analysis uses the Euclidian measure of distance and the complete-linkage method. For each activity, we calculate an index corresponding to the un-weighted product of the Importance and Level scores, rescaled between 0 and 1 for homogeneity purposes. This method has the advantage of giving a higher index to occupations that score high on both dimensions.

The results of the clustering analysis are presented in Table 1, where the first column shows the number of the cluster; the following columns the codes and names of the tasks, skills and knowledge areas allocated in that cluster; and the last column shows the knowledge-based asset associated with the cluster. The Duda and Hart (1973) criterion suggests that the optimal number of clusters to be 23. Organisation capital is the asset that is associated with the two largest clusters (Numbers 7 and 19), which together group 14 tasks, 14 skills and 3 knowledge areas. Computerised information appears clearly associated with cluster Number 15, which groups 7 tasks and one knowledge area, but no skills. Cluster Number 22, which groups 3 skills, including Programming, can also be associated with computerised information. The other skills in this cluster are Technology design and Operations analysis, which suggests that this cluster can be associated with R&D. Cluster Number 21 can also be associated with R&D, and groups 1 task, 1 skill and 3 knowledge areas. These two clusters capture only the scientific dimension of R&D, and tasks, skills or knowledge areas that would be associated to non-scientific R&D are more difficult to pin down and do not seem to form part of a coherent cluster. Hence our analysis remains confined to scientific R&D. Finally, design seems to stand out as a set of tasks and knowledge areas, with Cluster Number 4 capturing the technical dimension of design and cluster Number 13 capturing its artistic dimension.

It is important to note that we are interested in the *absolute* importance and level of a particular task, rather than its *relative* position within the task profile, as our aim is to identify occupations that perform tasks related to KBC assets in addition to, rather than in substitution of, other tasks. The case of Architects (SOC code 17-1010) is illustrative in this respect, as they attribute the highest importance (4.7/5) to the tasks “222. Thinking creatively” and “322. Drafting, Laying out and specifying technical devices, parts and equipment”, which are later identify as design-related tasks, while at the same time giving high importance (3.9/5) to tasks such as “421. Coordinating the activities of others” and “422. Developing teams”, which get identified as tasks related to organisational capital. This suggests that certain occupations might contribute to more than one KBC asset, and we report them as contributing to each asset, rather than only to one asset. Using a selection criterion based on absolute rather than relative answers seems more appropriate to fully capture the contribution of these occupations to all the forms of KBC assets considered.

Table 1. Results of the clustering analysis of tasks, skills and knowledge areas

Cluster No.	Task code	Task description	Skill code	Skill description	Know code	Knowledge description	KBC asset
1					10	Transportation	
1					81	Public Safety and Security	
2					91	Telecommunications	
3					21	Production and Processing	
4	322	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment			33	Design	Design
4					34	Building and Construction	Design
5	313	Controlling Machines and Processes	2630	Equipment Selection	35	Mechanical	
5	324	Repairing and Maintaining Mechanical Equipment	2680	Operation and Control			
5	122	Inspecting Equipment, Structures, or Material	2670	Operation Monitoring			
5	312	Handling and Moving Objects	2660	Equipment Maintenance			
5	311	Performing General Physical Activities	2690	Repairing			
5	314	Operating Vehicles, Mechanized Devices, or Equipment	2600	Troubleshooting			
5			2700	Quality Control Analysis			
6	325	Repairing and Maintaining Electronic Equipment	2640	Installation			
7	421	Coordinating the Work and Activities of Others	2530	Mgt. of Material Resources	11	Administration and Management	OC
7	422	Developing and Building Teams	2520	Mgt. of Financial Resources	16	Personnel and Human Resources	OC
7	424	Guiding, Directing, and Motivating Subordinates					OC
7	432	Staffing Organizational Units					OC
7	433	Monitoring and Controlling Resources					OC
8	416	Selling or Influencing Others			13	Economics and Accounting	
8					14	Sales and Marketing	
9					22	Food Production	
10	418	Performing for or Working Directly with the Public	2130	Persuasion	15	Customer and Personal Service	
10	417	Resolving Conflicts and Negotiating with Others	2140	Negotiation			
10			2110	Social Perceptiveness			
10			2160	Service Orientation			
11					52	Therapy and Counselling	
11					45	Psychology	
11					46	Sociology and Anthropology	
11					75	Philosophy and Theology	
12	415	Assisting and Caring for Others			51	Medicine and Dentistry	
13					73	Fine Arts	Design
14	431	Performing Administrative Activities			12	Clerical	
15	321	Interacting With Computers			31	Computers and Electronics	CI

15	212	Processing Information					CI
15	223	Updating and Using Relevant Knowledge					CI
15	214	Analysing Data or Information					CI
15	326	Documenting/Recording Information					CI
15	411	Interpreting the Meaning of Information for Others					CI
15	111	Getting Information					CI
16	213	Evaluating Information to Determine Compliance with Standards			82	Law and Government	
17					47	Geography	
17					74	History and Archaeology	
18					72	Foreign Language	
19	423	Training and Teaching Others	2150	Instructing	60	Education and Training	OC
19	425	Coaching and Developing Others	1230	Learning Strategies			OC
19	211	Judging the Qualities of Things, Services, or People	2470	Systems Analysis			OC
19	221	Making Decisions and Solving Problems	1210	Critical Thinking			OC
19	426	Provide Consultation and Advice to Others	2480	Systems Evaluation			OC
19	224	Developing Objectives and Strategies	1220	Active Learning			OC
19	412	Communicating with Supervisors, Peers, or Subordinates	2290	Complex Problem Solving			OC
19	226	Organizing, Planning, and Prioritizing Work	2450	Judgment and Decision Making			OC
19	225	Scheduling Work and Activities	1240	Monitoring			OC
19			2120	Coordination			OC
19			2540	Mgt. of Personnel Resources			OC
19			2510	Time Management			OC
20	414	Establishing and Maintaining Interpersonal Relationships	1140	Speaking	71	English Language	
20	413	Communicating with Persons Outside Organization	1110	Reading Comprehension	92	Communications and Media	
20	222	Thinking Creatively	1130	Writing			
20			1120	Active Listening			
21	123	Estimating the Quantifiable Characteristics of Products	1150	Mathematics	32	Engineering and Technology	R&D
21					42	Physics	R&D
21					41	Mathematics	R&D
22			2610	Operations Analysis			R&D/CI
22			2620	Technology Design			R&D/CI
22			2650	Programming			R&D/CI
23	121	Identifying Objects, Actions, and Events	1160	Science	44	Biology	
23	112	Monitor Processes, Materials, or Surroundings			43	Chemistry	

Source: OECD calculations based US Department of Labour's Occupational Information Network database, extracted April 2013.

Table 2 summarises the results of the clustering analysis and shows the allocation of tasks, skills and knowledge areas to the four KBC assets considered.

Table 2. Assignment of tasks, skills and knowledge areas to the four KBC assets.

Assets	Task code	task	Skills code	skill	Knowledge code	knowledge
Organisational capital	211	Judging the Qualities of Things, Services, or People	1210	Critical Thinking	11	Administration and Management
	221	Making Decisions and Solving Problems	1220	Active Learning		
	224	Developing Objectives and Strategies	1230	Learning Strategies		
	225	Scheduling Work and Activities	1240	Monitoring	16	Personnel and Human Resources
	226	Organizing and Prioritizing Work	2120	Coordination		
	412	Communicating with Inside	2150	Instructing		
	421	Coordinating Work and Activities	2290	Complex Problem Solving	60	Education and Training
	422	Developing and Building Teams	2450	Judgment and Decision Making		
	423	Training and Teaching Others	2470	Systems Analysis		
	424	Guiding, Directing, and Motivating Subordinates	2480	Systems Evaluation		
	425	Coaching and Developing Others	2510	Time Management		
	426	Provide Consultation and Advice	2520	Mgt. of Financial Resources		
	432	Staffing Organizational Units	2530	Mgt. of Material Resources		
	433	Monitoring and Controlling Resources	2540	Mgt. of Personnel Resources		
Design	322	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment			33	Design
					34	Building and Construction
					73	Fine Arts
R&D	123	Estimating the Quantifiable Characteristics of Products, Events, or Information	1150	Mathematics	42	Physics
			2610	Operations Analysis	32	Engineering & Technology
			2620	Technology Design		
			2650	Programming	41	Mathematics
Computerised Information	111	Getting Information	2650	Programming	31	Computers & Electronics
	212	Processing Information	2620	Technology Design		
	214	Analyzing Data or Information	2610	Operations Analysis		
	223	Updating and Using Knowledge				
	321	Interacting With Computers				
	326	Documenting/Recording Information				
	411	Interpreting the Meaning of Information for Others				

Source: OECD calculations based US Department of Labour's Occupational Information Network database, extracted April 2013.

From tasks to occupations

Data on employment by occupation and industry are needed to estimate the number of workers employed in KBC-related activities. For Europe, the main source of data on national occupational employment is the European Union Labour Force Survey (EU LFS), a household survey run on a quarterly basis by Eurostat, covering the 28 member countries of the European Union, as well as Iceland, Norway, Switzerland, Turkey and the Former Yugoslav Republic. Similar data for the United States are available from two different sources. On the one hand, the Current Population Survey (CPS), a household survey jointly sponsored by the US Census Bureau and the US Bureau of Labor Statistics, provides a wide range of statistics. The Annual Social and Economic (ASEC) Supplement of the CPS offers the most accurate information on employment and household income. On the other hand, the Occupational Employment

Statistics (OES), an establishment survey conducted on a yearly basis by the US Bureau of Labour Statistics, covers all full-time and part-time employees in non-farm industries. It produces employment and wage estimates for the country as a whole, for individual States, and for specific industries.

The methodological differences between these two surveys and their consequences for estimates of employment and earnings are well documented by Abraham and Spletzer (2007). Once differences in coverage are controlled for, by excluding the non-incorporated self-employed and the agricultural sector from the CPS, both surveys yield estimates of total employment that differ by less than 1.5% for the years 2004 to 2012[1]. In order to ensure the best possible compatibility between all these sets of data, we restrict the analysis to the use of household surveys, which are the EU LFS and the US CPS. This might lead to employment figures related to KBC that may be over-estimated compared to those that would be obtained using employer surveys.

The EU LFS uses the International Standard Classification of Occupations (ISCO, 2008), available at the 3 digit level, and covers 129 occupations. Both the US CPS and the ONET database use the American classification of occupations, the Standard Occupational Classification (SOC, 2010). The CPS data is available at 4 digit, and covers 506 occupations, while the ONET data is available at 5 digit and covers 903 occupations. ONET data have thus been aggregated to match the level of aggregation of the CPS classification. Further harmonisation efforts have been necessary between the CPS and the LFS and have been facilitated by the new structure of the ISCO 2008 classification, which is closer to the SOC classification compared to previous versions of the ISCO classification. The dataset used for the present selection of occupations covers 435 occupations for the years 2011 and 2012. Results are then aggregated to match the 129 occupations of the EU LFS. Additional results for previous years are based on the SOC 2000 and the ISCO 1988 and are available upon request.

From the selection of KBC activities reported in Table 2, the selection of occupations is performed using two separate albeit complementary criteria. The first consists in an analysis of the distribution of occupations with respect to their answers to the tasks, skills and knowledge areas specifically identified as related to the different knowledge-based assets. The second criterion conversely consists in performing clustering analysis to identify clusters of occupations according to their answers on all the tasks, skills and knowledge areas. The final selection of occupations corresponds to the minimum common denominator of the occupations identified as being KBC-relevant according to both criteria. The overlap between these two methodologies covers around 65% of the occupations selected by either methodology.

A distribution-based approach to identifying occupations related to KBC

The first methodology used aims at identifying those occupations providing higher importance and level answers to the tasks, skills and knowledge areas identified, relative to other occupations. The criteria used to do so combine the importance and level dimensions to account for the fact that respondents might attribute high importance to a task which they perform at a low level, implying that this task is not a core component of their activities.

1. Abraham and Spletzer (2007) however highlight the large differences in the estimates of employment in some types of occupations, management, as managerial jobs represented 10.5% of total employment in 2004 according to the CPS, while they represented only 4.8% according to the OES for the same year. The authors argue that this discrepancy can be driven by factors such as changes in the training of OES survey staff, especially in reporting the occupational title of the self-employed, the bias of CPS respondent towards reporting better regarded occupations, and the inability of surveys to adapt to the fast changing roles of occupational profiles in US firms.

- With respect to the Importance question, we rank occupations according to the *average* answer on the identified tasks, skills and knowledge areas for each of the four asset types considered.

- For the level questions, occupations are ranked on the basis of the *highest lowest* response to any of the KBC-related activities. This aims to ensure that all relevant TaSKs are performed at a comparatively high minimum level, and to impose homogeneity in the occupational profile, as it rules out occupations scoring high with respect to most TaSKs, but very low to a few.

The top quartile of occupations from both distributions is selected as being related to the relevant KBC asset. These are occupations for which the relevant TaSKs are on average relatively more important than they are for other occupations and are consistently performed at a comparatively higher level.

For organisational capital, R&D and computerised information, the combination of criteria based on the average importance and on the minimum level results is identifying 73, 71 and 73 occupations, respectively. In the case of design, the two criteria yield somewhat diverging results, and the overlap covers only 35 occupations.

A clustering analysis approach to identifying occupations related to KBC

In addition to the distribution-based identification criteria above we carry out a clustering analysis that groups occupations having similar answers for all 109 tasks. The methodology is the same as that used for the clustering analysis of tasks, and draws from both Feser (2003) and Lanz, Miroudot and Nordas (2011). The hierarchical clustering analysis performed also uses the index calculated as the un-weighted product of the Importance and the Level variables and the Euclidian (L2) distance between clusters calculated with the complete-linkage method. Following the Duda and Hart (1973) criterion occupations get grouped into 38 clusters.

For each cluster we calculate an average index for each of the four KBC assets, using only the elements identified in the first part of the analysis. Clusters are then ranked according to the average index for each asset, and we look for a cut-off point in the average index. For organisational capital, we identify 16 clusters, grouping 106 occupations; for R&D we identify 8 clusters that group 60 occupations; for computerised information we identify 9 clusters, grouping 75 occupations; for design we identify 6 clusters that group 46 occupations.

Combining the two approaches to identify KBC-related occupations

To ensure the robustness of our results, we use only those occupations that are selected both by the distribution criterion and the clustering analysis. The final selection of occupations covers 58 occupations relating to organisational capital, 56 occupations relating to computerised information, 46 occupations relating to R&D and 35 occupations for design. These results are then aggregated, from the 4 digit level to the 3 digit level, so as to match the level of aggregation of the EU LFS data. This last step requires specifying the proportion of each 4 digit occupation within the more aggregated 3 digit category. Due to limited data availability, these proportions are calculated from the US data, and applied to the other countries. For example, the aggregated category Artistic, cultural and culinary associate professionals (ISCO no. 343) consists of 6 different occupations. In this category, only Chefs and head cooks (ISCO no. 3434) are identified as contributing to organisational capital, and they represent on around 60% of the employment in the aggregated category. Likewise, Interior designers and decorators (ISCO no. 3432) and Gallery, museum and library technicians (ISCO no. 3433) are identified as contributing to design, and they represent on average 16% of the employment in the general category.

Table 3 shows the results of the selection of occupations at the 3 digit level. Organisational capital appears to be the asset that enters into the job description of the highest number of occupations, while design seems to be concentrated around a restricted number of occupations. A remarkable feature of these results is the large amount of overlap between the different KBC assets. Computerised information and R&D seem to be performed by nearly identical groups of occupations, and a large share of these also seem to be involved in design. This result has implications both for our estimates of employment, and for the investment in the human resources associated with these assets.

Table 3. Selection of KBC-related occupations

ISCO 3 digit	ISCO Title	OC	CI	R&D	Design
214	Engineering professionals (excluding electrotechnology)	√	√	√	√
216	Architects, planners, surveyors and designers	√	√	√	√
122	Sales, marketing and development managers	√	√	√	
132	Manufacturing, mining, construction, and distribution managers	√	√	√	
213	Life science professionals	√	√	√	
242	Administration professionals	√	√	√	
252	Database and network professionals	√	√	√	
263	Social and religious professionals	√	√	√	
331	Financial and mathematical associate professionals	√	√	√	
121	Business services and administration managers	√	√		
133	Information and communications technology service managers	√	√		
221	Medical doctors	√	√		
226	Other health professionals	√	√		
262	Librarians, archivists and curators	√			√
343	Artistic, cultural and culinary associate professionals	√			√
111	Legislators and senior officials	√			
112	Managing directors and chief executives	√			
134	Professional services managers	√			
141	Hotel and restaurant managers	√			
142	Retail and wholesale trade managers	√			
143	Other services managers	√			
243	Sales, marketing and public relations professionals	√			
312	Mining, manufacturing and construction supervisors	√			
334	Administrative and specialised secretaries	√			
522	Shop salespersons	√			
211	Physical and earth science professionals		√	√	√
251	Software and applications developers and analysts		√	√	√
311	Physical and engineering science technicians		√	√	√
351	Information and communications technology operations and user support technicians		√	√	√
212	Mathematicians, actuaries and statisticians		√	√	
215	Electrotechnology engineers		√	√	
265	Creative and performing artists				√
731	Handicraft workers				√
732	Printing trades workers				√

Source: OECD calculations based US Department of Labour’s Occupational Information Network database, extracted April 2013.

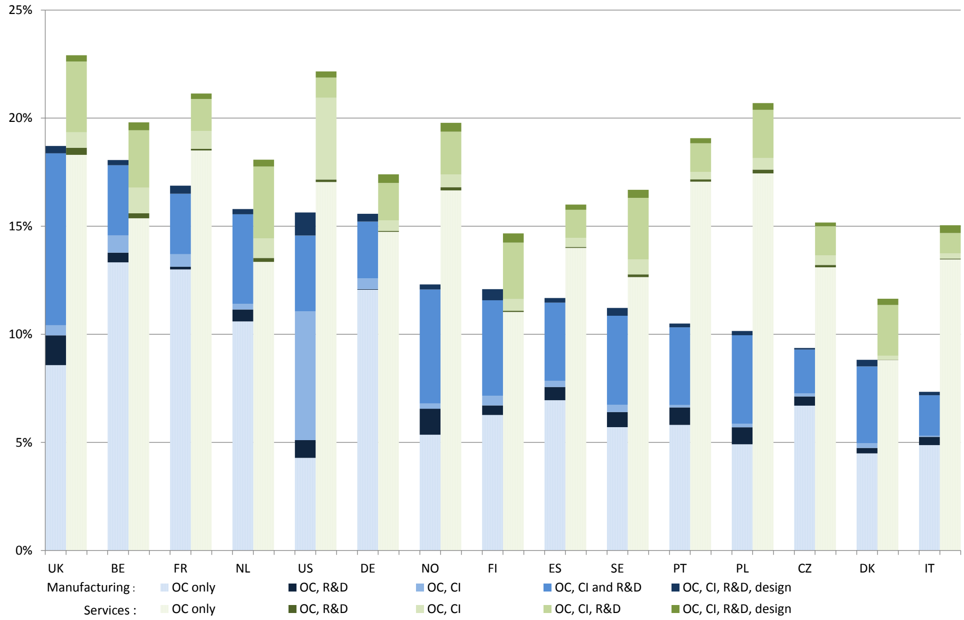
The fact that certain occupational categories work on different KBC assets suggests that labour cost measures of investment in these assets might involve double-counting in terms of employment figures. Data on time use on the job would be needed to understand the proportion of time devoted by different occupations to each of these assets. Possible overlaps between KBC assets also have implications for the analysis of the role of KBC in production and their impact on firm and aggregate economic performance. In particular, our results clearly suggest that there are complementarities between the different assets considered, and calls for future analysis to shed light on this important issue.

Quantifying the human resources contributing to KBC formation

From the occupations identified above, we now turn to employment data to quantify the human resources contributing to KBC formation for 15 countries. Detailed employment figures for the United States are obtained from the Current Population Survey, and for the other 14 countries are obtained from the EU Labour Force Survey. Estimates are calculated for the entire labour force, including both employees and the self-employed, for the total economy.

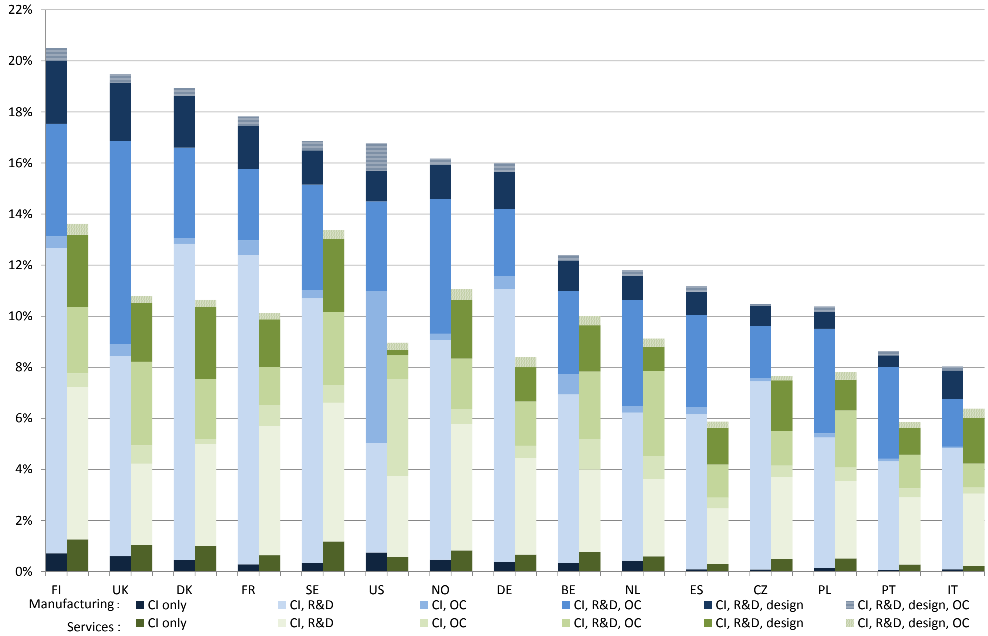
Figures 2 to 5 present the percentage of workers who contribute, respectively, to OC, computerised information, R&D and design, respectively. These graphs present the estimates for manufacturing and services in separate bars. The disaggregation between manufacturing and services shows that OC and design related occupations are more present in services than in manufacturing, while the contrary holds for computerised information and R&D. For each asset, the employment figures presented in the following graphs show varying degrees of overlap with other assets. As shown in Figure 2, the majority of employment related to organisation capital does not concern occupations that are also associated with other assets. This result is even more pronounced in services than in manufacturing, since the share of employment related only to OC is on average 82% in the services industries, while it is 58% in manufacturing. Figure 5 shows that similar results hold for design related employment, as an average of 60% of employment in manufacturing and 54% in services is composed of occupations that are only associated with design.

Figure 2. Organisational capital related workers in manufacturing and in services, as a percentage of total employed persons in the sector, 2012



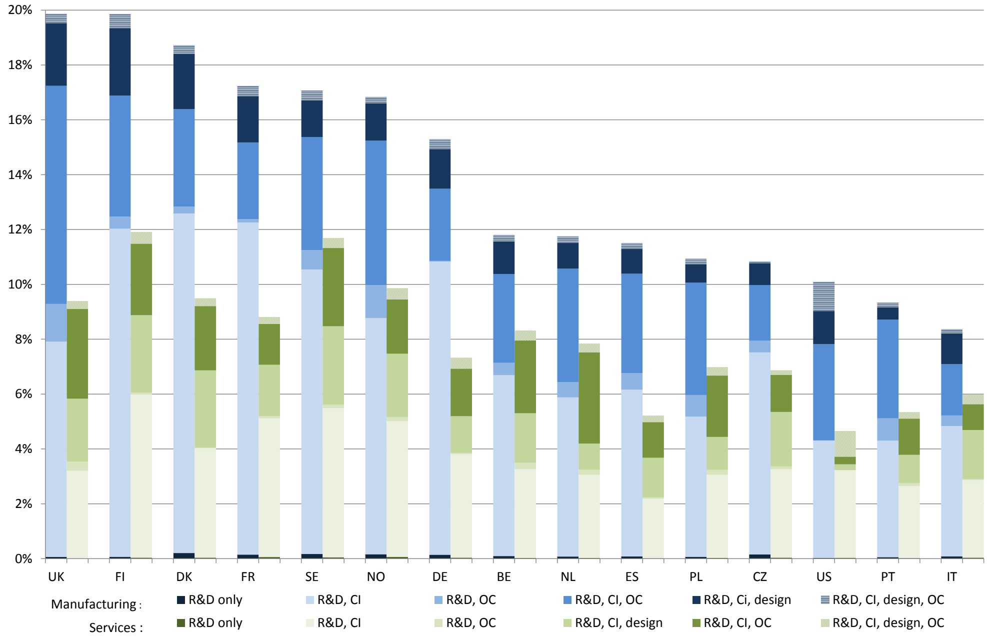
Source: OECD, based on United States Occupational Information Network Database, O*NET OnLine; United States Current Population Survey, US Census Bureau; and European Union Labour Force Survey, Eurostat, June 2013.

Figure 3. Computerised information related workers in manufacturing and in services, as a percentage of total employed persons in the sector, 2012



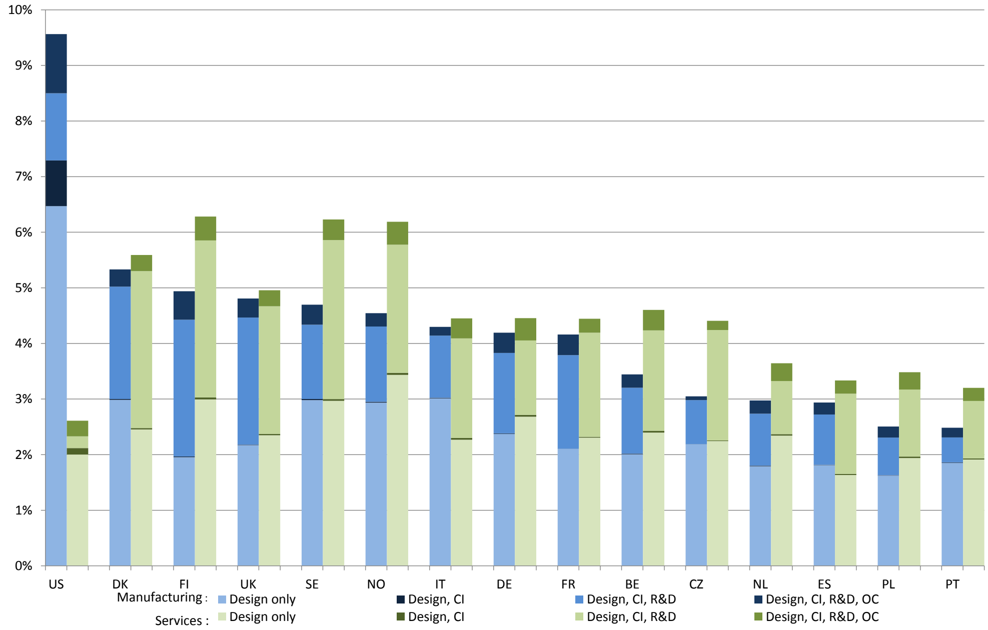
Source: OECD, based on United States Occupational Information Network Database, O*NET OnLine; United States Current Population Survey, US Census Bureau; and European Union Labour Force Survey, Eurostat, June 2013.

Figure 4. R&D related workers in manufacturing and in services, as a percentage of total employed persons in the sector, 2012



Source: OECD, based on United States Occupational Information Network Database, O*NET OnLine; United States Current Population Survey, US Census Bureau; and European Union Labour Force Survey, Eurostat, June 2013.

Figure 5. Design related workers in manufacturing and in services, as a percentage of total employed persons in the sector, 2012



Source: OECD, based on United States Occupational Information Network Database, O*NET OnLine; United States Current Population Survey, US Census Bureau; and European Union Labour Force Survey, Eurostat, June 2013.

Identifying cross-country differences in the application of the task-based methodology

The working hypothesis of the present approach is that the results derived from the American survey ONET hold more generally across OECD countries. The present section will seek to provide evidence in favour of this assumption using the background questionnaire of the Programme for the International Assessment of Adult Competencies (PIAAC) developed by the OECD.

This household survey of skills provides internationally comparable information on tasks performed at work for employees of 17 OECD countries. Designed in a comparable way to the Programme for International Student Assessment (PISA), the first round of PIAAC was carried out in the winter of 2011, and covers a sample of 5,000 adults aged between 16 and 65 in each country. The core of this programme is to evaluate the literacy, numeracy and problem-solving skills of the working age population. Alongside these tests, the programme also involved a detailed background questionnaire covering many aspects of educational background, work history and, relevant for our purposes, tasks and skills used at work.

The PIAAC Background Questionnaire covers 14 general tasks, such as “Sharing information with colleagues” or “working physically”, as well as 25 skills relating to literacy, numeracy and ICT use. For each of the 39 items, respondents are asked how often they perform these tasks or use these skills, on a scale of 1 (“Never”) to 5 (“Every day”). For the subsequent analysis, these individual answers are aggregated into a weigthed average by cou occupation, where the weights are the sampling weights. The occupation of respondents follows the ISCO classification, and is provided at the 2 digit level (and covers 40 categories). The ONET data thus provides comparatively more fine-grained information on the tasks performed at the occupational level. A strength of the PIAAC questionnaire is howver, the wealth of worker and firm specific information such as age, gender, firm size, public or private, or self-employed.

Identifying the tasks related to KBC assets

Following the approach spelled out in the previous section, we first begin by analysing the clustering of tasks into relevant groups. The results of the hierarchical clustering analysis, using the Euclidean measure of distance and the complete linkage method are presented in Table 4. To allow for comparison with the ONET analysis, we present the results related to all the countries and those relating only to the United States separately. The cluster stopping criteria suggest that the optimal number of clusters for all countries is 5 clusters, closely followed by 10 clusters. We therefore present both partitions. The stopping criteria for the United States suggest that 10 clusters are optimal. The first two columns present the list of tasks and the taskcodes, while the following two cloumns present the partitions into 10 and 5 groups respectively.

Table 4. Clustering analysis of tasks in PIAAC

All 17 countries				United States			
		Groups				Groups	
Task code	Task	10	5	Task code	Task	10	5
11	sharing work-related information	1	1	11	sharing work-related information	1	1
21	faced with simple problems	1	1	21	faced with simple problems	1	1
18	organising your own time	1	1	25	Read directions or instructions	1	1
16	planning your own activities	1	1	15	advising people	1	1
15	advising people	2	2	16	planning your own activities	2	1
27	Read newspapers or magazines	2	2	18	organising your own time	2	1
19	persuading or influencing people	2	2	26	Read letters memos or mails	2	1
39	Use a calculator	2	2	22	faced with complex problems	3	2
36	Fill in forms	2	2	12	instructing, training, and teaching	3	2
25	Read directions or instructions	2	2	30	Read manuals	3	2
26	Read letters memos or mails	3	2	27	Read newspapers or magazines	3	2
33	Write letters memos or mails	3	2	17	planning the activities of others	3	2
43	How often - For mail	4	2	19	persuading or influencing people	3	2
47	Word	4	2	20	negotiating with people	3	2
44	Work related info	4	2	36	Fill in forms	4	2
23	working physically	5	3	38	calculate fractions or percentages	4	2
24	using skills or accuracy with your hands or fingers	6	3	39	Use a calculator	4	2
12	instructing, training, and teaching	7	4	44	Work related info	5	2
17	planning the activities of others	7	4	33	Write letters memos or mails	5	2
22	faced with complex problems	7	4	43	How often - For mail	5	2
30	Read manuals	7	4	47	Word	5	2
32	Read diagrams, maps, schematics	7	4	46	Spreadsheets	5	2
35	Write reports	7	4	23	working physically	6	3
28	Read professional journals	7	4	24	using skills or accuracy with your hands or fingers	7	3
38	calculate fractions or percentages	8	4	13	making speeches or presentations	8	4
31	Read financial statements	8	4	29	Read books	8	4
37	Calculating costs or budgets	8	4	45	Conduct transactions	8	4
20	negotiating with people	8	4	40	Prepare charts graphs or tables	8	4
41	Use simple algebra or formulas	8	4	35	Write reports	8	4
46	Spreadsheets	8	4	28	Read professional journals	8	4
14	selling a product or a service	9	4	41	Use simple algebra or formulas	8	4
29	Read books	10	5	32	Read diagrams, maps, schematics	8	4
13	making speeches or presentations	10	5	14	selling a product or a service	9	4
45	Conduct transactions	10	5	37	Calculating costs or budgets	9	4

40	Prepare charts graphs or tables	10	5	31	Read financial statements	9	4
48	Programming language	10	5	34	Write articles	10	5
49	Real-time discussions	10	5	48	Programming language	10	5
42	Use advanced math or statistics	10	5	42	Use advanced math or statistics	10	5
34	Write articles	10	5	49	Real-time discussions	10	5

Source: OECD calculations based PIAAC database, extracted November 2014.

Despite minor differences in the hierearchical structure of the results, the structure of tasks seems to be broadly similar between the Unites States and the rest of the OECD countries included in the PIAAC. Of the four assets considered in the framework, OC is the only one that stands out as a result of this clustering analysis. We can identify two clusters of tasks that relate to this asset: one relating to individual organisation (Clusters 1 and 2 in the analysis for all countries and the United States, respectively), and one relating to organisation affecting other co-workers (Clusters 7 and 3 in the analysis for all countries and the United States, respectively). In the analysis for all countries, tasks related to planning are associated with literacy and problem solving skills. In the United States, planning tasks seem to be additionally linked with communication skills (i.e. influencing and negociating). The level of detail of the tasks contained in PIAAC do not allow us to clearly identify tasks that relate to the three other KBC assets considered above, namely, computerised information, R&D and design. While numeracy and ICT related skills seem to group into coherent clusters, their description is too general to be interpretable as pertaining to either of the three assets. Hence, the PIAAC data will only be used here to benchmark the task-based measurement of OC. In order to find a general pattern of OC-related tasks across countries, we use the results from the cross-country analysis for the following steps. Table 5 presents the list of 11 tasks considered for the selection of OC-related occupations.

Table 5. Selection of OC-related tasks

Taskcode	Task Description
11	Sharing work-related information with co-workers
12	Instructing, training, teaching people, individually or in groups
16	Planning your own activities
17	Planning the activities of others
18	Organising your own time
21	Faced with simple problems
22	Faced with complex problems
28	Read professional journals or publications
30	Read manuals or reference materials
32	Read diagrams maps or schematics
35	Write reports

Source: OECD calculations based PIAAC database, extracted November 2014.

From tasks to occupations

Having identified a set of tasks that correspond to the creation and accumulation of OC, we now turn to the identification of occupations that perform these tasks on a regular basis. To this end, we replicate the double approach spelled out above, looking both at the answers related only to the 11 tasks, as well as performing a clustering analysis using the information on all tasks.

A distribution-based approach to identifying occupations related to KBC

We consider first the distribution-based approach, where we rely only the answers on the 11 OC-related tasks identified above. For each occupation, we calculate the average response for the 11 OC tasks, across all countries. We select the top quartile of occupations (i.e. 10 occupations) that have the highest answer on these OC tasks. Their average response it 3.51 (3.64 for the United States in isolation), which corresponds to performing these tasks between once a month and once a week.

A cluster analysis approach to identifying occupations related to KBC

We complement the distribution-based approach with a clustering analysis of the occupations, aggregated across countries. This second approach retains the information on all the tasks to allocate occupations into groups, using again the Euclidian distance and complete linkage method. The cluster stopping rule suggests that the optimal partition of the occupation is 11 clusters. For each cluster, we then calculate the average response on the 11 OC tasks, and look for a cut-off point in the average. This suggests that the first 5 clusters, grouping 13 occupations, are relevant. These are clusters where the respondents answer they spend at least once a month on OC-related tasks. Similar results are obtained for the United States in isolation, although with fewer clusters and fewer occupations identified as performing OC-related tasks.

Combining the two approaches to identify KBC-related occupations

In order to ensure the robustness of the results, the final selection of OC-related occupations, as displayed in Table 6, is the overlap between the distribution-based and the clustering analyses. This overlap is very high, especially for the analysis grouping all countries. The final selection of occupations who can be considered as contributing to OC is in line with the results obtained from the ONET data. These results confirm the importance of managers in contributing to the formation and accumulation of OC in firms, but also point to the importance of other occupational categories, which might not be explicitly labelled as managers. Such occupations are Business and Administration professionals, Health and Teaching professionals, and Science and engineering and Information and communications technology professionals and associate professionals. That these last occupational categories appear to contribute to OC brings further evidence of the complementarity between different KBC asset types, as their occupational titles, if not the detailed description of the tasks they perform, also suggest that the contribute to KBC assets such as R&D, design and computerised information.

The results for the United States in isolation differ only slightly. It appears that American health professionals and business and administrative professionals do not perform OC-related tasks to a high enough degree, while ICT technicians do. Results disaggregated by country, available upon request, suggest that specific country profiles emerge, reflecting certain differences between countries in the way that occupational titles describe what employees perform on the job.

Table 3. Selection of OC-related occupations

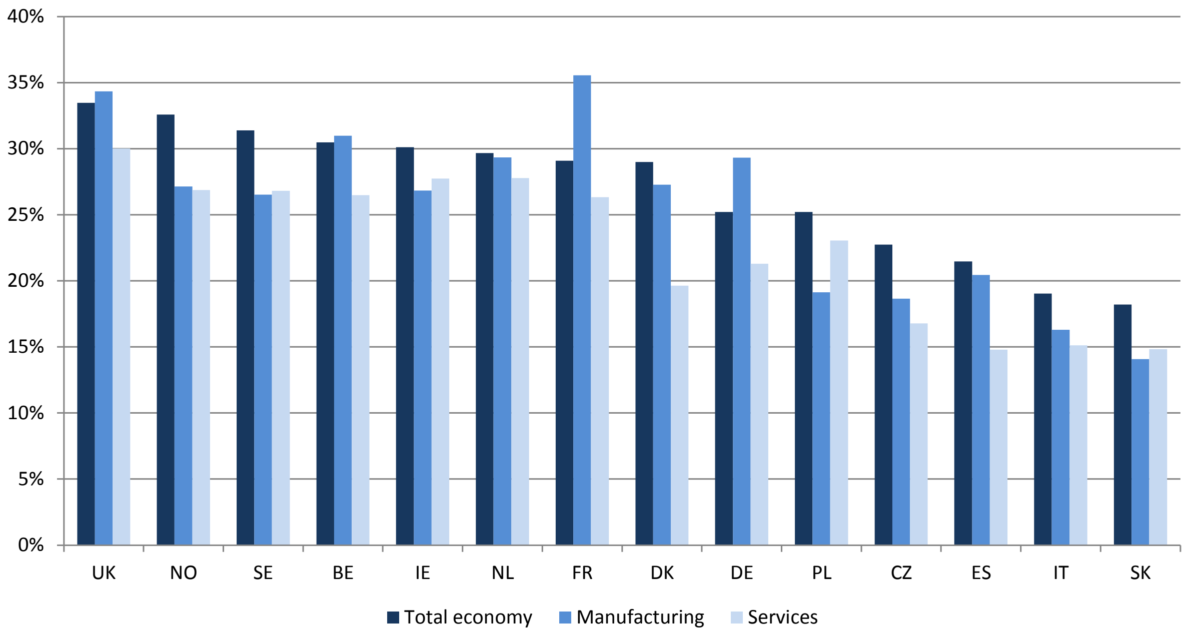
ISCO code	ISCO title	All countries Distr.	All countries Clust.	All countries FINAL	Unites States Distr.	Unites States Clust.	Unites States FINAL
11	Chief executives, senior officials and legislators	1	1	1	1	1	1
12	Administrative and commercial managers	1	1	1	1	1	1
13	Production and specialised services managers	1	1	1	1	1	1
14	Hospitality, retail and other services managers	1	1	1	1	1	1
21	Science and engineering professionals	1	1	1	1	1	1
22	Health professionals	1	1	1	1	0	0
23	Teaching professionals	1	1	1	1	1	1
24	Business and administration professionals	1	1	1	0	1	0
25	Information and communications technology professionals	1	1	1	1	1	1
26	Legal, social and cultural professionals	0	1	0	0	1	0
31	Science and engineering associate professionals	1	1	1	1	0	0
32	Health associate professionals	0	0	0	0	0	0
33	Business and administration associate professionals	0	1	0	0	1	0
34	Legal, social, cultural and related associate professionals	0	0	0	0	0	0
35	Information and communications technicians	0	1	0	1	1	1
41	General and keyboard clerks	0	0	0	0	0	0
42	Customer services clerks	0	0	0	0	0	0
43	Numerical and material recording clerks	0	0	0	0	0	0
44	Other clerical support workers	0	0	0	0	0	0
51	Personal service workers	0	0	0	0	0	0
52	Sales workers	0	0	0	0	0	0
53	Personal care workers	0	0	0	0	0	0
54	Protective services workers	0	0	0	0	0	0
61	Market-oriented skilled agricultural workers	0	0	0	0	0	0
62	Market-oriented skilled forestry, fishery and hunting workers	0	0	0	0	0	0
71	Building and related trades workers, excluding electricians	0	0	0	0	0	0
72	Metal, machinery and related trades workers	0	0	0	0	0	0
73	Handicraft and printing workers	0	0	0	0	0	0
74	Electrical and electronic trades workers	0	0	0	0	0	0
75	Food processing, wood working, garment and other craft and related trades workers	0	0	0	0	0	0
81	Stationary plant and machine operators	0	0	0	0	0	0
82	Assemblers	0	0	0	0	0	0
83	Drivers and mobile plant operators	0	0	0	0	0	0
91	Cleaners and helpers	0	0	0	0	0	0
92	Agricultural, forestry and fishery labourers	0	0	0	0	0	0
93	Labourers in mining, construction, manufacturing and transport	0	0	0	0	0	0
94	Food preparation assistants	0	0	0	0	0	0
95	Street and related sales and service workers	0	0	0	0	0	0
96	Refuse workers and other elementary workers	0	0	0	0	0	0
	TOTAL	10	13	10	10	11	8

Source: OECD calculations based PIAAC database, extracted November 2014.

Quantifying the human resources contributing to KBC formation

The EU Labour Force survey is used to calculate the human resources associated with the OC-related occupations identified. Figure 6 shows the proportion of workers who are associated with OC, for the total economy, for manufacturing and for services, for the 14 countries covered in PIAAC and by the EU LFS. The proportion of OC-related employees in the total economy ranges from 33% in the United Kingdom to 18% in the Slovak Republic. In general, manufacturing seems to employ a higher share of OC-related employees compared to the services sector, reaching a high of 36% for France and a low of 14% for the Slovak Republic. These figures are around 10 percentage points higher than those plotted in Figure 2, which can be explained by the higher level of aggregation of the PIAAC data. Indeed, in this latter exercise, we count the whole 2-digit category as belonging to OC, while in the exercise based on ONET, we could disaggregate the results to the 4-digit category. This suggest that the PIAAC based results are an upper-bound to the share of employment that can be considered as contributing to OC. The ranking of countries is quite similar between the two analyses, which suggests that the proposed task-based measure of organisational capital is relatively robust to the choice of dataset.

Figure 5. Organisational capital related workers in manufacturing and in services, as a percentage of total employed persons in the sector, 2012



Source: OECD, based on European Union Labour Force Survey, Eurostat, June 2013.

Advancing the KBC measurement agenda

This paper proposes a novel TaSK methodology that uses information on the tasks that employees perform on the job, their skills and knowledge base to identify those occupations that most contribute to the formation of four key KBC assets, namely OC, CI, R&D and design.

Estimates suggest that investment in these KBC assets vary across industries and countries and highlight the extent to which occupations contribute to the generation of several of the KBC types considered. Our results on the one hand provide evidence in support of the complementarity hypothesis often advanced by the literature, whereby for investment in KBC to be effective firms need investing simultaneously on more than one asset, e.g. OC and CI. On the other hand, our results emphasise the need to better apprehend the extent and importance of these complementarities, and indirectly question two main operational choices made in previous studies: to quantify investment in KBC assets in a separate fashion; and to assume, like it has been done in the case of OC, that own-account investment in this asset would correspond to the 20% of the salaries of managers. Our estimates suggest that a number of occupations are involved in the generation of up to four KBC asset types, and call for the need to better understand the way in which workers redistribute their time across the different tasks concerned. This would help to better estimate the proportion of workers' remuneration that should be imputed to each of the assets considered individually, and to make some first estimates about the value of complementarities and overlaps.

To this end, and to more precisely estimate and compare investment in KBC assets across industries and countries, figures would further need to rely on full time equivalent units of employment and on occupation-and-industry-specific salary information. Needless to say, this empirical work would need to rely on advancements in the theoretical and modelling work able to account for complementarities when investigating the relationship between investment in KBC and the performance of firms, industries and countries.

REFERENCES

Abraham, K. and J. Spletzer. 2007. Are the new jobs good jobs? in K. Abraham, J. Spletzer and M. Harper. *Labor in the New Economy*. University of Chicago Press.

Aral, S. and P. Weill. 2007. IT Assets, Organizational Capabilities, and Firm Performance: How Resource Allocations and Organizational Differences Explain Performance Variation. *Organization Science*. **18**(5) 763-780.

Autor, D., and M. Handel. 2009. Putting Tasks to the Test: Human Capital, Job Tasks and Wages. National Bureau of Economic Research Working Paper No. 15116.

Bresnahan, T., E. Brynjolfsson, and L. M. Hitt. 2002. Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm Level Evidence. *Quarterly Journal of Economics.* **117**(1) 339–76.

Cohen, L. E. 2013. Assembling Jobs: A Model of How Tasks Are Bundled Into and Across Jobs. *Organization Science*. **24**(2) 432-454

Corrado, C., C. Hulten, and D. Sichel. 2009. Intangible Capital and US Economic Growth. *Review of Income and Wealth* **55**(3) 661–685.

Crinó, R. 2009. Service Offshoring and White-Collar Employment. *Review of Economic Studies*. **77**(2) 595-632.

Dal Borgo, M., Goodridge P., Haskel J., and A. Pesole. 2013. Productivity and Growth in UK Industries: An Intangible Investment Approach. *Oxford Bulletin of Economics and Statistics*. 75(6) 806-834.

Duda, R. O. and P. E. Hart. 1973. *Pattern Classification and Scene Analysis.* Wiley and Son, New York.

Edquist, H. 2011. Can Investment in Intangibles Explain the Swedish Productivity Boom in the 1990s?. *Review of Income and Wealth*. **57**(4) 658-682

Feser, E. 2003. What Regions Do Rather than Make: A Proposed Set of Knowledge-based Occupation Clusters. *Urban Studies*. **40**(10) 1937-1958.

Firpo, S., N. Fortin, and T. Lemieux. 2011. Occupational Tasks and Changes in the Wage Structure. *IZA Discussion Paper.* No. 5542.

Goos, M, A. Manning and A. Salomons. 2010. Explaining Job Polarization in Europe: The Roles of Technology, Globalization and Institutions. *CEP Discussion Paper*. N. 1026.

Jensen J.B. and L. Kletzer. 2010. Measuring Tradable Services and the Task Content of Offshorable Services Jobs. in K. Abraham, J. Spletzer, and M. Harper (eds). *Labor in the New Economy*. University of Chicago Press.

Kaplan, S. N., Klebanov, M. M. and M. Sorensen. 2012. Which CEO Characteristics and Abilities Matter? *The Journal of Finance*. **67**(3)973–1007.

Lanz, R., S. Miroudot and H. K. Nordås. 2011. Trade in Tasks. OECD Trade Policy Working Papers, No. 117, OECD Publishing. Doi: *10.1787/5kg6v2hkvmmw-en* .

Ng, T. W. H., and D. C. Feldman. 2009. How Broadly does Education Contribute to Job Performance?. *Personnel Psychology*. **62**(1) 89–134.

OECD. 2013. *OECD Science, Technology and Industry Scoreboard 2013,* OECD, Paris.

O*NET OnLine, United States Occupational Information Network, www.onetonline.org/, last accessed April 2013.

Ployhart, R. E., and T. P. Moliterno. 2011. Emergence of the Human Capital Resource: A Multilevel Model. *Academy of Management Review*. **38**(1) 127-150.

Ritter, M. 2009. Offshoring and Occupational Specificity of Human Capital. *MPRA Paper*.

Santamaria, L., M. Nieto and A. Barge-Gil. 2009. Beyond formal R&D: Taking advantage of other sources of innovation in low- and medium-technology industries. *Research Policy* **38**(3) 507-517.

Scott, A. and A. Mantegna. 2009. Human Capital Assets and Structures of Work in the US Metropolitan Hierarchy (An Analysis Based on the O*NET Information System). *International Regional Science Review*. **32**(2) 173-194.

Squicciarini, M. and M. Le Mouel (2012). Defining and Measuring Investment in Organisational Capital: Using US Microdata to Develop a Task-based Approach. *OECD Science, Technology and Industry Working Papers* 2012/5, OECD Publishing. Doi: *10.1787/5k92n2t3045b-en .*

Squicciarini, M. and M. Le Mouel (forthcoming). Defining and Measuring Investment in Organisational Capital: A TaSK-based Approach. Mimeo (submitted for publication).

United States Bureau of Labor Statistics, Current Population Survey (CPS), www.bls.gov/cps/ (last accessed June 2013).

United States Bureau of Labor Statistics, Occupational Employment Statistics, http://bls.gov/oes/ (last accessed June 2013).

United States Bureau of Labor Statistics, Standard Occupational Classification, http://bls.gov/soc/.