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ABSTRACT

Differences in Job De-Routinization in OECD Countries: Evidence from PIAAC[1]

The aim of the paper is threefold. First, we compute differences on the degree of de-routinization of job contents 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 difference in the degree of de-routinization of job contents. Third, we test whether higher degrees of technology adoption are associated to higher wage inequality. Our results show remarkable differences in the degree of de-routinization of job contents across countries, being computer adoption at work a key significant driver of such differences. In particular, ICT use at work explains 13.4% (6.3%) of the cross-country unconditional (conditional) differences in de-routinization of job contents. Regarding the impact of adoption technology on wage inequality, our results indicate that although differences in ICT adoption explain an important and significant part of wage differentials, the effect is homogeneous for all the wage distribution, implying that we cannot find a significant association between wage inequality and technology adoption.

JEL Classification: J24, J31, O33

Keywords: routine-biased technological change, de-routinization, polarization, PIACC, RIF-Regressions, wage decomposition

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I. Introduction

Technological change 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 machines (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 years[2]. 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*.

Employment polarization, or the polarization of job contents, was initially described in the United States first by Acemoglu (1999) and more in depth by Autor, Katz, and Kearney (2007), in the United Kingdom by Goos and Manning (2007), in Germany by Spitz-Oener (2006), and later extended to a selected group of 15 European countries by Goos, Manning and Salomons (2009 and 2014). A recent overview by Acemoglu and Autor (2011) shows for the US that employment growth by occupation was monotone in occupational skill percentiles during the 1980s[3], with an employment decline of occupations below the median skill level and an employment increase of occupations above the median skill level. However, in the 1990s, the pattern changed: employment growth was faster at higher percentiles, but it was also slightly positive at occupations in low skill percentiles and negative at middle-skill percentiles. Finally, in the 2000s, the shift was extended towards employment growth concentrated among the lowest deciles of the skill distribution, with little changes in the middle and high ends of the skill distribution. In aggregate terms, the period 1979-2007 gives rise to a U-shaped pattern of employment growth by occupation skill percentiles in the United States. Goos, Manning

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

[3] Skill percentiles are measured as the employment-weighted percentile rank of an occupation´s mean log wage.

and Salomons (2014) depict the change in employment by three occupation groups in the period 1993-2006 for 16 EU countries[4]. Their findings indicate that the employment polarization has arisen, with employment declining in middle occupations in all countries, growing in high-wage occupations for most countries and either growing in absolute terms low-wage occupation or at least in relative terms with respect to middle-wage occupations. Acemoglu and Autor (2011) compare this evolution with the US in the same period and find that employment polarization appears to be at least as pronounced in the EU as in the US. As commented by Autor (2014), this process will have extremely important implications for the future of labor markets as well as education systems during the next decades.

A natural question following the Routine Biased Technological Change hypothesis is the effect that technology adoption can have, through the displacement of routine labor, 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 polarization process. In European countries, research has provided descriptive evidence on wage polarization for the UK and Germany[5] 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 jobs[6].

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 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

[4] The authors also provide aggregate numbers for all 16 EU countries and find an increase of 6.2% of high-wage occupations, a decrease of 7.8% of middle-wage occupations and a a slight increase of 1.6% of low-wage occupations.
[5] See for Machin (2011) for the UK, Dustmann and Ludsteck and Schönberg (2009) for Germany.
[6] This explanation is also consistent with the analysis by OECD (2011).

(see Spitz, 2007 and Autor and Handel, 2011). In particular, Spitz argues that job content changes in Germany take place mostly within, rather than between occupations[7]. To make the task framework more precise, it is clear that more research is needed using data at the worker level.

In addition, evidence on differences on the degree of Routine Biased Technical Change and its impact on employment and wages across countries has been gathered using either industry-level or occupation-level data. The work by Goos, Manning and Salomons (2014), which shows the pervasiveness of job polarization across 16 Western European Countries, follows Autor and Dorn (2013) and constructs observations at occupation level. The analysis by Massari, Naticchioni and Ragusa (2014)[8] use worker-level data for wage analysis, but the task measurements are considered at the occupation level, following in fact Goos, Manning, and Salomons (2014). Understanding the degree of polarization accounting for within-occupation heterogeneity would therefore be the next step for validating past comparable research across countries.

This paper sheds light on the phenomenon described in three different dimensions. First, we compute differences in the degree of de-routinization of job contents across a harmonized and hence comparable sample 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 job task heterogeneity within occupations when accounting for differences on the degree of de-routinization. To our knowledge, this approach has only been followed in two different and unrelated surveys in Germany (Spitz) and the US (Autor and Handel). Moreover, the data includes an accurate measurement of cognitive skills in literacy, numeracy and problem solving skills at the individual level to control for unobserved heterogeneity, and hence individuals with the same cognitive skills can be compared with regards to their job tasks.

Second, we assess whether greater adoption in ICT (a proxy for technological adoption) is associated with a greater degree of job de-routinization across countries as well as a larger net inflow of high-skill labor to tasks complementary with computer capital. Finally, we look at the extent to which such differences in computer adoption have an impact on the wage structure, as the employment polarization theory would predict. For both questions, we use worker-level data to control for within-occupation differences when comparing job de-routinization and wage structure across countries.

To do so, we use data from the Programme for the International Assessment of Adult Competencies (PIAAC) in 22 countries collected between 2011 and 2012. Given the

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7 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.

8 They do this using data from the European Community Household Panel (ECHP) and from the European Income and Living Conditions (EU-SILC).

cross-sectional nature of this data set, we cannot account for time dynamics to measure the de-routinization process that a country is experiencing in its labor market. On the flipside, PIAAC provides a snapshot to depict the stage of de-routinization in every country in the sample and test the job and wage polarization hypothesis. Moreover, the data provides information on wages, thus complementing the work by Goos, Manning and Salomon (2014), which can only look at labor demand dynamics.

Our findings stress the importance of ICT adoption at work to explain cross-country differences in the degree of job de-routinization. In particular, ICT use at work explains 13.4% of the cross-country differences in an unconditional model, and 6.2% of the cross-country differences in a conditional model (where we control for individual, ability and job characteristics for each worker and look into within-occupation differences). Second, results indicate that the differences in ICT adoption explain an important and significant part of the individual wage differentials, but the effect is proportionally similar along the whole wage distribution, implying that we cannot find an impact of ICT adoption on wage inequality measurements.

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 de-routinization and wage inequality for different OECD countries. Section 6 concludes.

II. Theoretical Framework

We follow Autor and Dorn (2013) theoretical framework, which present a general equilibrium model of routine task replacement. They consider an economy with two sectors which produce "goods" and "services", using as inputs computer capital and three labor (task) inputs: *Manual*, *Routine*, and *Abstract*. In the production function of goods, they assume that computer capital is a relative complement to abstract labor and a relative substitute for routine labor. The service production function uses only manual labor. There are two types of workers: high-skill workers supply abstract labor inelastically to the goods sector, while low-skill workers supply either manual or routine labor, depending on their (heterogeneous) skills at performing manual tasks. The main driver of the model is an exogenous decline of the price of capital. Their basic implication is that in equilibrium, provided that the elasticity of substitution in production between computer capital and routine labor is high relative to the elasticity of substitution in consumption between goods and services, low-skill labor flows accordingly from the production of goods to services. Given that routine occupations are found in the middle of occupational skill distribution, employment "polarizes". They note, however, that because workers who remain in the goods sector can be positively selected, the ratio of wages paid to workers in goods versus service occupations need not fall as rapidly as the ratio of wagers paid to an efficiency unit of routine versus manual task input.

The model is later extended to an integrated spatial equilibrium setting, with mobility of high-skill workers across local labor markets in response to changes in real earnings induced by the interaction between a uniformly falling price of automating routine tasks and regional heterogeneity in production specialization. The spatial equilibrium provides two implications of our interest. As the price of computer capital falls exogenously, local labor markets with initial specialization in routine tasks will experience the following:

(i) Greater adoption of information technology, coinciding with the displacement of labor from routine tasks and hence greater reallocation of low-skill workers from routine task-intensive occupations to service occupations (job polarization due to de-routinization), as well as a larger net inflow of high-skill labor to tasks complementary with computer capital.

(ii) Larger increases in wages for both high-skill *Abstract* and low-skill *Manual* labor (wage polarization).

For our purpose, we exploit these implications and consider different countries as local labor markets. Given the cross-sectional nature of our database, we observe differences in the degree of the de-routinization process across countries, but not the dynamics of such process. In this setting, Autor and Dorn (2013) model implies that similar workers across countries with lower (greater) relative price of computer capital will experience:

(i) Greater (lower) adoption of information technology, coinciding with a greater (lower) degree of job de-routinization.

(ii) Greater (lower) wage increases for both high-skill *Abstract* and low-skill *Manual* labor relative to those in the middle of the distribution.

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 States[9]. 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

[9] 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.

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 life[10]. As said previously, the variables of skills used at work (tasks) 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 analysis[11] 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 analysis[12]. These two indexes reflect non-manual routine job contents. We gather those two indexes with the

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

[11] 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.

[12] 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).

"Accuracy with hands and fingers" task[13], which reveal more routine manual tasks, and compute the first component of a principal component analysis.

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

Notes: Most questions provide answers in a scale of time frequencies[14] 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 frequencies[15] (Flexibility at Job). Level of Computer Use (G_Q06) includes three answers: straightforward, moderate and complex.

Table 1 depicts the job task items from the PIAAC background questionnaire that are used to construct each of the task indexes[16]. 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

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

[14] 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.

[15] 1=Not at all; 2=Very little; 3=To some extent; 4=To a high extent; 5= To a very high extent.

by using the questionnaire items related to cognitive analytical tasks (3 items), and interactive tasks (2 item).

Finally, we use information from the "Physical Work" item as our *Manual* task index. Two issues need attention regarding this task construction. 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* category of tasks would be best defined in terms of non-routine and hence non-codifiable tasks[17]. These would include, among others, dexterity, coordination, object handing 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 dissentangle between non-routine manual and non-manual routine. Still, we consider this to be the most sensitive approach.

To test the task polarization hypothesis, Autor and Dorn (2013) combine the three dimensions of task measures and construct a summary measure of Routine task-intensity (RTI), so that at the worker level we have:

$$RTI_i = \ln R_i - \ln A_i - \ln M_i$$

where R_i , A_i and M_i correspond to the values of *Routine*, *Abstract* and *Manual (*non-routine*)* tasks indexes respectively. The measure increases with the weight of *Routine* tasks for a given worker and decreases in the weight of *Abstract* and *Manual* non-routine tasks. To exploit more of its variation and the fact that the correlation with ICT use at work is higher, we define an alternative RTI construct:

$$RTI_i = R_i - A_i - M_i$$

Our index is highly correlated with Autor and Dorn (2013) specification (0.97) but we opt not to transform it in logs so as to prevent further transformations to ensure positive values of the task measures[18]. In addition, if we do such transformation, our RTI measure loses correlation with the Index of ICT use at work (-0.25 as opposed to -0.16). Table 2 presents country aggregates of task measurements and the our proposed RTI

[17] 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, tolos, 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*".

[18] For both index specifications, we first standardize each of the sub-components and then standardize the index to mean 0 and standard deviation 1 again. In the case of the Autor and Dorn specification, we would translate the sub-components so that these are defined positively before the log function is applied to each of them.

construct. The RTI definition depicts three groups of countries in terms of stages in the de-routinization process. The Nordic and Anglo-Saxon countries (United States, Finland, Denmark, Norway, Great Britain, Sweden, and Canada) form the group of countries in a more advanced stage of de-routinization, with between 0.2 and 0.4 standard deviations RTI less than the PIAAC average. We call these countries High De-routinized countries. A second group, formed by Central European countries (Germany, Austria, Ireland, Czech Republic, Estonia, Belgium and Netherlands) are in an intermediate stage of this de-routinization process. We define such group as Medium De-routinized countries. 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 de-routinization. This group of countries is defined as Low De-Routinized countries.

Table 2. Task measures by countries.

	RTI	Routine	Abstract	Manual
Korea	0.44	0.72	-0.09	-0.01
Italy	0.43	0.36	-0.45	0.00
Russia	0.39	0.62	-0.09	-0.02
Japan	0.26	0.08	-0.12	-0.28
France	0.23	0.15	-0.17	-0.11
Slovak Republic	0.22	0.10	-0.29	-0.02
Poland	0.13	0.06	-0.23	0.04
Spain	0.11	-0.06	-0.26	-0.02
Netherlands	0.09	0.06	-0.03	-0.09
Belgium	0.07	-0.05	-0.04	-0.13
Estonia	0.07	-0.13	-0.22	-0.03
Czech Republic	0.00	0.03	0.01	0.02
Ireland	-0.06	0.05	0.12	0.05
Austria	-0.09	-0.23	-0.11	0.03
Germany	-0.12	-0.18	0.01	0.03
Canada	-0.15	-0.21	0.13	-0.07
Sweden	-0.16	-0.28	0.04	-0.03
Great Britain	-0.16	-0.09	0.25	-0.03
Norway	-0.18	-0.23	0.13	-0.02
Denmark	-0.22	-0.35	0.04	0.03
Finland	-0.23	-0.38	0.30	-0.24
United States	-0.39	-0.35	0.21	0.18
Mean	0.00	0.00	0.00	0.00
Standard Deviation	1.00	1.00	1.00	1.00
Observations	77,867	77,867	77,867	77,867

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 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.

Table 3. Task measures by individual and job characteristics.

	RTI	Routine	Abstract	Manual
Gender				
Female	0.12	-0.01	-0.12	-0.11
Male	-0.10	0.00	0.10	0.10
Age				
20-24	-0.11	-0.12	-0.18	0.26
25-29	-0.11	-0.09	0.10	0.03
30-34	-0.07	-0.08	0.10	-0.05
35-39	-0.06	-0.10	0.10	-0.08
40-44	0.00	0.00	0.05	-0.04
45-49	0.04	0.04	-0.03	-0.01
50-54	0.10	0.15	-0.05	0.00
55-59	0.12	0.12	-0.08	-0.02
60-65	0.22	0.18	-0.18	-0.05
Education Level				
Lower Secondary or less	0.31	0.37	-0.69	0.48
Upper secondary	0.00	0.03	-0.18	0.21
Post-secondary or Tertiary Professional	-0.04	0.02	0.03	0.07
Tertiary (bachelor/master)	-0.09	-0.20	0.47	-0.50
Numeracy Skills (Quartile Group)				
Quartile 1	0.05	0.13	-0.38	0.41
Quartile 2	-0.01	0.03	-0.10	0.15
Quartile 3	0.02	0.01	0.08	-0.11
Quartile 4	-0.06	-0.17	0.38	-0.43
Literacy Skills (Quartile Group)				
Quartile 1	0.07	0.16	-0.38	0.41
Quartile 2	-0.03	0.02	-0.06	0.12
Quartile 3	-0.03	-0.04	0.11	-0.10
Quartile 4	-0.01	-0.13	0.31	-0.42
Public/Private				
Public	0.00	-0.02	0.16	-0.18
Private	0.00	0.01	-0.05	0.06
Size of workplace				
1-10 workers	0.10	0.06	-0.24	0.12
11-50 workers	-0.03	0.01	0.00	0.06
51-250 workers	0.01	0.05	0.05	-0.02
251-1000 workers	-0.05	-0.08	0.11	-0.10
more than 1000 workers	-0.10	-0.18	0.28	-0.28
On-the-Job-Training				
No	0.21	0.21	-0.25	0.07
Yes	-0.30	-0.29	0.36	-0.09
Occupation				
Legislators, Senior officials and managers	-0.45	-0.48	0.88	-0.51
Professionals	-0.11	-0.24	0.45	-0.49
Technicians and associate professionals	-0.14	-0.23	0.33	-0.30
Clerks	0.38	0.02	-0.11	-0.58
Service workers and shop and market sales workers	0.06	0.17	-0.35	0.41
Craft and related trades workers	-0.20	0.04	-0.26	0.67
Plant and machine operators and assemblers	0.35	0.59	-0.61	0.55
Elementary Occupations	0.32	0.51	-0.83	0.74
Sector				
Manufacturing	0.08	0.10	-0.06	0.02
Construction	-0.18	0.05	-0.08	0.46
Services	-0.02	-0.06	0.04	-0.06

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.

In particular the correlation between *Abstract* and *Manual* task intensities is negligible (-0.01) while negative and 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 issues related to our measurement of *Manual* tasks.

A deeper look at the task indexes is taken in Table 3, in which we disaggregate our RTI index and its two task components by a set of individual and job characteristics. As we can see, female workers show slightly higher RTI intensity, and this is a result of mainly less *Abstract* and *Manual* intensive tasks. Moreover, we can see that RTI index increases with age, and decreases with the level of education and (only slightly) with cognitive skills.

On job characteristics, we see that workers have a similar RTI in the private and public sectors, as the effect of *Abstract* (more prominent in public sector) and *Manual* (more prominent in the private sector) tasks cancel each other as a consequence of higher Routine and lower Abstract task intensities. Moreover, the RTI index shows important differences between the very small (less than 10 workers) and the very large (more than 251) firms. Following the underlying framework, it may be the case that technology adoption is closely related with firm size. With respect to worker occupations, RTI is low for the three high-skill occupations (managers, technicians and professionals), high for clerks, plant and machine operators (middle skill occupations) and construction (low-skill occupation) and takes lower values for the case of service workers (low-skill) and craft and trade workers (middle-skill). Finally, workers in manufacturing sector display a higher RTI when compared to services and construction. Services workers, compared with those in manufacturing, exhibit lower *Routine* and *Manual* and higher *Abstract* tasks intensities. Finally, workers receiving on-the-job-training display a significantly lower RTI index.

The implicit assumption underlying the task framework is that the decline in the price of computer capital (the exogenous driver of the model) 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 measurements[19]. In the previous section, Table 1 also displays the questionnaire items used to construct such index, computed choosing the first component of a principal component analysis[20].

[19] 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. We follow this approach.

[20] 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.

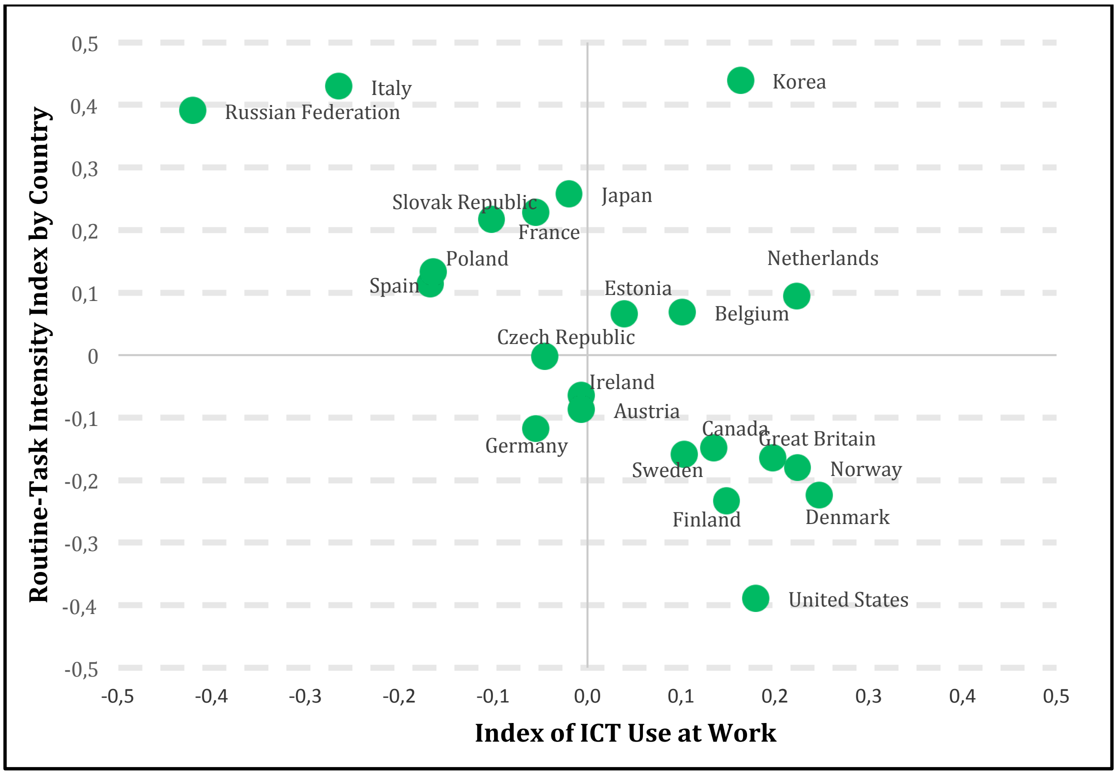
Table 4. ICT Use Index by countries.

	ICT Use Index		
	Obs	Mean	Std. Dev.
Russian Federation	1,690	-0.42	0.85
Italy	2,024	-0.27	0.97
Spain	2,490	-0.17	0.97
Poland	3,907	-0.16	0.98
Slovak Republic	2,559	-0.10	1.01
France	3,431	-0.06	0.98
Germany	3,107	-0.05	0.95
Czech Republic	2,728	-0.05	0.99
Japan	3,142	-0.02	0.94
Ireland	2,761	-0.01	1.00
Austria	2,789	-0.01	0.96
Estonia	4,333	0.04	1.02
Belgium	2,625	0.10	0.98
Sweden	2,688	0.10	0.89
Canada	14,456	0.13	1.00
Finland	3,051	0.15	0.91
Korea	2,954	0.16	1.12
United States	2,553	0.18	1.03
Great Britain	4,530	0.20	1.02
Netherlands	2,880	0.22	0.94
Norway	2,916	0.22	0.91
Denmark	4,253	0.25	0.98
Total	77,867	0.00	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, we exclude workers in non-profit firms and workers in Armed Forces and Skilled Agricultural and Fishery occupations.

As can be seen on Table 4, 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 RTI index by countries in Figure 1 indicates a strong relation between the two. This relation will later be explored, once the empirical strategy on the task de-routinization hypothesis is presented in next section.

Figure 1. ICT Use and RTI Index by countries.



Notes: The cross-country correlation between the two variables is -0.64.

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. Although there are similarities with RTI index country rankings, exploiting the variation of RTI and wages within and across countries will be crucial for our empirical approach on changes in the wage structure.

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

	Hourly Earnings with Bonus (USD) PPP		
	Obs	Mean	Std. Dev.
Norway	2,909	25.39	11.39
Denmark	4,091	25.17	11.09
Belgium	2,532	22.91	10.61
Netherlands	2,747	22.68	11.81
Ireland	2,602	22.51	13.52
Austria	2,622	20.14	11.19
Germany	3,006	20.06	12.03
Finland	3,066	19.82	8.31
Great Britain	4,380	19.33	13.98
Korea	2,898	18.47	17.08
Japan	3,032	16.83	13.76
Italy	1,738	16.75	10.82
France	3,430	16.09	8.48
Spain	2,320	15.74	10.52
Estonia	3,809	10.03	7.72
Poland	3,660	9.85	7.95
Czech Republic	2,450	9.43	6.11
Slovakia	2,398	8.93	6.55
Russian Federation	1,503	5.33	5.49
Total	55,193	15.52	12.65

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 6 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.

Table 6. Hourly Wages (USD-PPP) by individual and job characteristics

	Obs.	Mean	Std. Dev.
Gender			
Female	28,099	13.46	10.82
Male	27,094	17.31	13.80
Age			
20-24	6,004	10.54	8.31
25-29	6,707	12.74	9.98
30-34	6,813	14.83	11.28
35-39	6,913	16.24	12.58
40-44	7,187	17.22	13.16
45-49	6,953	17.12	14.03
50-54	6,248	16.51	13.09
55-59	5,365	17.36	14.51
60-65	3,003	16.05	14.49
Education Level			
Lower Secondary or less	7,406	13.44	9.43
Upper secondary	22,264	14.37	10.10
Post-secondary or Tertiary Professional	9,878	13.33	11.60
Tertiary (bachelor/master)	15,645	19.64	16.34
Numeracy Skills (Quartile Group)			
Quartile 1	10,871	12.57	9.90
Quartile 2	13,551	13.48	11.06
Quartile 3	14,710	15.00	12.08
Quartile 4	16,061	20.28	14.99
Literacy Skills (Quartile Group)			
Quartile 1	12,304	12.84	10.08
Quartile 2	14,480	14.23	11.52
Quartile 3	14,561	15.72	13.02
Quartile 4	13,848	19.11	14.51
Public/Private			
Public	16,439	16.03	12.26
Private	38,754	15.35	12.77
Size of workplace			
1-10 workers	13,611	12.91	10.69
11-50 workers	17,479	14.25	11.14
51-250 workers	13,061	15.69	12.22
251-1000 workers	6,601	18.73	14.47
more than 1000 workers	4,441	22.13	16.98
On-the-Job-Training			
No	31,329	13.58	11.94
Yes	23,864	18.96	13.12
Occupation			
Legislators, Senior officials and managers	3,754	26.00	19.72
Professionals	11,440	19.70	14.87
Technicians and associate professionals	8,974	17.74	12.35
Clerks	6,525	15.34	10.57
Service workers and shop and market sales workers	11,544	11.14	8.70
Craft and related trades workers	5,807	12.99	10.07
Plant and machine operators and assemblers	4,572	12.78	9.35
Elementary Occupations	2,577	11.81	10.25
Sector			
Manufacturing	15,966	16.55	13.33
Construction	3,555	14.31	10.51
Services	34,848	15.15	12.48

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.

IV. Computer adoption and the degree of Job De-Routinization

Empirical Strategy

In this section, we test whether the adaptation of Autor and Dorn (2013) model implications holds in our empirical setting. We assess the extent to which workers across countries with lower (greater) relative price of computer capital (hence experiencing greater (lower) adoption of information technology) experiment a greater (lower) degree of job de-routinization as well as a larger net inflow of high-skill labor to tasks complementary with computer capital. To test this implication, we consider for a given worker i a pooled linear model with country fixed effects δ_j for countries $j = 1 \dots 22$, where:

$$RTI_{ij} = \alpha + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_n \beta_{2n} X_{ijn}^{Skills} + \sum_o \beta_{3o} X_{ijo}^{Job} + \sum_p \beta_{4p} X_{ijp}^{Occ} + \beta_{5q} X_{ijq}^{ICT} + \delta_j + \varepsilon_{ij} \quad (1)$$

with X_{ij}^{Ind} being the individual worker characteristics (such as gender, age or level of education), X_{ij}^{Skills} being the worker literacy and numeracy cognitive skills, X_{ij}^{Job} being a vector of job characteristics (public or private firm, firm size and on-the-job training), X_{ij}^{Occ} being the 1-digit ISCO occupation code, and X_{ij}^{ICT} being the index of ICT use by the worker. Country fixed effects capture the cross-country differences in the Routine-task-intensity index that cannot be explained by the model. Therefore, we assess the contribution of different covariates to explain such differentials. As said before, our RTI index specification is defined as follows:

$$RTI_i = R_i - A_i - M_i$$

To capture both unconditional and conditional differences in *Routine* (relative to *Abstract*) task-intensity across countries, we estimate the following specifications. First we estimate equation (1) with only country fixed effects. These country fixed effects are the unconditional (raw) cross-country differentials in RTI use. 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 RTI and the extent to which disparities in cross-country differentials in RTI decrease when controlling for ICT use at work. This provides a first approximation to understand the role played by ICT in explaining RTI cross-country variation.

Table 7. Unconditional Differences of RTI across countries.

VARIABLES	(1)	(2)
Country Dummies (Germany as Reference)		
Austria	0.0305	0.0405*
	(0.0243)	(0.0241)
Belgium	0.187***	0.219***
	(0.0243)	(0.0241)
Canada	-0.0307	0.00894
	(0.0212)	(0.0212)
Czech Republic	0.116***	0.118***
	(0.0332)	(0.0325)
Denmark	-0.106***	-0.0429*
	(0.0225)	(0.0224)
Spain	0.231***	0.207***
	(0.0276)	(0.0273)
Estonia	0.184***	0.203***
	(0.0216)	(0.0214)
Finland	-0.115***	-0.0727***
	(0.0225)	(0.0226)
France	0.346***	0.346***
	(0.0242)	(0.0239)
Great Britain	-0.0469*	0.00588
	(0.0269)	(0.0265)
Ireland	0.0532*	0.0633**
	(0.0287)	(0.0284)
Italy	0.547***	0.503***
	(0.0301)	(0.0297)
Japan	0.376***	0.383***
	(0.0246)	(0.0241)
Korea	0.557***	0.603***
	(0.0257)	(0.0247)
Netherlands	0.212***	0.270***
	(0.0243)	(0.0241)
Norway	-0.0626***	-0.00423
	(0.0231)	(0.0232)
Poland	0.251***	0.228***
	(0.0252)	(0.0251)
Russian Federation	0.508***	0.432***
	(0.0416)	(0.0401)
Slovakia	0.335***	0.325***
	(0.0260)	(0.0253)
Sweden	-0.0406*	-0.00749
	(0.0242)	(0.0243)
United States	-0.271***	-0.222***
	(0.0276)	(0.0272)
ICT Use		-0.209***
		(0.00800)
Constant	-0.117***	-0.129***
	(0.0171)	(0.0170)
Observations	77,867	77,867
R-squared	0.095	0.137

Notes: Dependent variable is RTI index (definition). Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). ICT use index is recalculated without data from Canada, Sweden and the United States in the sample.

Table 7 presents the results of the unconditional specification. Taking Germany as country of reference, the results from column (1) resemble qualitatively to the country descriptive statistics of RTI presented on Table 2. When introducing ICT use at worker level, column (2) describes a large explanatory power of ICT use on RTI both in terms of strength (R-square of the model increases from 0.09 to 0.14) and slope. The marginal effect is statistical and economically significant, with an increase of a standard deviation in ICT use at work implying a decrease of 0.61 standard deviations of RTI.

In the second approximation to the model specification, we polish raw differences in RTI with compositional differences in individual and job characteristics. Hence, we compare the resulting country fixed effects in a regression of RTI on individual, job, skill and occupation controls with those obtained in when ICT is also included. This enables us to assess the extent to which disparities in RTI for comparable individuals across countries are due to differences in ICT adoption.

Table 8 depicts the results of the conditional specification, with each column including the previous column´s covariates plus a new set of variables. Taking Germany as the country of reference for the fixed effects, we start with column (1) similar to what we do in Table 7. When adding covariates in each column, the model specification shows that individual, job and occupational worker characteristics are important in explaining RTI differences across countries. We observe that country fixed effects do in fact change and slowly converge to the reference country when we start adding covariates. Specifically, the differences are reduced, both in magnitude and statistically, in columns (3), (4), (5) and (6), which correspond to incorporating cognitive skills, job characteristics, occupation as covariates, and more importantly ICT use.

Table 8. Conditional Differences of RTI across countries.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Country Dummies (Germany as Reference)						
Country Dummies	**X**	**X**	**X**	**X**	**X**	**X**
Individual Characteristics		**X**	**X**	**X**	**X**	**X**
Cognitive Skills			**X**	**X**	**X**	**X**
Job Characteristics				**X**	**X**	**X**
Occupation					**X**	**X**
ICT Use						-0.212***
						(0.0106)
Constant	0.0398**	0.0232	-0.0386	0.0575	0.165**	-0.205**
	(0.0197)	(0.0287)	(0.0719)	(0.0735)	(0.0802)	(0.0801)
Observations	79,567	77,867	77,867	77,867	77,867	77,867
R-squared	0.050	0.131	0.132	0.162	0.197	0.221

Notes: Dependent variable is RTI index without manual tasks. Control variables include country fixed effects for three columns, ICT use for columns (2) and (3) and ICT Use interacted with country fixed effects for column (3). Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Adding ICT use at work from column (5) to column (6) accounts for the differential impact of ICT use in a conditional model of RTI worker differentials that includes all covariates described in equation (1). Including ICT use at work increases the explanatory power (R2) from 0.197 to 0.221, while the marginal effect is similar to the conditional model.

Heterogeneity across sectors

Until now, we have estimated the impact of ICT use at work on the degree of job de-routinization without considering potential heterogeneity of such impact in different sectors such as manufacturing, services and construction. It may be the case that sectors such as manufacturing are more affected by this process than others, such as services or construction. Hence, we re-estimate these specifications separately for each sector. Table A.1 in the Annex describes the main results. The unconditional impact of ICT on job de-routinization is very similar in manufacturing and services (and similar to the aggregate impact), and smaller in construction. When we check the conditional impact, i.e., conditioning on comparable workers, the effect is similar and still very significant.

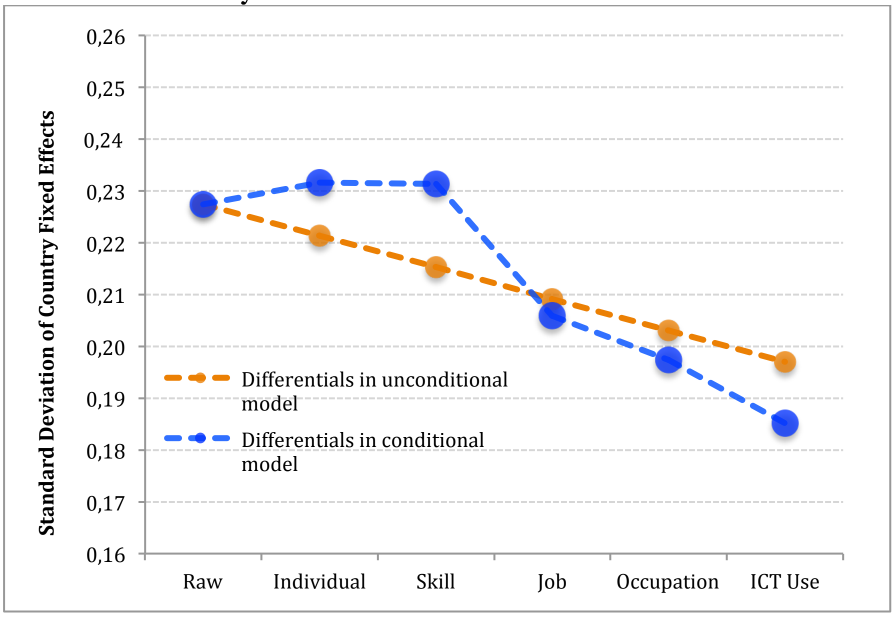
Interpretation of results

The first implication of our adaptation of Autor and Dorn (2013) model implies that similar workers across countries with lower (greater) relative price of computer capital will experience greater (lower) adoption if information technology, coinciding with a greater (lower) degree of job de-routinization as well as a larger net inflow of high-skill labor. Testing this implication requires measuring to what extent the disparity of cross-country differences in RTI is reduced if we introduce the index of ICT use at work in equation (1).

We show this for the unconditional model (see Table 7), but more importantly, for the conditional model in which cross-country differences in RTI are already polished from differences in individual and job characteristics (see Table 8). If the cross-country disparities in the de-routinization process decrease once we account for the use of ICT at work (adoption of information technology), this would mean that differences in job de-routinization would converge, hence providing evidence of the first implication of our cross-sectional adaptation of the Autor and Dorn (2013) model.

Figure 2 depicts the standard deviations of country fixed effects computed in Table 7 (orange dots) and Table 8 (blue dots). An advantage of such statistic is that it is invariant with respect to the country of reference chosen. For the unconditional model from Table 7, we compute the variation in country fixed effects with the raw specification in column (1) and the specification with ICT use at work in column (2). As we can see, the standard deviation falls from 0.227 to 0.197, which represents 13.4% of all variation of cross-country fixed effects for RTI differentials. Regarding the conditional model, we compute the variation in country fixed effects while gradually introducing individual, skill, job and occupation covariates. We observe that the variation drops more pronouncedly when adding job, occupation and also ICT use at work to our model.

Figure 2. RTI Country variation in conditional and unconditional models.

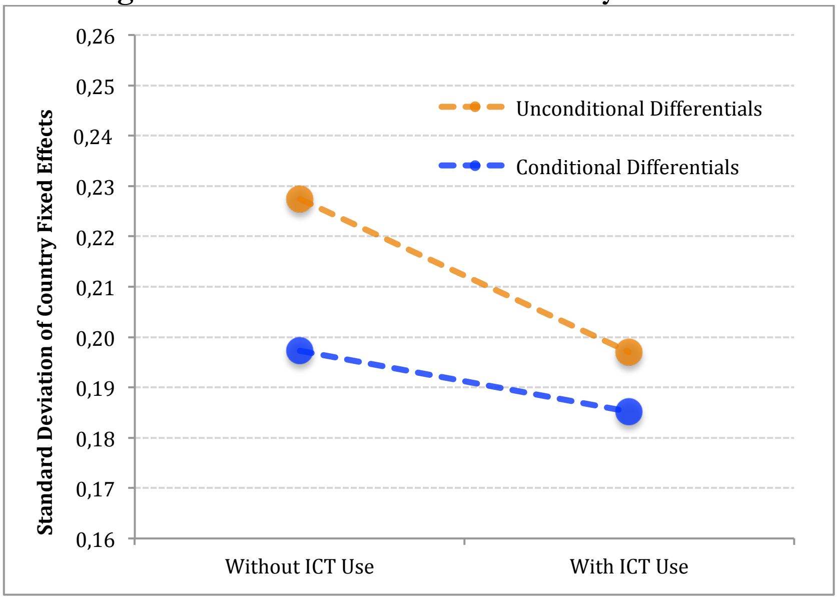


Note: We compute the standard deviations of country effects from Table 7.

In particular, we zoom the results in Figure 2 to observe only the last step from column (5) to column (6) of the unconditional model, so that we can assess the change in the variation in cross-country differentials in RTI when including ICT use at work. What we do is comparing both the unconditional and conditional models when introducing ICT use at work as a covariate. Figure 3 presents such comparison: as we already described in Figure 2, the drop in variation for the unconditional model is 13.4%. One could ask the extent to which this drop is partially by individual and job characteristics adjustments. However, conditioned differences in country fixed effects start at 0.197, but fall to 0.185 when adding ICT use at work as a covariate. This represents a notable 6.2% decrease in country variation in the conditional model[21].

[21] 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 3. Effect of ICT on RTI country variation.



Notes: We compute the standard deviations of country effects from Table 8.

Overall, we observe that ICT use at work is key in explaining differences in de-routinization across countries and, accounts at least 6% of all variation in a completely conditioned model, which even includes individual unobserved characteristics such as cognitive literacy and numeracy skills. A less comprehensive specification does increase this change gradually up to accounting 13% of country variation for the case of unconditional differences of RTI.

V. Computer adoption and Wage Polarization

Empirical Strategy

In this section, we focus on the second implication in our adapted theoretical model. As described in section II, we consider a framework in which similar workers across countries with lower (greater) relative price of computer capital will experience greater (lower) wage increases for both high-skill abstract and low-skill manual labor relative to those in the middle of the distribution. This is derived from the Autor and Dorn (2013) setting, which focus both on high-skill analytical and low-skill service job occupations. Moreover for Canada, Sweden and the United States there is no information beyond wage deciles. We exclude these countries from the sample given that we need variation within wage deciles in order to analyze differences in the wage structure.

Our objective is to study the relation between computer adoption and the wage structure across countries for comparable workers. In a standard wage regression, we include, following the previous section, individual and job characteristics, so that for a given worker i a pooled linear model with country fixed effects δ_j for countries[22] $j = 1 \dots 19$, we have:

$$Log\ W_{ij} = \alpha + \sum_m \beta_{1m} X_{ijn}^{Ind} + \sum_n \beta_{2n} X_{ijn}^{Skills} + \sum_o \beta_{3o} X_{ijo}^{Job} + \sum_p \beta_{4p} X_{ijp}^{Occ} + \beta_{5q} X_{ijq}^{ICT} + \delta_j + \varepsilon_{ij} \quad (2)$$

with $Log\ W_{ij}$ being the hourly log-wage, X_{ij}^{Ind} being the individual worker characteristics (such as gender, age or level of education), X_{ij}^{Skills} being the worker literacy and numeracy cognitive skills, X_{ij}^{Job} being a vector of job characteristics (public or private firm, firm size and on-the-job training), X_{ij}^{Occ} being the 1-digit ISCO occupation code, and X_{ij}^{ICT} being the index of ICT use by the worker. Country fixed effects capture the cross-country differences in log wages that cannot be explained by the model.

Table A.5 in the Annex presents the results of the wage regression. Results are those expected from the related literature. The gender wage gap is reduced from 24% to 18% when controlling for individual and job characteristics. Wages increase with level of education in a hump-shaped curve, and strongly related to cognitive numeracy (but not literacy) skills. Regarding job characteristics, the public sector advantage is not significant, wages grow with firm size, while workers with on-the-job training have a wage premium of 8%. Regarding occupations, wage premiums for managers, professionals and technician occupations are economically large even after controlling for individual characteristics. Finally, the impact of ICT use, our independent variable of interest, is positive and significant, with an increase of a standard deviation in ICT use associated with a 10% increase of wages.

To compare differences in the wage structure, we arbitrarily create three groups of countries by looking on Table 5 at average wages, our dependent variable of interest in equation (2). We choose this approach as opposed to decomposing 19 countries in two-by-two comparisons as this would add significant complexity to our empirical strategy and would make the interpretation of results more cumbersome. One could argue that there could be alternative country group choices by using one of our independent variables of interest (RTI, ICT) or even a measure of the wage structure, such as the level of wage inequality instead of the average wage level. However, we find very strong positive cross-country correlations between the level of development of a country, the level of wages, its intensity of technology adoption at work, the stage of de-routinization of jobs, and more importantly, its wage compression. This implies that the essence of the country groups will be qualitatively the same if we chose ICT use, RTI, wage inequality or the average wage, as we have finally done, to group the countries.

Therefore, we group our sample of countries into High, Medium, and Low wage countries. High-Wage countries include Norway, Denmark, Belgium, Netherlands, and

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

Ireland. For the group of Medium wage countries include Austria, Germany, Finland, Great Britain, Korea, Japan, Italy, France, and Spain. At some distance we group Eastern European countries (Estonia, Poland, Czech Republic Slovakia and Russian Federation) into the Low Wage countries[23].

Figure 4. Log Hourly Wage density, by country groups.

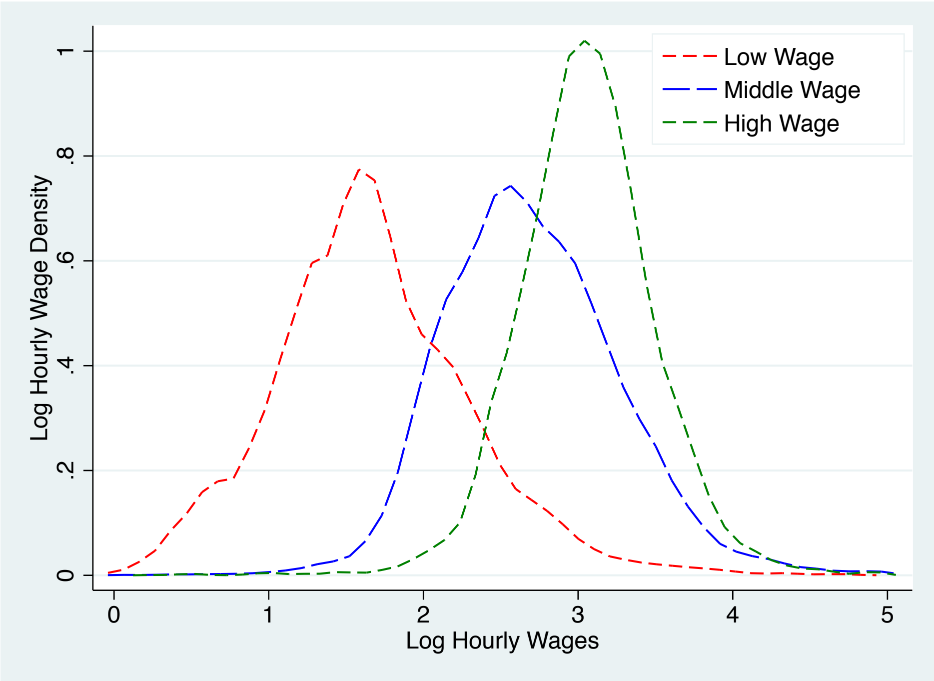


Figure 4 depicts the wage structure of the three groups. Clearly Low and Middle wage groups display larger wage dispersion than the High wage group. This brings another important remark to our empirical strategy. Whether the Autor and Dorn wage implication holds or not, descriptive evidence indicates lower wage inequality on countries (such as North or Central European) which have adopted technology more intensively and as a consequence stand in a more advanced stage in the de-routinization process. That being said, although observed differences in wage inequality will point in the different direction as the one suggested by our theoretical framework, this may have to do with other factors related to development and institutions.

Hence, our objective is to conduct a counterfactual exercise to understand the role played by differences of ICT use (differences in technology adoption) across countries in the wage distribution. It might be the case that ICT use contributes to enlarge wage inequality even though the observed overall dispersion is lower in high wage countries. This would mean that if High wage countries would display the same level of ICT use

[23]We group countries by average wage looking at results on Table 5. The group of Medium Wage countries is larger (9 countries as opposed of 5 countries in the High and Low Wage groups) given the small differences between those countries in terms of wages and the large distance of the border countries (Spain on the bottom and Austria on the top) with the other two groups. However, results do not change if we exclude "border" countries in each group and select instead 3 groups of countries with the (i) 4 highest average wages, (ii) 4 lowest average wages, and (iii) 4 middle-average wages.

than Low wage countries across the whole wage distribution, the wage compression would have been even larger in High wage countries like Finland, Norway or Denmark.

In our counterfactual analysis, we conduct a decomposition of the wage structure between the three groups. A classical approach is a Oaxaca-Blinder decomposition for the mean differences of a linear regression so that for a model with two groups of countries $k = \{0,1\}$, the conditional expectation is:

$$\mathrm{E}[Log\ W_k | X_{ku}] = \alpha_k + X_k' \beta_k \qquad (3)$$

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 groups. The mean difference of log wages between country groups in such specification can be written as:

$$\widehat{\Delta}\ Log\ \overline{W} = \sum_u (\overline{X_{1u}} - \overline{X_{0u}})\, \widehat{\beta_u^*} + \sum_u \overline{X_{1u}} \left(\widehat{\beta_{1u}} - \widehat{\beta_u^*}\right) + \sum_u \overline{X_{0u}} \left(\widehat{\beta_u^*} - \widehat{\beta_{0u}}\right) + \left(\widehat{\alpha_{k_1}} - \widehat{\alpha_{k_0}}\right) \qquad (4)$$

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 groups of countries. The first term of equation (4) is called *wage composition effect* and accounts for differences in mean covariates between both groups. 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 groups, as it loses relevant information on distributional dispersion, tails, or symmetry. To overcome such challenge, we follow Firpo, Fortin and Lemeiux (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 ICT adoption helps explain differences in wage inequality across countries, as the Autor and Dorn (2013) model would predict. The RIF function is a transformation of a dependent variable for a statistic of a given probability distribution. For a quantile q_τ:

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

where D is an indicator function and $f_I(.)$ 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:

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

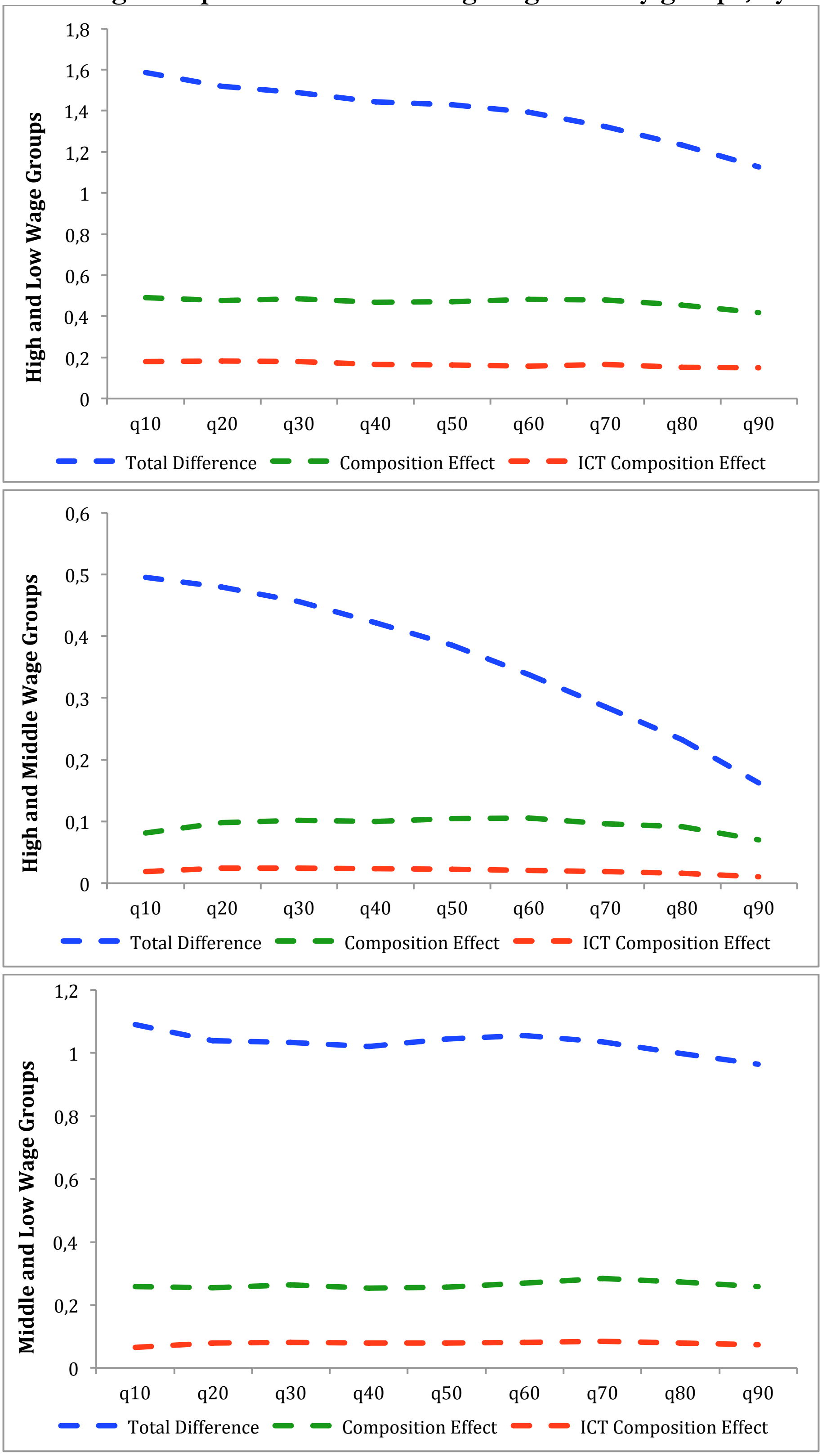
where $\hat{q}_\tau$is the sample quantile and $\hat{f}_I(\hat{q}_\tau)$ is the kernel density estimator. The method adds simplicity to DiNardo (1996), as unconditional distributions are easier to interpret in terms of marginal treatment effects of independent variables. Computing unconditional quantile 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 more simple way.

In our case, we substitute the over time changes of a given country (or group of countries) by a cross-sectional decomposition between two groups of countries. We focus on the composition effect of ICT use at work for each decile, while controlling for other individual and job characteristics. As said before, the advantage of the Firpo, Fortin and Lemieux approach is that the ICT use composition effect can be interpreted in a more simple way, while at the same time we account for worker differences in other dimensions.

Figure 5 depicts the detailed decomposition results for each decile when comparing the three Wage country groups with each other. Each figure presents for each decile the observed total hourly log wage differences between the two groups, the total composition effect due to differences in individual and job covariates, and in particular, composition effect due to differences in ICT use at work only. As we can observe, the wage gap between High with Middle or Low wage groups of countries tends to diminish with larger income groups, meaning that Low and Middle wage countries tend to display larger wage dispersion compared to High Wage countries, as we have already described in Figure 4. As said before, besides the degree of de-routinization implied by technology adoption, there are other factors that influence the structure of wages implying wage compression in this group of countries. The fact that we do not observe larger wage polarization in High wage countries does not mean that ICT adoption cannot have an effect pushing in the opposite direction of such compression.

Comparing High and Low wage country groups, we observe that the total composition effect as a percentage of the total difference goes from 31% for the lowest decile to 37% for the largest decile. For the case of Middle and Low wage groups, the proportion effect slightly increases from 24% (decile 10) to 27% (decile 90). Finally, for the comparison between High and Middle wage groups, the proportion explained by compositional differences grows from 16% to 43% as we advance in the wage distribution deciles. The remaining part of the differences remains therefore unexplained and is due to differences in the returns to individual and job characteristics, as well as other factors that the model cannot explain and which are likely to be much related to institutional labor market aspects.

Figure 5. Wage composition effects among Wage country groups, by deciles.



Note: Results depict log hourly wage (i) overall total difference; (ii) aggregate composition effect; and (iii) ICT use composition effect.

Finally, if the polarization hypothesis holds regarding the wage structure, one would expect that differences in ICT across different country groups would bring heterogeneous effects on the wage distribution, so that low and high-skilled workers would benefit more from ICT adoption relative to middle-skilled workers. If that was the case, compositional effects that arise from differences in ICT use when comparing two different wage groups should have a U-shape form. Although differences of ICT use help explaining individual wage differentials better than any other individual or job covariate, the proportion explained is relatively constant in the wage distribution, indicating that the impact is not unequal either low, middle, or high skill workers.

VI. Conclusion

In this paper we investigate cross-country differences in the degree of job de-routinization by exploiting the different stages in which OECD countries stand regarding technological change, hence the computer adoption at work. The Programme for International Assessment of Adult Competences 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 degree of de-routinization, 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.

We follow Autor and Dorn (2013) theoretical dynamic framework and adapt it to the cross-sectional nature of our database to test two of its implications. Following such model, we construct an index of Routine-Task-Intensity to compute the importance of *Routine* (manual and cognitive) relative to *Abstract* (cognitive and interpersonal) and *Manual* (non-routine) tasks in each job. The first implication of the model that we test is whether for comparable workers across countries, greater adoption in ICT (a proxy for technological adoption) coincides with a greater degree of job de-routinization as well as a larger net inflow of high-skill labor to tasks complementary with computer capital. Our findings indicate the importance of ICT adoption at work to explain cross-country differences in job de-routinization. In particular, ICT use at work explains 13.4% of the cross-country RTI differences in an unconditional model, and 6.3% of the cross country RTI differences in a conditional model (where we control for individual, ability and job characteristics for each worker).

Second, we test the extent to which job de-routinization has an impact, through the displacement of labor, on the wage distribution of countries, as the employment polarization would predict. We conduct a counterfactual analysis to decompose such differences into differences in composition effects related to individual and job characteristics, including ICT use. We do this for each decile of the distribution so we can assess the distributional impact of such compositional differences on the wage distribution. For this, we construct three groups of countries depending on their level of wages of their workers and decompose the differences on the wage structure of the three groups. Our findings indicate that the differences in ICT adoption explain an important and significant part of the gap in wages, but the effect is not very different along the wage distribution, implying that we cannot find a clear impact on wage inequality measurements.

From a policy perspective, our analysis indicates that the job de-routinization process is clearly underway for most developed countries, and that technology adoption is one of the main drivers of such process. As the relative price of technology continues its decreasing trend, technology adoption will increasingly substitute routine jobs by either manual non-routine or abstract ones. This process implies enormous changes for the needed capacities of the labor force, hence posing a clear challenge for the educational and on-the-job training systems of the developed societies. We must adapt our educations 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. Impact of ICT use on RTI by sectors.

	RTI	
	Unconditional	Conditional
All sectors	-0.209***	-0.212***
	(0.00800)	(0.0106)
Manufacturing	-0.215***	-0.236***
	(0.0129)	(0.0172)
Construction	-0.0808***	-0.0858**
	(0.0300)	(0.0417)
Services	-0.236***	-0.247***
	(0.0109)	(0.0138)

Note: The table reports marginal effects of ICT use at work in a linear model by sectors. This is conducted for both the conditional and unconditional models and using both RTI index specifications (without and with the manual index included).

Table A. 2. Wage regressions with individual and job characteristics.

Variables	Raw	Individual	Ability	Job	Occupation	ICT use
Gender		0.240***	0.218***	0.199***	0.190***	0.175***
		(0.00865)	(0.00893)	(0.00904)	(0.00986)	(0.00991)
Age (Reference= 40-44)		-0.288***	-0.284***	-0.275***	-0.242***	-0.236***
20-25		(0.0176)	(0.0176)	(0.0172)	(0.0169)	(0.0169)
		-0.172***	-0.170***	-0.167***	-0.146***	-0.149***
25-29		(0.0165)	(0.0164)	(0.0160)	(0.0159)	(0.0159)
		-0.0493***	-0.0439***	-0.0474***	-0.0386**	-0.0401***
30-34		(0.0167)	(0.0165)	(0.0160)	(0.0156)	(0.0155)
		0.0443***	0.0494***	0.0418***	0.0428***	0.0465***
35-39		(0.0156)	(0.0152)	(0.0147)	(0.0146)	(0.0144)
		0.0607***	0.0692***	0.0603***	0.0516***	0.0588***
45-49		(0.0166)	(0.0164)	(0.0159)	(0.0157)	(0.0156)
		0.0460***	0.0621***	0.0553***	0.0467***	0.0578***
50-54		(0.0169)	(0.0168)	(0.0162)	(0.0159)	(0.0156)
		0.0745***	0.0957***	0.0901***	0.0796***	0.0905***
55-59		(0.0223)	(0.0218)	(0.0217)	(0.0200)	(0.0199)
		-0.0516**	-0.0130	0.00573	0.00396	0.0209
60-65		(0.0224)	(0.0224)	(0.0218)	(0.0205)	(0.0205)
Education Level (Reference is Upper secondary)						
Lower secondary or less		-0.162***	-0.0943***	-0.0788***	-0.0562***	-0.0457***
		(0.0113)	(0.0117)	(0.0116)	(0.0113)	(0.0112)
Post-secondary and tertiary (professional)		0.161***	0.126***	0.104***	0.0625***	0.0525***
		(0.0139)	(0.0142)	(0.0141)	(0.0138)	(0.0137)
Tertiary (Bachelor/Master)		0.419***	0.344***	0.301***	0.172***	0.146***
		(0.0112)	(0.0123)	(0.0122)	(0.0135)	(0.0134)
Skills						
Literacy Skill			-0.000126	-4.89e-05	0.000130	0.000119
			(0.000250)	(0.000246)	(0.000255)	(0.000249)
Numeracy Skill			0.00227***	0.00188***	0.00119***	0.000933***
			(0.000229)	(0.000223)	(0.000226)	(0.000221)
Activities - Last year - On the job training				0.116***	0.0928***	0.0781***
				(0.00916)	(0.00902)	(0.00878)
Private Sector				-0.00408	0.0164	0.000855
				(0.0111)	(0.0111)	(0.0110)
Workplace size (Reference is 51 to 100 people)						
1 to 10 people				-0.134***	-0.121***	-0.117***
				(0.0118)	(0.0115)	(0.0113)
11 to 50 people				-0.0536***	-0.0505***	-0.0482***
				(0.0116)	(0.0112)	(0.0110)
51 to 250 people				0.0652***	0.0558***	0.0522***
				(0.0141)	(0.0139)	(0.0137)
more than 1000 people				0.182***	0.166***	0.159***
				(0.0206)	(0.0192)	(0.0191)
Occupation (Reference is Elementary Occupation)						
Legislators, senior officials and managers					0.524***	0.421***
					(0.0250)	(0.0257)
Professionals					0.342***	0.262***
					(0.0230)	(0.0234)
Technicians and associate professionals					0.264***	0.186***
					(0.0214)	(0.0220)
Clerks					0.159***	0.0740***
					(0.0203)	(0.0210)
Service Workers and shop and market sale workers					0.0325	0.0152
					(0.0206)	(0.0205)
Craft and related trade workers					0.139***	0.133***
					(0.0220)	(0.0219)
Plant and machine operators					0.0908***	0.0946***
					(0.0221)	(0.0220)
ICT Use						0.0494***
						(0.00318)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.842***	2.631***	2.053***	2.131***	2.124***	2.270***
	(0.0114)	(0.0164)	(0.0380)	(0.0410)	(0.0434)	(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.