Job Tasks and Wages in Developed Countries: Evidence from PIAAC[1]

Sara De La Rica
University of the Basque Country & ISEAK

Lucas Gortazar
University of the Basque Country & The World Bank Group

Piotr Lewandowski
IBS – The Institute for Structural Research

Abstract

This paper addresses the empirical relationship between job tasks and wages for a harmonized sample of 19 developed countries. We do so by using worker level PIAAC data to account for task heterogeneity within occupations. Our contribution is threefold: First, we compute abstract, routine and manual task measures that are found to be well validated vis a vis previous research. Second, we estimate task prices and find that a one standard deviation increase in abstract tasks is related to a 3.3 log point wage premium, whereas a 2.6 (2.9) log point wage penalty for each standard deviation of routine (manual) tasks. Third, we find suggestive evidence that the differences of task prices across countries can be attributed to both supply and demand side factors. Development factors and labour market institutions, in particular union coverage and strictness of employment protection legislation, seem to play a role in differences of all three task prices.

JEL codes: J24, J31, O33.
Keywords: Job Tasks, task approach, Computer use at work, job tasks prices, PIAAC.

[1] *E-mail*: sara.delarica@iseak.es, lgortazar@worldbank.org; and piotr.lewandowski@ibs.org.pl. Corresponding author: Sara de la Rica; Avda Lehendakari Aguirre, 83 - 48015 Bilbao (Spain)

I. Introduction

Recent technological change brings automation of tasks that follow precise and well-understood procedures or routines. Workplace computerization and robotisation replace humans in performing these routines, and hence lead to a gradual change of contents/tasks demanded in the workplace, especially in a range of low and medium-skill occupations. The theoretical and empirical study of the reshape of the structure of labour demand has been built by a growing body of literature, pioneered by Autor, Levy and Murnane (ALM) (2003), and followed by Acemoglu and Autor (2011), Autor and Handel (2013) (henceforth AH), Goos, Manning and Salomons (2014) and, more recently, by Acemoglu and Restrepo (2018a, 2018b). The new theoretical model is based on the task-based approach. Production requires tasks to be allocated to capital or labour, and new technologies require changes in the allocation of tasks to these factors of production. Such changes in the task content of production are found to be valuable to understand how labour demand is changing as a result of automation. In particular, ALM (2003), Acemoglu and Autor (2011) and Autor and Dorn (2012) find that computerization is associated with an increase of non-routine cognitive tasks and a decrease in routine manual and routine cognitive tasks.

The task framework, however, faces important challenges, and measurement is undoubtedly one of the most important ones. The first empirical studies used detailed occupation data (The Dictionary of Occupational Titles (DOT) or its successor, the Occupation Information Network (O*NET) to approximate job tasks. However, Spitz-Oener (2006), using data for Germany, and more recently, AH for the US, document substantial heterogeneity of job contents within even detailed occupations. These findings encourage the use of workplace level data rather than occupational based data to measure job contents/tasks adequately, primarily if the aim is to account for a precise estimation of task prices. This paper accounts for this need and uses individual information of job tasks to explore, firstly, cross-country differences in task endowments for a harmonized sample of developed countries. And secondly, and more importantly, we explore the link between tasks and wages by estimating task prices in a cross-country setting to devise country differentials in task prices and explore their potential drivers. We do so by using the Programme for the International Assessment of Adult Competencies (PIAAC), a survey which provides harmonized information across countries and contains very precise information on job contents at the worker level. Furthermore, PIAAC survey contains precise information on workers´ skill (results of numeracy and literacy cognitive tests) that goes beyond the educational attained level. This permits to estimate the factors underlying the intensity of task endowments as well as their prices conditional on a more precise measure of workers skills. For task price determination, this provides excellent controls of individual skills for the interpretation of task prices.

The need of a cross-country analysis stems from previous evidence that states that the process of de-routinization has not followed identical paths across countries. Hardy et al. (2018)

document an increase rather than a decrease in routine cognitive employment in the transition economies of Eastern and Central Europe. Gimpelson and Kapeliushnikov (2016) and Aedo et al. (2013) found similar results for Russia and Southern European countries, respectively. Hence, there is a need for an assessment of job tasks as well as task prices from a comparable sample of developed countries at the worker level. Ours is not the first study to use the PIAAC dataset to explore task contents and their cross-country differences. Recent studies, such as Marcolin et al. (2018) and Lewandowski et al. (2019) precede us in the use of PIAAC data to define the construction of a routine job index and their cross-country differentials. However, our study is the first to explore the link between tasks and wages, particularly to estimate task prices and their differentials across countries.

Task price polarization is, together with employment and wage polarization, a key implication of the Routine Bias Technological Change (RBTC). Acemoglu and Autor (2011) develop a model with three types of workers (high, medium and low skill) and a continuum of tasks. In equilibrium, the price paid for abstract and manual tasks increase relative to price paid for routine tasks, as a result of the excess of supply of middle skill workers due to their displacement into routine tasks. Cortes (2014) proposes a model where the task polarization occurs under the assumption that the substitutability between routine and abstract tasks is relatively low. In the same vein, the model developed by Autor and Dorn (2013) ensures task polarization under strong restrictions on the substitutability between computer capital and routine labour. More recently, Bohm (2020) develops a RBTC-Roy model where task price polarization is one of its main implications under perfect substitutability between routine labour and computer capital.

Empirical evidence of task price polarization has been found for the US, although evidence based on individual information (as opposed to occupational based information whose estimation of task prices is very imprecise) is scarce. In particular, Cortes (2014), using the Panel Study of Income Dynamics (PSID) from 1980 to 2007, finds an increase in the price of abstract tasks of around 15 (log) points, and a decrease of routine task prices of comparable magnitude.

In the absence of longitudinal, individual-level information – as in PIAAC or PDII - task price polarization cannot be tested. However, the task prices can be estimated. In particular, AH estimate task prices for the US and find that a one standard deviation increase in abstract tasks predicts a 7 log point wage premium, a one standard deviation increase in manual tasks results in a wage penalty of 11 log points, while an increase in routine tasks is not related to any significant difference in wages[2]. As our task measures resemble closely those of AH, our purpose is to estimate prices for abstract, routine and manual tasks for 19 developed countries, compare our results (for the US) with those found by AH and explore the cross-country differentials. Furthermore, PIAAC survey contains precise information on workers´ skill (results of numeracy and literacy cognitive tests) that goes beyond the educational level attained. This permits to

[2] See Table 5 of Autor and Handel (2013).

estimate task prices conditional on workers´ skills, and hence obtain a measure of the market demand for each of the constructed tasks[3].

Other studies that explore the link between tasks and wages with individual level data for the US are Firpo, Fortin and Lemieux (2013) and more recently Bohm (2020). Additionally, Spitz-Oener (2003) estimate task returns for Germany. The main contribution of this paper is to extend the single country analysis of task prices to a broad group of developed countries, show their differences and try to envisage potential drivers.

Our findings provide a relevant contribution to the literature. First, our task measures and the choice of items behind are well validated vis a vis previous research using PIAAC, as well as other worker-level studies such as AH. Averaged at the occupational-level, our task measures show very high correlations with respect to O*NET, specifically with regards to abstract tasks. Based on these measures, we depict the differences of tasks across countries, provide suggestive evidence on the importance of the within-occupation variation of task measures across countries, and relate those task disparities across countries with variables that reflect somehow country development (such as GDP per capita, ICT Capital stock or numeracy skills). Second, we estimate wage returns to tasks (task prices), and find that within occupations, a one standard deviation increase in abstract tasks is related to a 3.3 log point wage premium. For the case of routine (manual) tasks, the individual returns within occupations are a 2.6 (2.9) log point wage decrease for each standard deviation of routine tasks. Finally, we address the differences of task prices across countries by computing the relation between country level variables and task prices. We find suggestive evidence of the existence of supply and demand factors in explaining task returns: the higher the task endowment in a country, the more attenuated the positive or negative deviation in the price of this specific task. Development factors as well as labour market institutions, particularly union coverage and the strictness of employment protection legislation, seem to play a role in differences of all three task prices.

The rest of the paper is organized as follows. Section 2 discusses the data sources and the construction of task/job contents. Section 3 presents the descriptive results and decompositions of international differences in tasks. Section 4 turns to the estimation of task returns and focuses on their differentials and potential drivers. Section 5 concludes.

II. Data sources and Construction of Job Task Measures

Our sample includes 19 countries covered by PIAAC for which data on wages and task items are available: Belgium, Chile, Czech Republic, Denmark, Spain, France, Great Britain, Greece, Italy, Japan, Rep. of Korea, Lithuania, Netherlands, Norway, New Zealand, Poland, Slovakia, Slovenia, and the United States. For our sample, we consider employee respondents, aged 25-54, with

[3] Indeed, this is an advantage of PIAAC with respect to Princeton Data Improvement Initiative (PDII) , the database used by AH.

hourly wages between 0 and 150 USD (PPP), and exclude workers from non-profit firms or in agriculture. We also exclude workers for which some information is missing on the items used for task construction. We consider both full-time and part-time salaried workers – hence self-employed workers are excluded[4]. This leads to a sample of 37,607 workers in 19 countries.

To construct the measurements of task intensities, we use worker-level data on activities conducted at work. We follow the AH approach to construct abstract, routine and manual task measures. We also consider the framework proposed by Marcolin et al (2018) in order to construct a measure of routine tasks. We validate our approach by comparing our task measures averaged at the occupational level in the United States with those obtained from US O*NET occupational-specific task measures built by Acemoglu and Autor (2011).

We construct our measurements using the PIAAC background questionnaire which includes several questions on work habits and tasks performed in the workplace. Such questions are structured under different intensity responses of tasks and work habits. While some of them rely on more quantitative time inputs ("proportion of a workday spent on…" for which the answers stand between "Never" and "Every Day"), others are more qualitative responses that are less associated to time inputs ("to what extent you choose or change how you do …." for which the answers stand between "Not at all" and "To a very high extent").

We aim to construct reliable statistical indicators, and hence we exclusively pick items with the same quantitative input responses for the time intensity indicators of tasks. In particular, we focus on those with same structure of answers (Never; Less than once a month; Less than once a week but at least once a month; At least once a week but not every day; Every day).

We follow AH approach, whose analysis is based on the US PDII survey at the worker level, and use the first component of a principal component analysis (PCA) to derive continuous job task variables from items with multiples responses[5]. We apply the PCA to all countries in our sample using standardised weights which give each country equal total weight in the sample.

However, other approaches have been followed in studies that use individual level data on tasks. Marcolin et al (2018) and Lewandowski et al (2019) construct task indexes using PIAAC data by averaging items. Spitz-Oener (2006) compute means of binary variables on whether the worker either performs a certain task or not. Although our approach differs to these two alternatives, we

[4] We decide to keep part-time workers because we consider them an important part of the workforce. Nevertheless, we show descriptive analysis of tasks by full-time/part-time workers (table 4 below) and we run robustness checks for the task price section excluding part-time workers.

[5] Principal component analysis is a linear transformation of a set of variables which provides a set of linearly uncorrelated variables called principal components. This transformation is organized in in such a way that the first principal component has the largest possible variance in explaining data variability.

compare our results by re-constructing the task measures following both approaches[6]. All methods lead to very similar results: For the case of Spitz-Oener approach (means of transformed binary variables), the correlations are 0.93 for abstract, 0.82 for routine tasks and 0.96 for manual tasks. For the case of the standardized means (used by Marcolin et al (2018) and Lewandowski et al (2019)), correlations are 0.99 for abstract, and 0.87 for routine task (for manual task there is no comparison as the approach is the same, given that there are only two items and hence we compute the mean). Our proposed task framework and its link with PIAAC items is presented in Table 1 below.

Table 1. Task Framework with PIAAC data.

Task	PIAAC Questionnaire Item	Item No.
Abstract	Faced complex problems (<30 mins)	F_Q05b
	Use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques	G_Q03h
	Read articles in professional journals or scholarly publications	G_Q01d
	Planning the activities of others	F_Q03b
	Persuading/influencing people	F_Q04a
Routine	Planning your own activities (inverse)	F_Q03a
	Organizing your own time (inverse)	F_Q03c
	Instructing, training or teaching people, individually or in groups (inverse)	F_Q02b
	Making speeches or giving presentations (inverse)	F_Q02c
	Advising people (inverse)	F_Q2e
Manual	Working physically for a long period	F_Q06b
	Using skill or accuracy with hand or fingers	F_Q06c

Note: to ensure reliability of statistical constructs, all questions provide the same time answers: (i) Every Day; (ii) At least once a week but not every day; (iii) Less than once a week; (iv) Less than once a month; (v) Never.

For abstract tasks, we pick a combination of three analytical and two interpersonal tasks so that both dimensions of non-routine cognitive tasks are balanced. In line with AH we pick five items: (i) use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques (very similar to item 2 in AH[7]; (ii) face complex problems that take at least 30 minutes (almost equal to item 3 in AH[8]); (iii) planning the activities of others (quite

[6] For Marcolin et al (2018) or Lewandowski et al (2019) method, we compute average measures of the items. For Spitz-Oener (2006) method, we transform the five response items into binary variables by gathering the two highest (At least once a week but not every day; Every day) categories as a positive answer on the task being performed and by gathering the lowest three as a negative answer.

[7] Item 2 in AH corresponds to "frequency of mathematics tasks involving high-school or higher mathematics: algebra, geometry, trigonometry, probability/statistics or calculus".

[8] Item 3 in AH corresponds to "frequency of problem solving tasks requiring at least 30 minutes to find a good solution".

similar to item 4 of AH[9]); (iv) persuading or influencing people (similar to item 4 of AH); (v) read articles in professional journals or scholarly publications. This last item is included to avoid bias in the cognitive non-routine task exclusively towards numerical tasks, similar to what Lewandowski et al (2019) do.

Regarding the routine task index, we follow a mixed approach by combining Marcolin et al (2018) with AH. We first consider two items with quantitative response related to time inputs from Marcolin et al (2018), namely the inverse values of "planning your own activities" and "organizing your time" (which is also considered in AH through the "proportion of the workday spent performing short, repetitive tasks"). In addition, we consider AH proposal to include the absence of face-to-face interactions with different type of co-workers (customers or clients, suppliers or contractors, and students or trainees). In particular, we add three items reflecting lack of face-to-face interactions proposed by AH: instructing, training or teaching people; making speeches or presentations in front of five or more people; and advising people.

We decide against replicating Marcolin et al (2018) measure of routine intensity for two reasons. First, they use a heterogeneous mix of items from PIAAC, some of which are more related to quantitative inputs ("how often does your job involve….") like planning or organizing, but also follow qualitative response items ("to what extent can you choose or change …."). Such approach questions the reliability of results, as we may be measuring two different type of phenomena. Second, when we replicate the Marcolin et al (2018) choice with the four items proposed in their paper, the resulting index averaged at the occupational level for the US shows a low correlation with O*NET data (0.27), way below the correlation obtained by AH (0.48) with PDII US data or the correlation obtained by Lewandowski et al (0.55) with the US PIAAC data.

For manual tasks, we compute the mean of two items: "working physically for long periods" and "using skill or accuracy with hand or fingers". The first item is similar to the one used by AH ("the proportion of the workday spent performing physical tasks such as standing, operating machinery or vehicles, or making or fixing things by hand"). It also has the same quantitative responses pertaining to time intensity as the questions used for abstract and routine measures. The second item corresponds with the non-routine dimension of Autor and Acemoglu (2011) measure.

Table A.1 in the Annex displays basic statistical information of our tasks measures to give a first glance of their structure. Additionally, Table 2 displays the results of the principal component analysis and the correlations between each of the tasks. The first component obtained in the PCA for each task explains a relatively large share of variance: 44% for abstract (compared to 41% of AH) and 48% for routine (compared to 56% of AH). Moreover pair-wise correlations at the worker level for the full sample show a large negative correlation of -0.71 between abstract and routine tasks (much larger compared to -0.32 of AH), a smaller negative correlation of -0.21

[9] Item 4 of AH corresponds to "proportion of work day managing or supervising other workers".

between abstract and routine (slightly smaller compared to -0.31 of AH) and a smaller positive correlation of 0.16 between abstract and manual (slightly smaller than the 0.22 obtained by AH). Finally, we reconstruct the task measures with the US sample of workers only. The pair-wise correlations between manual tasks compared to abstract and routine tasks are slightly smaller when compared to that of the full sample, while the pair-wise correlation between abstract and routine tasks is similar to that of all country sample.

Table 2. Results of PCA and cross-tasks correlations

	Computation PCA (all countries)		**Pair-wise correlations (all countries)**			**Pair-wise correlations (US sample only)**		
	Number of components	Variation of first component	Abstract	Routine	Manual	Abstract	Routine	Manual
Abstract	5	0.444	1	-	-	1	-	-
Routine	5	0.478	-0.708	1	-	-0.704	1	-
Manual	1	-	-0.208	0.164	1	-0.144	0.119	1

Notes: own elaboration from PIAAC.

Statistical validation of task measures

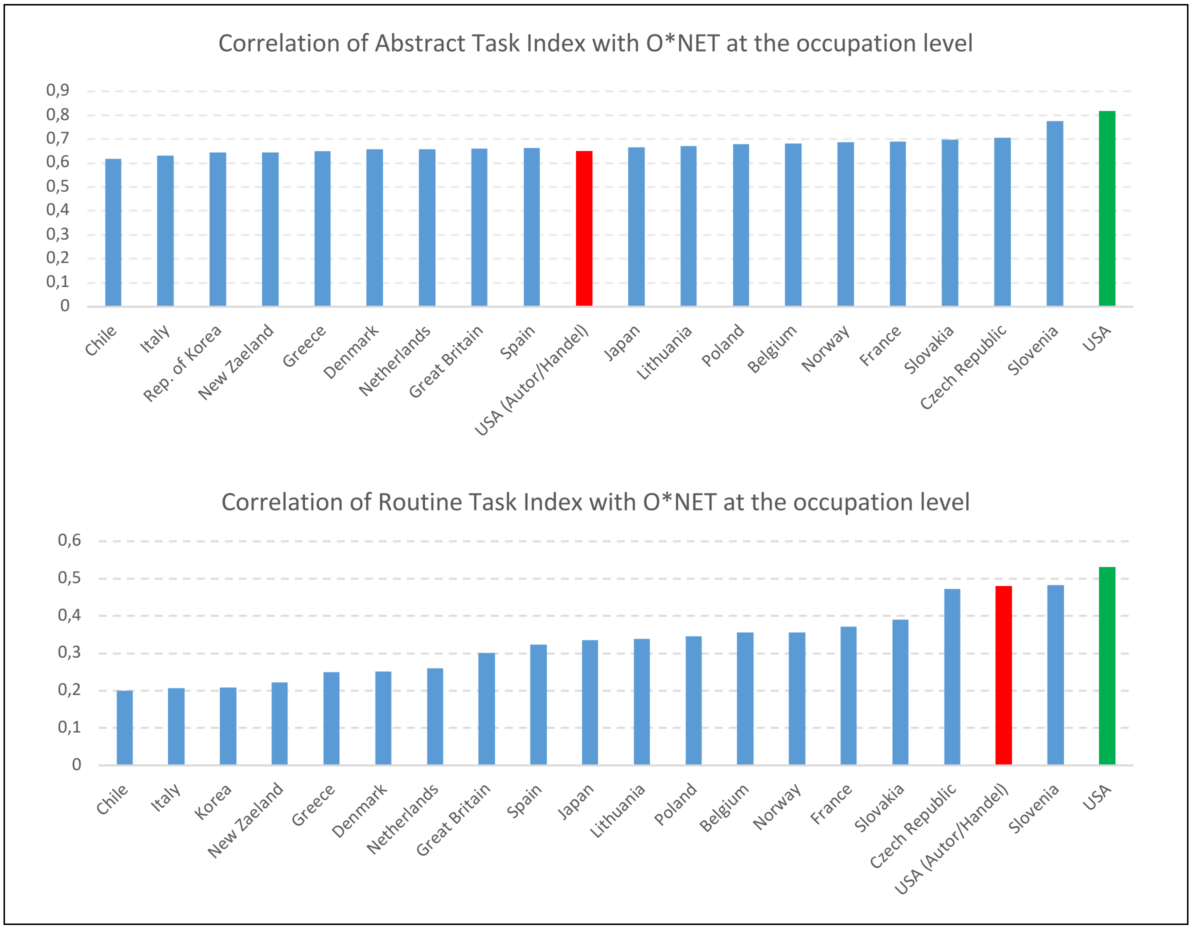
In order to validate our measures, we compare the survey-based measures averaged at the occupational level with the Acemoglu and Autor (2011) measures calculated with O*NET data. Given that some countries do only have data on occupations at the 3-digit level of the ISCO classification, we compute O*NET and PIAAC measures at 3-digit occupational level. We construct an abstract measure which represents a standardized mean of non-routine cognitive analytical and interpersonal tasks, a routine measure corresponding uniquely to the routine cognitive task of Acemoglu and Autor (2011) and a standardized mean of manual routine and non-routine tasks from Acemoglu and Autor (2011). Results are displayed in Figure 3.

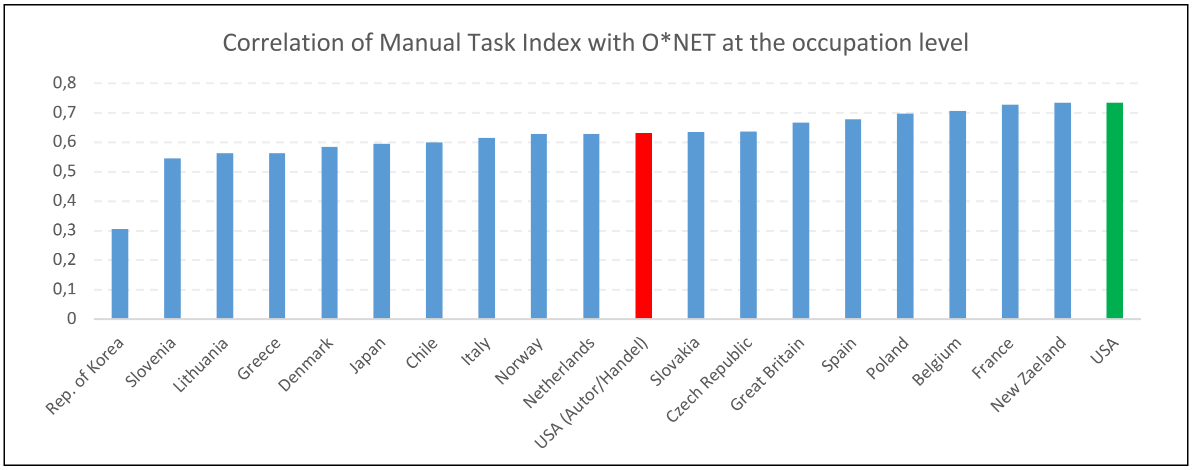
First, the abstract task measure is correlated positively and strongly (0.82) with O*NET data at the occupation level for the US, hence providing a solid validity check for our choice. In particular, it improves considerably the validity check by AH. This improvement may help explain the larger negative (compared to AH) correlation between abstract and routine tasks previously shown in Table 2. Moreover, in all countries the correlation between our measure and the O*NET- based measure exceeds 0.60, and in many of them it exceeds 0.65. The index displays a higher correlation in US, Slovenia, Czech Republic, Slovakia and France, and works worst in Chile, Italy and Korea.

Second, the correlation between the routine task measure and the relevant O*NET measure at the occupational level in the US is 0.53, higher to that obtained by AH (0.48) and similar than that of Lewandowski et al (0.55). The correlation stands between 0.2 and 0.5 for most countries, being the US, Norway, Slovenia, and France those where it works better and Greece, Japan and Lithuania where it works worst.

Third, the correlation for manual tasks in the US is high (0.73), higher to what is obtained by AH (0.63), and similar compared to Lewandowski et al (0.74). The correlation is above 0.54 for all countries, with the US, New Zealand, France and Belgium with better correlations and Rep. of Korea (figuring on the very bottom), Slovenia and Lithuania with the lowest correlations.

Figure 1. Correlation of task indexes with O*NET at the occupational level





Notes: own elaboration from PIAAC.

III. Job Task Descriptives and Cross-Country Disparities

Task descriptives

We display average task content of jobs for the sample of countries analysed across a set of individual covariates, which can be found in Table 4. The results show larger average values of abstract and manual tasks for males, whereas there are no gender differences on routine tasks. By age, abstract tasks display a concave shape, similar to the standard productivity/age profile, although we must be cautious with such interpretation, as cohort effects may interfere with age effects. The contrary is found for routine and manual tasks – they display a convex shape, which would also be consistent with the relative decrease of less qualified tasks (routine and manual) as productivity evolves with age, notwithstanding potential cohort effects. Abstract tasks increase by education level, and literacy and numeracy skills[10], whereas routine and manual tasks decrease by education level, with the decrease being more pronounced for manual tasks. Abstract tasks are more intensive in more qualified occupations, whereas the contrary is observed for routine (and to a lesser extent manual). Employees in the public sector display larger abstract and lower routine and manual tasks, relative to those in the private sector. Full-time workers have higher abstract tasks and lower routine tasks than part-time workers, while manual task intensity is similar for both groups. Finally, abstract tasks increase by firm size, whereas routine and manual decrease as the size of the firm increases in number of employees.

[10] Numeracy and Literacy skills are directly provided in PIACC dataset for each individual. The values reported in the table are the quartiles of the average of all 10 plausible values for each skill.

Table 4. Distribution of task measures by worker covariates

	Abstract	Routine	Manual
Female	-0.08	0.01	-0.06
Male	0.07	-0.01	0.05
Aged 25-29	0.00	0.01	0.04
Aged 30-34	0.08	-0.04	-0.02
Aged 35-39	0.06	-0.04	-0.03
Aged 40-44	0.02	-0.02	-0.04
Aged 45-49	-0.07	0.04	0.03
Aged 50-54	-0.10	0.07	0.03
Primary or lower secondary education	-0.63	0.56	0.41
Upper secondary education	-0.25	0.23	0.23
Post-secondary non-tertiary	0.16	-0.17	-0.05
Tertiary education	0.59	-0.51	-0.51
Numeracy Skill (Q1)	-0.48	0.43	0.41
Numeracy Skill (Q2)	-0.15	0.12	0.16
Numeracy Skill (Q3)	0.10	-0.10	-0.11
Numeracy Skill (Q4)	0.47	-0.39	-0.42
Literacy Skill (Q1)	-0.44	0.39	0.38
Literacy Skill (Q2)	-0.09	0.08	0.13
Literacy Skill (Q3)	0.17	-0.16	-0.15
Literacy Skill (Q4)	0.47	-0.41	-0.47
Legislators, senior officials and manage	0.98	-0.84	-0.51
Professionals	0.61	-0.60	-0.41
Technicians and associate professionals	0.31	-0.24	-0.30
Clerks	-0.13	0.12	-0.40
Service workers and shop and market sale	-0.40	0.30	0.32
Craft and related trades workers	-0.42	0.40	0.75
Plant and machine operators and assemble	-0.76	0.76	0.49
Elementary occupations	-0.82	0.79	0.52
Public Sector	0.21	-0.24	-0.14
Private Sector	-0.08	0.09	0.05
Full-time worker	0.06	-0.04	0.00
Part-time worker	-0.37	0.26	-0.01
Firm Size: 1-10 workers	-0.22	0.19	0.13
Firm Size: 11-50 workers	0.01	-0.04	0.04
Firm Size: 51-250 workers	0.05	-0.05	-0.04
Firm Size: 251-1000 workers	0.10	-0.02	-0.11
Firm Size: More than 1000 workers	0.30	-0.22	-0.22
Observations	37,607	37,607	37,607

Notes: results display values of standardized indexes for each task, with mean 0 and standard deviation 1 across the whole distribution. Individual observations are weighted so that countries are weighted equally.

Cross-Country Differences in Job Tasks among developed countries

In Table 5 below, we display country average values (standardized for all workers in the sample giving equal weights to all countries) of task variables. In particular, we find that the countries with the highest GPD per capita levels in our sample - New Zealand, Norway, Great Britain, Denmark, and the United States – display the highest positive values of abstract tasks. The lowest average values in abstract tasks are seen in Greece, Italy, Japan, Lithuania and Slovakia. An almost inverse relation is found for the case of routine tasks (with the cross-country correlation equal to -0.88), whereas a small cross-country correlation is found between manual tasks and abstract tasks (0.11) as well as routine tasks (-0.05). These cross-country patterns are consistent with those found by Lewandowski et al. (2019). The average level of manual tasks is the lowest in the Asian OECD countries (Japan, Rep. of Korea), and in Western European countries (France, Netherlands, Norway). On the other hand, it is high in the Central Eastern European countries and Chile. However, the average level of manual tasks is highest in New Zealand and the United States, which otherwise are characterised by high level of abstract tasks and low level of routine tasks. This implausible result suggests that the questions used to construct the manual measure, in particular "Working physically for a long period" are probably not entirely comparable between countries covered by PIAAC.[11]

Table 5: Job Task measures by countries

	Observations	Abstract	Routine	Manual
Belgium	2,007	0.00	0.01	-0.20
Chile	1,396	-0.02	-0.02	0.20
Czech Republic	1,709	0.01	0.16	0.05
Denmark	2,481	0.31	-0.41	0.04
Spain	1,856	-0.18	0.04	-0.16
France	2,587	-0.07	0.11	-0.26
Great Britain	3,263	0.31	-0.25	0.10
Greece	989	-0.24	0.38	0.06
Italy	1,390	-0.25	0.08	-0.02
Japan	2,122	-0.22	0.07	-0.54
Rep. of Korea	2,289	-0.08	0.15	-0.27
Lithuania	1,861	-0.46	0.15	0.25
Netherlands	1,922	0.14	-0.11	-0.23
Norway	2,042	0.38	-0.32	-0.32
New Zealand	1,992	0.50	-0.44	0.34
Poland	1,973	-0.03	0.03	0.17
Slovakia	1,779	-0.23	0.35	0.13
Slovenia	1,859	-0.16	0.25	0.33
United States	2,090	0.30	-0.22	0.33
Total Observations	37,607	0.00	0.00	0.00

Notes: Results display values of standardized indexes for each task across all the sample (giving equal weights to all countries), with mean 0 and standard deviation 1, averaged at the country level. Individual observations are weighted so that countries are weighted equally.

[11] Lewandowski et al. (2019) also found that the incidence of workers who are "Working physically for a long period" is implausibly high in the US. This may suggest that the US workers have interpreted this question as a question on long working hours rather than as a question on performing physically demanding tasks.

The task content measures based on PIAAC data show that the international differences in tasks are larger than suggested by O*NET-based task, where the differences between countries are entirely driven by the differences in occupational structures. In particular, the cross-country variance for the case of PIAAC (O*NET) is 0.061 (0.037) for abstract, 0.051 (0.015) for routine and 0.060 (0.028) for manual tasks.

In order to analyse to what extent the cross-country differences in task values can be attributed to differences in occupational structures, and to what extent to differences in occupation-specific task values, we apply a shift-share decomposition. For each task measure $i \in [abstract, routine, manual\}$, we decompose the difference between the average task content level in a country c, T_c^i, and the global average, T^i, (which equals zero) into the between-occupation, BO_c^i, within-occupation, , WO_c^i and interaction, INT_c^i, terms. Formally:

$$(T_c^i - T^i) = (\sum_{j \in ISCO} \alpha_{j,c} t_{j,c}^i - \sum_{j \in ISCO} \alpha_j t_j^i) = BO_c^i + WO_c^i + INT_c^i, \quad (1)$$

$$BO_c^i = \sum_{j \in ISCO} t_j^i (\alpha_{j,c} - \alpha_j), \quad (2)$$

$$WO_c^i = \sum_{j \in ISCO} \alpha_j (t_{j,c}^i - t_j^i), \quad (3)$$

$$INT_c^i = \sum_{j \in ISCO} (\alpha_{j,c} - \alpha_j)(t_{j,c}^i - t_j^i), \quad (4)$$

whereby:

- $t_{j,c}^i$ and t_j^i are the average values of task content i for workers in occupation j in country c, and on average across all countries in the sample, respectively,
- $\alpha_{j,c}^i$ and α_j^i are the shares of workers with in occupation j in total employment in country c, and on average across all countries in the sample, respectively,
- $ISCO$ is the set of 3-digit ISCO-08 occupations.

Moreover, to assess the contribution of each factor to the cross-country variance of T^i, we use the covariance-based decomposition proposed by Morduch and Sicular (2002). For instance, the contribution of the between-occupation factor, to the variance of RTI is defined as follows:

$$\sigma_{BO}^i = \frac{cov(BO_c^i, T_{c,}^i)}{var(T_{c,}^i)}, \quad (5)$$

and in the same way for the within-occupation and interaction effects. Results of the shift-share decomposition are presented in Figure 2 and the results of the covariance-based decomposition are presented in Table 6.

We find that the cross-country differences in PIAAC tasks result predominantly from differences in the average tasks contents within particular occupations defined at a detailed, 3-digit ISCO levels (Figure 2). About two thirds of the cross-country differences in abstract and routine tasks, and as much as 90% of the cross-country differences in manual tasks can be attributed to the within-occupation effect (Table 6).

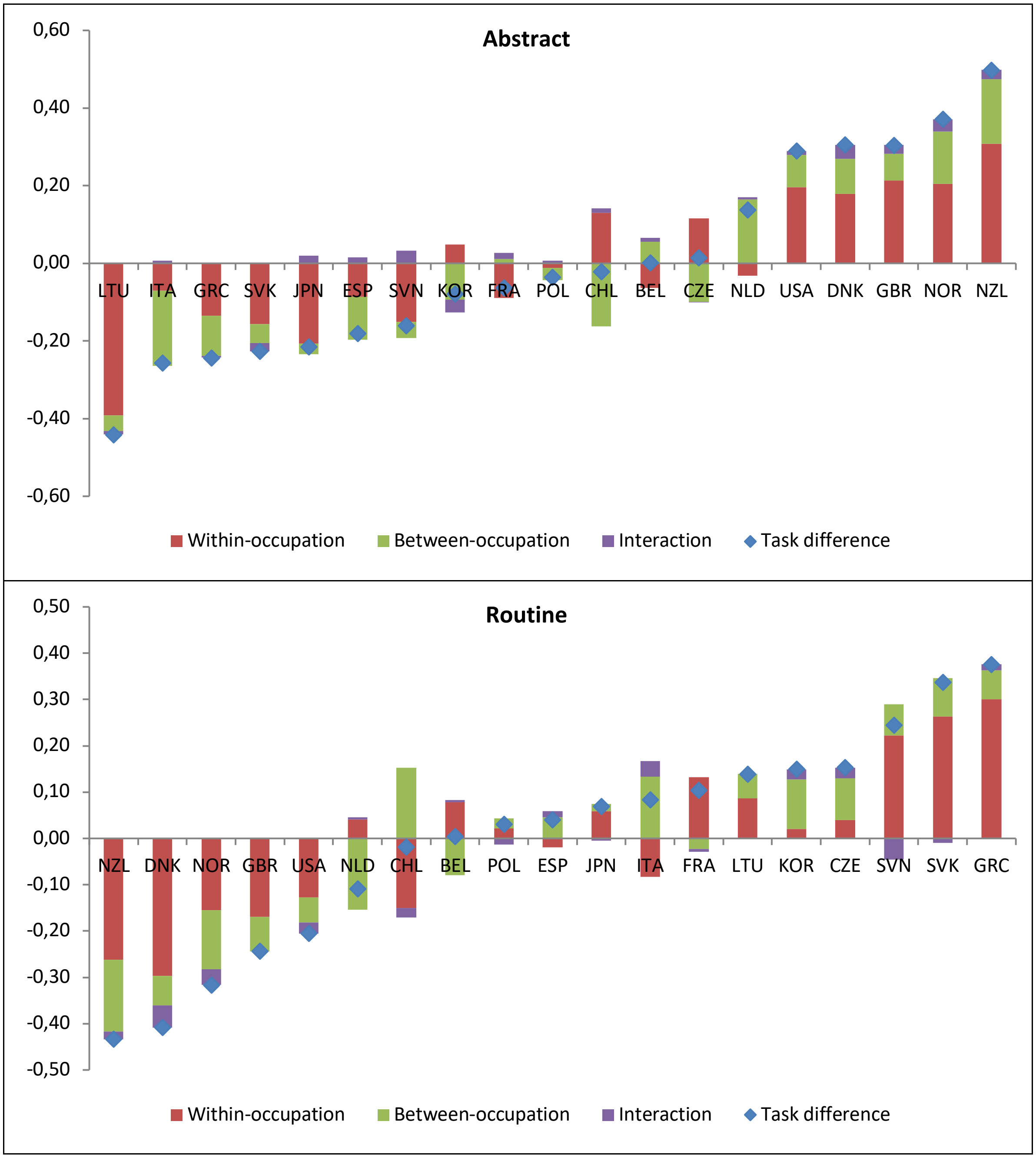
Moreover, the between- and within-occupation country effects are strongly correlated across countries for abstract (0.43) and routine (0.40) tasks. The correlation for manual tasks is virtually zero (0.04) but it turns positive (0.19) if two countries with spurious results for manual tasks (New Zealand and the US) are removed from the sample. This shows that countries that exhibit above-average shares of occupations rich in particular tasks also tend to exhibit above-average intensity of these tasks within occupations, as can be expected in line with the Roy-type model of allocation of tasks (Autor, 2013). In the case of O*NET-based tasks, the cross-country differences are almost entirely driven by differences in the occupational structures at a finer disaggregation level (Figure A.1 and Table A1 in the Annex).

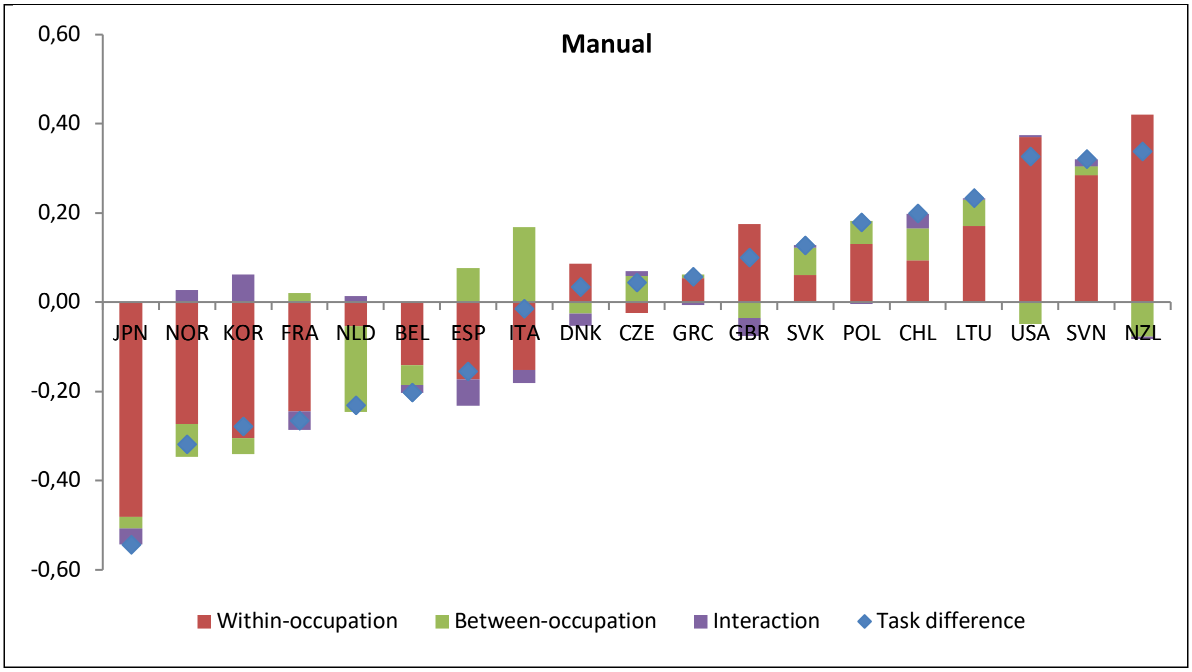
Table 6: Decomposition of cross-country variance in the average values of PIAAC-based task measures

	Abstract	Routine	Manual
Cross-country variance tasks	0.061	0.051	0.06-
Contribution of (in %)			
Within-occupation effect	64.2%	65.5%	90.4%
Between-occupation effect	32.1%	30.2%	7.8%
Interaction	3.7%	4.3%	1.8%

Notes: contributions calculated in line with equations (1) – (5).

Figure 2. The shift-share decomposition of cross-country differences in tasks according to PIAAC- based measures





Note: shift-share decomposition of differences between particular country and the sample average, based on 3-digit ISCO occupations.

Tasks and other development and institutional variables across countries

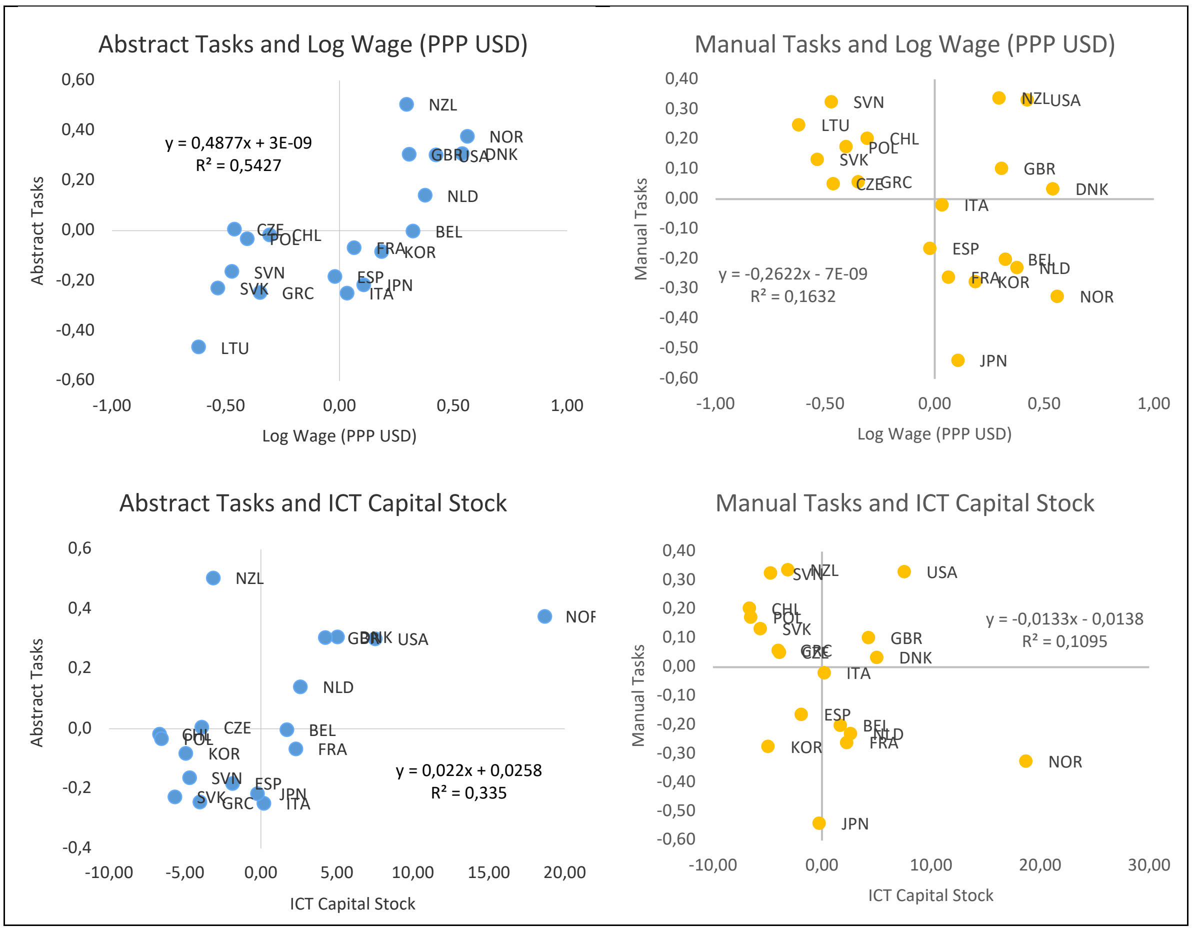
In order to shed light on the factors related to the cross-country differences in tasks, we start by an exploratory analysis which depicts the average task values to relevant country-level variables. Figure 3. plots these average task values against four different variables: log GDP per capita in USD PPP (to track economic development), numeracy skills (to track human capital, derived from PIAAC data), ICT capital stock per worker (to track technological development, derived from Eden and Gaggl (2019)) and employment legislation protection (to introduce a measure of labour institutions, following Broecke et al (2016)[12]). Given the high cross-country negative correlation (-0.88) between levels of abstract and routine tasks, the routine task cross-country comparisons are reported in Figure A.2 in the Annex. Moreover, a complete set of correlations between average levels of tasks and key country-level variables is displayed in Table A.2 in the Annex.

The average level of abstract tasks performed by workers is positively correlated with all dimensions displayed in Figure 3, except for the strictness of employment legislation protection (EPL). In particular, higher level of abstract tasks is performed by workers in countries with higher GDP (the cross-country partial correlation of 0.74, square root of R-2 of 0.543 in Figure

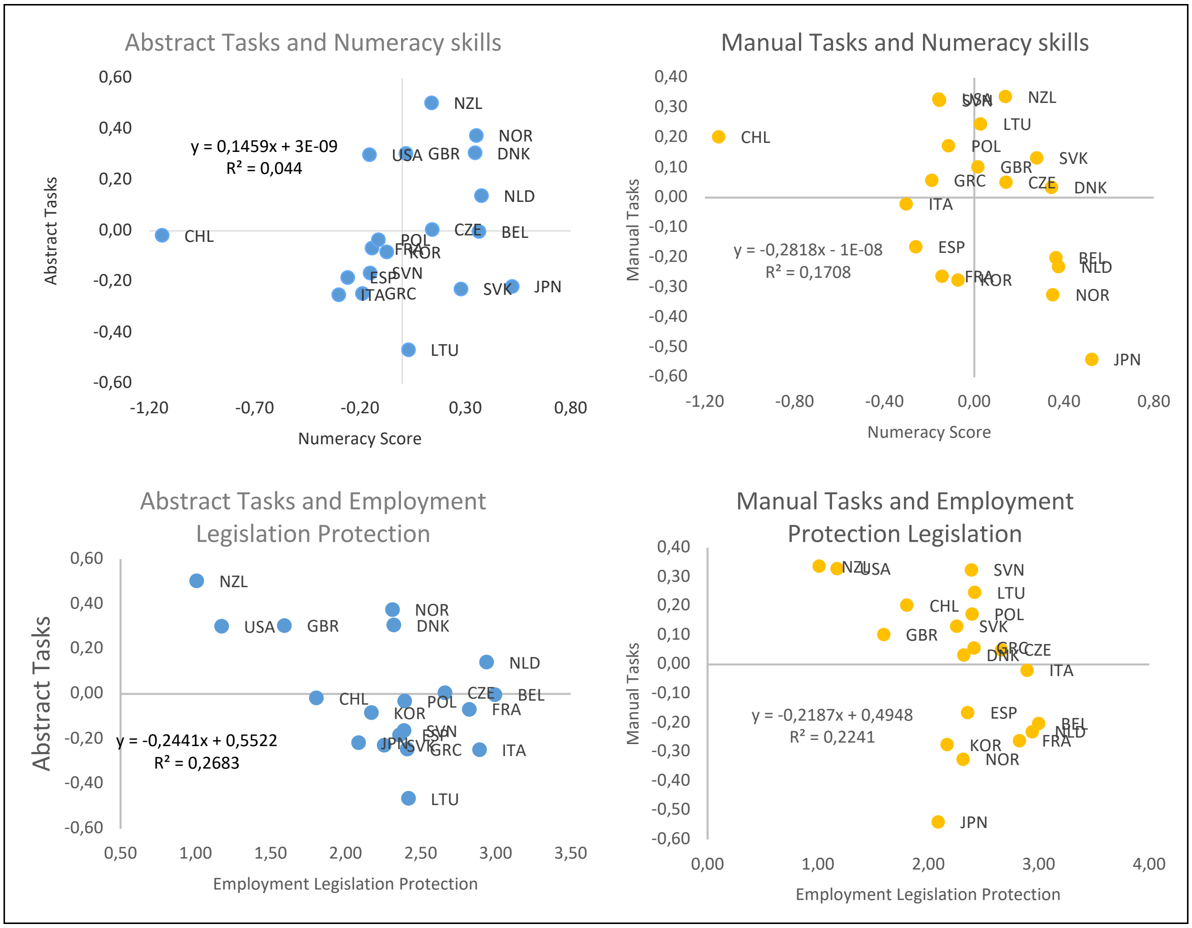
[12] We follow Broecke et al (2016) and consider three different measures of labour institutions (minimum wage, strictness of employment legislation protection and union density). The cross-country correlation with task measures is included for all three dimensions on Table A.2 in the Annex. We include employment legislation protection variable in Figure 3 as it is the one displaying the highest explanatory value of task measures across countries.

3), in countries with higher ICT capital stock per worker (correlation 0.58, square root of R-2 0.34), in countries with higher average numeracy skills (correlation 0.21, square root of R-2 0.04), and in countries with lower strictness of employment protection legislation (correlation 0.52, square root of R-2 0.27).[13] On the other hand, the average level of manual tasks is negatively correlated with all four factors (although it is weak in all four cases, with R-2 between 0.1 and 0.22 and hence correlation between 0.3 and 0.47). Finally, the strictness of EPL correlates negatively with abstract and manual task at the cross-country level.

Figure 3. Abstract and Manual Tasks country average and other relevant development measures across countries.



[13] For the case of numeracy skills, the relationship is weaker than in the case of other variables. This may be related to the presence of outliers such as Japan and Slovakia (much higher numeracy skills relative to the level of abstract tasks) or Great Britain and the United States (much lower numeracy skills relative to the level of abstract tasks).



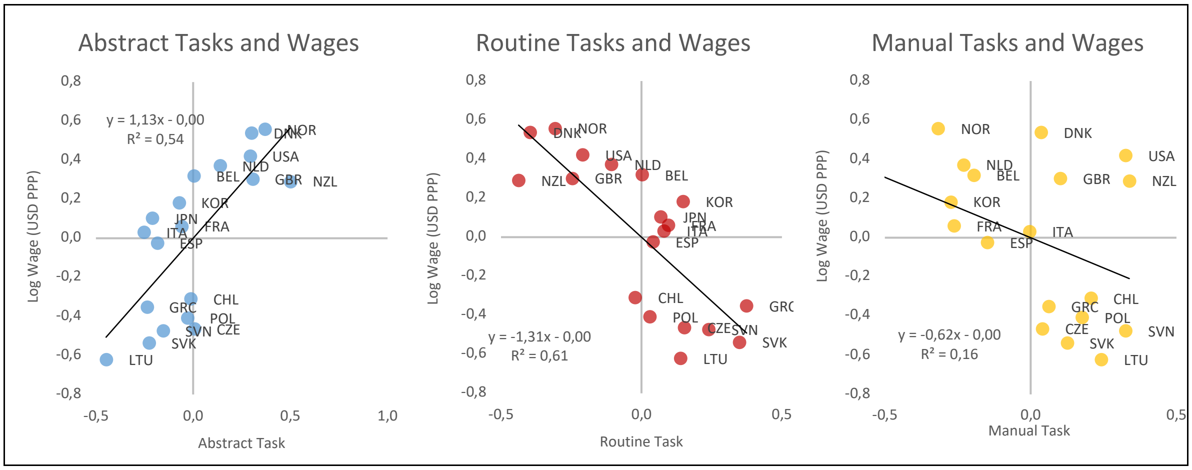
Data: All variables are demeaned at the country average. Own calculations for data on abstract tasks. Data on numeracy is based on the PIAAC test. Data on ICT Capital Stock were collected by Eden and Gaggl (2019). Data on employment protection legislation is derived from OECD Labour statistics.

IV. Task Prices

In this section we exploit the empirical relation between task prices and wages across countries. We start with a descriptive inspection of the cross-country differences in the relationship between task endowments and wages. This helps us understand later what is behind the cross-country differentials in task prices.

Figure 4 plots the cross-country differences of task endowments and average wages (USD PPP). In terms of wages, two clusters can be distinguished. First cluster which includes Anglo-Saxon countries, Nordic countries, Western European countries, as well as Spain and Italy, exhibits higher average wages than the other cluster which includes Eastern European countries as well as Greece and Chile. There is a clear positive relation between average level of wages and average value of abstract tasks, and a negative relation between wages and routine tasks. For manual tasks, the relation is negative but weaker than in the case of routine tasks, mostly due to the fact that some high-wage countries like the US, Great Britain, New Zealand and Denmark display positive levels of manual tasks.

Figure 4. Tasks and wages across countries.



Data: All variables are demeaned at the country average.

Task prices – Basic Empirical Approach

The wage data reported in PIAAC corresponds to hourly earnings with bonuses for wage and salary earners. Moreover, for consistent comparisons, we use the conversion data to $USD, corrected in Purchasing Power Parity (PPP), constructed by the OECD. We follow AH and start by estimating a linear model for each of the task for the pool for the 19 countries in our sample[14] ($\mathbf{j = 1 \ldots 19}$).

$$Log\ W_{ij} = \alpha + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_o \beta_{2o} X_{ijo}^{Job} + \ \beta_{3k} Task_{ijk} + \beta_{3k} \overline{Task_{ijk}} + \delta_j + \varepsilon_{ij} \quad (6)$$

with $Log\ W_{ij}$ being the hourly log-wage, X_{ij}^{Ind} individual worker characteristics: these include gender, age or level of education, but importantly, a comparable measure of individual ability approximated by the individual test scores of numeracy skills[15]. Thanks to the inclusion of the skill measure, the estimated task prices capture the task price that is conditional on a precise supply component of worker ability (almost always unobserved in other data) and hence is primarily driven by demand forces. X_{ij}^{Job} includes a vector of job characteristics (public or private firm, firm size and on-the-job training), and $Tasks_{ijk}$ are the intensity of each specific task k (abstract, routine and manual) which each worker reports to exert in her work. Additionally, to net out the pure individual job task prices from the association between job tasks and occupations, we include also the average mean of each task at occupation-country level. This is

[14] We do so because of the high correlation between task measures at the worker and occupation level, which would pose collinearity issues and hamper interpretation of coefficients.
[15] Given the high correlation between literacy and numeracy skills, we only include the first one, given its higher predictive power on wages.

a leave-out mean, representing the average intensity of k-th task for all workers from a particular country in occupation *p* except for the *i-th* worker.

Table 6 displays the results of two empirical specifications of the relationship between wages and tasks: without and with task averaged at the country-occupation level[16]. The first key result is that abstract prices are positive and routine and manual prices are negative (although the relationship exhibited between wages and manual tasks is weaker). When we control for the task measures averaged at the country-occupational level, the returns to individual tasks decrease by half in the case of abstract, by 70% for routine tasks, and by 30% in the case of manual tasks. This confirms the result, also found by AH, that individual-level task prices are to some extent driven by the occupational selection of workers with comparative advantage in performing particular tasks.

We find that within occupations, a one standard deviation increase in abstract tasks is related to a 3 log point wage premium. In the case of routine tasks, the individual price within occupations are a 3 log point wage decrease for each standard deviation of routine tasks. In the case of manual tasks, our results show a decrease of 2.7 log point wage per standard deviation of manual tasks. In terms of individual returns, a gender wage gap is observed, as well as an increase of returns with age, level of education, on the job training, firm size, ICT use at work [17], and numeracy skills. Returns to individual and job characteristics, especially returns to education, numeracy skills, and computer use slightly decrease when the average job task measures at occupation/country level are controlled for. Similarly, the returns to the ICT use at work are lower when task prices at the occupation level are considered. This is related to the fact that worker´s occupation and intensity of ICT use are related.

Table 6. Estimation of Task Prices – Log Wage Regressions

	Abstract		Routine		Manual	
Task Price	0.0639***	0.0331***	-0.0508***	-0.026***	-0.0355***	-0.0295***
	(0.00515)	-0.00464	-0.00402	-0.00448	-0.00474	-0.00505
Task Price (Occupation level)		0.129***		-0.112***		-0.0224***
		(0.0128)		(0.0119)		(0.0083)
Male	0.160***	0.162***	0.169***	0.174***	0.176***	0.177***
	(0.00738)	(0.00734)	(0.00761)	(0.0077)	(0.00786)	(0.0078)
Upper Secondary	0.0468***	0.0374***	0.0475***	0.041***	0.06***	0.0559***
	(0.0118)	(0.012)	(0.0123)	(0.0124)	(0.0118)	(0.0121)
Post-secondary or Tertiary Professional	0.116***	0.0888***	0.119***	0.0971***	0.131***	0.129***
	(0.0132)	(0.014)	(0.0141)	(0.0145)	(0.0136)	(0.014)
Tertiary (Bachelor/Master)	0.274***	0.223***	0.28***	0.239***	0.289***	0.284***
	(0.0125)	(0.0159)	(0.0127)	(0.0144)	(0.0131)	(0.0137)
30-34	0.0805***	0.0779***	0.083***	0.081***	0.084***	0.083***
	(0.011)	(0.0101)	(0.011)	(0.0107)	(0.011)	(0.011)
35-40	0.148***	0.145***	0.149***	0.148***	0.151***	0.15***

[16] As a robustness check, we have re-estimated the model including only full-time workers. Although results are not reported, they exhibit the same patterns as those displayed in table 6. They are available under request.

[17] The variable ICT at work is taken from the PIACC database. It is the first component derived out of a Principal Component Analysis of the following PIACC questionnaire items: (i) use the internet in order to better understand issues related to your work (G_Q05C); (ii) conduct transactions on the internet (G_Q05D); (iii) use spreadsheet software, for example Excel (GQ05E); (iv) participate in real time discussions on the internet (G_Q05H).

	(0.0101)	(0.0103)	(0.0099)	(0.0102)	(0.01)	(0.01)
40-44	0.196***	0.191***	0.193***	0.195***	0.199***	0.198***
	(0.0105)	(0.0104)	(0.00993)	(0.0103)	-0.0101	(0.0105)
45-49	0.201***	0.194***	0.201***	0.197***	0.202***	0.201***
	(0.0127)	(0.0128)	(0.0013)	(0.013)	(0.013)	(0.0126)
50-54	0.207***	0.199***	0.208***	0.202***	0.208***	0.206***
	(0.0225)	(0.0228)	(0.0223)	(0.0226)	(0.0077)	(0.0227)
On the Job Training	0.0462***	0.0416***	0.0471***	0.044***	0.0609***	0.0609***
	(0.00838)	(0.0087)	(0.008)	(0.0083)	(0.00773)	(0.0077)
Private sector	-0.00316	0.00823	-0.003	0.0125	-0.0101	-0.0086
	(0.0114)	(0.012)	(0.0119)	(0.0121)	(0.0113)	(0.0114)
Firm Size: 1-10 workers	0.0918***	0.093***	0.0919***	0.0939***	0.094***	0.0939***
	(0.0161)	(0.0162)	-0.0162	(0.0163)	(0.0162)	(0.0162)
Firm Size: 11-50 workers	0.127***	0.129***	0.128***	0.132***	0.125***	0.125***
	-0.0167	(0.0168)	(0.0168)	(0.0169)	(0.0164)	(0.0116)
Firm Size: 251-1000 workers	0.191***	0.195***	0.195***	0.204***	0.186***	0.186***
	(0.0182)	(0.0185)	(0.0182)	(0.019)	(0.018)	(0.0179)
Firm Size: More than 1000 workers	0.242***	0.243***	0.244***	0.252***	0.238***	0.248***
	(0.0201)	(0.0202)	(0.0204)	(0.0207)	(0.02)	(0.02)
ICT use at work	0.0779***	0.0601***	0.0885***	0.0753***	0.0958***	0.0913***
	-0.00453	-0.00479	(0.0038)	-0.00387	-0.0038	(0.004)
Numeracy skills	0.00115***	0.000998***	0.0012***	0.00101***	0.00118***	0.00116***
	(0.00014)	-0.00016	(0.00014)	-0.00015	-0.00015	-0.00015
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.082***	2.121***	2.073***	2.09***	2.08***	2.09***
	(0.0334)	(0.0352)	-0.0327	(0.0336)	(0.0354)	(0.0351)
Observations	37607	37607	37607	37607	38,835	37607
R-squared	0.456	0.462	0.456	0.46	0.453	0.454

Notes: Data reflects log hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD$. We exclude earnings below USD$1 and above USD$150. All regressions cluster standard errors at the occupation level. Regressions have been conducted using complex sampling weights (weighted so that countries are weighted equally) and conducted for all plausible values for numeracy skills.

Note that our models differ slightly from the AH model because the we use worker-level measure of skill supply (available in PIAAC but not available in PDII) and control for particular tasks separately. In order to check the extent to which our results would be similar to AH, we replicate the AH model – we include the three tasks together as explanatory variables (and individual and occupational level task variables). Results (presented in Table A.4 in the Annex) show similarities with respect to sign and size of effects of AH (see Table 6, column 4 of AH)[18]. The returns of tasks when they are introduced jointly in the estimation (Table A.4 annex) with respect to introducing them separately (Table 6) are lower in particular for occupational level coefficients of routine and manual tasks. Indeed, the latter are no longer significantly different from zero for wages. This might be due to high collinearity of the task variables.

In the second specification of the Table A.4 in the Annex we additionally control for numeracy skills, given the predictive power of this variable for wages, available in PIACC data and not in

[18] For abstract, individual positive returns are lower compared to AH (2% vs 9% per s.d. of task), occupational-level returns are higher relative to AH (12% vs 7% per s.d. of stask), and the aggregate effect is similar. For routine tasks, individual returns are negative and significant (3% per s.d. of task), whereas for the case of AH, the effect is not significant; the occupational-level returns are not significant, similar to what happens in AH. For manual tasks, individual returns are negative and account to 4% per standard deviation of manual tasks, slightly lower relative to 9% in AH; the occupation-level effect is not-significant, similar to AH.

AH database. Two key findings emerge. First, the magnitude of the individual and occupation level returns to tasks is slightly reduced (by around 10-20%). This suggest that the estimates of task prices on data which have no measures of workers' abilities or skills can be overestimated by to noticeable extent. Second, the effect of key socio-demographic characteristics (like gender, level of education) is also reduced by controlling for workers' numeracy skills.

Moreover, it is to be noted that the differences in task returns across countries are noticeable. To see this, we include an interaction term of country dummies and individual task measures in equation (6). Results are reported in Table A.5 in the Annex for each task model, with our main specification including task values across country-level occupations (columns 2, 4, 6 of Table 6). Abstract tasks present positive returns for all countries except Belgium, Denmark, Greece and Norway whereas manual task present negative returns for all countries in the sample except for Belgium and Denmark. Regarding routine tasks, although the average return is negative, five countries present positive (although small) returns to tasks, whereas the Czech Republic presents high positive returns (8 percent per task s.d.). More importantly, the differences of returns across countries are large in magnitude: the standard deviation of returns is relevant compared to the mean return across countries.

Accounting for cross-country differences in task prices

To dig deeper into the observed differences in task prices across countries, we follow Hanushek et al. (2015) by adapting the pooled model to account for cross-country differences in task prices. While Hanushek et al. (2015) aimed to capture differences in returns to skills, we aim to capture differences in task prices. We estimate the country-specific task prices (one for each task), approximated by the interaction of the individual task prices with different country-level variables, in order to establish stylized facts related to task prices across countries. Formally, we estimate a log-wage equation pooled model, where in addition to all variables previously included as well as country fixed effects, we consider the interaction term between a country-level covariate $\overline{\Delta_{lk}}$ (reflecting different measures $l = 1 \dots m$ of country development and institutions) and worker-level task measures, with β_{5lk} being the interaction coefficient of interest for each country-level variable l and each task k.

$$Log\ W_{ij} = \alpha + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_o \beta_{2o} X_{ijo}^{Job} + \beta_{3k} Task_{ijk} + \beta_{4k}\overline{Task_{ijk}} + \beta_{5lk}\, Task_{ijk} * \overline{\Delta_{lk}} + \delta_j + \varepsilon_{ij} \quad (7)$$

The country-level variables reflect a wide set of dimensions of development, including human capital (numeracy skills), income, ICT capital stock per worker, and labour market institutions (the same as those used Section III). We also consider average task endowments at the country level (abstract, routine, manual). All the country-level variables are demeaned relative to the international average across countries, which allows better understanding the variation in task prices across countries through differences in country contexts (always relative to the mean country value). Table 7 presents the results of such interaction effect captured by β_{5lk} in equation (7) for each combination of tasks $k = 1,2,3$ at the individual level. A positive (negative) sign of our coefficient of interest β_{5lk} means that the higher the country endowment in a specific task or development variable, the higher (lower) the price of such task[19].

First, the interactions between abstract task prices and development level, numeracy skills and ICT capital stock are negative, attenuating the positive effect of development level and ICT capital stock per worker. In the case of routine and manual tasks, the interactions with GDP and ICT capital stock per worker are positive. This indicates that higher development level and higher ICT capital stock attenuate to some extent the direct negative price that workers get for performing these tasks.

Second, we find evidence that the cross-country differences in labour market institutions are associated with the cross-country differences in tasks prices. For union coverage and EPL, there are significant negative interactions with abstract task prices, and positive interactions with routine and manual task prices. No relationship is found regarding minimum wage (relative to median wage of full-time workers) and task prices across countries. Although we do not attempt to give any causal interpretation to these results, they are consistent with the fact that unions tend to compress the wage distribution. They are also consistent with Hanushek et al (2015) finding that higher unionization is associated with lower returns to skills. As such, wherever union coverage and EPS are high, prices of highly qualified tasks (abstract) are likely to be relatively lower whereas prices of lower qualified tasks (routine and manual) would turn to be relatively higher. Still, this is a tentative interpretation which should be taken with caution.

In order to ascertain the magnitude of the relations between task prices and country, we estimate a pooled model controlling for key country-level institutional variables (column 10 of Table 7). We find that EPL remains significant for all three tasks (negative for abstract, positive for routine and manual tasks). Union coverage is also negatively associated with abstract tasks prices. Finally, ICT capital stock is negatively (positively) associated to abstract (manual) task prices, whereas the level of numeracy is positively associated with routine tasks.
Next, to assess the economic significance of these effects, we compute counterfactual simulations in the vein of Hanushek et al. (2015) by multiplying the estimated partial correlation coefficient (column 10) by differences in particular variables between countries in our dataset. For instance, the recorded differences in ICT capital stock per worker translate into noticeable variation in abstract task prices, ranging from the minimum of -0.08 in Chile to the maximum of 0.05 in Norway. Similarly, for labour market institution, abstract task prices conditional on EPL values range from -0.01 (Belgium) and 0.06 (US) and returns to abstract tasks depending on union coverage varies from -0.01 (Denmark) and 0.03 (France).

[19] Given that Table 7 is an extension of the model whose estimation is reported in Table 6, only the interaction effects are reported. Full estimation results are available upon request.

Table 7. Accounting for differences in returns to tasks across countries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Abstract Tasks										
Average Return	0.033***	0.033***	0.031***	0.033***	0.033***	0.032***	0.033***	0.033***	0.033***	0.019***
* Log GDP PC	-0.055***									0.077
* Numeracy		-0.045***								-0.032
* ICT Capital Stock			-0.002***							-0.005**
* Minimum Wage				0.030						-0.037
* EPL					-0.042***					-0.037***
* Union Coverage						-0.149***				-0.071***
* Abstract Tasks							-0.016			
* Routine Tasks								0.000		
* Manual Tasks									0.042***	
Routine Tasks										
Average Return	-0.025***	-0.025***	-0.021***	-0.026***	-0.026***	-0.024***	-0.025***	-0.026***	-0.026***	-0.012***
* Log GDP PC	0.061***									-0.069
* Numeracy		0.066***								0.076***
* ICT Capital Stock			0.002***							0.004
* Minimum Wage				-0.091						0.056
* EPL					0.031***					0.021**
* Union Coverage						0.111***				0.013
* Abstract Tasks							0.039**			
* Routine Tasks								-0.010		
* Manual Tasks									-0.019	
Manual Tasks										
Average Return	-0.030***	-0.030***	-0.032***	-0.030***	-0.032***	-0.030***	-0.030***	-0.029***	-0.033***	-0.026***
* Log GDP PC	0.043***									-0.066
* Numeracy		0.035**								0.021***
* ICT Capital Stock			0.002***							0.005
* Minimum Wage				0.003						0.022
* EPL					0.039***					0.037**
* Union Coverage						0.085***				0.020
* Abstract Tasks							-0.017			
* Routine Tasks								-0.006		
* Manual Tasks									-0.085***	
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Countries	19	19	18	16	19	19	19	19	19	16
Observations	37607	37607	35746	29833	37607	37607	37607	37607	37607	29833

Notes: Only country-level interaction terms (added with the average effect) are included, with the United States being country of reference (and hence having an interaction term equals zero). The model for ICT Capital stock includes all countries but Lithuania, for which data is not available. The model for minimum wage includes all countries but Denmark, Italy and Norway, i.e. countries which don't have national minimum wages. All regressions cluster standard errors at the occupation level. Regressions have been conducted using complex sampling weights (weighted so that countries are weighted equally) and conducted for all plausible values for numeracy skills.

Finally, we find some evidence that the more abundant are particular tasks in the country, the higher are the individual prices that workers get for performing the other tasks. In particular, the abstract task prices are higher in countries with higher average level of manual tasks, whereas the routine task prices are higher in in countries with higher average abstract task level. For manual tasks, there is a negative relation between manual task return and task endowments. Overall, the scarcer manual tasks are, the higher is their price.

V. Conclusion

This paper addresses the empirical relationship between job tasks and wages for a harmonized sample of 19 developed countries. The first empirical evidence on such relationship was based on occupation-level data. However, Spitz-Oener (2006), and more recently, Autor and Handel (2013), using worker level data, document substantial heterogeneity of job contents within even detailed occupations. These findings encourage the use of workplace level data rather than occupational based data to measure job contents/tasks adequately, primarily if the aim is to account for a precise estimation of task prices.

We account for this need and use individual information of job tasks to explore, firstly, cross-country differences in task endowments and secondly, and more importantly, the link between tasks and wages by estimating task prices in a cross-country setting and exploring their potential drivers. We do so by using the Programme for the International Assessment of Adult Competencies (PIAAC), a survey which provides harmonized information across countries and contains very precise information on job contents at the worker level. Moreover, PIAAC provides information on individual numeracy and literacy cognitive skills, and hence provides excellent controls of individual skills for the interpretation of task prices.

We construct three task measures: abstract, routine and manual tasks and compare our choices and method of aggregation which those previously constructed with PIAAC dataset. Additionally, we validate our measures with those previously constructed at occupation level for the US (O*NET), as well as with those constructed by Autor and Handel (2013) from PDII dataset (for the US). The task content measures based on PIAAC data show that the international differences in tasks are larger than suggested by O*NET-based task measures, where the differences between countries are entirely driven by the differences in occupational structures. From a shift-share analysis we find that the cross-country differences in PIAAC tasks result predominantly from differences in the average tasks contents within particular occupations defined at a detailed, 3-digit ISCO levels (about 100 occupations). Additionally, when relating task disparities across countries with variables that reflect country development, such as GDP per capita, ICT capital stock per worker or numeracy skills, we find that abstract tasks correlate positively with the development level of a country, the ICT capital stock and the numeracy skill of workers.

For the estimation of task prices, we estimate a log (hourly) wage model where the main covariate is the task (abstract, routine or manual) endowment. First, we do so by pooling all countries together and control for the usual demographic and job variables, as well as for individual cognitive skills (in particular, the numeracy skill level), which controls for usually unobserved ability. Conditional on this, prices of tasks must be seen as mostly driven by demand factors. We find that within occupations, a one standard deviation increase in abstract tasks is related to a 3.3 log point wage premium. For the case of routine tasks, The individual (within occupations) prices for performing routine tasks associated to a 2.6 log point wage decrease for each standard deviation of routine tasks. Finally, for manual, our results show a decrease of 2.9 log point wage per standard deviation of manual tasks.

In order to account for cross-country differences of task prices, we estimate models with interactions between the individual task prices (relative to the US) and the country level key covariates. We find a negative relationship between task prices and the task endowment, which highlights the importance of supply and demand factors in the task price determination. Additionally, the interactions between task prices and country level key covariates are sizable. In particular, abstract task prices and development level and ICT capital stock are negative, attenuating the positive effect of development level and ICT capital stock. In the case of routine and manual tasks, the interactions with GDP and ICT capital stock are positive, which shows that higher development level and higher ICT capital stock attenuate to some extent the direct negative return to these tasks. Additionally, we find significant negative interactions between union coverage and EPS with abstract task prices, and positive interactions with routine task prices. Although we do not attempt to give any causal interpretation to these results, they are consistent with the fact that unions tend to compress the wage distribution. On the contrary, the effect of minimum wage, once the other labour market institutions are included, is negligible.

From a policy perspective, this study contributes to a fundamental policy discussion such as the impact of technological change and automation of the job content of workers, and its implications on wages. This will be at the core of social sciences in the coming decades. Our paper provides a consistent and promising avenue of future research on the consequences of technological change on the labor markets from an international perspective, whenever second or third waves of PIAAC (or national longitudinal studies) data are implemented worldwide. Moreover, it confirms the importance of collecting worker level information of job activities and habits (already discussed in previous studies for the US and Germany), and hence the need to complement occupation-level analysis with individual-level data.

VI. References

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Handbook of Labor economics (Vol. 4, pp. 1043-1171). Elsevier.

Acemoglu, D. And P. Restrepo (2017), "Robots and Jobs: Evidence from US Labor Markets" NBER Working Paper No. w23285

Aedo, C., Hentschel, J., Moreno, M., & Luque, J. (2013). From occupations to embedded skills: a cross-country comparison. World Bank Group, Washington, D.C.

Autor, David H-, Frank Levy & Richard J. Murnane (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration." The Quarterly Journal of Economics, vol. 118(4), pages 1279-1333, November.

Autor, David H., and David Dorn (2013) "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." American Economic Review, 103(5): 1553-97.

Autor, David H. and Michael J. Handel (2013) "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages". Journal of Labor Economics, 31(2): S59-S96.

Bohm, M. (2020), "The Price of Polarization: Estimating Task Prices under Routine-Biased Technical Change" forthcoming in Quantitative Economics.

Broecke, Stijn, G. Quintini and M. Vandeweyer (2016), "Wage Inequality and Cognitive Skills: Re-Opening the Debate", NBER WP, NO. 21965.

Cortes, G. M. (2016): "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data," Journal of Labor Economics, vol. 34, issue 1, 63-105

Eden, Maya, Gaggl, Paul. (2019). Do poor countries really need more IT?. World Bank Economic Review, lhy022, https://doi.org/10.1093/wber/lhy022 .

Firpo, S. N.M. Fortin and T. Lemieux (2011), "Occupational Tasks and Changes in the Wage Structure", IZA DP No. 5542.

Gimpelson, Vladimir, and Rostislav Kapeliushnikov (2016), "Polarization or upgrading? Evolution of employment in transitional Russia." Russian Journal of Economics 2, vol.2, pp: 192-218.

Goos, Marteen, A. Manning and A. Salomons (2014), "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring", American Economic Review, vol. 104, no. 8, August

Hanusheck, E, Guido Schwerdt, Simon Wiederhold & Ludger Woessman (2015),"Returns to skills around the world: Evidence from PIAAC, European Economic Review 73 pp: 103-130

Hardy, W., Keister, R., & Lewandowski, P. (2018). Educational upgrading, structural change and the task composition of jobs in Europe. Economics of Transition, 26 (2), 201–231.

Lewandowski, Piotr, A. Park, W. Hardy and D. Yang (2019), "Technology, Skills and Globalization: Explaining International Differences in Routine and Non Routine work using Survey Data" IBS WP No. 04/2019.

Marcolin, Luca, S. Miroudot and M. Squicciarini (2018), "To be (routine) or not to be (routine), that is the question: A cross-country task-based answer", Industrial and Corporate Change, pp. 1-25.

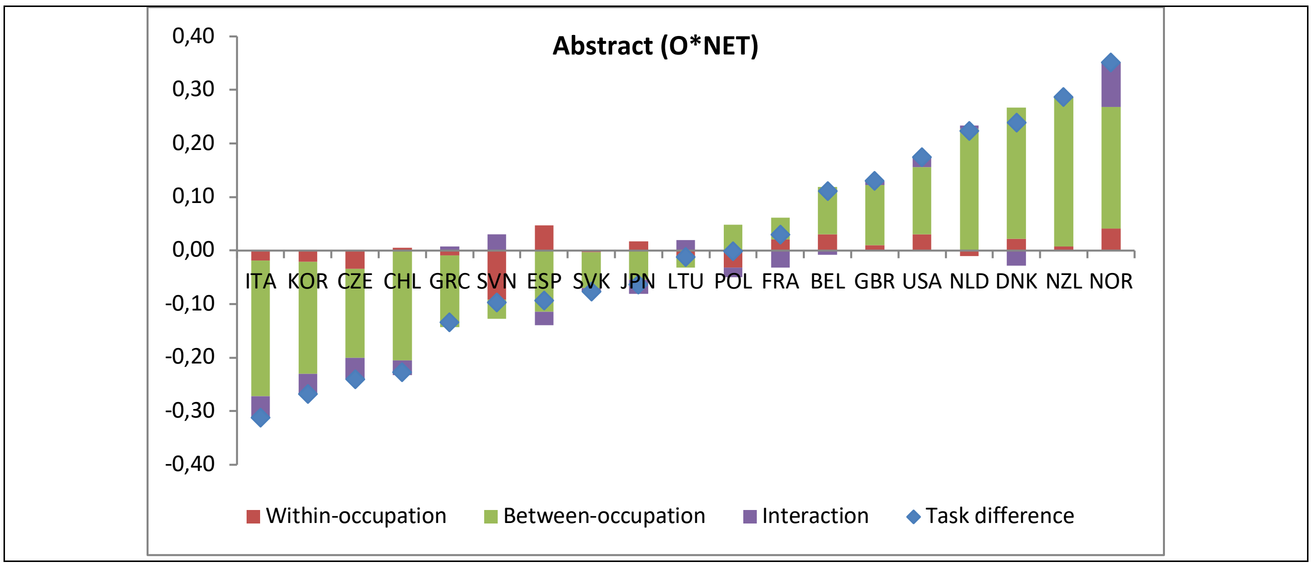
Spitz-Oener, Alexandra (2006) "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure." Journal of Labor Economics, 24(2), pp 235-270.

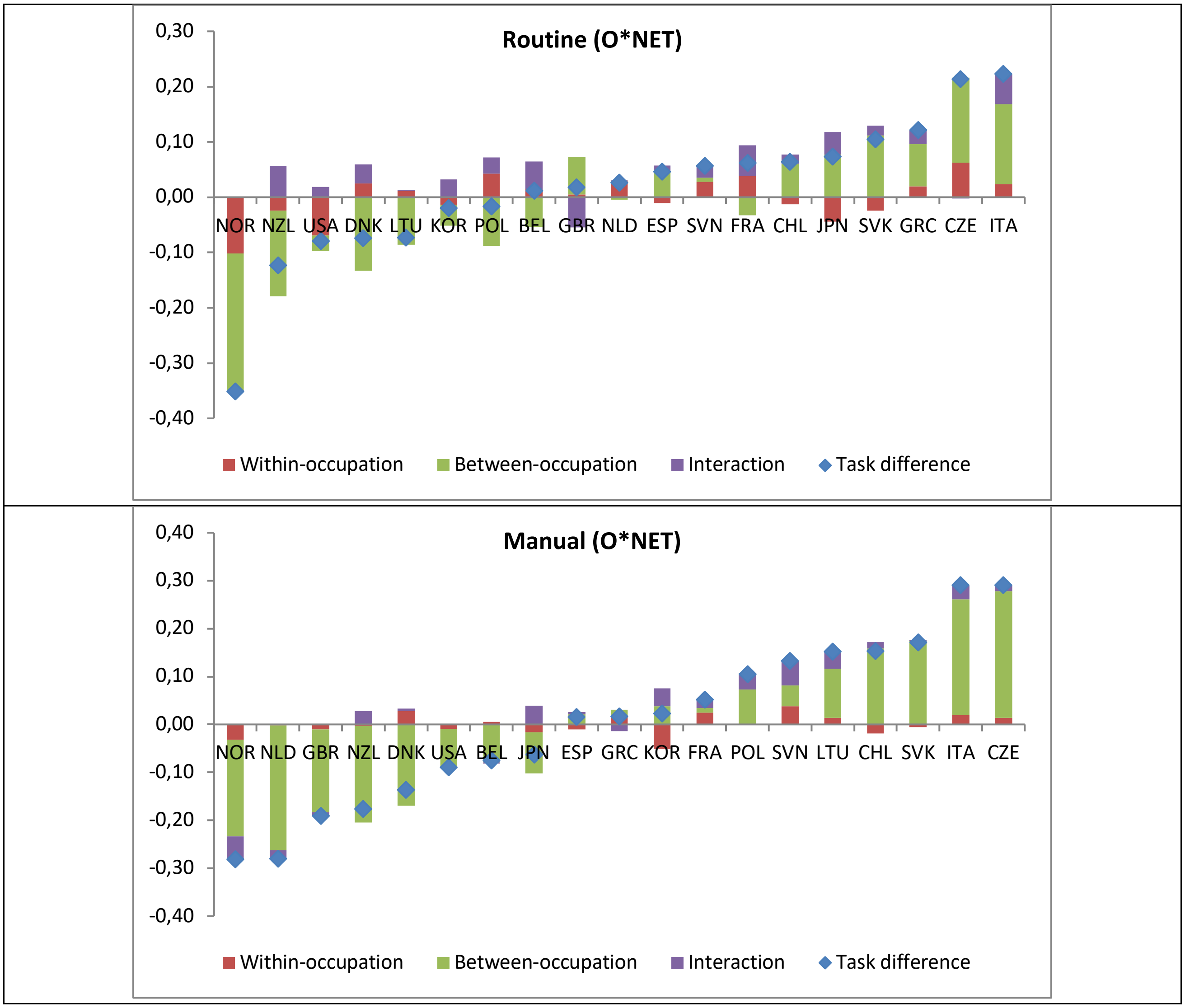
VII. Annex – Tables and Figures

Table A.1. Descriptive Statistics of Task measures

	Abstract	Routine	Manual
Max	2.88	2.09	1.11
Minimum	-1.51	-1.80	-1.69
Median	0.04	-0.20	-0.29
Mean	0.00	0.00	0.00
Standard Deviation	1.00	1.00	1.00
Number of Observations	37,607	37,607	37,607
Number of Cells	2,163	1,952	9

Figure A.1. The shift-share decomposition of cross-country differences in tasks according to O*NET-based task measures





Note: shift-share decomposition of differences between particular country and the sample average, based on 3-digit ISCO occupations.

Table A.2: Decomposition of cross-country variance in the average values of O*NET-based tasks

	Abstract	Routine	Manual
Cross-country variance tasks	0.037	0.015	0.028
Contribution of (in %)			
Within-occupation effect	7.7%	20.6%	4.3%
Between-occupation effect	82.8%	76.8%	87.7%
Interaction	9.5%	2.6%	8.0%

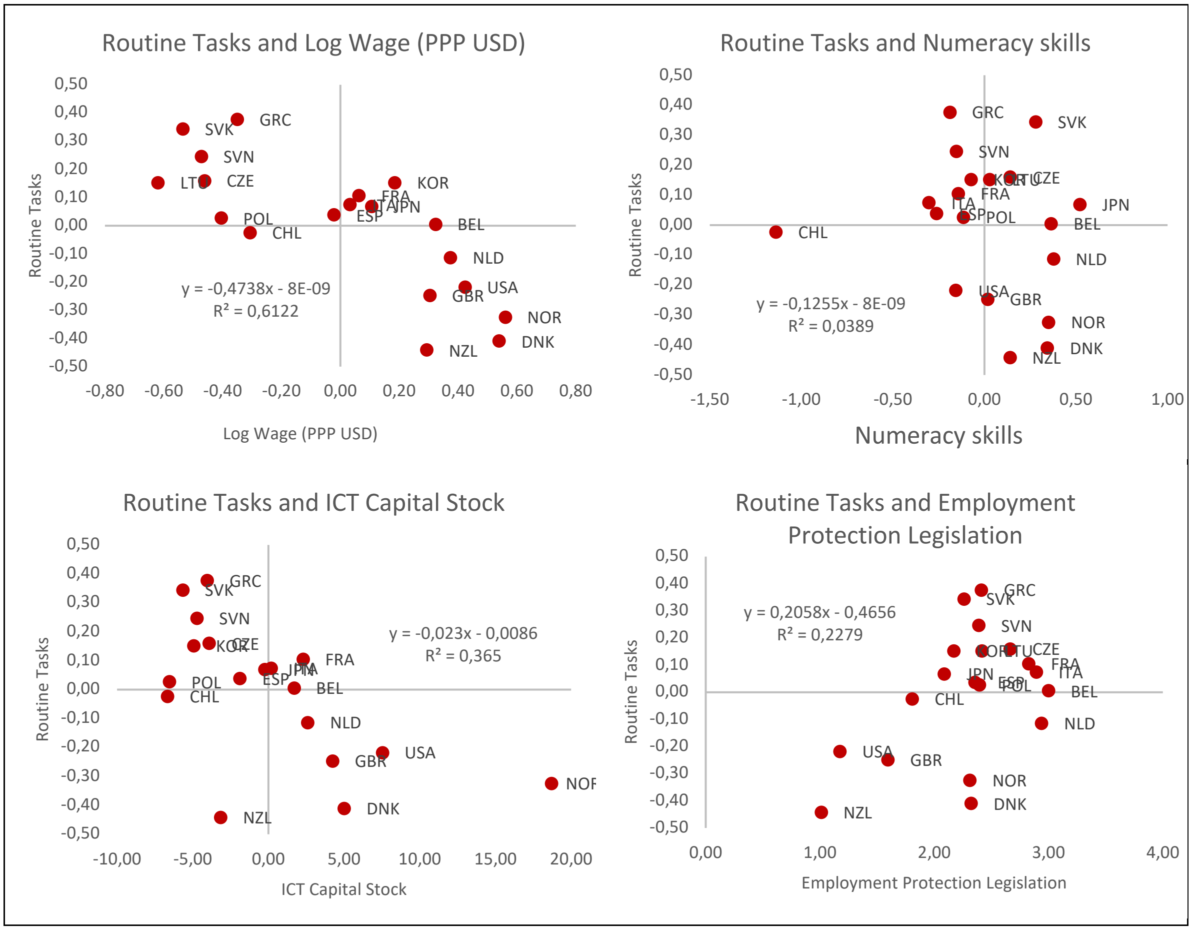
Notes: contributions calculated in line with equations (1) – (5).

Table A.3. Cross-country correlations of task endowments.

	Abstract	Routine	Manual	Log Wage (PPP USD)	Log GDP pc (PPP USD)	Literacy score	Numeracy score	ICT Capital Stock	Minimum wage (relative to median)	Employment protection legislation	Union Coverage (%)
Abstract	1	-0.88	0.11	0.74	0.63	0.35	0.21	0.58	0.07	-0.52	0.38
Routine	-	1	-0.05	-0.78	-0.65	-0.33	-0.20	-0.60	-0.03	0.48	-0.47
Manual	-	-	1	-0.40	-0.42	-0.43	-0.41	-0.33	0.31	-0.47	-0.18
Log Wage (PPP USD)	-	-	-	1	0.88	0.48	0.36	0.77	-0.14	-0.20	0.53
Log GDP pc (PPP USD)	-	-	-	-	1	0.61	0.56	0.92	-0.32	-0.03	0.52
Literacy score	-	-	-	-	-	1	0.93	0.42	-0.56	-0.05	0.16
Numeracy score	-	-	-	-	-	-	1	0.40	-0.53	0.19	0.36
ICT Capital Stock	-	-	-	-	-	-	-	1	-0.28	-0.03	0.54
Minimum wage (relative to median)	-	-	-	-	-	-	-	-	1	-0.05	0.07
Employment protection legislation	-	-	-	-	-	-	-	-	-	1	0.22
Union Coverage (%)	-	-	-	-	-	-	-	-	-	-	1

Data: All variables are demeaned at the country average. Own calculations for data on abstract tasks. Data on numeracy is based on the PIAAC test. Data on ICT Capital Stock were collected by Eden and Gaggl (2019). Data on employment legislation protection and minimum wage are derived from OECD Labour statistics. Data from union coverage is derived from ILO statistics.

Figure A.2. Routine Tasks and other relevant development measures across countries.



Data: All variables are demeaned at the country average. Own calculations for data on abstract tasks. Data on numeracy is based on the PIAAC test. Data on ICT Capital Stock were collected by Eden and Gaggl (2019). Data on employment protection legislation is derived from OECD Labour statistics.

Table A.4. Pooled model of task returns (AH, 2013)

	AH (2013)	AH (2013) + Numeracy Skills
Abstract	0.0255***	0.0241***
	(0.00476)	(0.00669)
Abstract (Occupation level)	0.130***	0.122***
	(0.0119)	(0.0186)
Routine	-0.0240***	-0.0227***
	(0.00440)	(0.0063)
Routine (Occupation level)	-0.00114	-0.00008
	(0.0118)	(0.0146)
Manual	-0.0411***	-0.0382***
	(0.00375)	(0.0052)
Manual (Occupation level)	0.0193***	-0.0229**
	(0.00711)	(0.0094)
Male	0.175***	0.165***
	(0.00582)	(0.0071)
Upper Secondary	-0.0548***	0.0348***
	(0.00905)	(0.0123)
Post-secondary or Tertiary Professional	0.0556***	0.0832***
	(0.00874)	(0.0145)
Tertiary (Bachelor/Master)	0.194***	0.210***
	(0.00830)	(0.017)
30-34	0.0764***	0.0774***
	(0.00977)	(0.0106)
35-40	0.142***	0.143***
	(0.00982)	(0.0104)
40-44	0.184***	0.188***
	(0.00974)	(0.0104)
45-49	0.186***	0.191***
	(0.00985)	(0.0226)
50-54	0.187***	0.195***
	(0.0102)	(0.0226)
On the Job Training	0.0433***	0.0411***
	(0.00608)	(0.0085)
Private sector	0.0132*	0.011
	(0.00687)	(0.0121)
Firm Size: 1-10 workers	-0.132***	0.0925***
	(0.00828)	(0.0162)
Firm Size: 11-50 workers	-0.0372***	0.128***
	(0.00757)	(0.0157)
Firm Size: 251-1000 workers	0.0677***	0.195***
	(0.00972)	-0.018
Firm Size: More than 1000 workers	0.115***	0.242***
	(0.0113)	(0.02)
ICT use at work	0.0583***	0.0531***
	(0.00412)	-0.0051
Numeracy skills		0.00095***
		-0.00016
Country Fixed Effects	Yes	Yes
Constant	2.549***	2.15***
	(0.0171)	-0.036
Observations	37607	37607
R-squared	0.461	0.463

Notes: Data reflects log hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD$. We exclude earnings below USD$1 and above USD$150. All regressions cluster standard errors at the occupation level. Regressions have been conducted using complex sampling weights (weighted so that countries are weighted equally) and conducted for all plausible values for numeracy skills.

Table A.5. Country-level returns from interaction term between country-dummies and individual tasks.

	Abstract Tasks	Routine Tasks	Manual Tasks
United States	0.067	-0.043	-0.107
Belgium	-0.028	0.019	-0.002
Chile	0.103	-0.122	-0.064
Czech Republic	0.004	0.083	-0.038
Denmark	-0.024	0.011	-0.001
Spain	0.035	-0.047	-0.025
France	-0.001	0.000	-0.005
Great Britain	0.061	-0.054	-0.048
Greece	-0.011	-0.012	-0.033
Italy	0.003	-0.002	-0.011
Japan	0.084	-0.048	-0.005
Rep. Of Korea	0.075	-0.078	-0.054
Lithuania	0.082	-0.069	-0.014
Netherlands	0.026	-0.014	-0.024
Norway	0.003	0.004	-0.001
New Zealand	0.049	0.003	-0.090
Poland	0.055	-0.044	-0.061
Slovakia	0.026	-0.004	-0.047
Slovenia	0.048	-0.033	-0.065
Min	-0.028	-0.122	-0.107
Max	0.103	0.083	-0.001
Mean	0.035	-0.024	-0.037
SD	0.039	0.044	0.031
SD/Mean	1.125	-1.874	-0.860

*Note*s: Only country-level interaction terms (added with the average effect) are included, with the United States being country of reference (and hence having an interaction term equals zero). Data reflects log hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD$. We exclude earnings below USD$1 and above USD$150. All regressions cluster standard errors at the occupation level. Regressions have been conducted using complex sampling weights (weighted so that countries are weighted equally) and conducted for all plausible values for numeracy skills.