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Job Tasks and Wages in Developed Countries: Evidence from PIAAC ☆

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ABSTRACT

This paper addresses the empirical relationship between job tasks and wages for a harmonised 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 visa-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 there is a 2.6 to 2.9-log-point wage penalty for each standard deviation of routine (manual) tasks. Development factors and labour market institutions, particularly union coverage and strictness of employment protection legislation, seem to play a role in the differences in all three task prices.

1. Introduction

Recent technological change has led to the automation of tasks that follow precise and well-understood procedures or routines. As workplace computerisation and robotisation have been replacing the humans who previously performed these routines, there has been a gradual change in the contents/tasks demanded in the workplace, especially in a range of low- and medium-skill occupations. The theoretical and empirical study of the reshaping of the structure of labour demand has been the focus of a growing body of literature pioneered by Autor, Levy and Murnane (ALM) (2003), and further developed 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 used in these analyses is based on the task-based approach. Production requires the allocation of tasks to capital or labour, and new technologies require changes in the allocation of tasks to these factors of production. Tracking such changes in the task content of production has been found to be valuable for understanding how labour demand is changing as a result of automation. In particular, ALM (2003), Acemoglu and Autor (2011), Autor and Dorn (2013) and Goos et al. (2014) have found that computerisation is associated with an increase in non-routine cognitive tasks and a decrease in routine manual and routine cognitive tasks.

There are, however, significant challenges associated with using the task framework, with measurement undoubtedly being among them. To approximate job tasks, the first empirical studies drew upon a detailed occupation dataset, The Dictionary of Occupational Titles (DOT), or its successor, the Occupation Information Network (O*NET). However, Spitz-Oener (2006) using data for Germany, and more recently, AH for the US, documented substantial heterogeneity in job contents even within detailed occupations. These findings encourage the use of workplace-level data rather than occupational-based data to measure job contents/tasks, especially if the aim is to provide a precise estimation of task prices. In this paper, we account for this need, and use individual information on job tasks to explore, first, cross-country differences in task endowments for a harmonised sample of developed countries. A second and more important aim of our study is to explore the link between tasks and wages by estimating task prices in a cross-country setting in order to devise country differentials in task prices, and to examine their potential drivers. We do so by using data from the Programme for the International Assessment of Adult Competencies (PIAAC), a survey that provides harmonised information across countries, and that contains very precise information on job contents at the worker level. Furthermore, the PIAAC survey data contain precise information on workers' skills (based on the results of numeracy and literacy cognitive tests) that goes beyond the educational level attained. These data enable us to estimate the factors that underlie the intensity of task en-

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dowments, as well as their prices conditional on a more precise measure of workers' skills. Moreover, these survey data provide excellent controls of individual skills that we can use in determining and interpreting task prices.

A cross-country analysis of these developments is needed because previous evidence has shown that the process of de-routinisation has not followed identical paths across countries. Hardy et al. (2018) documented 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 clear a need for an assessment of job tasks as well as task prices based on 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), have used PIAAC data to construct a routine job index and the 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.

Empirical evidence on task prices is scarce. In the US, AH found that a one-standard-deviation increase in abstract tasks predicts a seven-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[1]. Other studies that have explored 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) estimated task returns for Germany. This paper's main contributions are to extend the single-country analysis of task prices to a broad group of developed countries, to show their differences, and to try to envisage potential drivers. As our task measures closely resemble those of AH, our aims are to estimate prices for abstract, routine and manual tasks for 19 developed countries; to compare our results (for the US) with those found by AH; and to explore the cross-country differentials. Furthermore, the PIAAC survey data contain precise information on workers' skills (based on the results of numeracy and literacy cognitive tests) that goes beyond the educational level attained. These data enable us to estimate task prices conditional on workers' skills, and, hence, to obtain a measure of the market demand for each of the constructed tasks[2].

Our findings represent a relevant contribution to the literature. First, our task measures, and the items these measures are based on, are well-validated vis-a-vis previous research using the 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 for abstract tasks. Based on these measures, we depict the differences in tasks across countries, provide suggestive evidence on the importance of the within-occupation variation in task measures across countries, and relate those task disparities across countries with variables that have been shown to reflect countries' development levels (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 routine (manual) tasks, we find that 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 in task prices across countries by computing the relationship between country level variables and task prices. We find suggestive evidence that supply-and-demand factors can help to explain task returns: i.e., the higher the task endowment in a country is, the more attenuated the positive or the negative deviation in the price of this specific task is. Development factors, as well as labour market institutions – particularly union coverage and the strictness of employment protection legislation – seem to play a role in the differences in all three task prices.

The rest of the paper is organised 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 discusses the estimation of task returns, and focuses on their differentials and potential drivers. Section 5 concludes.

2. 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, the Czech Republic, Denmark, Spain, France, Great Britain, Greece, Italy, Japan, the Republic of Korea, Lithuania, the Netherlands, Norway, New Zealand, Poland, Slovakia, Slovenia, and the United States. For our sample, we consider employee respondents aged 25-54 with hourly wages between zero and 150 USD (PPP), and exclude workers in non-profit firms or in agriculture. We also exclude workers for whom 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[3]. 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 questionnaire, which includes several questions on work habits and tasks performed in the workplace. As our aim is to construct reliable statistical indicators, we exclusively pick items with the same quantitative input responses for the time intensity indicators of tasks. In particular, we focus on those tasks with the 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). Our proposed task framework and its link with PIAAC items is presented in Table 1 below.

We follow the approach of AH, whose analysis was 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[4]. We apply the PCA to all countries in our sample using standardised weights that give each country equal total weight in the sample.

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 regression techniques (very similar to item 2 in AH[5]; (ii) face complex problems that take at least 30 minutes (almost equal to item 3

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

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

[3] We decided to keep part-time workers because we consider them an important part of the workforce. Nevertheless, we show a 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.

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

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

Table 1
Task framework with PIAAC data.

Task	PIAAC questionnaire item	Item no.
	Face complex problems (<30 mins)	F_Q05b
Abstract	Use more advanced math or statistics such as calculus, complex algebra, trigonometry, or use 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
	Planning your own activities (inverse)	F_Q03a
	Organising your own time (inverse)	F_Q03c
Routine	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 hands or fingers	F_Q06c

Note: To ensure the reliability of the 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.

in AH[6]); (iii) planning the activities of others (quite similar to item 4 of AH[7]); (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 ensure that the cognitive non-routine tasks are not biased towards numerical tasks, in line with Lewandowski et al. (2019).

Regarding the routine task index, we follow a mixed approach by combining the approaches used by Marcolin et al. (2018) and AH. We first consider two items with quantitative responses related to time inputs from Marcolin et al. (2018): namely, the inverse values of "planning your own activities" and "organising your time" (which is also considered in AH, through the "proportion of the workday spent performing short, repetitive tasks"). In addition, we consider the proposal of AH to include the absence of face-to-face interactions with different types of co-workers (customers or clients, suppliers or contractors, and students or trainees). In particular, we add three items reflecting a 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 have decided against replicating the measure of routine intensity proposed by Marcolin et al. (2018) for two reasons. First, they used 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 organising, but some of which also follow qualitative response items ("To what extent can you choose or change …?"). The use of this approach could undermine the reliability of our results, as it could mean that we are measuring two different types of phenomena. Second, when we attempted to replicate the four-item measure proposed by Marcolin et al. (2018), the resulting index averaged at the occupational level for the US showed a correlation with O*NET data (0.27) that was much lower than 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 hands 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 to the non-routine dimension measure of Autor and Acemoglu (2011).

Our approach differs slightly from those used in other studies that are based on individual-level data on tasks. Marcolin et al. (2018) and Lewandowski et al. (2019) constructed task indexes using PIAAC data by averaging items. Spitz-Oener (2006) computed means of binary variables on whether the worker does or does not perform a certain task. Although our approach differs from these two alternatives, we compare our results by reconstructing the task measures following both approaches[8]. All of the methods generate very similar results. When the Spitz-Oener (2006) approach (means of transformed binary variables) is applied, the correlations are 0.93 for abstract tasks, 0.82 for routine tasks and 0.96 for manual tasks. When the standardised means approach (used by Marcolin et al. (2018) and Lewandowski et al. (2019)) is applied, the correlations are 0.99 for abstract tasks and 0.87 for routine tasks (for manual tasks, there is no comparison as the approach is the same, given that there are only two items; hence, we compute the mean).

The results of the principal component analysis and, more importantly, the pair-wise correlations between each of the tasks for all countries and for the US sample only, are shown in Table 2. The pair-wise correlation between the abstract and routine tasks is strong and negative, and is similar in size in both the overall sample and the US sample. The correlation between abstract and manual tasks is negative, while the correlation between routine and manual tasks is positive. However, both are much weaker than the correlation between the abstract and routine tasks. They are also slightly weaker in the US sample than in the overall sample. Additionally, Table A.1 in the Annex displays the basic statistical information of our tasks measures.

2.1. 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 only have data on occupations at the three-digit level of the ISCO classification, we compute O*NET and PIAAC measures at the three-digit occupational level. We construct an abstract measure that represents a standardised 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 standardised mean of manual routine and non-routine tasks from Acemoglu and Autor (2011). Results are displayed in Figure 3.

First, as the abstract task measure is correlated positively and strongly (0.82) with O*NET data at the occupation level for the US, it provides a solid validity check for our choice. In particular, it improves

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

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

[8] For the Marcolin et al. (2018) and the Lewandowski et al. (2019) methods, we compute average measures of the items. For the 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.

Notes: Own elaboration from PIAAC.

Fig. 1. Correlation of task indexes with O*NET at the occupational level
Notes: Own elaboration from PIAAC.

Table 2
Results of PCA and cross-tasks correlations.

	Computation PCA (all countries) Number of components	Variation of first component	Pair-wise correlations (all countries) Abstract	Routine	Manual	Pair-wise correlations (US sample only) 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.

considerably the validity check by AH. Moreover, in all countries, the correlation between our measure and the O*NET-based measure exceeds 0.60; and in many countries, it exceeds 0.65. The index displays a higher correlation in the US, Slovenia, the Czech Republic, Slovakia and France; and a lower correlation in Chile, Italy and Korea.

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

Third, the correlation for manual tasks in the US is high (0.73). Thus, the correlation is higher than that obtained by AH (0.63), and is similar to that of Lewandowski et al. (0.74).[9] The correlation is above 0.54 for all countries, with the US, New Zealand, France, and Belgium having higher correlations; and the Republic of Korea (at the very bottom), Slovenia and Lithuania having the lowest correlations.

3. Job Task Descriptives and Cross-Country Disparities

3.1. Task descriptives

We display the average task content of jobs for the sample of countries analysed across a set of individual covariates, which can be found in Table 3. The results show larger average values for abstract and manual tasks among males, but no gender differences in the average values for routine tasks. By age, abstract tasks display a concave shape that is similar to the standard productivity/age profile. However, we should be cautious in interpreting these results, as cohort effects may interfere with age effects. The opposite pattern is found for routine and manual tasks – they display a convex shape, which appears to be consistent with the relative decrease in less qualified tasks (routine and manual) as productivity evolves with age, regardless of the potential cohort effects. The likelihood of performing abstract tasks increases by educational level and by literacy and numeracy skills[10], whereas the likelihood of performing routine and manual tasks decreases by education level, with the decline being more pronounced for manual tasks. In more qualified occupations, abstract tasks are more prevalent, whereas routine tasks (and, to a lesser extent, manual tasks) are less prevalent. Employees in the public sector are more likely than their counterparts in the private sector to perform abstract tasks, and are less likely to perform routine and manual tasks. Full-time workers tend to perform more abstract tasks and fewer routine tasks than part-time workers, while the levels of manual task intensity are similar for both groups. Finally, the prevalence of abstract tasks increases by firm size (based on the number of employees), whereas the prevalence of routine and manual tasks decreases as the size of the firm size increases.

[9] That finding that the correlations between our task measures and O*NET measures are higher than those obtained by AH may be related to the sample size: the US PIAAC sample is more than double the size of the PDII survey sample used by AH.

[10] Information on numeracy and literacy skills is directly provided in the 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 3
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 management	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 sales	-0.40	0.30	0.32
Craft and related trades workers	-0.42	0.40	0.75
Plant and machine operators and assemblers	-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 standardised indexes for each task, with a mean of zero and a standard deviation of one across the whole distribution. Individual observations are weighted so that countries are weighted equally.

3.2. Cross-country differences in job tasks among developed countries

In Table 4 below, we display country average values (standardised for all workers in the sample giving equal weights to all countries) of the 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 for abstract tasks. The lowest average values for abstract tasks are seen in Greece, Italy, Japan, Lithuania and Slovakia. An almost inverse relationship is found for 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 lowest average levels of manual tasks are observed in the Asian OECD countries (Japan, Republic of Korea)

Table 4
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 standardised indexes for each task across all of the sample (giving equal weights to all countries), with a mean of zero and a standard deviation of one, averaged at the country level. Individual observations are weighted so that countries are weighted equally.

and in Western European countries (France, Netherlands, Norway). On the other hand, we also find that the average levels of manual tasks are relatively high in the Central Eastern European countries and Chile; and are highest in New Zealand and the United States, which are otherwise characterised by high levels of abstract tasks and low levels of routine tasks. These implausible results suggest that the questions used to construct the manual measure, and particularly the question about “working physically for a long period”, are probably not entirely comparable between countries covered by the PIAAC.[11]

The task content measures based on PIAAC data show that the international differences in tasks are larger than those suggested by O*NET-based task measures, in which 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 tasks, is 0.051 (0.015) for routine tasks and is 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 they can be attributed 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^i_c, and the global average, T^i, (which equals zero) into the between-occupation, BO^i_c, within-occupation, WO^i_c, and interaction, INT^i_c, terms. Formally:

$$\left(T^i_c - T^i\right) = \left(\sum_{j\in ISCO} \alpha_{j,c} t^i_{j,c} - \sum_{j\in ISCO} \alpha_j t^i_j\right) = BO^i_c + WO^i_c + INT^i_c, \quad (1)$$

$$BO^i_c = \sum_{j\in ISCO} t^i_j \left(\alpha_{j,c} - \alpha_j\right), \quad (2)$$

$$WO^i_c = \sum_{j\in ISCO} \alpha_j \left(t^i_{j,c} - t^i_j\right), \quad (3)$$

[11] Lewandowski et al. (2019) also found that the incidence of workers who report “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 about long working hours, rather than as a question about performing physically demanding tasks.

Table 5
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).

$$INT^i_c = \sum_{j\in ISCO} \left(\alpha_{j,c} - \alpha_j\right)\left(t^i_{j,c} - t^i_j\right), \quad (4)$$

whereby:

- $t^i_{j,c}$ and t^i_j 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;
- $\alpha^i_{j,c}$ and α^i_j are the shares of workers within occupation j in total employment in country c, and on average across all countries in the sample, respectively;
- *ISCO* is the set of three-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:

$$\sigma^i_{BO} = \frac{cov\left(BO^i_c,\ T^i_c\right)}{var\left(T^i_c\right)}, \quad (5)$$

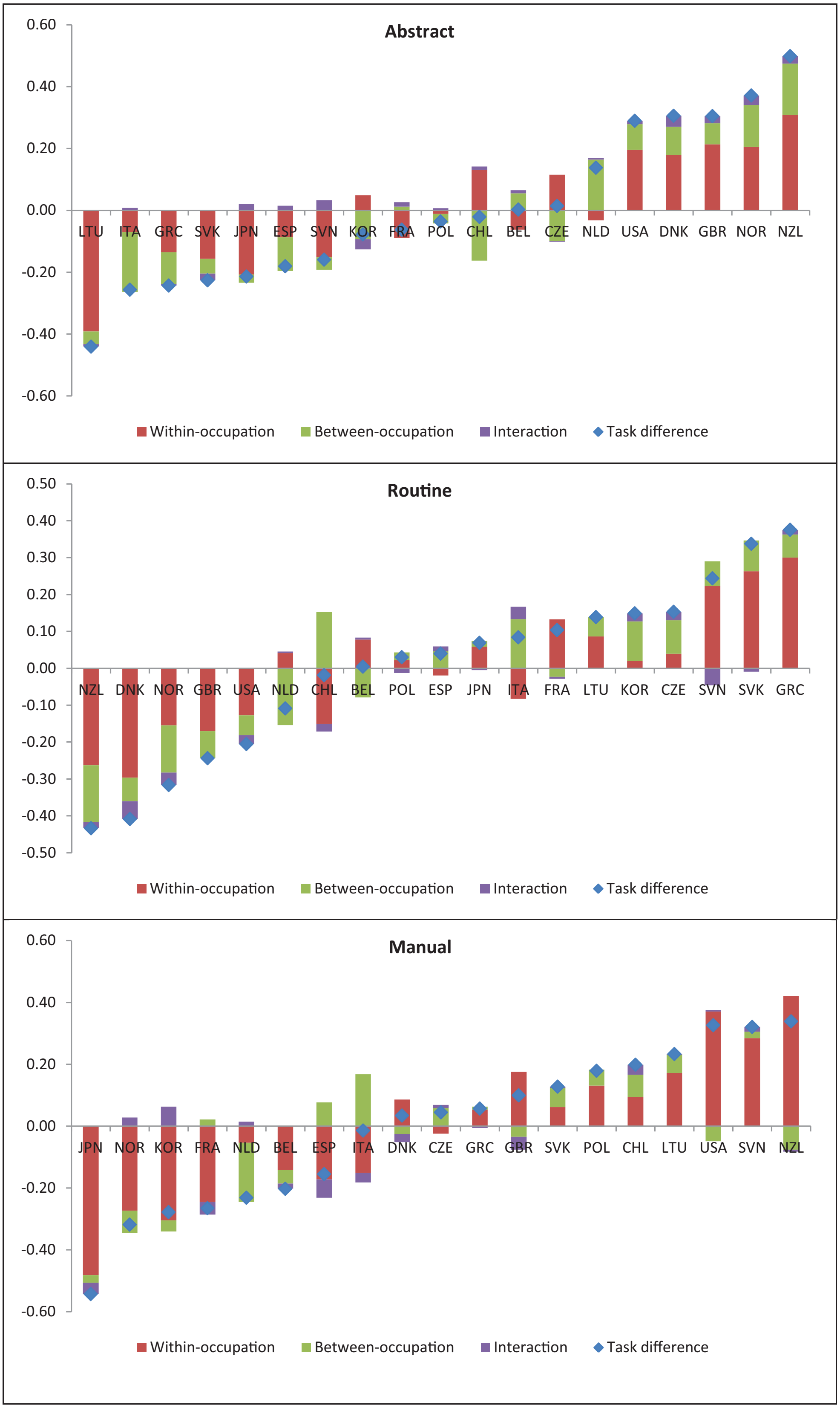
and in the same way as for the within-occupation and interaction effects. The results of the shift-share decomposition are presented in Figure 2, and the results of the covariance-based decomposition are presented in Table 5.

We find that the cross-country differences in PIAAC tasks mainly stem from differences in the average tasks contents within particular occupations defined at detailed, three-digit ISCO levels (Figure 2). About two-thirds of the cross-country differences in the prevalence of abstract and routine tasks, and as much as 90% of the cross-country differences in the prevalence of manual tasks, can be attributed to the within-occupation effect (Table 5).

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. These findings indicate that countries with above-average shares of occupations rich in particular tasks also tend to have above-average intensities of these tasks within occupations, in line with the Roy-type model of allocation of tasks (Autor, 2013). For 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 A.2 in the Annex).

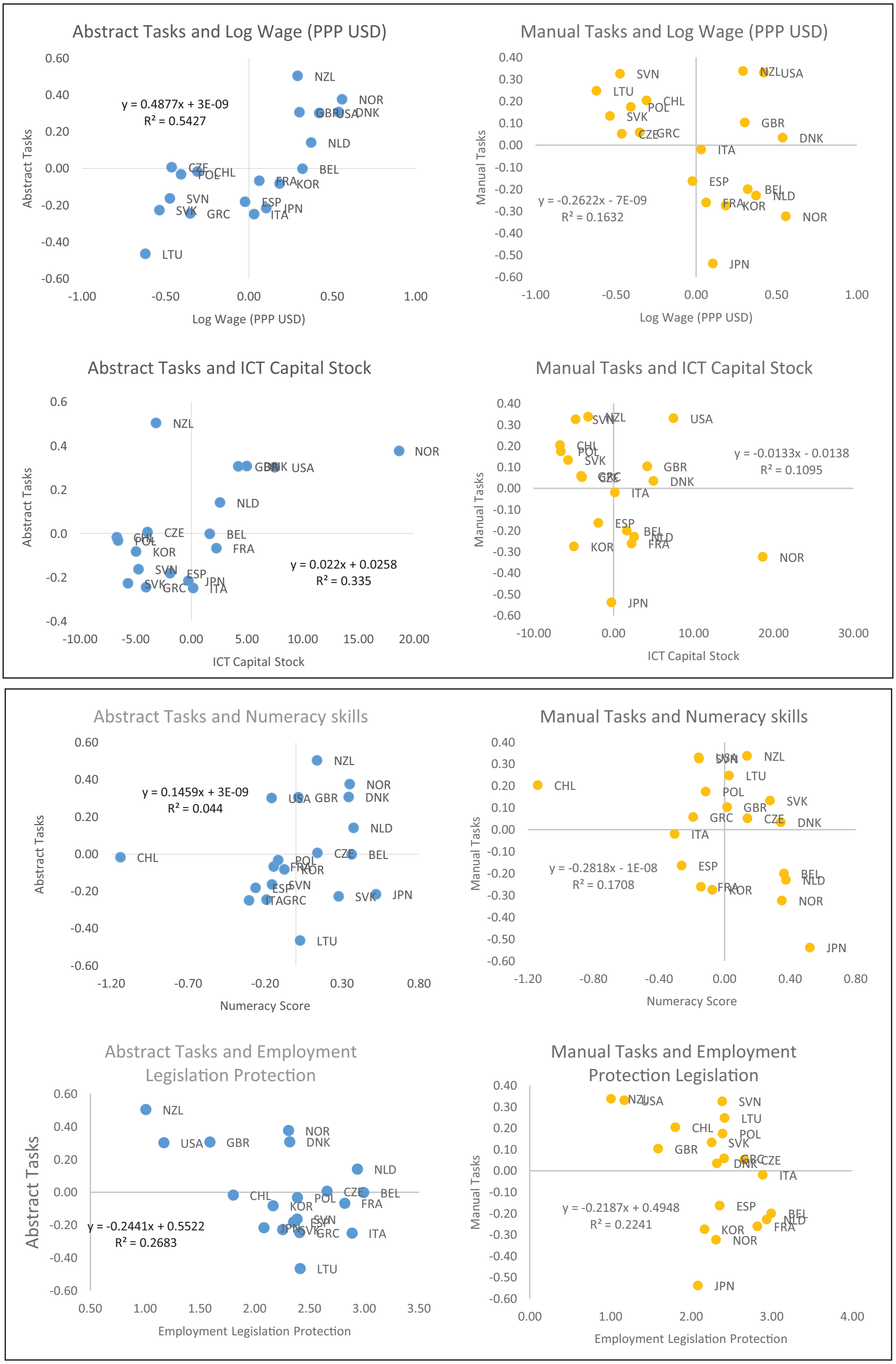
3.3. Tasks and other development and institutional variables across countries

In order to shed light on the factors related to the cross-country differences in task values, we start by performing an exploratory analysis that examines the average task values in relation 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



Note: Shift-share decomposition of differences between particular countries and the sample average, based on three-digit ISCO occupations.

Fig. 2. The shift-share decomposition of cross-country differences in tasks according to PIAAC-based measures
Note: Shift-share decomposition of differences between particular countries and the sample average, based on three-digit ISCO occupations.



Data: All variables are demeaned at the country average. Own calculations for data on abstract tasks. Data on numeracy are based on the PIAAC test. Data on ICT capital stock were collected by Eden and Gaggl (2020). Data on employment protection legislation are derived from OECD Labour statistics.

Fig. 3. Abstract and manual tasks country average 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 are based on the PIAAC test. Data on ICT capital stock were collected by Eden and Gaggl (2020). Data on employment protection legislation are derived from OECD Labour statistics.

PIAAC data), ICT capital stock per worker (to track technological development, derived from Eden and Gaggl (2020)) 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 cross-country comparisons for routine tasks 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 levels of abstract tasks performed by workers are positively correlated with all dimensions displayed in Figure 3, except for the strictness of employment legislation protection (EPL). In particular, higher levels of abstract tasks are 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 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 less restrictive employment protection legislation (correlation 0.52, square root of R-2 0.27).[13] On the other hand, the average levels of manual tasks are negatively correlated with all four factors (although the correlation is weak in all four cases, with R-2 being between 0.1 and 0.22, and, hence, the correlation being between 0.3 and 0.47). Finally, the strictness of EPL correlates negatively with abstract and manual task levels across countries.

4. Task Prices

In this section, we examine the empirical relationship between task prices and wages across countries. We start by conducting a descriptive inspection of the cross-country differences in the relationship between task endowments and wages. This will help us understand later what is behind the cross-country differentials in task prices.

Figure 4 plots the cross-country differences in task endowments and average wages (USD PPP). For wages, two clusters can be distinguished. The first cluster, which includes the Anglo-Saxon countries, the Nordic countries, the Western European countries, as well as Spain and Italy, has higher average wages than the other cluster, which includes Eastern European countries as well as Greece and Chile. There is a clear positive relationship between the average level of wages and the average value of abstract tasks, and a negative relationship between wages and routine tasks. For manual tasks, the relationship is negative but weaker for routine tasks, mainly because some high-wage countries like the US, Great Britain, New Zealand, and Denmark have positive levels of manual tasks.

4.1. Task prices – Basic Empirical Approach

The wage data reported in the 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. Following AH, we start by estimating a linear model for each of the tasks for the pool for the 19 countries in our sample[14] ($\mathbf{j} = 1 \ldots 19$).

$$Log\ W_{ij} = \alpha + \sum_{m} \beta_{1m} X_{ij}^{m} + \sum_{n} \beta_{2n} Z_{ij}^{n} + \sum_{1}^{k} \beta_{3k} Task_{ij}^{k} + \sum_{1}^{k} \beta_{4k} \overline{Task_{ij}^{k}} + \delta_j + \varepsilon_{ij} \quad (6)$$

Where $Log\,W_{ij}$ denotes the hourly log-wage of individual *i* in country *j*, X_{ij}^{m} capture the vector of *m* individual worker characteristics, such as gender, age or level of education. But more importantly, it is a comparable measure of individual ability approximated by the individual test scores of numeracy skills[15]. Z_{ij}^{n} includes the pool of *n* job characteristics (public or private firm, firm size, and on-the-job training. Finally, $Task_{ij}^{k}$ captures the value (intensity) for each specific task *k* (abstract, routine and manual) that each worker reports performing in his/her work. Additionally, to net out the pure individual job task prices from the association between job tasks and occupations, we also include the average mean of each task k at occupation-country level $\overline{Task_{ij}^{k}}$. This is a leave-out mean, representing the average intensity of the k-th task for all workers from a particular country in each occupation except for the *i-th* worker.

Task price regressions are displayed in Tables 6 and Table A.4 in the Annex. In Table 6, we include the three tasks together as explanatory variables, as well as individual- and occupational-level task variables. Column 1 of Table 6 replicates the AH model. In the second specification (column 2), we additionally control for numeracy skills, given the predictive power of this variable for wages. Information on these skills is available in the PIACC data, but not in the PDII survey data used by AH. Results from column 1 indicate similarities with respect to the sign and the size of effects of AH (see Table 6, column 4 of AH)[16]. Abstract prices are positive and routine, and manual prices are negative. Furthermore, the magnitude of these prices is higher when they are introduced jointly in the estimation than when they are introduced separately (Table A.4). This might be due to a collinearity of the task variables.

Two additional key findings emerge from comparing column 1 and column 2 of Table 6. First, the magnitude of the individual- and occupation-level task price is slightly reduced (by around 10-20%). This suggests that the estimates of task prices based on data that have no measures of workers' abilities or skills may be too high. Second, while the impact of tasks is smaller, it remains significant, which highlights the value of the task framework in explaining within- and between-occupational wage differences.

Finally, in terms of individual returns, a gender wage gap is observed, along with an increase of returns with age, level of education, on-the-job training, firm size, ICT use at work[17], and numeracy skills. However, the effects of key socio-demographic characteristics (like gender, level of education) are also reduced by controlling for workers' numeracy skills.

[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 in Table A.2 in the Annex. We include an employment legislation protection variable in Figure 3, as it is the one that has the highest explanatory value of the task measures across countries.

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

[14] We do so because of the high correlation between task measures at the worker and occupation levels, which would cause collinearity issues, and would hamper interpretation of the coefficients.

[15] We only include numeracy skills because these skills have a higher predictive power regarding wages, and because there is a strong correlation between numeracy and literacy cognitive skills.

[16] For abstract tasks, individual positive returns are lower than they are in AH (2% vs 9% per s.d. of task); occupational-level returns are higher than they are in AH (12% vs 7% per s.d. of task), and the aggregate effects are similar. For routine tasks, individual returns are negative and significant (3% per s.d. of task), whereas in AH, the effects are not significant and the occupational-level returns are not significant. For manual tasks, individual returns are negative and amount to a 4% per standard deviation of manual tasks, slightly lower than the 9% in AH. The occupation-level effect is not significant, as in AH.

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

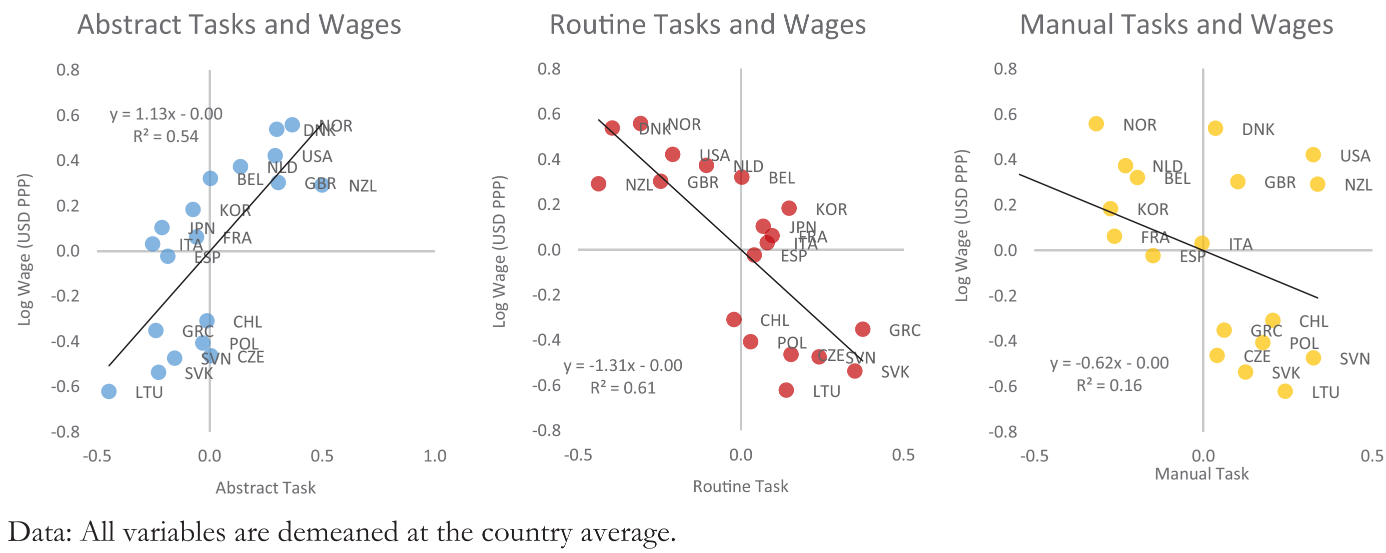


Fig. 4. Tasks and wages across countries.
Data: All variables are demeaned at the country average.

Table A.4 in the Annex displays log wage estimations that include each task separately, with and without task averages at the country-occupation level[18]. As in Table 6, the abstract prices are positive and routine, and the manual prices are negative (although the relationship between wages and manual tasks is weaker). When we control for the task measures averaged at the country-occupational level, the estimated task prices decrease by 50% for abstract tasks, by 70% for routine tasks, and by 30% for manual tasks. These findings confirm the observation, also reported by AH, that individual-level task prices are to some extent driven by the occupational selection of workers with a comparative advantage in performing particular tasks.

Moreover, the differences in the task prices across countries are noticeable. To illustrate these differences, we include an interaction term of country dummies and individual task measures in equation (6). The 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 provide positive returns for all countries in the sample except Belgium, Denmark, Greece and Norway; whereas manual tasks provide negative returns for all countries in the sample except Belgium and Denmark. Although the average return for routine tasks is negative, the returns are positive (although small) for five countries, and are strongly positive (eight per cent per task s.d.) for the Czech Republic. More importantly, the differences in the returns across countries are large in magnitude: i.e., the standard deviation of returns is more relevant than the mean return across countries.

4.2. 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 stylised 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 $\overline{\Delta_{ik}}$ (reflecting different measures $l = 1 \ldots m$ 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.

$$Log\ W_{ij} = \alpha + \sum_{m} \beta_{1m} X_{ij}^{m} + \sum_{n} \beta_{2n} Z_{ij}^{n} + \sum_{1}^{k} \beta_{3k} Task_{ij}^{k} + \sum_{1}^{k} \beta_{4k} \overline{Task_{ij}^{k}} + Task_{ij}^{k} * \overline{\Delta_{lk}} + \delta_j + \varepsilon_{ij} \quad (7)$$

The country-level variables reflect a broad set of dimensions of development, including human capital (numeracy skills), income, ICT capital stock per worker, and labour market institutions (the same as the dimensions used in 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 for a better understanding of 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 an 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 a task[19].

First, we find that 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. For routine and manual tasks, the interactions with GDP and ICT capital stock per worker are positive. This finding indicates that a higher development level and higher ICT capital stock attenuate to some extent the direct negative price workers receive 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

[18] As a robustness check, we re-estimated the model including only full-time workers. Although the results are not reported, they exhibit the same patterns as those displayed in Table A.4. They are available upon request.

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

Table 6
Estimation of task prices – log wage regressions.

	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's/master's degree)	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 have been conducted for all plausible values for numeracy skills.

task 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 between the minimum wage (relative to the median wage of full-time workers) and task prices across countries. Although we do not attempt to provide any causal interpretation of these results, they are consistent with the observation that unions tend to compress the wage distribution. They are also consistent with the finding of Hanushek et al. (2015) that higher levels of unionisation are associated with lower returns to skills. It thus appears that wherever union coverage and EPS are high, the prices of highly qualified tasks (abstract) are likely to be relatively low, whereas the prices of less qualified tasks (routine and manual) are likely to be relatively high. Still, this is a tentative interpretation which should be taken with caution.

In order to ascertain the magnitude of the relationship 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 tasks, and positive for routine and manual tasks). Union coverage is also negatively associated with abstract tasks prices. Finally, ICT capital stock is negatively (positively) associated with 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

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

Abstract Tasks										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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 the country of reference (and, hence, having an interaction term equal to zero). The model for ICT capital stock includes all countries but Lithuania, for which no data are available. The model for minimum wage includes all countries but Denmark, Italy and Norway; i.e., countries that have no 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.

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 institutions, abstract task prices conditional on EPL values range from -0.01 (Belgium) to 0.06 (US), and returns to abstract tasks depending on union coverage vary from -0.01 (Denmark) to 0.03 (France).

Finally, we find some evidence that the more abundant particular tasks in the country are, the higher the individual prices workers receive for performing the other tasks. In particular, the returns for performing abstract tasks are higher in countries with higher manual task endowments, whereas returns for performing routine tasks are higher in countries with higher abstract task endowments. For manual tasks, there is a negative relationship between manual task returns and task endowments. Overall, the less prevalent manual tasks are, the higher the prices associated with performing them are.

5. Conclusion

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

Building on these findings, we used individual information on job tasks to explore, first, cross-country differences in task endowments. A second and more important aim of our study was to assess the link between tasks and wages by estimating task prices in a cross-country setting and exploring their potential drivers. We did so by using the Programme for the International Assessment of Adult Competencies (PIAAC), a survey that provides harmonised information across countries, and contains very precise information on job contents at the worker level. Moreover, as the PIAAC contains information on individual numeracy and literacy cognitive skills, it provides excellent controls of individual skills for the interpretation of task prices.

We constructed three task measures: abstract, routine and manual tasks. We then compared our choices and method of aggregation with those previously constructed using the PIAAC dataset. Additionally, we validated our measures with those previously constructed at the occupation level for the US (O*NET), as well as with those constructed by Autor and Handel (2013) from the PDII dataset (for the US). The task content measures based on the PIAAC data showed that the international differences in tasks are larger than those suggested by O*NET-based task measures, with the differences between countries being entirely driven by the differences in occupational structures. Using a shift-share analysis, we found that the cross-country differences in the PIAAC tasks stem mainly from differences in the average task contents within particular occupations, defined at a detailed, three-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 found that abstract tasks correlated positively with the development level of a country, the ICT capital stock and the numeracy skills of workers.

For the estimation of task prices, we estimated a log (hourly) wage model in which the main covariate was the task (abstract, routine or manual) endowment. First, we pooled all countries together and controlled for the usual demographic and job variables, as well as for individual cognitive skills (particularly numeracy skills) in order to control for usually unobserved ability. Conditional on this process, the prices of tasks must be seen as being mostly driven by demand factors. We found that within occupations, a one-standard-deviation increase in abstract tasks was related to a 3.3-log-point wage premium. For routine tasks, the individual (within occupations) prices for performing routine tasks were associated with a 2.6-log-point wage decrease for each standard deviation of routine tasks. Finally, for manual tasks, our results showed a 2.9-log-point wage decrease per standard deviation of manual tasks.

In order to account for cross-country differences in task prices, we estimated models with interactions between the individual task prices (relative to the US) and the country-level key covariates. We found a negative relationship between task prices and the task endowment, which highlights the importance of supply-and-demand factors in the determination of task prices. Additionally, the interactions between the task prices and the country-level key covariates were sizable. In particular, the relationships between the abstract task prices and the development level and the ICT capital stock were negative, attenuating the positive effects of the development level and the ICT capital stock. For routine and manual tasks, the interactions with GDP and ICT capital stock were positive, which showed that a higher development level and higher ICT capital stock attenuated to some extent the direct negative returns to these tasks. Additionally, we found significant negative interactions between union coverage and EPS and abstract task prices, and positive interactions between union coverage and EPS and routine task prices. Although we do not attempt to offer any causal interpretation of these results, they are consistent with the observation that unions tend to compress the wage distribution. By contrast, we found that the effect of the minimum wage was negligible once the other labour market institutions were included.

From a policy perspective, this study contributes to fundamental policy discussions on issues such as the effects of technological change and automation on the job content of workers, and their implications for wages. This issue 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 impact of technological change on the labour markets from an international perspective, which can be pursued when the second or third waves of PIAAC (or national longitudinal studies) data are implemented worldwide. Moreover, our findings confirm 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.

Annex

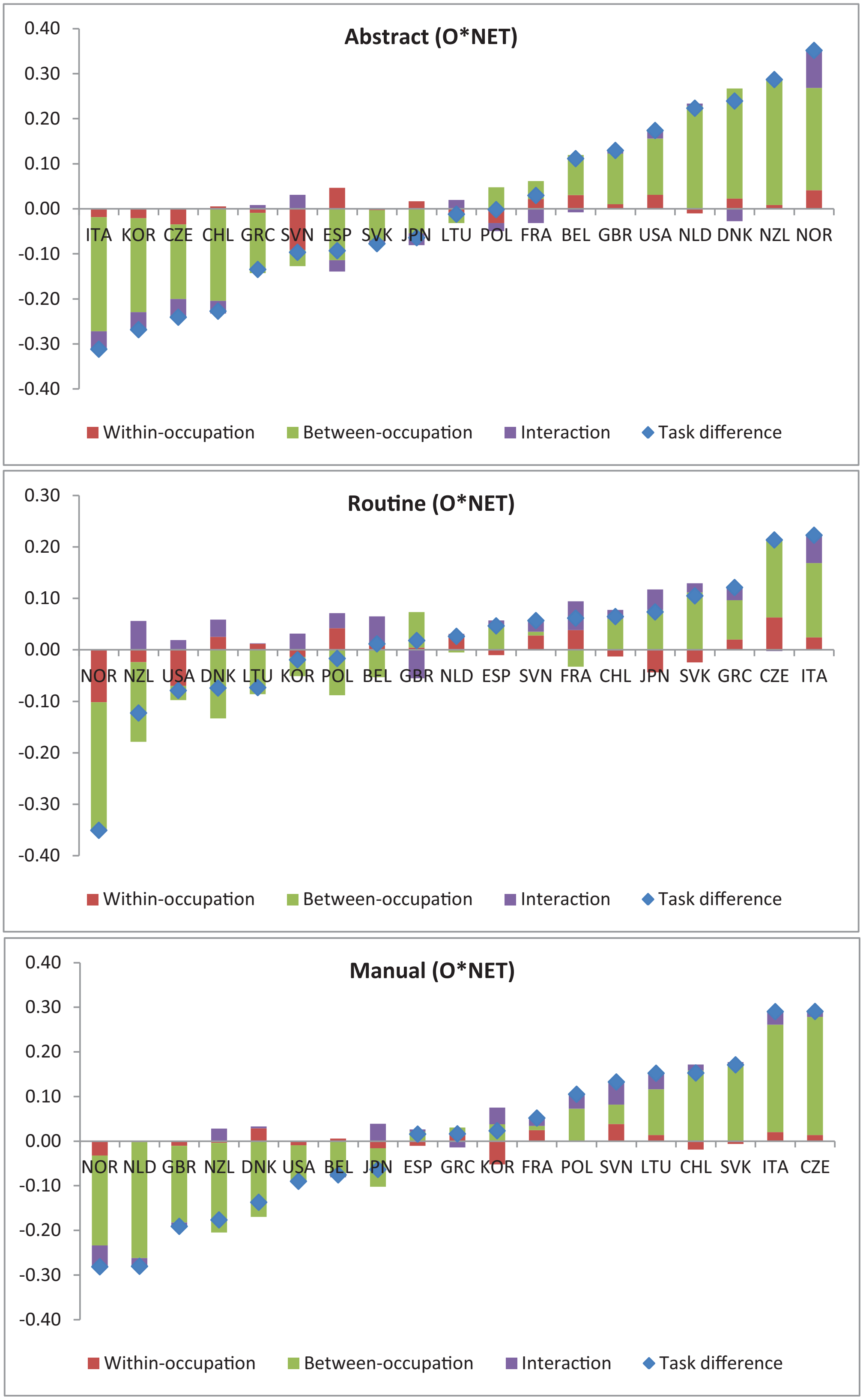
Table A.1
Descriptive statistics of task measures.

	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
Number of observations per cell (average)			
Average	17.39	19.27	4178.56
Median	3	3	2404
Minimum	1	1	1165
Maximum	3575	1742	11557

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).



Note: Shift-share decomposition of differences between particular countries and the sample average, based on three-digit ISCO occupations.

Fig. 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 countries and the sample average, based on three-digit ISCO occupations.

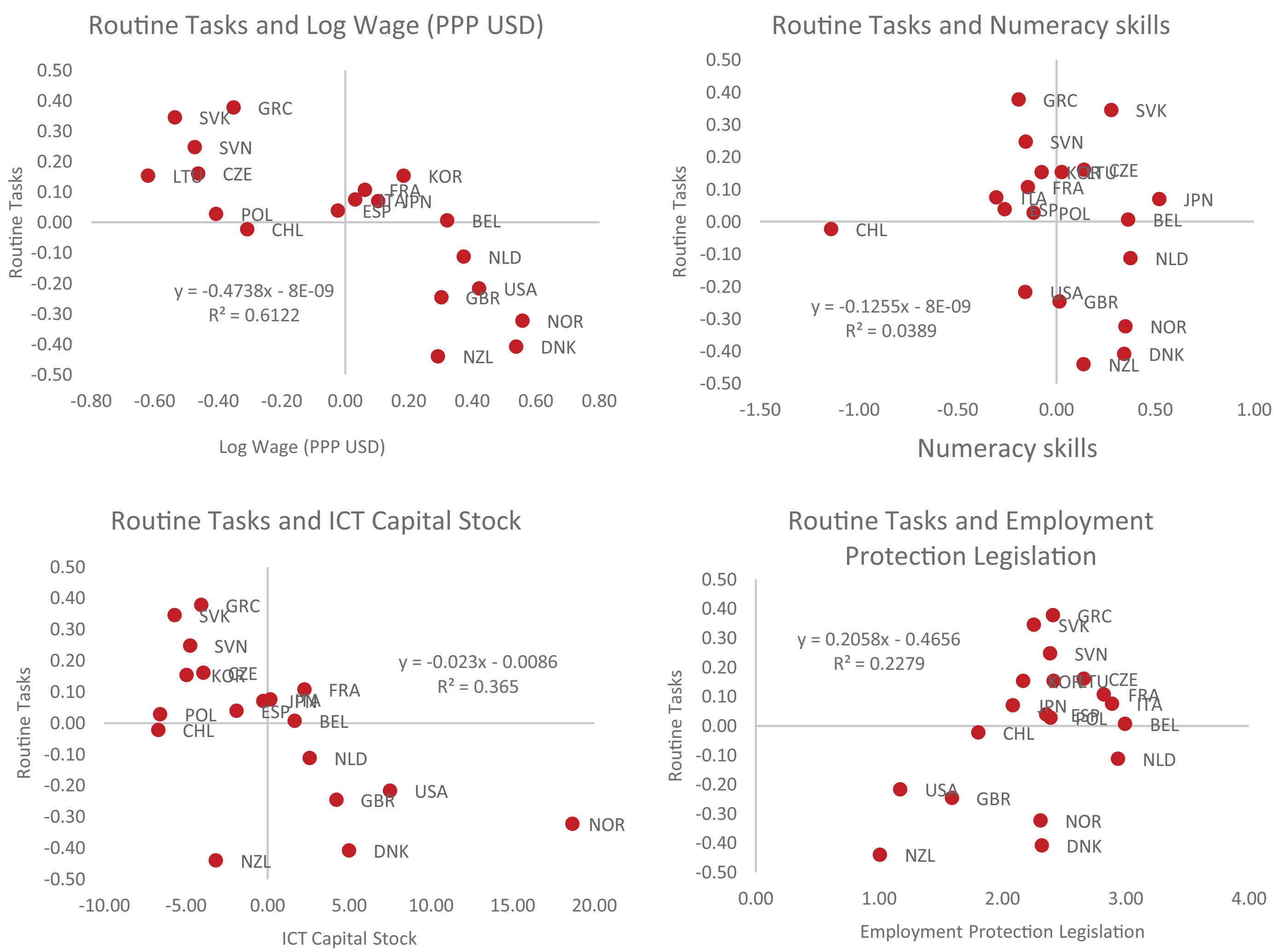


Fig. A.2. Routine tasks and other relevant development measures across countries.
Data: All variables are demeaned at the country average. Own calculations for data on abstract tasks. Data on numeracy are based on the PIAAC test. Data on ICT Capital Stock were collected by Eden and Gaggl (2020). Data on employment protection legislation are derived from OECD Labour statistics.

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 are based on the PIAAC test. Data on ICT capital stock were collected by Eden and Gaggl (2020). Data on employment legislation protection and minimum wage are derived from OECD Labour statistics. Data from union coverage are derived from ILO statistics.

Table A.4
Estimation of task prices (separately by task) – 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's/master's degree)	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***
	(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 reflect 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 the 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

Notes: Only country-level interaction terms (added with the average effect) are included, with the United States being the country of reference (and, hence, having an interaction term equal to zero). Data reflect 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.

References

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

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

Autor, David H., Dorn, David, 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market.". American Economic Review 103 (5), 1553–1597.

Autor, David H., Handel, Michael J., 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.

Eden, Maya, Gaggl, Paul, 2020. Do poor countries really need more IT? World Bank Economic Review 34 (1), 48–62.

Gimpelson, Vladimir, Kapeliushnikov, Rostislav, 2016. Polarization or upgrading? Evolution of employment in transitional Russia. Russian Journal of Economics 2 (2), 192–218.

Goos, Marteen, Manning, A., Salomons, A., 2014. Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. American Economic Review 104 (8) August.

Hanushek, E, Schwerdt, Guido, Wiederhold, Simon, Woessman, Ludger, 2015. Returns to skills around the world: Evidence from PIAAC. European Economic Review 73, 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, Miroudot, S., Squicciarini, M., 2018. “To be (routine) or not to be (routine), that is the question: A cross-country task-based answer. Industrial and Corporate Change 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), 235–270.