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Digitalization at work, Job Tasks and Wages: Cross-Country evidence from PIAAC¹

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Abstract

The aim of the paper is threefold. First, we compute differences on job tasks (Abstract, Routine and Manual) across a harmonized and hence comparable sample of Anglo-saxon, many European and even Asian advanced countries. We do so by using very precise information on job contents at the worker level, which allows for job task heterogeneity within occupations. Second we assess the extent to which computer adoption leads to the observed differences of job contents across countries. Third, we test the impact of tasks at work on average wages and wage inequality. Our results show remarkable differences in the degree of polarization of job contents across countries, being computer adoption at work a key significant driver of such differences. In particular, ICT use at work explains 10.0% (7.7%) of the cross-country conditional differences in Abstract (Routine) tasks at work. Finally, our results indicate that although differences in tasks explain an important and significant part of wage differentials (similar to what is found in Autor and Handel, 2013), we cannot find a clear pattern in the explanation of wage inequality gaps by looking at differences in task endowments and task returns.

JEL codes: J24, J31, O33.

Keywords: Digitalization, Job Tasks, RIF-Regressions, Wage Decomposition, PIACC

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I. Introduction

In this paper, we compute differences in job tasks/contents (Abstract, Routine and Manual contents) across a harmonized and hence comparable sample of countries that includes Anglo-Saxon (US, Canada, Australia, UK), many European and even Asian (Japan and South Korea) advanced countries. We do so by using very precise information on job contents at the worker level, which allows for looking at job task heterogeneity within occupations. Furthermore, we assess to what extent differences in the adoption in ICT at work - a proxy for digitalization-help predict differences in job task demands across countries. Finally, we relate Job Contents with wage inequality. Our results show remarkable differences in Job Tasks across countries, being computer adoption at work a key significant driver of such differences. Although our findings indicate that differences in tasks explain an important and significant part of wage differentials, we cannot find a clear pattern in the explanation of wage inequality gaps by looking at differences in task endowments and task returns.

The phenomenon of technological change and digitalization has been leading, for the last two decades, to a gradual change in job contents (tasks): those tasks that are complementary to computers have increased (non-codifiable, non-repetitive, called non-routine tasks), whereas those more liable to substitution by computers (codifiable and repetitive tasks, called routine tasks) are decreasing. The basic driver of such theory is an exogenous decline in the relative price of computer capital (identified with technological progress), which increases computer adoption at work, hence altering the allocation of labor across different task inputs. Specifically, computer capital and labor are relative complements in carrying out non-routine tasks, while computer capital and labor and are perfect substitutes in carrying out routine tasks. The theory of Skill Biased Technological Change (SBTC), which describes a shift in the production technology that favors high-skilled over unskilled labor, was twisted by Autor, Levy, and Murnane (2003) into a more nuanced version. The Autor-Levy-Murnane seminal contribution provides a new theoretical framework supported by extensive US evidence of reduced labor inputs of routine manual and routine cognitive tasks together with increased labor inputs of non-routine cognitive and interpersonal tasks. This phenomenon, referred as the Routine Biased Technological Change (RBTC), or equivalently de-routinization of job tasks, has been extensively complemented with US evidence over the last years². Empirical studies describe an increase in non-qualified and non-codifiables jobs, hence not easily substitutable by computers, and highly connected with low-skill services which involve jobs intensive in manual non-routine and interpersonal tasks. The increase in the share of high-skill abstract and low-skill manual jobs, together with the decline on routine jobs, has later been named in the literature as *employment polarization*.

² See Autor and Dorn (2013) for a more detailed discussion.

A natural question that emerges is the impact of this change in the demand of job contents on the wage distribution. In the US, Acemoglu and Autor (2011) document a U-shape (polarized) growth of wages by skill percentile in the 1988-2008 period, with both Firpo, Fortin and Lemieux (2013) and Autor and Dorn (2013) illustrating how technology adoption has played a significant role in the wage structure, leading to a wage polarization process. In European countries, research has provided descriptive evidence on wage polarization for the UK and Germany³ but this phenomenon can hardly be extended to other countries. Massari, Naticchion and Ragusa (2014) describe the joint structure of wages during 1996-2007 of twelve European countries and analyze the impact of job task changes on wage structural changes by using a similar approach as Firpo, Fortin and Lemieux (2013). They find little evidence of wage polarization given an observed increase in wage inequality in the lower tail of the distribution. When decomposing changes in the conditional wage structure, they provide a potential explanation of the lack of wage increase in low-skill jobs: changes in labor institutions (through increases of part-time and temporary jobs) in many European countries entailed a negative impact over the lower part of the wage distribution, outbalancing the polarization effect on low-skill jobs⁴.

The majority of empirical studies in this field have analyzed the *employment polarization* phenomenon with data disaggregated either at the industry or at most, at the occupation level. Past research decomposes each occupation into a vector of task intensities, with updates of the content of each occupation throughout time. In the US, two data sources have been feeding the occupation-level empirical approach: the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET), both offering job content descriptions from detailed firm information. As explained by Autor (2013), the approach of assigning job contents to occupations presents an important limitation: assigning task measures to occupations overlooks heterogeneity of job tasks among individuals within an occupation. In fact, empirical research has found important heterogeneity of job content at the worker level within detailed occupations (see Spitz, 2007 and Autor and Handel, 2011). In particular, Spitz argues for the case of Germany that job content changes take place mostly within, rather than between occupations⁵. To make the task framework more precise, it is clear that more research is needed using data at the worker level.

Our paper contributes to this literature in three different dimensions: First, by depicting cross-country differentials in Abstract, Routine and Manual Tasks for 22 OECD countries. We do so by using the Programme for the International Assessment of Adult Competencies (PIAAC), which allows for harmonized information across countries. Second, we try to measure the link

³ See for Machin (2011) for the UK, Dustmann and Ludsteck and Schönberg (2009) for Germany.

⁴ This explanation is also consistent with the analysis by OECD (2011).

⁵ Spitz documents the case of Germany in the period 1979-1999 and divides job contents in five categories: non-routine analytic, non-routine interactive routine cognitive, routine manual, and non-routine manual. Results from a shift-share analysis show that task changes within occupations account for 85%, 87%, 99%, 86% and 98% respectively of the total change in tasks in 1979-1999.

between ICT use and job tasks. Although the data at hand does not allow us to identify a structural impact of ICT use on job tasks, the cross-country comparisons can help us understand better the link between ICT penetration and differences in the job tasks demands. Finally, we relate differences in Task Endowments and in Task Returns with wage inequality, measured by the Gini Index, across countries.

Our findings stress the relevance of differences in Computer Adoption at work to understand cross-country differences in the intensity of Abstract, Routine and Manual contents. In particular, computer adoption, measured by the intensity of ICT use at work, explains 10% (9%) of the cross-country differences in abstract (Routine) job contents in an estimation which already conditions upon equal individual and job characteristics. On the contrary, ICT use does not help understand disparities across countries in manual Tasks. Second, abstract, and to a lesser extent Routine and Manual tasks are important predictors for average wages. Marginal increases in abstract tasks increase wages whereas Routine and manual contents decrease them. Finally, we compare wage inequality across countries and assess, in a two-by-two country basis, the extent to which differences in task endowments and in task returns contribute to explain such inequalities. We do not see a clear pattern across countries and hence speculate, as it is out of the scope of the study, that other factors, primarily of an institutional nature, must be considered to account for differences in wage inequality.

The paper is organized as follows: Section 2 elaborates on the underlying theoretical background followed in this research. Section 3 discusses the data sources and a discussion on data sources and task measurement construction. Section 4 and 5 present empirical tests of the impact of technology adoption on the degree of task content differences and the relation of those with the wage structure for different OECD countries. Section 6 concludes.

II. Theoretical Framework - The Task Assignment Model

The "Task Assignment" model was first developed by Autor, Levy and Murnane (2003) and later extended by Acemoglou and Autor (2011) and Autor and Dorn (2013), among others. The main innovative issue of this approach, as Autor (2013) states, is that the key units of production are not factors of production, as usual, but rather, job tasks which, once combined, produce output.

To lay out the simple task-based framework described in Autor (2013), consider a static environment where only one unique final good, (Y), is produced with a CES technology. $Y(i)$ is the production level of task i . There are three types of labor, high (H), medium (M) and low skill workers (L), each of them supply inelastically H, M and L units of labor, respectively. Each of the available $Y(i)$ tasks presents a production function such as:

$$Y(i) = A_L \alpha_L(i) l(i) + A_M \alpha_M(i) m(i) + A_H \alpha_H(i) h(i)$$

The A term represents factor-augmenting technology. Each of the α_k terms reflect the productivity of low, medium and high skill workers in each task i , and $l(i)$, $m(i)$ and $h(i)$ are the number of low, medium and high productivity workers allocated to each task i .

Each task could be in principle performed by low, medium and high skill workers as well as by capital. However, under this setting, each worker decides the combination of tasks to be performed at her job on the basis of *her comparative advantage* across tasks, given her skills. In equilibrium, formally derived in Acemoglu and Autor (2011), there is a continuum of tasks where the least complex ones are being supplied by the low-qualified workers, the intermediate ones are supplied by medium-qualified workers and the most complex ones are done by highly qualified workers.

The task approach has been used to study, among others, the impact of computerization on job task demand at work. The introduction of computerization in the labor market clearly alters job contents demands, as it substitutes workers performing repetitive and codifiable tasks whereas complements those who perform non-routine and interactive tasks. This leads to the decline of jobs (and job occupations) which entail primarily routine and codifiable tasks, whereas other jobs, which require higher components of non-routine, interactive tasks, emerge. This is the well-documented phenomenon of Job Polarization in the employment distribution, which has been found for most advanced countries, and attributed at least in part to computerization.

In the Task Model, as Autor, Levy and Murnane (2003) first stated, the introduction of Computerization is driven by a relative decline in the price of computer capital. However, such relative decline has not taken place simultaneously in all countries, and hence the extent of digital penetration at work and hence the demand for job tasks is expected to differ across countries.

The use of a harmonized sample of 22 countries allows us to explore empirically the extent to which differences in computer penetration at work are associated to differences in job tasks. Furthermore, we can measure the extent to which such differences in job tasks drive differences in the wage structure across different countries.

III. Data sources, Task Measures, and Descriptive Statistics

Data

Our empirical approach uses data from the Programme for the International Assessment of Adult Competencies (PIAAC), carried out by the Organization for Economic Co-operation and Development (OECD) in 2011 and 2012 in 22 participating countries: Austria, Belgium, Canada, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great Britain, Ireland, Italy, Japan, South Korea, Netherlands, Norway, Poland, Russian Federation, Slovak

Republic, Sweden and the United States⁶. The data sample contains 166,000 observations, which represent a total population of 724 million adults aged 16 to 65. The survey includes a personal interview comprising a questionnaire followed by a skills assessment of literacy, numeracy and problem-solving skills in technology environments. The questionnaire contains information about personal background, education and training, current work status, work history, and skills used at current job (or last job) and everyday life⁷. As said previously, the variables of activities or contents (tasks) used at work are particularly appropriate for the analysis within occupations. In addition, the PIAAC skills assessment provides an accurate measurement of cognitive skills, an excellent proxy to control for unobserved heterogeneity. Beyond the assessment of specific reading, mathematical or technology contents, the skill assessment framework of PIAAC emphasizes the ability of workers to apply background knowledge, a unique feature used by OECD in their assessments of cognitive skills.

Task Measures and ICT use

Using data from the worker responses of activities conducted at work, we construct measurements of task intensities. Our analysis follows Autor, Katz and Kearney (2006), which collapse the original five task measures from Autor, Levy and Murnane (2003) to three task aggregates: *Abstract* (which includes cognitive and interpersonal non-routine), *Routine* (which includes cognitive and manual routine) and *Manual* (non-routine manual) tasks.

Most items of the background questionnaire display answers with five categories denoting frequency at which certain tasks are performed at work (e.g. 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). Given the similarity with such data responses, we follow Autor and Handel (2013) to construct the indexes for each of the three dimensions using the first component of a principal component analysis⁸ and then compute the indexes into their standardized form.

For the *Routine* task index, we first generate two different sub-task indexes for *lack of flexibility and repetitiveness at job* (4 questionnaire items) and *lack of adaptation* (3 questionnaire items), again aggregated by principal component analysis⁹. These two indexes

⁶ Data collection for the Survey of Adult Skills took place from August 1st 2011 to March 31st 2012 in most participating countries. In Canada, data collection took place from November 2011 to June 2012; and France collected data from September to November 2012.

⁷ PIAAC defines the skills used at work as the types of activities performed at the workplace. For consistency with past research, we call them job tasks or job contents.

⁸ Autor and Handel (2013) follow a principal component analysis to derive continuous job task variables taking advantage of multiple responses of items. The data from Spitz (2006) only contains binary information on whether the worker either performs a certain task or not, and aggregate measures are constructed as percentage of activities performed for each category of tasks (*abstract*, *routine* and *manual*). As a robustness check of our approach with PIAAC data, comparing both approaches leads to very similar results, with correlations of 0.92 for the *Routine* index, 0.98 for the *Abstract* index and 1 for the *Manual* index.

⁹ PIAAC Database also constructs similar indexes for both Lack of flexibility and Lack of adaptation, called TASKDISC and LEARNATWORK. We invert the order of categorical responses to reflect the lack of task intensity. The correlation between our construct and PIAAC composites is therefore negative, but very high (>0.95).

reflect non-manual routine job contents. We gather those two indexes with the “Accuracy with hands and fingers” task¹⁰, which reveal more routine manual tasks, and compute the first component of a principal component analysis.

Table 1 depicts the job task items from the PIAAC background questionnaire that are used to construct each of the task indexes¹¹. The table is presented by constructing three task indexes first proposed by Autor, Katz, and Kearney (2006). When elaborating the *Abstract* task index, we compute the first component of a principal component analysis by using the questionnaire items related to cognitive analytical tasks (3 items), and interactive tasks (2 item).

Table 1. Task Framework with PIAAC Data

Task	Category	PIAAC Questionnaire Item	Item No.
Abstract	Cognitive and Interpersonal Non-Routine	Read Diagrams, Maps or Schematics	G_Q01h
		Write Reports	G_Q02c
		Faced complex problems (>30 mins)	F_Q05b
		Persuading/Influencing People	F_Q04a
		Negotiating with people	F_Q04b
Routine	Flexibility at Job (Cognitive Routine)	Change Sequence of Task	D_Q11a
		Change how do work	D_Q11b
		Change speed of work	D_Q11c
		Change working hours	D_Q11d
	Lack of Adaptation (Cognitive Routine)	Learn work-related things from co-workers	D_Q13a
		Learning-by-doing from tasks performed	D_Q13b
		Keeping up to date with new products/services	D_Q13c
	Manual Routine	Hand/Finger Skill Accuracy	F_Q06c
Manual	Manual (Non-Routine and Routine)	Physical work	F_Q06b
ICT Use		Use internet for understanding issues related to work	G_Q05c
		Conduct Transactions on the internet.	G_Q05d
		Use spreadsheet software (Excel)	G_Q05e
		Use a Programming language	G_Q05g
		Level of Computer Use	G_Q06

¹⁰ This item has been widely used in the literature, From Autor, Dorn and Murnane (2003) to Autor and Dorn (2014).

Notes: Most questions provide answers in a scale of time frequencies¹² of activities in tasks (Abstract tasks, Lack of adaptation tasks, Manual Routine and Non-Routine tasks) and some of them provide answers in intensity of frequencies¹³ (Flexibility at Job). Level of Computer Use (G_Q06) includes three answers: straightforward, moderate and complex.

Finally, we use information from the “Physical Work” item as our *Manual* task index. Two issues need attention regarding this task measure. First, the fact that we use only one item allows for little variance of our measurement of *Manual* tasks, as it can only take 5 different values. Second, the *Manual* construction of tasks in the Autor, Katz and Kearney (2006) framework is specified as a non-routine and hence non-codifiable variable¹⁴. These would include, among others, dexterity, coordination, object handling or spatial orientation tasks. Unfortunately, PIACC dataset does not include items to learn about these non-routine manual job contents and hence, there is not a completely clean way to disentangle between non-routine manual (which corresponds to the *Manual* task defined in Autor, Katz and Kearney) and routine manual (which is one of the two components of the *Routine* task in Autor, Katz and Kearney). Still, we consider this to be the most sensitive approach.

Table 2 depicts average values of each of the task variables explained above. The Nordic and Anglo-Saxon countries (United States, Finland, Denmark, Norway, Great Britain, Sweden, and Canada) form the group of countries where jobs exhibit a higher intensity of abstract job contents and a lower intensity of Routine contents. Hence, we might say that these countries are in a more advanced stage of employment polarization. A second group, formed by Central European countries (Germany, Austria, Ireland, Czech Republic, Estonia, Belgium and Netherlands) are in an intermediate stage of this process. Finally, Southern (Spain, Italy, and France) and Eastern (Poland, Russian Federation and Slovakia) European countries together with Japan and Korea form the group of countries that are experiencing the earlier stages of employment polarization.

The cross-country comparison between the three task indexes shows a high and negative correlation between Abstract and Routine indexes (-0.52), while the relation with Manual task goes along with the polarization hypothesis, although very modestly. In particular the correlation between Abstract and Manual task intensities is negligible (-0.01) while negative and

¹² 1=Never; 2=Less than once a month; 3= Less than once a week but at least once; 4=At least once a week but not every day; 5=every day.

¹³ 1=Not at all; 2=Very little; 3=To some extent; 4=To a high extent; 5= To a very high extent.

¹⁴ For the manual non-routine category, both Spitz and Autor and Handel use activities that are clearly identifiable as non-routine. Spitz uses as response of activity: “*Repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving or accommodating*”, while Autor and Handel use four activities: (i) operating vehicles, mechanized devices, or equipment; (ii) time spent using hands to handle, control, or feel objects, tools, or controls; (iii) manual dexterity; (iv) spatial orientation. From the Dictionary of Occupational Titles (DOT), Autor and Dorn (2014) use “eye-hand-foot coordination” variable for the manual (non-routine) task and “finger dexterity” to be included as the manual part of the routine construct. Finally, Acemoglu and Autor (2011) use from the Occupational Information Network (O*NET “*pace determined by speed of equipment*”, “*controlling machines and processes*” and “*spend time making repetitive motions*” for routine manual tasks and “*operating vehicles, mechanized devices, or equipment*”, “*spend time using hands to handle, control or feel objects, tools or controls*”, “*manual dexterity*” or “*spatial orientation*”.

very small (-0.04) between Routine and Manual tasks. Previous studies have found stronger correlations between Manual (non-routine) and the other two tasks, and the fact that we find such a small correlation may be related to the measurement issues of Manual tasks.

Table 2. Task measures by countries.

	Observations	Abstract		Routine		Manual		ICT Use	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Austria	2,744	-0.11	0.98	-0.23	0.86	0.04	1.02	-0.01	0.96
Belgium	2,602	-0.04	1.02	-0.05	0.87	-0.13	1.02	0.10	0.98
Canada	13,941	0.13	0.99	-0.21	0.90	-0.07	1.00	0.13	1.00
Czech Republic	2,686	0.02	1.06	0.03	0.94	0.02	1.01	-0.04	0.99
Germany	3,084	0.01	0.97	-0.18	0.84	0.03	1.02	-0.06	0.95
Denmark	4,226	0.04	0.88	-0.35	0.81	0.03	0.97	0.25	0.98
Spain	2,434	-0.26	1.02	-0.07	1.01	-0.02	1.03	-0.17	0.97
Estonia	4,184	-0.21	0.91	-0.13	0.88	-0.04	0.99	0.05	1.03
Finland	3,038	0.29	0.85	-0.38	0.73	-0.24	0.92	0.15	0.91
France	3,415	-0.18	1.02	0.15	0.95	-0.10	0.98	-0.06	0.98
Great Britain	4,342	0.25	1.03	-0.08	0.97	-0.02	1.01	0.18	1.02
Ireland	2,741	0.13	1.04	0.06	0.99	0.05	1.04	-0.01	1.00
Italy	2,000	-0.45	0.95	0.36	0.99	0.01	1.04	-0.27	0.97
Japan	3,134	-0.13	0.96	0.08	0.87	-0.28	0.95	-0.02	0.94
Korea	2,950	-0.09	1.00	0.72	1.06	-0.01	0.97	0.16	1.12
Netherlands	2,871	-0.03	0.97	0.06	0.90	-0.09	1.03	0.22	0.95
Norway	2,774	0.12	0.82	-0.22	0.74	-0.01	0.96	0.21	0.91
Poland	3,883	-0.24	0.94	0.06	0.97	0.05	1.04	-0.17	0.99
Russia	1,674	-0.08	0.98	0.61	1.13	-0.04	0.99	-0.41	0.85
Slovakia	2,491	-0.29	1.01	0.10	1.02	-0.02	1.04	-0.10	1.01
Sweden	2,663	0.04	0.85	-0.28	0.79	-0.03	0.99	0.10	0.89
United States	2,543	0.20	0.99	-0.34	0.90	0.18	0.97	0.18	1.03

Notes: The sample includes employed respondents aged 20-64 currently working for which variables in section IV are well defined and have non missing values. For regression purposes and due to few observations, we exclude workers in non-profit firms and workers in Armed Forces and Skilled Agricultural and Fishery occupations.

As stated before, the implicit assumption underlying the task framework is that the decline in the price of computer capital (the exogenous driver of digitalization) is equivalent to an increase in computer adoption at work. Measuring computer adoption at work is therefore key in this analysis. To exploit as much variation as possible, we construct an index of computer use at work (ICT use) following the same approach as with other task measurements¹⁵. Table 2 depicts such index for each of the countries under analysis, and the questionnaire items used to

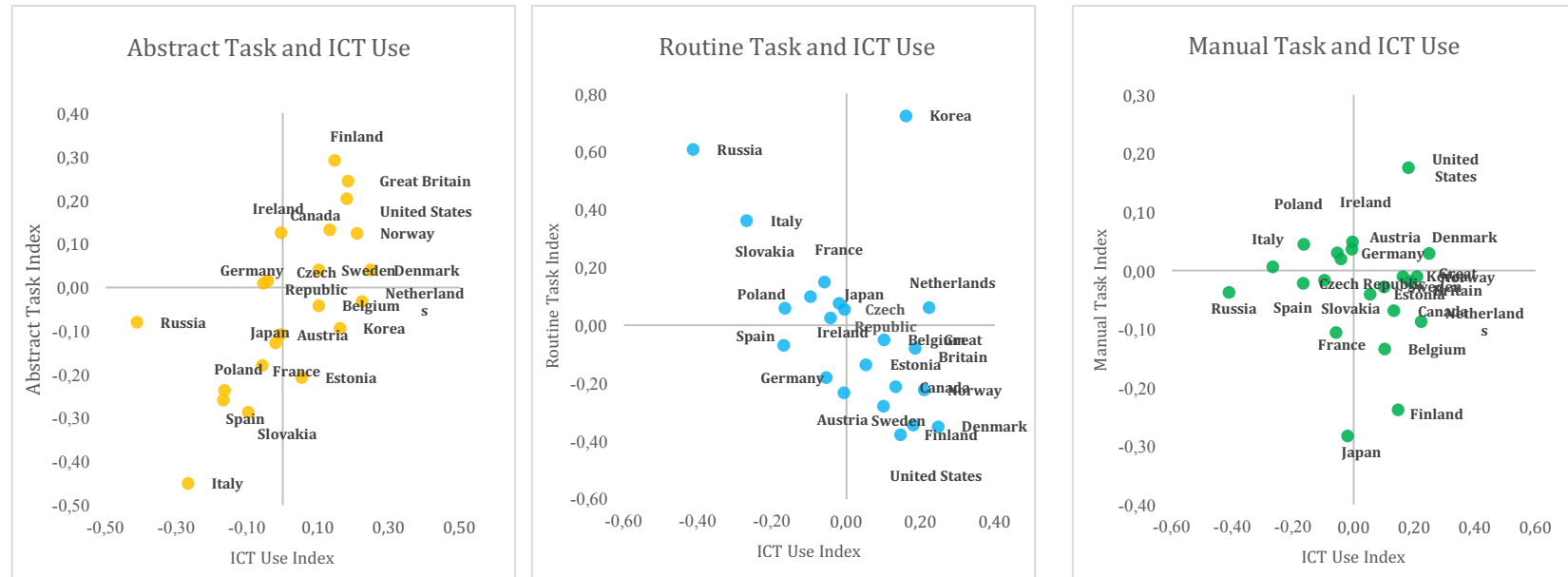
¹⁵ Spitz (2006) uses a dummy variable of computer use by workers. Autor and Dorn (2013) use an adjusted computers-per-worker measure with data at the firm level.

construct such index are detailed at the bottom of Table 1. As with the rest of the task components, the ICT index of computer use at work has been constructed choosing the first component of a principal component analysis¹⁶.

As Table 2 shows, workers in Nordic (Denmark, Finland, Netherlands, or Sweden) as well as Anglo-Saxon (Canada, Great Britain, or the United States) countries have adopted technology more intensively compared to workers in Central Europe, and even more compared to workers in Southern and Eastern European countries. Workers in Japan and Korea adopt ICT at work slightly faster compared to the PIAAC sample average. A simple scatter plot of the mean ICT use at work and each of the three task measures, presented in Figure 1, indicates a strong positive correlation between ICT use and abstract contents, a strong and negative correlation between ICT use and Routine job contents, and a very small correlation between ICT use and Manual Job Contents. We deep into these relationships in the next section.

¹⁶ We include a subset of all related items provided in the questionnaire when constructing the index of ICT use. This arbitrary decision is based on two reasons: we exclude items with little variation in responses and pick only one item from those that are highly correlated. We include in this index the variable asking workers about their level of computer use and, besides “straightforward”, “moderate” and “complex” levels of use, we consider non-respondents as an additional category of responses.

Figure 1. ICT Use and Task, Routine and Manual Tasks by countries.



Notes: The sample includes employed respondents aged 20-64 currently working for which variables in section IV are well defined and have non missing values. For regression purposes and due to few observations, we exclude workers in non-profit firms and workers in Armed Forces and Skilled Agricultural and Fishery occupations. The cross-country correlation is 0.65 between Abstract Tasks and ICT use, -0.53 between Routine Tasks and ICT Use, and -0.04 between Manual Tasks and ICT Use.

Wage Data

The wage data reported by PIAAC that we use corresponds to hourly earnings with bonuses for wage and salary earners. For Canada, Sweden and the United States, continuous data on earnings at the individual level is not public. For this reason, we exclude the data of these three countries in our sample on wages. For consistent comparisons, we use the conversion data to \$USD, corrected in Purchasing Power Parity (PPP), constructed by OECD. As can be seen in Table 5, Nordic European as well as Anglo-Saxon countries form the group of countries with highest hourly wages, later followed by Central European, Asian and Southern European countries. Eastern European countries display the lowest mean wages.

Table 5. Hourly Wages (USD) PPP corrected, by countries.

	Hourly Earnings with Bonus (USD) PPP		
	Obs	Mean	Std. Dev.
Norway	2742	25.33	11.36
Denmark	4036	25.17	10.99
Belgium	2504	22.94	10.59
Netherlands	2723	22.68	11.83
Ireland	2563	22.65	13.56
Austria	2573	20.15	11.22
Germany	2947	20.10	12.00
Finland	2996	19.90	8.27
Great Britain	4166	19.34	14.02
Korea	2894	18.47	17.09
Japan	3000	16.87	13.80
Italy	1714	16.71	10.75
France	3305	16.14	8.51
Spain	2254	15.84	10.60
Estonia	3661	10.08	7.77
Poland	3603	9.80	7.93
Czech Republic	2394	9.45	6.05
Slovakia	2302	8.97	6.61
Russia	1453	5.36	5.48
Total	53,830	15.57	12.67

Notes: Data reflects hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD\$. The sample includes employed respondents aged 20-64 currently working for which variables in section V are well defined and have non missing values. For regression purposes, we exclude workers in non-profit firms and workers in *Armed Forces* and *Skilled Agricultural and Fishery* occupations. We exclude earnings below USD\$1 and above USD\$150.

Table A.2 in the Annex presents descriptive statistics of hourly wages by individual and job characteristics for the resulting sample. The results are the expected ones from the literature. Male hourly wages are significantly higher than females (around 20 percent), while wages increase with age until age 45-49, where they stabilize, reflecting a hump-shaped curve. Moreover, wages increase with education level as well as literacy and numeracy cognitive skills. Regarding job characteristics, wages public and private sector workers are almost identical, while wages increase in the size of firm as well as with provision of On-the-Job-Training (OJT). Looking at 1-digit occupations, we observe that managers, professional and technicians have significantly higher wages, with craft, machine operators, and elementary occupation workers being paid the least. Finally, little wage differences are observed when looking at sector of the economy, probably given different composition effects and country specialization.

IV. Computer adoption and Job Tasks

Empirical Strategy

In this section, we assess the explicit relationship between computer adoption at work, proxied by ICT use, and each of the three tasks constructed before which describe the type of job contents that each worker performs at work¹⁷. To explore this relationship, we consider for a given worker i a pooled linear model with country fixed effects δ_j for countries $j = 1 \dots 22$, where:

$$T_{kij} = \alpha + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_n \beta_{2n} X_{ijn}^{Skills} + \sum_o \beta_{3o} X_{ijo}^{Job} + \beta_{k5} ICT_{ij} + \beta_{k6} \overline{ICT}_{jp} + \delta_{kj} + \varepsilon_{kij} \quad (1)$$

where T_{kij} represents the intensity of k^{th} -job task (k = abstract, routine, manual) for individual i in country j . In addition, X_{ij}^{Ind} is a vector of individual worker characteristics (such as gender, age or level of education), X_{ij}^{Skills} includes worker literacy and numeracy cognitive skills, X_{ij}^{Job} is a vector of job characteristics (public or private firm, firm size and on-the-job training), ICT_{ij} captures the use of individual i of ICT at work. Finally, \overline{ICT}_{jp} represents the average value of computer adoption at occupation-country level. This variable is a "leave-out" mean, as it represents the average ICT use for all workers from a particular country in occupation p except for the i -th worker. The introduction of the latter allows the coefficient of ICT at worker level

¹⁷ Some authors, such as Wiederhold et al (2016) exploit the relationship between ICT skills and wages, instead of ICT use at work. However, for our purpose, we prefer to use ICT use rather than skills, given that the latter explicitly provides information only on the supply side (workers), whereas ICT use at work captures more the "market" requirements, rather than only skills. Nevertheless, as a robustness check, we add ICT skills for a sample of countries for which there is information.

to capture the impact of computer at work within occupations, hence netting out the predictive power of occupations when relating ICT use and the intensity of Job Tasks¹⁸.

In addition, country fixed effects capture the cross-country differences in the respective task measure index that cannot be explained by the model. Later on, we assess how those fixed effects vary once we include different covariates in the model.

Results

We estimate the following specifications for the three constructed tasks. First we estimate equation (1) with only country fixed effects. We define these country fixed effects as the *unconditional* (raw) cross-country differentials in the use of the k^{th} Task measure. Then, we include ICT use at work as a covariate, which enables us to compute the *unconditional* marginal effect of ICT use at work on the particular job task and the extent to which disparities in cross-country differentials in such task decrease when netting out from differences in ICT use at work. This provides a first approximation to understand the role played by ICT in explaining differences in the intensity in Abstract, Routine and Manual job tasks across countries. These specifications are provided in Panel I of Table 7.

Next, we estimate the conditional impact of ICT use on each of the tasks by polishing raw differences in job tasks with compositional differences in individual and job characteristics. Hence, we compare the resulting country fixed effects in a regression of each measure of Job Tasks on individual, job, skill, sector controls with those obtained in when ICT is also included. In the latter, we also include average ICT use at occupation level for each country, so that individual ICT use reflects within-occupations computer adoption, and its coefficient is net out from occupational impact. We do so in Panel IIA (for Abstract Tasks), Panel IIB (For Routine tasks) and Panel IIC (for Manual Task) of Table 7.

Results of the unconditional predictive power of ICT use on each of the Job Tasks (Panel I of Table 7) indicate that the marginal impact of ICT use on Abstract tasks is by far the highest in absolute terms. The impact is strong and positive and explains 30% of the differences in Abstract Job contents across countries - as revealed by the R^2 coefficient. Second, ICT use and the intensity of Routine and Manual Tasks are negatively related, but the predictive power of the former on both Routine and Manual Tasks is not as high as for Abstract Tasks. When we condition the impact of ICT use at work on other individual and job covariates, column (2) of Panel IIA reveals that the predictive power decreases with respect to the one exhibited in the unconditional model, as expected, but ICT still remains as a significant predictor of Abstract Tasks. If in addition we net out such impact from average ICT use at occupation level, as it is

¹⁸ Instead of introducing the average use of ICT at occupation level, one could introduce occupational dummies. From an empirical prospective, results do not change, but for our purpose, which is to estimate the predictive power of individual ICT use at work for Job Tasks we have preferred to net out the potential effect of occupations in this way.

done in column (3), we observe that the predictive power of ICT does not decrease. Both are significant and positive predictors of Abstract Tasks. Moreover, it is interesting to see that the marginal impact of individual ICT use on Abstract Tasks remains unchanged. Finally, column (4) includes sector dummies to measure the average impact within sectors, and the results again remain unchanged.

The Conditional impact of ICT use at work on Routine and Manual Tasks also decreases when controlling for individual and job characteristics (column 2 of Panel IIB and IIC, respectively), and as before, remains a negative predictor of Routine and Manual Tasks when average values of these tasks at occupation level (column 3 Panel IIB and IIC) and sector fixed effects (column 4) are added.

Table 7: Impact of ICT Use on Tasks

Dep. Variables	Panel I: Unconditional Impact of ICT use on Tasks					
	Abstract		Routine		Manual	
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual and Job Characteristics						
Sector Dummy						
ICT Use at Work		0.529*** (0.00748)		-0.329*** (0.00759)		-0.466*** (0.00734)
Av. ICT Use by Occup.						
Constant	0.00945 (0.0193)	0.0387** (0.0159)	-0.179*** (0.0168)	-0.197*** (0.0161)	0.0311 (0.0202)	0.00535 (0.0167)
Observations	76,420	76,420	76,420	76,420	76,420	76,420
R-squared	0.035	0.304	0.115	0.219	0.021	0.229

Notes: For country dummies, we use Germany as country of reference. Robust standard errors in parentheses (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7 (Cont.) Impact of ICT Use on Tasks - Conditional Impact

Dep. Variables	Panel IIA:				Panel IIB:				Panel IIC:			
	Conditional Impact of ICT on Abstract Task				Conditional Impact of ICT on Routine Tasks				Conditional Impact of ICT on Manual Tasks			
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and Job Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector Dummy				Yes				Yes				Yes
ICT Use at Work		0.359*** (0.00996)	0.355*** (0.01000)	0.361*** (0.00997)		-0.268*** (0.00958)	-0.267*** (0.00971)	-0.273*** (0.00966)		-0.230*** (0.00980)	-0.242*** (0.00982)	-0.238*** (0.00984)
Av. ICT Use by Occup.			0.228*** (0.0166)	0.220*** (0.0166)			-0.121*** (0.0173)	-0.114*** (0.0172)			-0.449*** (0.0170)	-0.451*** (0.0171)
Constant	-1.169*** (0.0699)	-0.745*** (0.0713)	-0.335*** (0.0653)	-0.307*** (0.0659)	0.233*** (0.0736)	-0.138 (0.0849)	-0.347*** (0.0749)	-0.373*** (0.0748)	1.309*** (0.0660)	1.000*** (0.0674)	0.469*** (0.0655)	0.465*** (0.0657)
Observations	76,420	76,420	76,420	76,420	76.42	76.42	76.42	76.42	76,420	76,420	76,420	76,420
R-squared	0.241	0.388	0.369	0.372	0.181	0.261	0.246	0.248	0.198	0.342	0.325	0.327

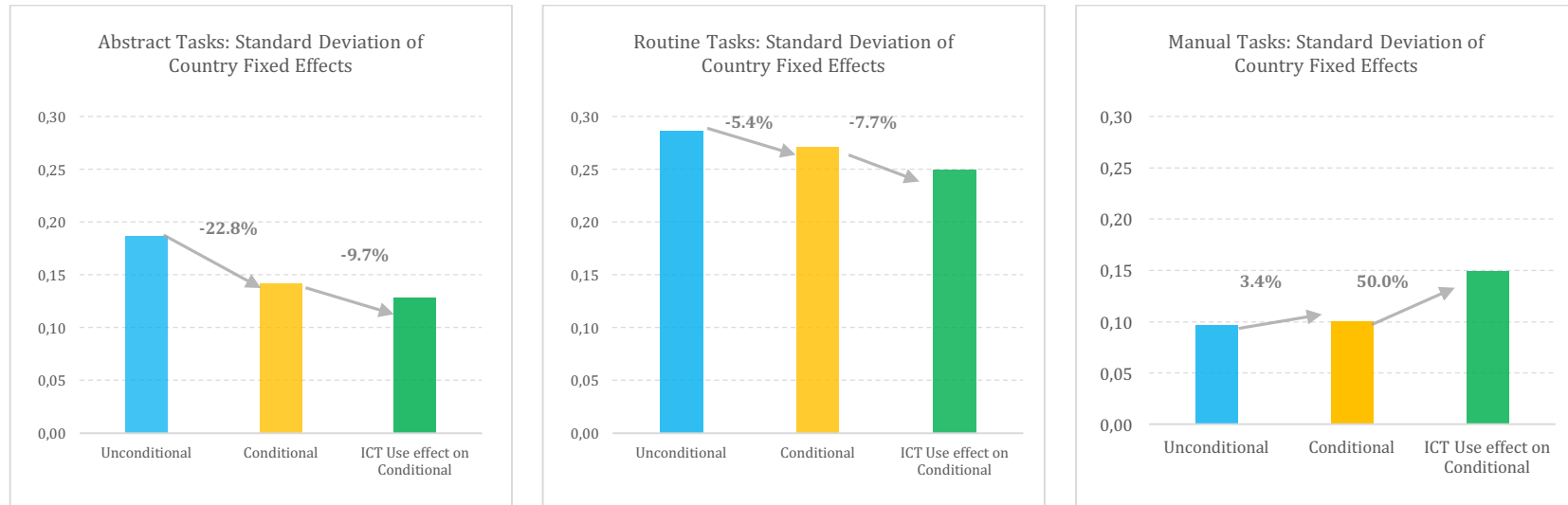
Note: Dependent variable are the Task constructs. For country dummies, we use Germany as country of reference. Individual characteristics include gender, age, and level of education. Skill characteristics include average literacy and numeracy score in the PIAAC test. Job characteristics include firm ownership, firm size, and on-the-job training activities. Robust standard errors in parentheses (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$. Mean ICT Use is computed for each occupation and country in the sample.

Once we have measured the predictive power of individual ICT use at work for Job Tasks, we can measure the extent to which differences in ICT use drive disparities in Job Tasks across countries. To do so we use the country fixed effects estimated in Table 7 (column (1), (3) and (5) of Panel I) respectively for each task. These represent the disparities across countries of each of the three tasks under consideration in the unconditional specification. Later we compare them with the country fixed effects obtained from the different conditional specifications. For the conditional specifications, we pick the columns (1) and (3) of each Task in Panels IIA, IIB and IIC.

Figure 2 displays the variation in country fixed effects with the three specifications for each of the three tasks (Abstract, Routine and Manual). For Abstract Tasks, the standard deviation falls from 0.185 to 0.142 when including the main covariates of the conditional model. When including ICT Use (and ICT Use at the occupation level) on this conditional specification, the standard deviation drops to 0.128, implying a 9.7% of all variation of cross-country fixed effects for Abstract Tasks conditional differences. For the case of Routine Tasks, the standard deviation decreases from 0.28 (unconditional) to 0.268 (conditional model). Later, when including ICT use at the individual level, the contribution of such specification reduces the standard deviation again to 0.25, a 7.7% of the total variation of the conditional model. Finally, the model specification for the case of Manual task does not allow to explain much of the differences across countries, neither when including the conditional model specification nor when adding the marginal individual effect of ICT use at work. To the contrary, if anything, the standard deviation slightly increases, especially when including ICT use in the conditional model specification. We suspect that the nature of the variable construct (already discussed in the previous section) and the fact that the complementarities of Manual work and technology are less obvious could be the reasons for why the model is unable to capture some of the cross-country variation in Manual tasks with ICT use at work¹⁹.

¹⁹ Results including ICT use interacted with country fixed effects (column (3) of Table 7 and column (7) and Table 8) do not vary qualitatively when compared with a homogenous effect ICT use at work for all countries.

Figure 2. Impact of ICT on Tasks: Country Disparities Effects in the unconditional and conditional models.



Note: The graph depicts the standard deviation of the Country Fixed effects in of the regressions computed in Table 7. The standard deviation is independent of the country of reference chosen in the model. We denote by "Conditional" the standard deviation of the country fixed effects when the regression of tasks controls for individual and job characteristics. The third column depicts such standard errors when we add to the controls of column 3 on Table 7 ICT Use and average ICT use by occupation, hence netting out disparities in tasks across countries not only from individual and job characteristics, but also from differences in ICT use.

Robustness check: Heterogeneity across sectors

Until now, we have estimated the impact of ICT use at work on the degree of job task differences without considering potential heterogeneity of such impact across different sectors such as manufacturing, services and construction. In the final column of table 7, sector fixed effects have been added, but we think that job contents in each sector should be estimated separately allowing not only for differences in composition, but also in returns. Hence, we re-estimate these specifications separately for each sector. Table A.3 in the Annex describes the main results. The unconditional impact of ICT on job task differences is very similar in manufacturing and services (and similar to the aggregate impact), and smaller in construction. When we check the conditional impact of ICT use at work, (i.e., conditioning on comparable workers) the effect of ICT use on job tasks is similar to the one presented before for the aggregate conditional impact and still very significant.

Robustness check: ICT use and ICT skills

For an adequate estimate of the impact of digitalization on job tasks, we must assume exogeneity of ICT use at work. In principle ICT use at work should reflect the "market value" of digitalization, which is a result of supply and demand market forces. However, one could argue that ICT use reflects primarily ICT skills - supply forces. If individuals self-select into jobs based on their comparative advantage and hence on their skills, and if ICT use captures primarily ICT skills, then an estimation of job tasks on ICT use would not recover average impact of ICT use on job tasks. In this section, we measure the impact of ICT use at work conditional on ICT skills, hence netting out the potential self-selection of workers into jobs on the basis of their skills.

PIAAC dataset provides information of ICT skills, but only for a sub-sample of countries²⁰. The variable is denoted in PIAAC as *Problem Solving*, which specifically means "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (OECD, 2013, p. 86). As a robustness check of the previous results, we select the sample of countries which provide information on this variable and re-estimate the model, netting out the impact of ICT use at work from ICT skills, which clearly reflects ICT worker abilities. To avoid potential sources of biases, the sample variables of the task constructs and the ICT use index need to be recalibrated without observations of the three countries that are excluded from the sample.

²⁰ The sample does not include workers in Spain, France and Italy.

Table A.4 in the Annex displays the result for each job task by controlling for ICT skills in the conditional model results previously described. As can be seen, coefficient of ICT use at the worker and occupation level do not vary when including ICT Skills in the model, which keeps being relevant with broadly similar R^2 values. Moreover, we can see that there is no ICT Skills effect over Abstract and Manual tasks, whereas we observe a negative and significant effect on Routine tasks, reflecting the lack of complementarities between ICT and Problem Solving Skills with repetitive and codifiable activities at the workplace.²¹

V. Job Tasks and the Wage Structure

Empirical Strategy

Our purpose in this section is to measure the predictive power of job tasks for average wages as well as compute the extent to which different composition and returns of job tasks across countries drive differences in the wage structure, in particular in wage inequality.

Job Tasks and Average Wages

To estimate the predictive power of job tasks on average wages, we estimate a standard wage regression, and include individual and job characteristics, as well as the individual reported intensity on Abstract, Routine and Manual tasks. We estimate this in a pooled linear model for the nineteen countries we have data on wages for²² ($j = 1 \dots 19$).

$$\begin{aligned} \text{Log } W_{ij} = & \alpha + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_n \beta_{2n} X_{ijn}^{Skills} + \sum_o \beta_{3o} X_{ijo}^{Job} + \\ & \sum_k \beta_{4k} \text{Task}_{ijk} + \sum_k \beta_{5k} \overline{\text{Task}_{jk}} + \delta_j + \varepsilon_{ij} \quad (2) \end{aligned}$$

with $\text{Log } W_{ij}$ being the hourly log-wage, X_{ij}^{Ind} individual worker characteristics (such as gender, age or level of education), X_{ij}^{Skills} capture worker literacy and numeracy cognitive skills, X_{ij}^{Job} include a vector of job characteristics (public or private firm, firm size and on-the-job training), and Task_{ijk} are the intensity of Abstract, Routine and Manual tasks which each worker reports to exert in her work. To net out this individual effect from the relationship between tasks and occupations, we include also the average mean of each task at occupation-country level. As before, this mean is a leave-out men, representing the average intensity of k-th task for all workers from a particular country in occupation p except for the i -th worker.

²¹Computing the country fixed effects after including ICT Skills in the model does not alter the results discussed in Figure 2.

²² Given that the data in Canada, US and Sweden is removed from the sample, the number of countries is reduced from 22 to 19.

Results

Cross-Country Correlations between Tasks and Wages

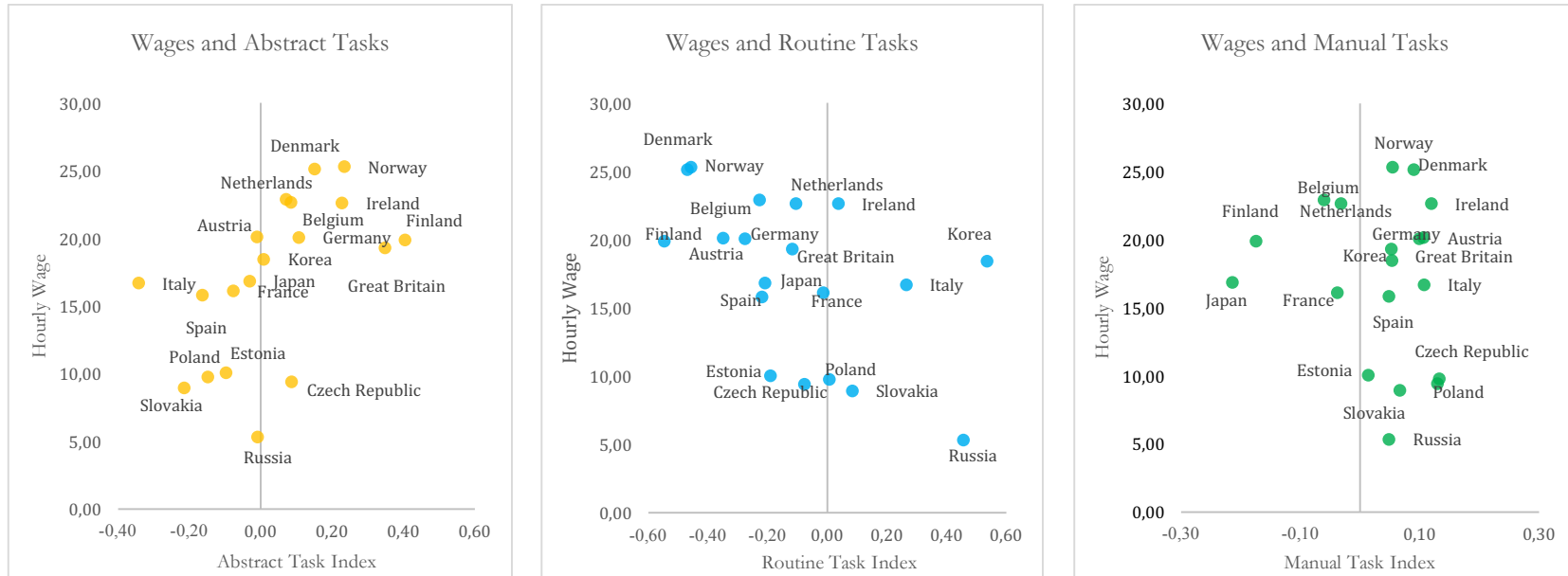
Before presenting estimates of the impact of each of the tasks on average wages, it is interesting to look at the correlations between them across countries in Figure 3. The first figure represents a very strong and positive correlation between wages and Abstract tasks. Countries such as the Nordic Countries, The Netherlands, Ireland, Great Britain are among those with high wages and high Abstract Job contents. On the other extreme, countries such as Poland, Slovakia, Estonia or Spain are among the group which present lower average wages and lower intensity of Abstract tasks. A mirror image can be found in the second figure, which relates average wages and Routine tasks. Those countries where the relationship between average wages and Abstract tasks is highly positive are those with high wages and low intensity of Routine tasks (and the other way round). Finally, there is not a clear pattern in the correlation between average wages and Manual tasks, as shown in the third figure.

The impact of Tasks on Average Wages

Second, Table 8 presents the predictive power of each of the tasks under consideration on average (log) hourly wages. We present eight different specifications, each of them including different set of covariates. In particular, column 1 depicts results from the unconditional impact of each of the tasks on wages. In this estimation we only control for country fixed effects, and hence, the impact of tasks we estimate is a within-country estimation, but not conditioned by any other determinant. It is noticeable that the predictive power of Abstract, Routine and Manual Tasks on average wages (within countries) is very strong - the R^2 reaches 0,52. In addition the impact of Abstract is very strong and positive, whereas Routine and Manual Job contents strongly decrease wages. Column (2) nets out the impact of individual tasks from average tasks at occupational-country level, which polish the effect of occupations for wages. It is interesting to see that, whereas the predictive power of the model increases, the impact of each of the tasks, primarily that of Abstract tasks, remains barely unchanged.

Each of the subsequent columns adds different set of covariates. In particular, the last column conditions on all set of individual characteristics, including literacy and numeracy skills, job characteristics, such as type of contract, type of firm and sector, and the index of ICT use at work. Conditioned on all these covariates, and netting out the effect of average task by occupation, we still find an increase of 6% on average wages at an increase of one-standard deviation of Abstract tasks and a decrease of 2% (4%) on average wages at an increase of one-standard deviation of Routine (Manual) tasks. Hence, we can conclude stating that Abstract job content is a powerful and positive predictor of wages, whereas Routine and Manual job contents are also (but less) powerful but negative predictor of average wages. Although the magnitude of results slightly differs, this is consistent with the results found in Autor and Handel (2013).

Figure 3. Correlations between Tasks and Wages: Cross-country differences.



Notes: Task and ICT Use Indices are defined for a sample which includes countries with earnings data, defined as hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD\$, and in the range between USD\$1 and USD\$150. Data included observations include employed respondents aged 20-64 currently working for which variables in section IV are well defined and have non missing values. The cross-country correlation is 0.53 between Abstract Tasks and ICT use, -0.52 between Routine Tasks and ICT Use, and -0.15 between Manual Tasks and ICT Use.

**Table 8: Estimation of (Log) Hourly Wages on Tasks
(unconditional and conditional on other covariates)**

VARIABLES	1	2	3	4	5	6	7
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual + Job Characteristics			Yes	Yes	Yes	Yes	Yes
Sector Dummies							Yes
Abstract	0.171*** (0.00510)	0.115*** (0.00532)		0.0870*** (0.00552)	0.0618*** (0.00548)	0.0497*** (0.00567)	0.0620*** (0.00550)
Routine	-0.0191*** (0.00569)	-0.0135** (0.00584)		-0.0321*** (0.00554)	-0.0264*** (0.00567)	-0.0208*** (0.00567)	-0.0268*** (0.00566)
Manual	-0.0947*** (0.00446)	-0.0626*** (0.00527)		-0.0582*** (0.00460)	-0.0430*** (0.00513)	-0.0333*** (0.00533)	-0.0428*** (0.00513)
Abstract (Mean Occ)		0.676*** (0.0257)			0.375*** (0.0254)	0.371*** (0.0253)	0.357*** (0.0265)
Routine (Mean Occ)		0.505*** (0.0413)			0.224*** (0.0417)	0.227*** (0.0415)	0.203*** (0.0440)
Manual (Mean Occ)		0.0659*** (0.0133)			0.0326*** (0.0126)	0.0530*** (0.0128)	0.0255** (0.0125)
ICT Use at Work						0.0491*** (0.00597)	
Constant	2.831*** (0.0102)	2.897*** (0.0135)	2.134*** (0.0418)	2.336*** (0.0420)	2.428*** (0.0429)	2.466*** (0.0431)	2.465*** (0.0433)
Observations	53,830	53,830	53,830	53,830	53,830	53,830	53,830
R-squared	0.525	0.557	0.584	0.606	0.618	0.620	0.619

Notes: Task Indices are defined for a sample which includes countries with earnings data, defined as hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD\$, and in the range between USD\$1 and USD\$150. Data included observations include employed respondents aged 20-64 currently working for which variables in section IV are well defined and have non missing values.

Do tasks contribute to explain differences in Wage Inequality Across Countries?

One of the potential consequences of job polarization is the increase in wage inequality. Empirical results find confounding results with respect to this hypothesis. Therefore, we want to measure the extent to which differences in the job tasks endowments and job tasks returns help explain differences in wage inequality (measured by Gini index) across countries. To do so, we compute a counterfactual exercise to understand the role played by differences in Job Tasks (endowments and returns) across countries in the wage distribution. In our counterfactual analysis, we choose one country as reference and then conduct a decomposition of the wage structure between each of the countries and the reference one. A classical approach

is a Oaxaca-Blinder decomposition for the mean differences of a linear regression so that for a model with two countries $k = \{0,1\}$, the conditional expectation is:

$$E[\text{Log } W_k | X_{ku}] = \alpha_k + X'_k \beta_k \quad (3)$$

where $X_{ku} = [X_{k1}, X_{k2}, X_{k3}, \dots, X_{kU}]$ is a $U \times 1$ vector of covariates. The Oaxaca and Ransom (1994) generalization for the linearized decomposition allows computing a pooled model for both countries. The mean difference of log wages between countries in such specification can be written as:

$$\widehat{\Delta \text{Log } \bar{W}} = \sum_u (\overline{X_{1u}} - \overline{X_{0u}}) \widehat{\beta}_u^* + \sum_u \overline{X_{1u}} (\widehat{\beta}_{1u} - \widehat{\beta}_u^*) + \sum_u \overline{X_{0u}} (\widehat{\beta}_u^* - \widehat{\beta}_{0u}) + (\widehat{\alpha}_{k_1} - \widehat{\alpha}_{k_0}) \quad (4)$$

here $\widehat{\beta}_u^*$ are the coefficients in the pooled model for each covariate, $\overline{X_{ku}}$ are the sample means of each worker covariate and $\widehat{\alpha}_{k_1}, \widehat{\alpha}_{k_0}, \widehat{\beta}_{1u}, \widehat{\beta}_{0u}$ are the OLS estimates of the intercepts and coefficients for the two countries under comparison. The first term of equation (4) is called *wage composition effect* and accounts for differences in mean covariates between both countries. The second, third and forth terms are jointly called *wage structure effect* and account for the differences in returns of the set of covariates, including the intercept.

The mean decomposition offers a very limited approach to understand differences in wage structure between two different countries, as it loses relevant information on distributional dispersion, tails, or symmetry. To overcome such challenge, we follow Firpo, Fortin and Lemieux (2013) analysis for the US and Massari, Naticchioni and Ragusa (2014) for Europe. Both analyses decompose the over time changes of percentiles of the wage distribution in a given country (or group of countries), as well as the difference between such percentiles. They use Re-centered Influence Functions (RIF) regression method proposed by Firpo, Fortin and Lemieux (2009). This method can be seen as a generalization of the Oaxaca-Blinder decomposition that can be applied to any distributional statistic, including non-linear forms such as quantiles. This is particularly interesting for our purpose, where we want to test whether differences in Task Endowments and in Task Returns help explain differences in wage inequality across countries. The RIF function is a transformation of a dependent variable for a statistic of a given probability distribution. For a quantile q_τ :

$$RIF(I; q_\tau) = q_\tau + \frac{\tau - D(I \leq q_\tau)}{f_I(q_\tau)} \quad (5)$$

where D is an indicator function and $f_I(\cdot)$ is the density of the marginal distribution of the dependent variable (in our case, the hourly log wage). The sample counterpart of such function is therefore:

$$RIF(I; \hat{q}_\tau) = \hat{q}_\tau + \frac{\tau - D(I \leq \hat{q}_\tau)}{\hat{f}_I(\hat{q}_\tau)} \quad (6)$$

where \hat{q}_τ is the sample quantile and $\hat{f}_I(\hat{q}_\tau)$ is the kernel density estimator. The method adds simplicity to DiNardo (1996), as unconditional distributions are easier to interpret in terms of marginal treatment effects of independent variables. Computing unconditional quantile regressions is not feasible, given that the law of iterated expectations only holds for linear functions. The RIF-regression approach solves this by linearly approximating quantile regressions, which can hence be interpreted in a simpler way.

In our case, we focus on the composition and wage structure effect of task endowments for each decile of the wage distribution, while controlling for other individual and job characteristics. We then compute the Gini Index for each country and assess the contribution of differences in task endowments and task returns to explain differences in the Gini index. We conduct a decomposition of the wage structure in a two-by-two country basis, picking Denmark as the reference for three reasons: (i) it is the country with highest ICT use index; (ii) it is the country with lowest wage inequality, expressed by the Gini Index; (iii) it is one of the countries with highest intensity of Abstract tasks and lower intensity of Routine tasks (highest job polarization).

Table 9 presents the results. The first column depicts the Gini Gap between each of the countries Index in Wages for each of the countries. Countries are ranked from lowest to highest Gini Gap. The first thing to note is that there are countries, such as Norway, Belgium, Finland, Netherlands, France and Austria, where differences in wage inequality with Denmark are very small. For these countries it makes no much sense to decompose the Gini Gap, as there is very little to decompose. A second group of countries is composed by Ireland, Italy, GB, Germany, Spain, the Czech Republic and Japan, where the gap in the Gini Index varies from -0,03 (in Ireland) to -0,058 (Japan). For these group of countries, which exhibit a "medium Gini gap", we see no clear pattern with respect to the contribution of differences in task endowments and task returns to explain the gap in the Gini Index. In particular, in Great Britain, Germany, Czech Republic and Spain, these differences do not contribute to explain the gap in the Gini index. Instead, they would increase those differences had these countries the same task endowments and task returns than Denmark. However, for Ireland, differences in tasks (both endowments and returns) contribute to understand the gap in the Gini index. In particular, 66% of the gap can be explained by the differences in tasks. Or in other words, if Ireland had the same task endowments and tasks returns than Denmark, the gap in the Gini Index between the two countries would diminish in 66%. Finally, there is a third group for which the gap in the Gini index with respect to Denmark is highest. These are Slovakia, Poland, Korea, Estonia and particularly Russia, with the highest gap by far. For the latter, differences in task endowments and task returns clearly contribute to explain differences in the Gini index. However, for the other countries, we do not see a clear pattern, although in most

of them, differences in returns to tasks do seem to be a contributor to understand differences in the Gini index with respect to Denmark.

Table 9: Gini Index for Wages and the Contribution of Tasks to explain disparities in Gini

	Total Gini Gap	Endowment Effect of Tasks (%)	Return Effect of Tasks (%)
Norway	0,000	-807,1%	2316,3%
Belgium	-0,006	78,1%	-168,3%
Finland	-0,007	24,3%	618,3%
Netherlands	-0,018	9,1%	-13,0%
France	-0,019	13,5%	-21,2%
Austria	-0,020	-11,1%	-8,9%
Ireland	-0,032	43,5%	23,0%
Italy	-0,034	15,6%	0,3%
Great Britain	-0,038	-97,5%	-16,8%
Germany	-0,047	-10,1%	-0,4%
Spain	-0,047	-9,1%	2,4%
Czech Republic	-0,049	-74,9%	-8,7%
Japan	-0,058	-20,6%	3,1%
Slovakia	-0,084	-14,0%	3,2%
Poland	-0,086	-42,4%	-2,3%
Korea	-0,086	0,5%	3,3%
Estonia	-0,093	-17,5%	52,0%
Russia	-0,145	102,7%	56,2%

Summarizing, we see no clear pattern with respect to the contribution of task endowments and task returns to explain differences in the Gini index across countries. Although for some countries, such as Ireland and Russia, differences in tasks do seem to be clear predictor of differences in wage inequality, for the rest of countries there are likely to be other factors, possibly institutional ones, which should be introduced to account for differences in wage inequality across countries. This might be a topic of interest for further research.

VI. Conclusion

In this paper we investigate cross-country differences in the intensity of Job Tasks, particularly Abstract, Routine and Manual job tasks. In particular, we look at the role played by differences in computer adoption at work to understand such differences. In addition, we estimate the predictive power of job tasks to help explain differences in the wage structure across countries.

To do so, the Programme for International Assessment of Adult Competences (PIACC) offers a harmonized worker-level data set for 22 countries. The dataset provides very precise information on job contents at the worker level, which allows for job task heterogeneity within occupations when accounting for differences on the job contents, a unique feature only followed in national surveys in the past. Additionally, the data includes an accurate measurement of cognitive skills in literacy, numeracy and problem solving skills so that unobserved worker characteristics can be accounted for.

Our Theoretical framework is the "Task Assignment Model", developed by Autor (2013), where contrary to the canonical model, where the inputs are factors of production, L and K, the inputs in this framework are tasks or job contents that each worker chooses, given her skills and based on her comparative advantage. Following such model, we construct indexes for Abstract, Routine and Manual job contents at a worker level, and present cross-country differences for average levels. The Nordic and Anglo-Saxon countries (United States, Finland, Denmark, Norway, Great Britain, Sweden, and Canada) form the group of countries where jobs exhibit a higher intensity of Abstract job contents and a lower intensity of Routine contents. Hence, we might say that these countries are in a more advanced stage of employment polarization. A second group, formed by Central European countries (Germany, Austria, Ireland, Czech Republic, Estonia, Belgium and Netherlands) are in an intermediate stage of this process. Finally, Southern (Spain, Italy, and France) and Eastern (Poland, Russian Federation and Slovakia) European countries together with Japan and Korea form the group of countries that are experiencing the earlier stages of Employment Polarization.

Next, we explore the relationship between computer adoption at work and cross country differences in Job Tasks. After confirming that computer at work has a high predictive power for the three job tasks, we find that for Abstract Tasks, conditioned on individual (including skills) and job characteristics, differences in computer adoption account for 10% of all variation in Abstract task across countries. For Routine tasks, the contribution is lower, and accounts for 7,7% of those task differences. Finally, differences in ICT adoption across countries are not related to disparities in Manual job contents.

Finally, we deep into the relationship between Job Tasks and average wages and on wage inequality. We find that job tasks are high predictors of average wages. In particular, we find an increase of 6% on average wages at an increase of one-standard deviation of Abstract tasks and a decrease of 2% (4%) on average wages at an increase of one-standard deviation of Routine (Manual) tasks, similar to what is found by Autor and Handel (2013). When we try to assess whether differences in task endowments and in task returns contribute to explain differences in wage inequality across countries, in particular, in the Gini index, we do not find a clear pattern. For Ireland and Russia, we confirm that had these countries had the same task endowments and returns than Denmark, their wage inequality would be largely reduced and would be very similar to the one observed for Denmark. For the rest of the countries, although it looks that

differences in task returns contribute somehow to explain differences in wage inequality, more research is needed to better understand these differences. Probably, we should consider differences in institutional determinants, many of them not included here, although this is out of the scope of this paper.

From a policy perspective, our analysis indicates that the job polarization process is clearly underway for most developed countries, and that computer adoption is one of the main drivers of such process. As the relative price of technology continues its decreasing trend, digitalization at work will increasingly substitute Routine jobs by either Manual or Abstract ones. This process implies enormous changes for the skills needed among the current and future labor force, hence posing a clear challenge for the educational and on-the-job training systems of the developed countries. We must adapt our education system in order to promote the development of analytical and interactive skills in our youth. If we do not take this process seriously enough, we will face sooner than later a very worrisome mismatch between the labor market needs and the skill supply of our labor force, with enormous individual and social costs.

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VIII. Annex

Table A.1. Distribution of Task Measures by Individual and Job Characteristics

	Observations	Abstract		Routine		Manual	
		Mean	SD	Mean	SD	Mean	SD
Gender							
Female	39.053	-0,12	0,99	0,00	0,97	-0,11	1,01
Male	37.367	0,10	1,00	0,00	1,02	0,10	0,98
Age							
20-24	8.062	-0,18	0,97	-0,12	0,94	0,27	0,96
25-29	8.959	0,10	0,96	-0,09	0,92	0,02	0,99
30-34	9.242	0,10	0,99	-0,08	0,99	-0,04	1,00
35-39	9.465	0,10	0,97	-0,10	0,93	-0,08	0,99
40-44	9.858	0,05	1,00	0,00	0,98	-0,04	1,01
45-49	9.806	-0,03	1,02	0,04	1,03	-0,01	1,00
50-54	8.992	-0,05	1,01	0,15	1,04	0,00	0,99
55-59	7.556	-0,08	1,03	0,12	1,05	-0,02	1,01
60-65	4.480	-0,19	1,02	0,18	1,14	-0,05	1,01
Education Level							
Lower Secondary or less	9.388	-0,70	0,91	0,38	1,09	0,48	0,90
Upper secondary	28.085	-0,18	0,97	0,03	1,00	0,21	0,98
Post-secondary or Tertiary Professional	16.814	0,03	0,96	0,02	1,03	0,07	0,98
Tertiary (bachelor/master)	22.133	0,47	0,86	-0,20	0,88	-0,50	0,87
Numeracy Skills (Quartile Group)							
Quartile 1	16.320	-0,38	1,03	0,13	1,12	0,41	0,93
Quartile 2	18.650	-0,10	0,99	0,03	1,03	0,15	0,99
Quartile 3	19.818	0,08	0,97	0,02	0,97	-0,11	0,98
Quartile 4	21.632	0,38	0,86	-0,17	0,84	-0,43	0,89
Literacy Skills (Quartile Group)							
Quartile 1	17.525	-0,38	1,03	0,16	1,13	0,41	0,93
Quartile 2	19.719	-0,06	0,99	0,02	1,01	0,12	0,99
Quartile 3	19.737	0,11	0,97	-0,04	0,96	-0,10	0,99
Quartile 4	19.439	0,30	0,88	-0,13	0,86	-0,42	0,91
Public/Private							
Public	23.810	0,15	0,95	-0,01	0,96	-0,18	0,97
Private	52.610	-0,05	1,01	0,00	1,01	0,06	1,00
Size of workplace							
1-10 workers	18.365	-0,24	0,99	0,06	1,02	0,12	0,99
11-50 workers	24.049	0,00	0,99	0,01	1,00	0,06	0,99
51-250 workers	18.207	0,05	1,01	0,05	1,00	-0,02	1,01
251-1000 workers	9.448	0,11	0,99	-0,08	0,98	-0,09	1,00
more than 1000 workers	6.351	0,28	0,95	-0,18	0,97	-0,28	0,97
On-the-Job-Training							
No	42.889	-0,25	0,98	0,21	1,03	0,06	1,01
Yes	33.531	0,35	0,92	-0,29	0,87	-0,09	0,98
Occupation							
Legislators, Senior officials and managers	5.780	0,87	0,69	-0,47	0,83	-0,51	0,83
Professionals	16.451	0,45	0,80	-0,23	0,84	-0,49	0,88
Technicians and associate professionals	13.079	0,33	0,89	-0,23	0,87	-0,30	0,94
Clerks	8.402	-0,11	0,94	0,03	0,91	-0,58	0,84
Service workers and shop and market sales worker	15.373	-0,35	0,99	0,18	1,06	0,41	0,90
Craft and related trades workers	7.741	-0,26	0,94	0,05	1,00	0,67	0,74
Plant and machine operators and assemblers	5.978	-0,60	0,84	0,58	1,11	0,54	0,86
Elementary Occupations	3.616	-0,83	0,80	0,50	1,08	0,73	0,72
Sector							
Manufacturing	21.401	-0,07	1,01	0,10	1,04	0,02	1,00
Construction	4.969	-0,09	0,99	0,05	1,00	0,46	0,89
Services	50.050	0,04	0,99	-0,05	0,98	-0,06	1,00

Notes: the sample includes employed respondents aged 20-64 currently working for which variables in section IV are well defined and have non missing values. For regression purposes and due to few observations, we exclude workers in non-profit firms and workers in Armed Forces and Skilled Agricultural and Fishery occupations.

Table A.2. Hourly Wages (USD-PPP) by individual and job characteristics

	Obs.	Mean	Std. Dev.
Gender			
Female	27,463	13.48	10.83
Male	26,367	17.38	13.83
Age			
20-24	5,896	10.58	8.36
25-29	6,585	12.74	9.96
30-34	6,663	14.81	11.20
35-39	6,759	16.36	12.61
40-44	7,007	17.35	13.23
45-49	6,768	17.25	14.08
50-54	6,050	16.50	13.13
55-59	5,202	17.45	14.60
60-65	2,900	15.99	14.50
Education Level			
Lower Secondary or less	7,131	13.47	9.44
Upper secondary	21,685	14.42	10.09
Post-secondary or Tertiary Professional	9,693	13.39	11.64
Tertiary (bachelor/master)	15,321	19.66	16.38
Numeracy Skills (Quartile Group)			
Quartile 1	11,707	12.87	10.10
Quartile 2	14,137	14.27	11.54
Quartile 3	14,231	15.75	13.05
Quartile 4	13,755	19.07	14.48
Literacy Skills (Quartile Group)			
Quartile 1	10,362	12.59	9.91
Quartile 2	13,184	13.53	11.05
Quartile 3	14,407	14.96	12.09
Quartile 4	15,877	20.32	14.98
Public/Private			
Public	16,112	16.02	12.28
Private	37,718	15.41	12.80
Size of workplace			
1-10 workers	13,216	12.93	10.72
11-50 workers	17,008	14.28	11.15
51-250 workers	12,764	15.80	12.23
251-1000 workers	6,484	18.70	14.48
more than 1000 workers	4,358	22.14	17.02
On-the-Job-Training			
No	30,466	13.63	11.99
Yes	23,364	18.98	13.12
Occupation			
Legislators, Senior officials and managers	3,638	26.04	19.83
Professionals	11,245	19.69	14.87
Technicians and associate professionals	8,744	17.75	12.34
Clerks	6,376	15.38	10.62
Service workers and shop and market sales workers	11,304	11.19	8.73
Craft and related trades workers	5,658	13.01	10.09
Plant and machine operators and assemblers	4,384	12.92	9.39
Elementary Occupations	2,481	11.95	10.34
Sector			
Manufacturing	15,829	16.57	13.35
Construction	3,527	14.31	10.54
Services	34,474	15.18	12.49

Notes: Data reflects hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD\$. The sample includes employed respondents aged 20-64 currently working for which variables in section V are well defined and have non missing values. For regression purposes, we exclude workers in non-profit firms and workers in *Armed Forces* and *Skilled Agricultural and Fishery* occupations. We exclude hourly earnings with bonus below USD\$1 and above USD\$150.

Table A.3. Task Regressions across Sectors

Panel A: Manufacturing												
VARIABLES	Unconditional						Conditional					
	Abstract		Routine		Manual		Abstract		Routine		Manual	
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and Job Characteristics	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
ICT Use at the Occupation Level and Country							0.622*** (0.0254)	0.284*** (0.0294)	-0.398*** (0.0274)	-0.139*** (0.0299)	-0.654*** (0.0244)	-0.445*** (0.0276)
ICT Use at the Worker Level		0.543*** (0.0122)		-0.355*** (0.0132)		-0.494*** (0.0121)		0.372*** (0.0191)		-0.286*** (0.0176)		-0.231*** (0.0172)
Constant	0.0223 (0.0323)	0.0331 (0.0251)	-0.114*** (0.0284)	-0.121*** (0.0264)	0.00988 (0.0341)	0.000108 (0.0277)	-0.772*** (0.120)	-0.440*** (0.112)	0.103 (0.135)	-0.153 (0.137)	0.517*** (0.111)	0.311*** (0.111)
Observations	21,401	21,401	21,401	21,401	21,401	21,401	21,401	21,401	21,401	21,401	21,401	21,401
R-squared	0.035	0.358	0.126	0.257	0.031	0.302	0.357	0.427	0.243	0.282	0.373	0.400
Panel B: Construction												
VARIABLES	Unconditional						Conditional					
	Abstract		Routine		Manual		Abstract		Routine		Manual	
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and Job Characteristics	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
ICT Use at the Occupation Level and Country							0.676*** (0.0519)	0.420*** (0.0605)	-0.298*** (0.0617)	-0.214*** (0.0710)	-0.558*** (0.0527)	-0.255*** (0.0607)
ICT Use at the Worker Level		0.501*** (0.0267)		-0.219*** (0.0261)		-0.567*** (0.0268)		0.293*** (0.0339)		-0.0966*** (0.0356)		-0.348*** (0.0379)
Constant	0.110 (0.0702)	0.311*** (0.0646)	-0.130** (0.0622)	-0.218*** (0.0611)	0.440*** (0.0757)	0.212*** (0.0524)	-0.673*** (0.247)	-0.581** (0.245)	0.310 (0.282)	0.279 (0.282)	0.0278 (0.179)	-0.0817 (0.174)
Observations	4,969	4,969	4,969	4,969	4,969	4,969	4,969	4,969	4,969	4,969	4,969	4,969
R-squared	0.083	0.286	0.181	0.219	0.093	0.419	0.378	0.410	0.274	0.278	0.466	0.523
Panel C: Services												
VARIABLES	Unconditional						Conditional					
	Abstract		Routine		Manual		Abstract		Routine		Manual	
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual and Job Characteristics	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
ICT Use at the Occupation Level and Country							0.426*** (0.0207)	0.168*** (0.0209)	-0.297*** (0.0211)	-0.0984*** (0.0216)	-0.618*** (0.0202)	-0.464*** (0.0223)
ICT Use at the Worker Level		0.532*** (0.00999)		-0.332*** (0.00991)		-0.421*** (0.00993)		0.369*** (0.0124)		-0.284*** (0.0121)		-0.221*** (0.0126)
Constant	-0.00928 (0.0255)	0.0133 (0.0214)	-0.227*** (0.0220)	-0.241*** (0.0213)	0.00255 (0.0264)	-0.0153 (0.0225)	-0.708*** (0.0882)	-0.328*** (0.0830)	-0.177* (0.0945)	-0.470*** (0.0925)	0.796*** (0.0849)	0.567*** (0.0858)
Observations	50,050	50,050	50,050	50,050	50,050	50,050	50,050	50,050	50,050	50,050	50,050	50,050
R-squared	0.036	0.286	0.102	0.204	0.025	0.181	0.278	0.352	0.186	0.232	0.245	0.271

Note: Dependent variable are the Task constructs. For country dummies, we use Germany as country of reference. Individual characteristics include gender, age, and level of education. Skill characteristics include average literacy and numeracy score in the PIAAC test. Job characteristics include firm ownership, firm size, and on-the-job training activities. Robust standard errors in parentheses (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4. Task Regressions and ICT Skills of workers

VARIABLES	Abstract		Routine		Manual	
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Individual and Job Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
ICT Use at the Occupation Level and Country	0.237*** (0.0224)	0.237*** (0.0223)	-0.0801*** (0.0234)	-0.0787*** (0.0233)	-0.484*** (0.0224)	-0.484*** (0.0224)
Ict Use at the Worker Level	0.344*** (0.0125)	0.342*** (0.0127)	-0.262*** (0.0120)	-0.255*** (0.0123)	-0.225*** (0.0120)	-0.223*** (0.0122)
Problem Solving Skills		0.000469 (0.000482)		-0.00167*** (0.000538)		-0.000543 (0.000475)
Constant	-0.204** (0.0894)	-0.230** (0.0940)	-0.634*** (0.0996)	-0.542*** (0.106)	0.538*** (0.0885)	0.568*** (0.0933)
Observations	56,497	56,497	56,497	56,497	56,497	56,497
R-squared	0.299	0.299	0.222	0.224	0.330	0.330

Note: The sample excludes Spain, France and Italy. Dependent variable are the Task constructs from the newly constructed sample. For country dummies, we use Germany as country of reference. Individual characteristics include gender, age, and level of education. Skill characteristics include average literacy and numeracy score in the PIAAC test. Job characteristics include firm ownership, firm size, and on-the-job training activities. Robust standard errors in parentheses (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A. 5. Wage regressions with individual and job characteristics.

Variables	Raw	Individual	Ability	Job	Occupation	ICT use
Gender		0.240*** (0.00865)	0.218*** (0.00893)	0.199*** (0.00904)	0.190*** (0.00986)	0.175*** (0.00991)
Age (Reference= 40-44)		-0.288*** (0.0176)	-0.284*** (0.0176)	-0.275*** (0.0172)	-0.242*** (0.0169)	-0.236*** (0.0169)
20-25		-0.172*** (0.0165)	-0.170*** (0.0164)	-0.167*** (0.0160)	-0.146*** (0.0159)	-0.149*** (0.0159)
25-29		-0.0493*** (0.0167)	-0.0439*** (0.0165)	-0.0474*** (0.0160)	-0.0386** (0.0156)	-0.0401*** (0.0155)
30-34		0.0443*** (0.0156)	0.0494*** (0.0152)	0.0418*** (0.0147)	0.0428*** (0.0146)	0.0465*** (0.0144)
35-39		0.0607*** (0.0166)	0.0692*** (0.0164)	0.0603*** (0.0159)	0.0516*** (0.0157)	0.0588*** (0.0156)
45-49		0.0460*** (0.0169)	0.0621*** (0.0168)	0.0553*** (0.0162)	0.0467*** (0.0159)	0.0578*** (0.0156)
50-54		0.0745*** (0.0223)	0.0957*** (0.0218)	0.0901*** (0.0217)	0.0796*** (0.0200)	0.0905*** (0.0199)
55-59		-0.0516** (0.0224)	-0.0130 (0.0224)	0.00573 (0.0218)	0.00396 (0.0205)	0.0209 (0.0205)
60-65		-0.162*** (0.0113)	-0.0943*** (0.0117)	-0.0788*** (0.0116)	-0.0562*** (0.0113)	-0.0457*** (0.0112)
Lower secondary or less		0.161*** (0.0139)	0.126*** (0.0142)	0.104*** (0.0141)	0.0625*** (0.0138)	0.0525*** (0.0137)
Post-secondary and tertiary (professional)		0.419*** (0.0112)	0.344*** (0.0123)	0.301*** (0.0122)	0.172*** (0.0135)	0.146*** (0.0134)
Tertiary (Bachelor/Master)						
Literacy Skill			-0.000126 (0.000250)	-4.89e-05 (0.000246)	0.000130 (0.000255)	0.000119 (0.000249)
Numeracy Skill			0.00227*** (0.000229)	0.00188*** (0.000223)	0.00119*** (0.000226)	0.000933*** (0.000221)
Activities - Last year - On the job training				0.116*** (0.00916)	0.0928*** (0.00902)	0.0781*** (0.00878)
Private Sector				-0.00408 (0.0111)	0.0164 (0.0111)	0.000855 (0.0110)
1 to 10 people				-0.134*** (0.0118)	-0.121*** (0.0115)	-0.117*** (0.0113)
11 to 50 people				-0.0536*** (0.0116)	-0.0505*** (0.0112)	-0.0482*** (0.0110)
51 to 250 people				0.0652*** (0.0141)	0.0558*** (0.0139)	0.0522*** (0.0137)
more than 1000 people				0.182*** (0.0206)	0.166*** (0.0192)	0.159*** (0.0191)
Occupation (Reference is Elementary Occupation)						
Legislators, senior officials and managers					0.524*** (0.0250)	0.421*** (0.0257)
Professionals					0.342*** (0.0230)	0.262*** (0.0234)
Technicians and associate professionals					0.264*** (0.0214)	0.186*** (0.0220)
Clerks					0.159*** (0.0203)	0.0740*** (0.0210)
Service Workers and shop and market sale workers					0.0325 (0.0206)	0.0152 (0.0205)
Craft and related trade workers					0.139*** (0.0220)	0.133*** (0.0219)
Plant and machine operators					0.0908*** (0.0221)	0.0946*** (0.0220)
ICT Use						0.0494*** (0.00318)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.842*** (0.0114)	2.631*** (0.0164)	2.053*** (0.0380)	2.131*** (0.0410)	2.124*** (0.0434)	2.270*** (0.0443)
Observations	55,193	55,193	55,193	55,193	55,193	55,193
R-squared	0.436	0.552	0.564	0.586	0.612	0.619

Notes: Dependent variable is log hourly wage in USD (PPP) Robust standard errors in parentheses (***) $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). The ICT Use index was reconstructed with the sample of all countries except Canada, Sweden and the United States.