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**Differences in Job De-Routinization in
OECD countries: Evidence from PIAAC**

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Abstract

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 41% (25%) 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 codes: J24, J31, O33.

Keywords: Routine-Biased Technological Change, De-routinization, Polarization, PIACC, RIF-Regressions, Wage Decomposition

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El cambio tecnológico, producido por una caída relativa del precio del capital tecnológico, está transformando gradualmente el contenido de los trabajos: aquellas tareas que son complementarias a la tecnología y los ordenadores (tareas no rutinarias) han ganado importancia, mientras que aquellas más susceptibles de ser sustituidas por máquinas (repetitivas y rutinarias) la han perdido. Este fenómeno, inicialmente explicado por Autor, Levy y Murnane (2003) ha sido ampliamente descrito en Estados Unidos, incluyendo nuevos estudios que explican un aumento en trabajos poco cualificados con tareas manuales no-rutinarias e interpersonales, muy ligadas al sector de los servicios. La combinación de estos dos fenómenos se conoce como polarización del empleo. La evidencia al respecto es concluyente: desde 1980 se está produciendo una polarización del empleo, no solo en Estados Unidos, sino también en Europa (Goos, Manning, Salomons, 2014) a igual o mayor magnitud.

Una pregunta natural que surge en relación con este fenómeno es el efecto que puede tener sobre los salarios, a través de la desaparición de empleos rutinarios, normalmente ubicados en la parte central de la distribución salarial. En el caso de Estados Unidos, la evidencia apunta en esa dirección (Acemoglu y Autor, 2011), pero en Europa el fenómeno descrito no se ha observado más que en el Reino Unido (Machin, 2011) y Alemania (Dustmann, Ludsteck y Schönberg, 2009), y no se puede extender al resto de países. Como apuntan Massari, Naticchoini y Ragusa (2014), es posible que la ausencia de crecimiento salarial en ocupaciones situadas en la parte baja de la distribución salarial se deba a un aumento del empleo a tiempo parcial y a la temporalidad. La mayoría de estos estudios analizan la polarización del empleo con datos desagregados a nivel de ocupación o de industria, pero los estudios que usan datos a nivel trabajador -en especial Spitz (2006) para Alemania- demuestran la importancia del cambio de tareas en el empleo intra-ocupación, y no sólo inter-ocupación.

Este artículo trata de ilustrar dicho fenómeno, que denominamos des-rutinización del empleo, tomando como fuente la base de datos de PIAAC (diseñada por la OCDE), recogida en 2012 y con valiosa información a nivel de trabajador acerca de las tareas que éste desempeña en su empleo, además de información precisa sobre sus habilidades cognitivas. En concreto se aportan tres resultados de interés.

Primero, calculamos las diferencias en el grado de des-rutinización de las tareas de los trabajos entre países con una muestra comparable y armonizada de 22 países. Observamos que los países más des-rutinizados son los de Europa del norte y los Anglosajones, con un grupo de países con un grado intermedio de des-rutinización que incluye a Europa central y Japón y Corea del Sur y finalmente un grupo de países en un estadio menos avanzado de des-rutinización, que incluyen Europa del sur y Europa del este.

Segundo, evaluamos hasta qué punto el uso de TICs en el trabajo (una variable que refleja la adopción tecnológica) está asociado con una mayor des-rutinización de los trabajos entre países, al igual que un mayor aumento de empleo de alta cualificación cuyas tareas son complementarias al capital tecnológico. En particular, encontramos que el uso de TICs en el trabajo explica el 41% de las diferencias internacionales en un modelo no condicionado (sin

comparar trabajadores similares) y un 25% de las diferencias internacionales en un modelo condicionado (comparando trabajadores similares).

Finalmente, evaluamos hasta que punto y a través de la polarización del empleo, se producen diferencias en la estructura salarial entre países. Nuestros resultados indican que las diferencias en el uso de TICs en el trabajo explica una parte importante de las diferencias de salarios, pero el efecto es proporcional en toda la distribución salarial, lo cual implica que no podemos identificar un impacto del uso de TICs en el trabajo sobre diversas medidas de desigualdad salarial.

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 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*.

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 1980s³, 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

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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 countries⁴. 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 Germany⁵ 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 jobs⁶.

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

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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 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 occupations⁷. 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 41% of the cross-country differences in an unconditional model, and 25% of the cross-country differences in a conditional model (where we control for individual, ability and job characteristics for each worker). 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. Regarding 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 wages 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 States⁹. 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

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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 life¹⁰. 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 analysis¹¹ and then compute the indexes into their standardized form.

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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.

Table 1. Task Framework with PIAAC Data

Task	Sub-Task	Category	PIAAC Questionnaire Item	Item
Abstract	Cognitive Non-routine	Reading	Read Letters, Memos, or e-mails	G_Q01b
			Read Articles in newspapers, magazines or newsletters	G_Q01c
			Read Articles in professional journals or publications	G_Q01d
			Read Diagrams, Maps or Schematics	G_Q01h
		Writing	Write letters, memos or e-mails	G_Q02a
			Write Reports	G_Q02c
		Numeracy	Use or Calculate Fractions, decimals or percentages	G_Q03b
			Use a calculator (Hand or Computer Based)	G_Q03c
			Prepare charts, graphs or tables	G_Q03f
			Use simple algebra or formulas	G_Q03g
		Reasoning	Faced complex problems (>30 mins)	F_Q05b
	Interactive Non-routine		Manage employees	D_Q08a
			Making speeches or give presentations	F_Q02c
			Advising people	F_Q02e
			Planning activities of others	F_Q03b
			Persuading/Influencing People	F_Q04a
			Negotiating with people	F_Q04b
Routine	Cognitive Routine	Flexibility at Job	Change Sequence of Task	D_Q11a
			Change how do work	D_Q11b
			Change working hours	D_Q11d
			Plan own activities	F_Q03a
			Organize own time	F_Q03c
		Lack of Adaptation	Learn work-related things from co-workers	D_Q13a
			Learning-by-doing from tasks performed	D_Q13b
Manual	Manual (both routine + non-routine)		Physical work	F_Q06b
			Hand/Finger Skill Accuracy	F_Q06c
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
			Level of Computer Use	G_Q06

Notes: Most questions provide answers in a scale of time frequencies¹² of activities in tasks (reading, writing, numeracy, cognitive reasoning, interactive, lack of adaption, manual, questions F_Q03a and F_Q03c, and ICT use) and some of them provide answers in intensity of frequencies¹³ (Flexibility at Job except F_Q03a and F_Q03c). Level of Computer Use (G_Q06) includes three answers: straightforward, moderate and complex.

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.

Table 1 depicts the job task items from the PIAAC background questionnaire that are used to construct each of the task indexes¹⁴. We first aggregate the items into five different sub-tasks following Autor, Levy and Murnane (2003), and then collapse them into three tasks proposed by Autor, Katz, and Kearney (2006). When elaborating the *Abstract* task index, we compute the first component of a principal component analysis for the cognitive non-routine sub-task category, by using the questionnaire items related to reading tasks (4 items), writing tasks (2 items), numeracy tasks (4 items) and cognitive reasoning tasks (1 item). Similarly we compute the first component of a principal component analysis for the items related to the interactive non-routine sub-task. Then, we aggregate the two constructs using principal components again.

For the *Routine* task index, we generate by the same procedure two different sub-task indexes for *lack of flexibility and repetitiveness at job* (5 questionnaire items) and *lack of adaptation* (3 questionnaire items), again aggregated by principal component analysis.

Finally, we use information in two additional items to construct the *Manual* task index, therefore computing the standardized mean of the two items. An important constraint in the measurement of manual tasks is that the items *frequency of physical work* and *skill/accuracy with hand or fingers* cannot be exclusively categorized as non-routine tasks. This introduces considerable measurement error in the Manual task index, as it prevents us from disentangling manual routine from manual non-routine job contents, which is crucial when understanding the degree of job de-routinization. Indeed, past literature has only considered non-routine, non-codifiable activities when constructing the *Manual* task index¹⁵ initially proposed in Autor, Katz, and Kearney (2006).

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). With worker-level data, for each worker i following Autor and Dorn (AD) we would have

$$RTI - AD_i = \ln R_i - \ln A_i - \ln M_i$$

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

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¹⁴ We include a subset of all related items provided in the questionnaire when constructing the indexes. This arbitrary decision is based on two reasons: we exclude items with little variation in responses and pick only one from those which are highly correlated.

¹⁵ 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, Katz, and Kearney (2006) 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. From the Occupational Information Network (O*NET), Acemoglu and Autor (2011) use “*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*”.

for a given worker and decreases in the weight of *Abstract* and *Manual* non-routine tasks. As mentioned before, from PIACC data, we cannot disentangle the manual routine from the manual non-routine component, distinction that turns out to be crucial when identifying Manual tasks in the theoretical context of the Routine Biased Technological change. Given this drawback from PIACC dataset, we have opted to remove the manual index from the proposed measure of Autor and Dorn (2013) and focus instead on the *Routine* versus abstract tasks, which are the two types of job contents directly affected by this process – manual non-routine tasks are also affected, but more indirectly, through the displacement of Routine content towards *Manual* non-routine ones. Hence, the resulting index we work with for the empirical analysis is computed as follows¹⁶:

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

Table 2 presents country aggregates of task measurements and the RTI constructs. Our proposed RTI definition depicts three groups of countries in terms of stages in the de-routinization process. The Nordic and Anglo-Saxon countries (Finland, Norway, Sweden, Denmark, United States, Great Britain, Canada, and Netherlands) 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 (Austria, Belgium, Czech Republic, Germany, and Estonia) together with Ireland and Japan 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 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.

The cross-country comparison between the three task indexes shows a very high and negative correlation between Abstract and Routine indexes (-0.71), while the relation with manual task goes along with the polarization hypothesis, although very modestly. In particular the correlation between Abstract and Manual intensities is positive and small (0.13) while negative and small (-0.10) between Routine and Manual. 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 is a result from the aggregation of both routine and non-routine manual job contents in the manual task definition. This confirms our doubts about the measurement error of the Manual task items from the worker questionnaire¹⁷.

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¹⁶ We transform the task indexes into a 0 to 10 scale, so that their logarithmic values are appropriately defined. Moreover, values between 0 and 0.1 are redefined in 0.1.

¹⁷ Countries with high Abstract intensities do not necessarily have high levels of Manual task intensities, therefore implying variation in country ranking depending on the RTI specification used. For comparability purposes, we also include the Autor and Dorn (AD) RTI specification in Table A.1 in the Annex. As we can see, Japan, Netherlands, Sweden or Finland workers perform significantly less manual-intensive tasks, therefore with higher RTI following AD definition. The opposite holds for Korea, Slovakia, US or Great Britain, because of their high intensity in performing manual tasks.

Table 2. Task measures by countries.

	RTI	Routine	Abstract	Manual
Italy	0.41	4.93	3.24	6.11
Russian Federation	0.34	5.33	3.59	5.22
Korea	0.28	5.32	4.04	5.03
Slovak Republic	0.27	4.68	3.61	6.43
Poland	0.21	4.57	3.75	6.66
Spain	0.15	4.01	3.60	5.54
France	0.09	4.29	3.93	5.18
Germany	0.04	4.20	4.11	6.37
Belgium	0.03	4.05	4.06	5.45
Czech Republic	0.03	4.31	4.18	6.16
Japan	0.02	4.29	4.07	4.09
Ireland	0.01	4.52	4.49	6.83
Estonia	-0.01	3.96	4.03	6.52
Austria	-0.01	3.95	4.10	6.31
Netherlands	-0.04	4.12	4.28	5.44
Great Britain	-0.16	4.10	4.80	6.59
Canada	-0.19	3.87	4.63	6.38
United States	-0.24	3.83	4.87	7.33
Denmark	-0.30	3.40	4.56	6.36
Norway	-0.33	3.56	4.85	5.11
Sweden	-0.34	3.41	4.62	5.68
Finland	-0.43	3.28	5.10	5.30
Mean	0.00	4.29	4.25	6.02
Standard Deviation	1.00	2.07	2.44	3.59
Number of Observations	79,567	79,950	80,150	80,560

Notes: The RTI index does consider the manual index in the construct. The sample includes employed respondents aged 20-64 currently working. 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.

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 intensive tasks. Moreover, we can see that RTI index increases with age, and decreases with the level of education and cognitive skills.

Table 3. Task measures by individual and job characteristics.

	RTI	Routine	Abstract
Gender			
Female	0.04	4.31	4.09
Male	-0.04	4.27	4.40
Age			
20-24	0.10	4.26	3.67
25-29	-0.07	4.13	4.40
30-34	-0.11	4.12	4.51
35-39	-0.12	4.06	4.55
40-44	-0.06	4.23	4.43
45-49	0.03	4.35	4.26
50-54	0.09	4.54	4.14
55-59	0.12	4.52	4.09
60-65	0.21	4.65	3.77
Education Level			
Lower Secondary or less	0.79	5.31	2.35
Upper secondary	0.14	4.53	3.75
Post-secondary or Tertiary Professional	-0.02	4.36	4.25
Tertiary (bachelor/master)	-0.48	3.52	5.67
Numeracy Skills (Quartile Group)			
Quartile 1	0.44	4.88	3.15
Quartile 2	0.07	4.45	3.97
Quartile 3	-0.09	4.23	4.50
Quartile 4	-0.41	3.61	5.38
Literacy Skills (Quartile Group)			
Quartile 1	0.45	4.91	3.12
Quartile 2	0.05	4.42	4.07
Quartile 3	-0.14	4.12	4.61
Quartile 4	-0.35	3.71	5.20
Public/Private			
Public	-0.14	4.16	4.74
Private	0.05	4.33	4.09
Size of workplace			
1-10 workers	0.18	4.45	3.65
11-50 workers	0.00	4.30	4.25
51-250 workers	-0.02	4.37	4.39
251-1000 workers	-0.11	4.14	4.56
More than 1000 workers	-0.29	3.79	5.04
On-the-Job-Training			
No	0.26	4.73	3.57
Yes	-0.38	3.65	5.24
Occupation			
Legislators, Senior officials and managers	-0.88	2.82	7.03
Professionals	-0.51	3.46	5.67
Technicians and associate professionals	-0.38	3.67	5.17
Clerks	-0.06	4.28	4.22
Service workers and shop and market sales workers	0.18	4.64	3.62
Craft and related trades workers	0.34	4.75	3.15
Plant and machine operators and assemblers	0.76	5.75	2.32
Elementary Occupations	1.22	5.80	1.61
Sector			
Manufacturing	0.11	4.51	3.99
Construction	0.18	4.52	3.74
Services	-0.08	4.14	4.45

Notes: the sample includes employed respondents aged 20-64 currently working. 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.

On job characteristics, we see that in the private sector, workers have a higher RTI index 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 higher RTI scores for workers in small firms as a result of more Routine and less Abstract intensive contents, and the opposite taking place in the largest firms. With respect to worker occupations, RTI is low for the three high-skill occupations (managers, technicians and professionals) and very high for the three low-skill occupations (craft, plant and machine operators, and elementary occupations). Finally, workers in manufacturing sector display a higher RTI when compared to services or construction. Services workers, compared with those in manufacturing, exhibit lower Routine and higher Abstract tasks intensities. Finally, workers receiving on-the-job-training display a significantly lower RTI index.

Table 4. ICT Use Index by countries.

	ICT Use Index		
	Obs	Mean	Std. Dev.
Russian Federation	1,804	-0.49	0.94
Italy	2,089	-0.33	1.03
Poland	4,060	-0.20	1.04
Spain	2,598	-0.20	1.00
Slovak Republic	2,641	-0.15	1.06
France	3,648	-0.09	0.96
Czech Republic	2,803	-0.06	1.03
Germany	3,198	-0.02	0.96
Estonia	4,470	0.01	1.08
Japan	3,205	0.02	0.92
Ireland	2,801	0.03	1.01
Austria	2,855	0.04	0.96
Korea	3,008	0.09	1.09
Belgium	2,717	0.11	0.97
Canada	14,815	0.18	0.96
United States	2,607	0.20	0.99
Sweden	2,813	0.20	0.82
Finland	3,149	0.22	0.85
Great Britain	4,665	0.22	0.98
Netherlands	2,931	0.26	0.90
Denmark	4,321	0.28	0.91
Norway	3,386	0.30	0.85
Total	80,584	0.00	1.00

Notes: the sample includes employed respondents aged 20-64 currently working. For regression purposes, we exclude workers in non-profit firms and workers in Armed Forces and Skilled Agricultural and Fishery occupations.

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 measurements¹⁸. 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 analysis¹⁹. 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 -0.85.

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

¹⁸ 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.

¹⁹ 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.

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	3340	25.32	11.14
Denmark	4132	25.09	11.12
Belgium	2602	22.93	10.92
Netherlands	2783	22.54	11.80
Ireland	2653	22.28	13.62
Austria	2677	20.14	11.38
Germany	3050	20.00	12.03
Finland	3091	19.78	8.31
Great Britain	4486	19.25	14.04
Korea	2947	18.40	17.10
Japan	3077	16.71	13.71
Italy	1790	16.60	10.78
France	3520	16.00	8.48
Spain	2396	15.57	10.45
Estonia	3868	10.03	7.78
Poland	3754	9.79	7.91
Czech Republic	2502	9.35	6.25
Slovakia	2437	8.87	6.54
Russian Federation	1584	5.15	5.43
Total	56,689	15.35	12.64

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 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 above USD\$150.

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

	Obs.	Mean	Std. Dev.
Gender			
Female	28,829	13.34	10.86
Male	27,858	17.11	13.77
Age			
20-24	6,193	10.42	8.29
25-29	6,875	12.65	9.99
30-34	6,961	14.73	11.22
35-39	7,086	16.07	12.57
40-44	7,367	16.97	13.14
45-49	7,159	16.96	14.10
50-54	6,407	16.43	13.12
55-59	5,522	17.03	14.50
60-65	3,119	15.84	14.43
Education Level			
Lower Secondary or less	7,750	13.34	9.42
Upper secondary	22,803	14.27	10.08
Post-secondary or Tertiary Professional	10,113	13.12	11.61
Tertiary (bachelor/master)	16,001	19.41	16.38
Numeracy Skills (Quartile Group)			
Quartile 1	13,453	12.71	10.13
Quartile 2	14,702	14.14	11.47
Quartile 3	14,440	15.65	13.15
Quartile 4	14,089	18.93	14.52
Literacy Skills (Quartile Group)			
Quartile 1	13,293	12.59	10.19
Quartile 2	13,705	13.35	11.02
Quartile 3	14,099	15.15	12.38
Quartile 4	15,587	20.34	14.97
Public/Private			
Public	16,926	15.77	12.29
Private	39,687	15.22	12.76
Size of workplace			
1-10 workers	13,979	12.82	10.69
11-50 workers	17,803	14.10	11.15
51-250 workers	13,319	15.55	12.29
251-1000 workers	6,739	18.65	14.46
more than 1000 workers	4,543	22.09	16.97
On-the-Job-Training			
No	32,374	13.40	11.93
Yes	24,295	18.87	13.10
Occupation			
Legislators, Senior officials and managers	3,778	25.82	19.77
Professionals	11,538	19.45	14.93
Technicians and associate professionals	9,061	17.59	12.39
Clerks	6,579	15.24	10.57
Service workers and shop and market sales workers	9,909	11.15	8.69
Craft and related trades workers	5,856	12.90	10.07
Plant and machine operators and assemblers	4,625	12.67	9.34
Elementary Occupations	4,700	11.06	9.45
Sector			
Manufacturing	16,224	16.41	13.32
Construction	3,607	14.27	10.49
Services	35,654	15.01	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 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 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 technician occupations have significantly higher wages, with craft machine operators elementary occupations 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.

Finally, Figure 2 illustrates the intensities of task measures together with the deciles of the wage distribution (a proxy for skill allocation in the labor market). Understanding this relation is important as our underlying theoretical framework constantly associates high-skill workers with *Abstract* tasks, middle-skill workers with *Routine* tasks and low-skill workers with *Manual* tasks. We observe a strong positive relation between *Abstract* tasks and wages and a negative one between *Routine* tasks and wages. Although we cannot neglect compositional differences of task intensities between different countries in a single sample, the pattern is clearly consistent with what we would observe as the de-routinization process takes place.

Figure 2. Wage percentiles and Task Measures.

Note. 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 regression purposes, we exclude workers in non-profit firms and workers in *Armed Forces* and *Skilled Agricultural and Fishery* occupations. Data from Canada, Sweden and the United States is not available.

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:

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

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)	(3)
<i>Country Dummies (Germany as Reference)</i>			
Austria	-0.0516* (0.0287)	-0.0133 (0.0220)	-0.00888 (0.0220)
Belgium	-0.00865 (0.0288)	0.0777*** (0.0216)	0.0975*** (0.0220)
Canada	-0.232*** (0.0233)	-0.107*** (0.0184)	-0.119*** (0.0188)
Czech Republic	-0.0122 (0.0353)	-0.0291 (0.0266)	-0.0279 (0.0260)
Denmark	-0.336*** (0.0248)	-0.146*** (0.0193)	-0.145*** (0.0206)
Spain	0.112*** (0.0314)	0.00372 (0.0245)	-0.0182 (0.0232)
Estonia	-0.0453* (0.0246)	-0.0179 (0.0191)	-0.0185 (0.0190)
Finland	-0.471*** (0.0238)	-0.310*** (0.0189)	-0.342*** (0.0198)
France	0.0466* (0.0273)	0.00916 (0.0211)	-0.00122 (0.0204)
Great Britain	-0.195*** (0.0293)	-0.0396* (0.0226)	-0.0330 (0.0243)
Ireland	-0.0291 (0.0303)	0.00779 (0.0240)	0.00725 (0.0242)
Italy	0.367*** (0.0348)	0.171*** (0.0271)	0.162*** (0.0245)
Japan	-0.0154 (0.0258)	0.0130 (0.0201)	0.0135 (0.0200)
Korea	0.239*** (0.0280)	0.310*** (0.0216)	0.309*** (0.0220)
Netherlands	-0.0832*** (0.0278)	0.0939*** (0.0211)	0.128*** (0.0230)
Norway	-0.371*** (0.0237)	-0.165*** (0.0185)	-0.191*** (0.0196)
Poland	0.171*** (0.0307)	0.0586** (0.0236)	0.0511** (0.0222)
Russian Federation	0.297*** (0.0450)	0.0140 (0.0363)	0.0125 (0.0314)
Slovakia	0.234*** (0.0316)	0.158*** (0.0235)	0.142*** (0.0225)
Sweden	-0.376*** (0.0260)	-0.230*** (0.0203)	-0.229*** (0.0217)
United States	-0.282*** (0.0285)	-0.141*** (0.0228)	-0.154*** (0.0240)
ICT Use		-0.620*** (0.00737)	-0.642*** (0.0179)
ICT Use * Country Effects		No	Yes
Constant	0.0398** (0.0197)	0.0259* (0.0154)	0.0254* (0.0152)
Observations	79,567	79,483	79,483
R-squared	0.050	0.414	0.417

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 the large explanatory power of ICT use on RTI both in terms of strength (R^2 of the model increases from 0.05 to 0.41) 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 0.62 standard deviations of RTI. As a robustness check of our model specification, column (3) allows for heterogeneous impacts of ICT use by allowing an interaction effect between ICT use for each country. Results show little variation in the magnitude, both in terms of the impact of ICT use on RTI and the model explanatory power.

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.

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 (R^2) from 0.41 to 0.50, while the marginal effect is smaller than in the conditional model (-0.42 as opposed to -0.62) but still significant and large. In column (7), we allow for heterogeneous impacts of ICT use at work with an interaction between ICT use for each country, similar to what we do in Table 7. Results do not change substantially, with similar country fixed effects and a similar coefficient for ICT use at work.

Table 8. Conditional Differences of RTI across countries.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Country Dummies (Germany as Reference)</i>							
Austria	-0.0516* (0.0287)	-0.137*** (0.0261)	-0.110*** (0.0252)	-0.162*** (0.0246)	-0.0814*** (0.0218)	-0.0438** (0.0199)	-0.0387* (0.0200)
Belgium	-0.00865 (0.0288)	-0.0220 (0.0259)	0.0211 (0.0250)	-0.00437 (0.0242)	0.0517** (0.0216)	0.0692*** (0.0196)	0.0858*** (0.0200)
Canada	-0.232*** (0.0233)	-0.119*** (0.0219)	-0.183*** (0.0218)	-0.179*** (0.0212)	-0.110*** (0.0190)	-0.0779*** (0.0177)	-0.0887*** (0.0182)
Czech Republic	-0.0122 (0.0353)	-0.0335 (0.0327)	-0.0187 (0.0317)	0.0294 (0.0310)	-0.00843 (0.0269)	-0.00875 (0.0246)	-0.00843 (0.0241)
Denmark	-0.336*** (0.0248)	-0.374*** (0.0227)	-0.327*** (0.0221)	-0.302*** (0.0216)	-0.244*** (0.0198)	-0.144*** (0.0182)	-0.147*** (0.0194)
Spain	0.112*** (0.0314)	0.0115 (0.0288)	-0.0529* (0.0284)	-0.0286 (0.0278)	-0.0152 (0.0257)	-0.0415* (0.0238)	-0.0566** (0.0227)
Estonia	-0.0453* (0.0246)	-0.00772 (0.0223)	-0.0228 (0.0218)	-0.00795 (0.0212)	-0.0360* (0.0189)	-0.00574 (0.0178)	-0.00699 (0.0177)
Finland	-0.471*** (0.0238)	-0.408*** (0.0219)	-0.366*** (0.0219)	-0.305*** (0.0215)	-0.341*** (0.0197)	-0.280*** (0.0182)	-0.314*** (0.0190)
France	0.0466* (0.0273)	-0.0198 (0.0246)	-0.0727*** (0.0240)	-0.139*** (0.0236)	-0.0576*** (0.0212)	-0.0491** (0.0196)	-0.0552*** (0.0192)
Great Britain	-0.195*** (0.0293)	-0.217*** (0.0272)	-0.246*** (0.0264)	-0.215*** (0.0255)	-0.166*** (0.0228)	-0.0858*** (0.0209)	-0.0804*** (0.0223)
Ireland	-0.0291 (0.0303)	0.0245 (0.0280)	-0.0484* (0.0275)	-0.0270 (0.0270)	-0.00188 (0.0246)	0.0130 (0.0229)	0.0142 (0.0232)
Italy	0.367*** (0.0348)	0.0909*** (0.0319)	0.0603* (0.0309)	0.0130 (0.0306)	0.0668** (0.0279)	0.0660** (0.0258)	0.0560** (0.0236)
Japan	-0.0154 (0.0258)	0.0412* (0.0237)	0.0843*** (0.0237)	0.0390* (0.0231)	0.0329 (0.0210)	0.0121 (0.0193)	0.0142 (0.0194)
Korea	0.239*** (0.0280)	0.263*** (0.0249)	0.203*** (0.0249)	0.198*** (0.0245)	0.158*** (0.0225)	0.229*** (0.0207)	0.229*** (0.0211)
Netherlands	-0.0832*** (0.0278)	-0.149*** (0.0257)	-0.0996*** (0.0249)	-0.0562** (0.0241)	0.0633*** (0.0217)	0.108*** (0.0198)	0.137*** (0.0215)
Norway	-0.371*** (0.0237)	-0.323*** (0.0224)	-0.300*** (0.0215)	-0.319*** (0.0212)	-0.261*** (0.0195)	-0.167*** (0.0179)	-0.194*** (0.0192)
Poland	0.171*** (0.0307)	0.278*** (0.0274)	0.207*** (0.0273)	0.181*** (0.0267)	0.163*** (0.0238)	0.0999*** (0.0222)	0.0896*** (0.0210)
Russian Federation	0.297*** (0.0450)	0.544*** (0.0431)	0.462*** (0.0420)	0.329*** (0.0416)	0.290*** (0.0370)	0.0970*** (0.0352)	0.0715** (0.0308)
Slovakia	0.234*** (0.0316)	0.235*** (0.0285)	0.269*** (0.0277)	0.231*** (0.0272)	0.213*** (0.0237)	0.173*** (0.0217)	0.155*** (0.0208)
Sweden	-0.376*** (0.0260)	-0.379*** (0.0244)	-0.335*** (0.0238)	-0.354*** (0.0231)	-0.302*** (0.0207)	-0.225*** (0.0190)	-0.225*** (0.0201)
United States	-0.282*** (0.0285)	-0.202*** (0.0261)	-0.307*** (0.0265)	-0.269*** (0.0257)	-0.199*** (0.0232)	-0.128*** (0.0215)	-0.142*** (0.0225)
ICT Use						-0.424*** (0.00865)	-0.437*** (0.0167)
Individual Characteristics		X	X	X	X	X	X
Cognitive Skills			X	X	X	X	X
Job Characteristics				X	X	X	X
Occupation					X	X	X
ICT Use						X	X
ICT use * Country Dummy							X
Constant	0.0398** (0.0197)	0.192*** (0.0279)	1.309*** (0.0694)	1.389*** (0.0700)	1.719*** (0.0691)	0.955*** (0.0657)	0.988*** (0.0661)
Observations	79,567	79,526	79,525	78,883	78,156	78,077	78,077
R-squared	0.050	0.215	0.245	0.279	0.413	0.500	0.503

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 (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$).

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.2 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 diminishes somewhat in every sector, but remains very significant and similar to what we have seen at the aggregate level. Results are similar if we consider the Autor and Dorn (2013) RTI index, although smaller in magnitude, probably related to the measurement error of Manual tasks described in the previous section.

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 of 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 are reduced if we introduce the index of ICT use at work in equation (1). Moreover, given our identification problems, the displacement of *Routine* tasks cannot be accounted in differences in *Manual* tasks and will only be assessed in differences in abstract tasks.

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 3 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 0.231 to 0.138, which represents almost 41% 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, more importantly, ICT use at work to our model.

Figure 3. 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 3 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 4 presents such comparison: as we already described in Figure 3, the drop in variation for the unconditional model is 41%. 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 0.168, but fall to 0.125 when adding ICT use at work as a covariate. This represents a notable 25% decrease in country variation in the conditional model²⁰.

Overall, we observe that ICT use at work is crucial in explaining differences in de-routinization across countries and, accounts at least 25% 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 40% of country variation for the case of unconditional differences of RTI.

²⁰ 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 4. Effect of ICT on RTI country variation.

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

A final issue regarding our approach is to test whether these results are sensitive to including the manual task index as part of the RTI index. In the Annex, Table A.3 and Table A.4 include regression results for both unconditional and conditional model specifications, and Figure 4 shows the same comparison of the unconditional and conditional models when introducing ICT use at work as a covariate. Results show that the decrease is still important but less pronounced for both model specifications and close to 10%. Our interpretation is that this has to do with the fact that the PIAAC database does not allow disentangling manual routine from non-routine job contents, which are impacted differently by ICT adoption at work.

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 countries²¹ $j = 1 \dots 19$, we have:

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

with $\text{Log } W_{ij}$ being the hourly log-wage, X_{ijn}^{Ind} being the individual worker characteristics (such as gender, age or level of education), X_{ijn}^{Skills} being the worker literacy and numeracy cognitive skills, X_{ijo}^{Job} being a vector of job characteristics (public or private firm, firm size and on-the-job training), X_{ijp}^{Occ} being the 1-digit ISCO occupation code, and X_{ijq}^{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 wage gender 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

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²¹ Given that the data in Canada, US and Sweden is removed from the sample, 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 countries²².

Figure 5. Log Hourly Wage density, by country groups.

Figure 5 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

²²We 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:

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

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 groups. The mean difference of log wages between country groups 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 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 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 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 :

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

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 $\hat{q}_\tau$ 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 6 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 5. 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 Middle wage groups with the Low wage group of countries, we observe that the total composition effect represents a similar amount (around 35% and 28% respectively) for all the deciles of the wage distribution. For the comparison between Middle and Low wage groups, the proportion explained by compositional differences grows from 18% to 44% 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 6. 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) tasks relative to *Abstract* (cognitive and interpersonal) 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 41% of the cross-country RTI differences in an unconditional model, and 25% 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 proportionally similar for all the wage distribution, implying that we cannot find an 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 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.

VII. References

- Acemoglu, Daron. 1999. "Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence." *American Economic Review*, 89(5): 1259-1278.
- Autor, David H., Frank Levy & Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics*, vol. 118(4), pages 1279-1333, November.
- Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review*, 96(2): 189-194.
- Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review*, 103(5): 1553-97.
- Autor, David H. and Michael J. Handel. 2013. "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages". *Journal of Labor Economics*, 31(2): S59-S96.
- Autor, David H. 2014. "Skills, Education, and the Rise of Earnings Inequality Among the "Other 99 Percent". *Science*, May 2014: 344 (6186), 843-851.
- Cabrales, Antonio, Juan J. Dolado, and Ricardo Mora. 2014. Dual Labour Markets and (Lack of) On-the-Job Training: PIAAC Evidence from Spain and other EU Countries. *IZA Discussion Papers* No. 8649.
- Dustmann, Christian, Johannes Ludsteck and Uta Schönberg. 2009. Revisiting the German Wage Structure. *Quarterly Journal of Economics* 124(2): 843-881.
- Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2009. "Unconditional Quantile Regressions." *Econometrica*, 77(3): 953-973.
- Firpo, Sergio, Nicole M. Fortin, and Thomas Lemieux. 2011. "Occupational Tasks and Changes in the Wage Structure." *IZA Discussion Papers* No. 5542.
- Goos, Maarten, and Alan Manning. 2007. "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain." *Review of Economics and Statistics* 89 (1): 118-123.
- Goos, Maarten, Alan Manning, and Anna Salomons. 2009. "Job Polarization in Europe." *American Economic Review*, 99(2): 58-63.
- Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review*, 104(8): 2509-26.

Hanushek, Eric, Guido Schwerdt, Simon Wiederhold, and Ludger Woessmann. 2015. "Returns to Skills around the World: Evidence from PIAAC." *European Economic Review*, Volume 73, January 2015: 103-130.

Machin, Steven. 2011. "Changes in UK Wage Inequality Over the Last Forty Years," in P. Gregg and J. Wadsworth (eds.) *The Labour Market in Winter - The State of Working Britain*

Massari, Riccardo, Paolo Naticchion, and Giuseppe Ragusa. 2014. "Unconditional and Conditional Wage Polarization in Europe." *IZA Discussion Papers* No. 8465.

Oaxaca, Ronald, and Michael R. Ransom. 1994. "On Discrimination and the Decomposition of Wage Differentials." *Journal of Econometrics*, 1995, 61(1), pp 5-21.

OECD. 2011. *Divided We Stand: Why Inequality Keeps Rising*, OECD Publishing.

OECD. 2013. *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. OECD Publishing.

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

VIII. Annex

Table A.1. Task Measures by countries, including Autor and Dorn specification

	RTI	RTI-AD	Routine	Abstract	Manual
Italy	0.41	0.31	4.93	3.24	6.11
Russian Federation	0.34	0.38	5.33	3.59	5.22
Korea	0.28	0.23	5.32	4.04	5.03
Slovak Republic	0.27	0.08	4.68	3.61	6.43
Poland	0.21	0.05	4.57	3.75	6.66
Spain	0.15	0.27	4.01	3.60	5.54
France	0.09	0.30	4.29	3.93	5.18
Germany	0.04	-0.01	4.20	4.11	6.37
Belgium	0.03	0.21	4.05	4.06	5.45
Czech Republic	0.03	-0.02	4.31	4.18	6.16
Japan	0.02	0.39	4.29	4.07	4.09
Ireland	0.01	-0.17	4.52	4.49	6.83
Estonia	-0.01	-0.14	3.96	4.03	6.52
Austria	-0.01	-0.03	3.95	4.10	6.31
Netherlands	-0.04	0.12	4.12	4.28	5.44
Great Britain	-0.16	-0.27	4.10	4.80	6.59
Canada	-0.19	-0.23	3.87	4.63	6.38
United States	-0.24	-0.42	3.83	4.87	7.33
Denmark	-0.30	-0.27	3.40	4.56	6.36
Norway	-0.33	-0.03	3.56	4.85	5.11
Sweden	-0.34	-0.13	3.41	4.62	5.68
Finland	-0.43	-0.22	3.28	5.10	5.30
Mean	0.00	0.00	4.29	4.25	6.02
Standard Deviation	1.00	1.00	2.07	2.44	3.59
Number of Observations	79,567	79,486	79,950	80,150	80,560

Notes: RTI does not consider manual tasks in the construct as opposed to Autor and Dorn specification (RTI-AD). The sample includes employed respondents aged 20-64 currently working. 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. Impact of ICT use on RTI by sectors.

	RTI		RTI-AD	
	Unconditional	Conditional	Unconditional	Conditional
All sectors	-0.620*** (0.007)	-0.423*** (0.008)	-0.206*** (0.007)	-0.217*** (0.01)
Manufacturing	-0.679*** (0.013)	-0.483*** (0.017)	-0.198*** (0.013)	-0.256*** (0.018)
Construction	-0.504*** (0.025)	-0.317*** (0.031)	-0.097*** (0.025)	-0.122*** (0.029)
Services	-0.603*** (0.009)	-0.425*** (0.01)	-0.234*** (0.01)	-0.237*** (0.013)

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. 3. Unconditional Differences using Autor and Dorn RTI specification.

VARIABLES	(1)	(2)	(3)
<i>Country Dummies (Germany as Reference)</i>			
Austria	-0.0186 (0.0251)	-0.00628 (0.0248)	-0.00917 (0.0248)
Belgium	0.223*** (0.0258)	0.252*** (0.0257)	0.241*** (0.0255)
Canada	-0.217*** (0.0208)	-0.176*** (0.0206)	-0.185*** (0.0206)
Czech Republic	-0.0115 (0.0317)	-0.0169 (0.0314)	-0.0155 (0.0315)
Denmark	-0.262*** (0.0231)	-0.200*** (0.0229)	-0.206*** (0.0231)
Spain	0.278*** (0.0286)	0.242*** (0.0285)	0.254*** (0.0290)
Estonia	-0.125*** (0.0218)	-0.116*** (0.0215)	-0.118*** (0.0214)
Finland	-0.207*** (0.0235)	-0.154*** (0.0237)	-0.200*** (0.0235)
France	0.311*** (0.0252)	0.298*** (0.0252)	0.307*** (0.0250)
Great Britain	-0.258*** (0.0256)	-0.207*** (0.0248)	-0.185*** (0.0253)
Ireland	-0.158*** (0.0264)	-0.146*** (0.0256)	-0.146*** (0.0257)
Italy	0.319*** (0.0318)	0.254*** (0.0317)	0.281*** (0.0326)
Japan	0.400*** (0.0269)	0.408*** (0.0266)	0.407*** (0.0266)
Korea	0.237*** (0.0265)	0.260*** (0.0254)	0.276*** (0.0253)
Netherlands	0.127*** (0.0257)	0.184*** (0.0255)	0.177*** (0.0257)
Norway	-0.0207 (0.0238)	0.0473** (0.0241)	-0.0317 (0.0237)
Poland	0.0585** (0.0262)	0.0205 (0.0258)	0.0269 (0.0263)
Russian Federation	0.387*** (0.0422)	0.294*** (0.0414)	0.327*** (0.0435)
Slovakia	0.0955*** (0.0270)	0.0703*** (0.0261)	0.0542** (0.0264)
Sweden	-0.120*** (0.0250)	-0.0719*** (0.0252)	-0.116*** (0.0249)
United States	-0.410*** (0.0249)	-0.363*** (0.0243)	-0.355*** (0.0247)
ICT Use		-0.206*** (0.00773)	-0.133*** (0.0186)
ICT Use * Country Effects		No	Yes
Constant	-0.0109 (0.0175)	-0.0152 (0.0174)	-0.0136 (0.0173)
Observations	79,486	79,404	79,404
R-squared	0.108	0.148	0.154

Notes: Dependent variable is RTI index with manual tasks following Autor and Dorn (2013) specification. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table A. 4. Conditional Differences using Autor and Dorn RTI specification.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>Country Dummies (Germany as Reference)</i>							
Austria	-0.0186 (0.0251)	-0.0275 (0.0249)	-0.0199 (0.0249)	-0.0555** (0.0247)	-0.0271 (0.0244)	-0.00803 (0.0242)	-0.0115 (0.0241)
Belgium	0.223*** (0.0258)	0.231*** (0.0257)	0.239*** (0.0258)	0.221*** (0.0256)	0.231*** (0.0255)	0.240*** (0.0253)	0.225*** (0.0249)
Canada	-0.217*** (0.0208)	-0.189*** (0.0213)	-0.213*** (0.0219)	-0.209*** (0.0216)	-0.179*** (0.0214)	-0.163*** (0.0212)	-0.175*** (0.0212)
Czech Republic	-0.0115 (0.0317)	-0.0149 (0.0316)	-0.0148 (0.0317)	0.0309 (0.0314)	0.0270 (0.0309)	0.0270 (0.0308)	0.0273 (0.0310)
Denmark	-0.262*** (0.0231)	-0.284*** (0.0230)	-0.270*** (0.0232)	-0.243*** (0.0231)	-0.219*** (0.0230)	-0.168*** (0.0228)	-0.179*** (0.0228)
Spain	0.278*** (0.0286)	0.209*** (0.0292)	0.191*** (0.0295)	0.221*** (0.0293)	0.201*** (0.0290)	0.187*** (0.0289)	0.199*** (0.0292)
Estonia	-0.125*** (0.0218)	-0.129*** (0.0216)	-0.138*** (0.0217)	-0.114*** (0.0216)	-0.0989*** (0.0214)	-0.0841*** (0.0213)	-0.0886*** (0.0212)
Finland	-0.207*** (0.0235)	-0.211*** (0.0237)	-0.218*** (0.0245)	-0.156*** (0.0244)	-0.150*** (0.0243)	-0.119*** (0.0240)	-0.167*** (0.0238)
France	0.311*** (0.0252)	0.277*** (0.0249)	0.257*** (0.0253)	0.209*** (0.0251)	0.233*** (0.0249)	0.238*** (0.0249)	0.246*** (0.0247)
Great Britain	-0.258*** (0.0256)	-0.289*** (0.0254)	-0.310*** (0.0257)	-0.288*** (0.0257)	-0.289*** (0.0254)	-0.248*** (0.0250)	-0.229*** (0.0254)
Ireland	-0.158*** (0.0264)	-0.151*** (0.0266)	-0.178*** (0.0271)	-0.154*** (0.0268)	-0.154*** (0.0266)	-0.147*** (0.0262)	-0.150*** (0.0263)
Italy	0.319*** (0.0318)	0.211*** (0.0325)	0.205*** (0.0326)	0.170*** (0.0323)	0.188*** (0.0318)	0.188*** (0.0315)	0.214*** (0.0321)
Japan	0.400*** (0.0269)	0.403*** (0.0267)	0.394*** (0.0277)	0.360*** (0.0275)	0.354*** (0.0272)	0.342*** (0.0269)	0.338*** (0.0270)
Korea	0.237*** (0.0265)	0.244*** (0.0260)	0.219*** (0.0266)	0.219*** (0.0263)	0.179*** (0.0261)	0.215*** (0.0255)	0.226*** (0.0254)
Netherlands	0.127*** (0.0257)	0.0684*** (0.0261)	0.0655** (0.0265)	0.105*** (0.0261)	0.136*** (0.0259)	0.158*** (0.0255)	0.144*** (0.0257)
Norway	-0.0207 (0.0238)	-0.0501** (0.0242)	-0.0500** (0.0242)	-0.0599** (0.0240)	-0.0264 (0.0247)	0.0217 (0.0245)	-0.0577** (0.0244)
Poland	0.0585** (0.0262)	0.0673** (0.0262)	0.0443* (0.0266)	0.0266 (0.0263)	0.0464* (0.0260)	0.0132 (0.0258)	0.0125 (0.0265)
Russian Federation	0.387*** (0.0422)	0.451*** (0.0432)	0.426*** (0.0427)	0.323*** (0.0426)	0.348*** (0.0424)	0.249*** (0.0430)	0.269*** (0.0456)
Slovakia	0.0955*** (0.0270)	0.0835*** (0.0271)	0.0901*** (0.0270)	0.0626** (0.0265)	0.0733*** (0.0261)	0.0523** (0.0257)	0.0373 (0.0260)
Sweden	-0.120*** (0.0250)	-0.142*** (0.0253)	-0.141*** (0.0255)	-0.150*** (0.0252)	-0.114*** (0.0252)	-0.0748*** (0.0249)	-0.118*** (0.0245)
United States	-0.410*** (0.0249)	-0.405*** (0.0247)	-0.445*** (0.0259)	-0.419*** (0.0255)	-0.390*** (0.0250)	-0.354*** (0.0246)	-0.345*** (0.0249)
ICT Use						-0.218*** (0.0101)	-0.137*** (0.0191)
Individual Characteristics		X	X	X	X	X	X
Cognitive Skills			X	X	X	X	X
Job Characteristics				X	X	X	X
Occupation					X	X	X
ICT Use						X	X
ICT use * Country Dummy							X
Constant	-0.0109 (0.0175)	0.0527* (0.0274)	0.204*** (0.0682)	0.293*** (0.0692)	0.530*** (0.0707)	0.138* (0.0725)	0.117* (0.0712)
Observations	79,486	79,446	79,445	78,805	78,078	78,001	78,001
R-squared	0.108	0.130	0.132	0.155	0.185	0.208	0.214

Notes: Dependent variable is RTI index with manual tasks following Autor and Dorn (2013) specification. 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 (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

Figure 7. Effect of ICT use on RTI country variation (AD specification).

Notes: We compute the standard deviations of country effects from Table A.3 and Table A.4. RTI index is computed including the Manual task index.

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

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Gender		0.240*** (0.00856)	0.217*** (0.00883)	0.198*** (0.00896)	0.189*** (0.00973)	0.178*** (0.00968)
<i>Age (Reference= 40-44)</i>		-0.163*** (0.0111)	-0.0944*** (0.0115)	-0.0802*** (0.0114)	-0.0541*** (0.0112)	-0.0378*** (0.0110)
20-25		0.162*** (0.0138)	0.128*** (0.0140)	0.105*** (0.0139)	0.0616*** (0.0138)	0.0519*** (0.0136)
25-29		0.420*** (0.0111)	0.345*** (0.0122)	0.302*** (0.0121)	0.172*** (0.0135)	0.142*** (0.0133)
30-34		-0.288*** (0.0174)	-0.285*** (0.0173)	-0.277*** (0.0171)	-0.242*** (0.0169)	-0.237*** (0.0169)
35-39		-0.174*** (0.0164)	-0.172*** (0.0163)	-0.166*** (0.0159)	-0.145*** (0.0159)	-0.149*** (0.0158)
45-49		-0.0494*** (0.0165)	-0.0441*** (0.0163)	-0.0486*** (0.0158)	-0.0392** (0.0155)	-0.0395** (0.0154)
50-54		0.0424*** (0.0155)	0.0475*** (0.0150)	0.0406*** (0.0146)	0.0422*** (0.0145)	0.0467*** (0.0144)
55-59		0.0596*** (0.0164)	0.0678*** (0.0162)	0.0596*** (0.0157)	0.0510*** (0.0156)	0.0600*** (0.0155)
60-65		0.0470*** (0.0167)	0.0629*** (0.0166)	0.0557*** (0.0161)	0.0466*** (0.0158)	0.0606*** (0.0154)
<i>Education Level (Reference is Upper secondary)</i>		0.0715*** (0.0219)	0.0924*** (0.0214)	0.0897*** (0.0215)	0.0802*** (0.0200)	0.0947*** (0.0197)
Lower secondary or less		-0.0529** (0.0221)	-0.0148 (0.0221)	0.00706 (0.0216)	0.00648 (0.0204)	0.0307 (0.0204)
Post-secondary and tertiary (professional)						
Tertiary (Bachelor/Master)						
<i>Skills</i>						
Literacy Skill			-0.000176 (0.000246)	-7.33e-05 (0.000244)	0.000103 (0.000254)	0.000121 (0.000249)
Numeracy Skill			0.00231*** (0.000225)	0.00189*** (0.000221)	0.00119*** (0.000225)	0.000862*** (0.000222)
Activities - Last year - On the job training				0.117*** (0.00911)	0.0927*** (0.00899)	0.0717*** (0.00866)
Private Sector				-0.00363 (0.0110)	0.0165 (0.0111)	0.00380 (0.0109)
<i>Workplace size (Reference is 51 to 100 people)</i>						
1 to 10 people				-0.135*** (0.0117)	-0.122*** (0.0115)	-0.116*** (0.0112)
11 to 50 people				-0.0550*** (0.0115)	-0.0517*** (0.0112)	-0.0494*** (0.0109)
51 to 250 people				0.0640*** (0.0140)	0.0552*** (0.0138)	0.0507*** (0.0136)
more than 1000 people				0.180*** (0.0205)	0.166*** (0.0192)	0.158*** (0.0189)
<i>Occupation (Reference is Elementary Occupation)</i>						
Legislators, senior officials and managers					0.533*** -0.0215	0.399*** -0.0226
Professionals					0.351*** -0.019	0.250*** -0.0197
Technicians and associate professionals					0.273*** -0.0169	0.167*** -0.018
Clerks					0.167*** -0.0156	0.0493*** -0.017
Service Workers and shop and market sale workers					0.0467*** -0.0167	0.0119 -0.0167
Craft and related trade workers					0.147*** -0.0181	0.133*** -0.0179
Plant and machine operators					0.0987*** -0.0182	0.0951*** -0.018
ICT Use						0.0991*** (0.00583)
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.839*** (0.0113)	2.630*** (0.0163)	2.054*** (0.0373)	2.136*** (0.0406)	2.125*** (0.0407)	2.125*** (0.0407)
Observations	56,524	56,501	56,496	56,108	55,481	55,481
R-squared	0.436	0.551	0.564	0.585	0.611	0.611

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.