

Job Tasks and Wages across the world: Evidence from PIAAC¹

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Abstract

This paper addresses for the first time differences on job tasks across a harmonized sample of 20 countries across the world by using very precise information on job contents at the worker level. In addition, the relationship between job contents and individual and job characteristics as well as with computer use at work, both across and within occupations, is assessed. Then, we estimate the empirical relationship between job tasks and wages, assuming that workers self-select into occupations based on comparative advantage. Our results indicate, first, that New Zealand and Great Britain display the largest values in non-routine cognitive and personal tasks, whereas routine contents are found to be highest in Lithuania and Turkey. Second, computer use at work is a key factor in explaining differences in job contents, both between and within occupations. Finally, job tasks exert substantial predictive power for wage differences across and within occupations. Our individual-based job tasks measures are validated by comparing them with those previously used with O*NET database.

JEL codes: J24, J31, O33.

Keywords: Job Tasks, task approach, Computer use at work, job tasks returns, PIAAC.

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I. Introduction

The phenomenon of technological change is leading to an automation of a range of low and medium-skill occupations, in particular those whose contents follow precise and well-understood procedures or routines. Workplace computerization leads to an automation of these routines and hence to a gradual change of contents/tasks demanded at the workplace. Such computerization is driven by a decline in the relative price of computer capital (identified with technological progress), which increases computer and technology adoption at firms and the workplace, hence altering the allocation of labor across different task inputs. Specifically, computer capital and labor are relative complements in carrying out non-routine/non-codifiable tasks, while computer capital and labor are substitutes in carrying out routine/codifiable tasks. Indeed, Autor, Levy and Murnane (2003) document a change in the occupational distribution of employment – employment polarization –, and assesses that computerization is indeed a key driver to understand such changes.

Understanding employers' behavior with respect to their labor demands in the face of computerization requires a theoretical framework which specifically links skill requirements with technological change. The traditional Mincerian human capital model was very successful in explaining the relationship between wages and investment in human capital but given its supply based nature, was not helpful in understanding skill demand requirements. Autor, Levy and Murnane (ALM) (2003) and, more recently, Acemoglu and Autor (2011) developed a new theoretical task framework rooted in a fundamental difference between skills and tasks. In this framework, the basic units of production are job content/tasks, which are supplied by production factors (labor and capital) which combined can produce units of output. Assignment of factors to tasks are determined in equilibrium by comparative advantage, and hence each task is done by the least-cost factor.

This task framework, however, still faces important challenges, and measurement is undoubtedly one of the most important ones. The first empirical studies used detailed occupation data to approximate job tasks. However, tasks may share similarities across very different occupations and hence the occupation data approach does not allow to identify such similarities in an objective way. A subsequent set of empirical studies used two datasets from surveys which offered job descriptors (contents) to each occupation – the Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET) –. Autor and Dorn (2011), Acemoglu and Autor (2011), Goos, Manning and Salomons (2014), among others, have recently used these datasets for the measurement of task contents. However, although this approach assigns job descriptors to occupations objectively (and hence can be validated by the agencies which supply them) this has two major drawbacks. The first one is that these job descriptors – DOT and O*NET – are derived from US surveys. Whereas for some OECD countries the occupational based job descriptors may be similar to the US ones, for other countries such approximation may induce to large errors in job contents. The second limitation

is that this approach overlooks job tasks heterogeneity within occupations. In fact, empirical research has found important heterogeneity in job content at the worker level within detailed occupations (see Spitz-Oener, 2006 and Autor and Handel (AH), 2013). In particular, Spitz-Oener argues for the case of Germany that job content changes take place mostly within, rather than between occupations². Hence, measuring job tasks at the workplace remains critical for an accurate understanding of tasks, relate them to occupations, human capital and other demographics, as well as for identifying its link with wages in the verge of a technological transformation.

The empirical studies that measure tasks at the worker level are, to date, single-country analysis (Spitz-Oener, 2006 and AH, 2013). Our paper extends the empirical assessment of task measurement at a worker level to a broad sample of countries. Specifically, we compute differences in the tasks content of jobs across a harmonized and hence comparable sample of countries that includes European, Asian and American countries. There is evidence that the process of de-routinization has not followed identical paths across countries. Hardy et al (2016) document an increase rather than a decrease in routine cognitive employment in the transition economies of Eastern and Central Europe and Gimpelson and Kapeliushnikov (2016) and Aedo et al (2013) found similar results for Russia and Southern European countries, respectively. Hence, there is a need for an assessment of job tasks around the world from a comparable sample of countries at the worker level.

In order to do so, we use the Programme for the International Assessment of Adult Competencies (PIAAC), a survey which provides harmonized information across countries. We use very precise information on job contents at the worker level, which allows for looking at job task heterogeneity within occupations and hence understand the nuanced interplay between job demand, tasks, occupational sorting and earnings. At the same time, given the availability of worker level information of the intensity of computer use at work, we assess the empirical relationship between computerization at work and the task content of workers. This is indeed the first of the three contributions of our paper to the literature, i.e., to depict comparable cross-country differentials in the ALM task framework for 20 OECD and non-OECD countries.

The second contribution of this paper is to learn about the relationship between job contents and other demographics and job characteristics, in particular, the role played by worker sorting into occupations in determining job tasks, as well as the association between computerization at work and the type of tasks that workers perform. Such analysis is conducted by conditioning on very detailed and unique measures of worker cognitive skills, which help to disentangle such relationship from potential confounding worker effects. Finally, our third contribution is to

² 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.

assess the predictive power of job tasks on worker wages: we do so under the task approach, which assumes that workers self-select into jobs according to their comparative advantage.

Our findings show that New Zealand and Great Britain display the largest values in non-routine cognitive and personal tasks. On the other side, routine (cognitive and manual) are found to be highest in Lithuania and Turkey. Second, computer use at work is revealed as a key factor in explaining differences in job contents, both between and within occupations. Third, job tasks exert a high predictive power to explain wage differences, even within occupations. Additionally, results are consistent with the assumption held by the task approach that workers self-select into occupations based on their comparative advantage. Finally, our individual-based task measures are validated by comparing them with those which would be obtained when assigning job descriptors from O*NET dataset (which have been previously used in the literature), bringing even nuances that can add more value in future research.

The rest of the paper is organized as follows. Section 2 discusses the data sources and a discussion on data sources and the construction of task/job contents. Section 3 and 4 present empirical estimates of task determinants and the relation between tasks and wages. Section 5 concludes.

II. Data sources, Job Task Measures, and Descriptives across countries

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) through two waves –first, in 2011-2012 and second, in 2014-2015 -in 31 participating countries: Austria, Belgium, Canada, Chile, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great Britain, Greece, Ireland, Israel, Italy, Japan, South Korea, Lithuania, Netherlands, Norway, New Zealand, Poland, Russian Federation, Singapore, Slovak Republic, Slovenia, Sweden, Turkey and the United States³. The data sample contains 201,033 observations, which represent a total population of 815 million adults aged 16 to 65. The survey includes a personal interview comprising a questionnaire followed by a skills assessment of literacy, numeracy and problem-solving skills in technology environments.

The questionnaire contains information about personal background, education and training, current work status, work history, and skills used at current job (or last job) and everyday life⁴. As said previously, the variables of job contents (tasks) used at work are particularly appropriate for the analysis within occupations. In addition, the PIAAC skills assessment provides an

³ 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.

⁴ 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.

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 cognitive skill assessments.

This paper aims at understanding the task content of jobs in a framework where occupational sorting drives worker choices. Unfortunately, not all countries in the sample provide detailed occupation-level information at more than one digit. Therefore, we lose 11 countries from the sample, and remain with 20 countries for the analysis: Belgium, Chile, Cyprus, Czech Republic, Denmark, Spain, France, Great Britain, Greece, Italy, Japan, South Korea, Lithuania, Netherlands, Poland, New Zealand, Russian Federation, Slovak Republic, Slovenia and Turkey.

Constructing Worker-level Task Measures

Using data from the worker responses of activities conducted at work, we construct measurements of task intensities. We follow the original Autor, Levy and Murnane (2003) approach that defines five task measurements: Non-routine cognitive, non-routine personal, routine cognitive, routine manual, and non-routine manual.

We construct a set of indices based on the PIAAC background questionnaire. The background questionnaire displays answers on work habits and tasks performed at the workplace, normally organized through different types of frequency answers. To keep consistency in the aggregation of answers into indexes, we restrict our set of items used to those which have the frequency category on responses to the question which starts by: “How often does does your job usually involve...”. The responses are organized as five qualitative time inputs: (i) Every Day; (ii) At least once a week but not every day; (iii) Less than once a week; (iv) Less than once a month; (v) Never.

We follow Autor and Handel (2013) to construct the indexes for each of the dimensions using the first component of a principal component analysis⁵. Due to data limitations on manual tasks, we only construct four of the five job tasks: non-routine cognitive, non-routine personal, routine cognitive and routine manual. For the non-routine cognitive task index, we use three different items: (i) write reports; (ii) read diagrams, maps or schematics; and (iii) face complex problems that take at least 30 minutes. We construct the non-routine personal task index with the following items: (i) planning the activities of others; (ii) persuading or influencing people. The routine cognitive task index is constructed with four different items: (i) learning-by-doing at work; (ii)

⁵ 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. As a robustness check with our approach, data comparing both methods leads to similar results, with correlation of 0.90 for non-routine cognitive tasks, 0.78 for non-routine personal tasks, and 0.92 for routine cognitive tasks.

organizing own time; (iii) instructing, training or teaching people, individually or in groups; (iv) making speeches or giving presentations in front of five or more people. The last two items follow the approach used by Autor and Handel (2013), which construct the routine cognitive index emphasizing the importance of the lack of face-to-face interactions.

Table 1. Task Framework with PIAAC Data

Task	PIAAC Questionnaire Item	Item No.
Non-routine cognitive	Write Reports	G_Q02c
	Read Diagrams, Maps or Schematics	G_Q01h
	Faced complex problems (>30 mins)	F_Q05b
Non-routine personal	Planning the activities of others	F_Q03b
	Persuading/Influencing People	F_Q04a
Routine cognitive	Learning-by-doing from tasks performed	D_Q13b
	Organizing your own time	F_Q03c
	Instructing, training or teaching people	F_Q02b
	Making speeches or giving presentations	F_Q02c
Routine manual	Hand and finger dexterity	F_Q06b

Notes: all questions provide the same time categorical answers: (i) Every Day; (ii) At least once a wee but not every day; (iii) Less than once a week; (iv) Less than once a month; (v) Never.

The manual routine index is constructed from the item “using skill or accuracy with hands or fingers”, which has been widely used in the task literature (see Autor, Levy and Murnane (2003) and Autor and Dorn (2014)). Table 1 depicts the job task items from the PIAAC background questionnaire that are used to construct each of the task indexes. For non-routine manual task tasks, an alternative would be to use the question on “Physical Work”. Nevertheless, the non-routine manual task constructed in, for example, the Autor, Katz and Kearney (2006) approach is a non-codifiable type of work⁶. These should include, among others, task such as dexterity, coordination, object handing or spatial orientation tasks. Unfortunately, PIACC dataset does not include items to learn about these non-routine manual job contents and hence, we decide not to use any non-routine manual task measure in our approach.

Our sample consists of 51,056 observations (from 20 countries for which occupation at more than 1-digit is available) that are well defined for each item of the task framework, as well as the

⁶ 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 (2013) use four activities: (i) operating vehicles, mechanized devices, or equipment; (ii) time spent using hands to handle, control, or feel objects, tolos, or controls; (iii) manual dexterity; (iv) spatial orientation. From the Dictionary of Occupational Titles (DOT), Autor and Dorn (2014) use “eye-hand-foot coordination” variable for the manual (non-routine) task and “finger dexterity” to be included as the manual part of the routine construct. Finally, Acemoglu and Autor (2011) use from the Occupational Information Network (O*NET “*pace determined by speed of equipment*”, “*controlling machines and processes*” and “*spend time making repetitive motions*” for routine manual tasks and “*operating vehicles, mechanized devices, or equipment*”, “*spend time using hands to handle, control or feel objects, tools or controls*”, “*manual dexterity*” or “*spatial orientation*”.

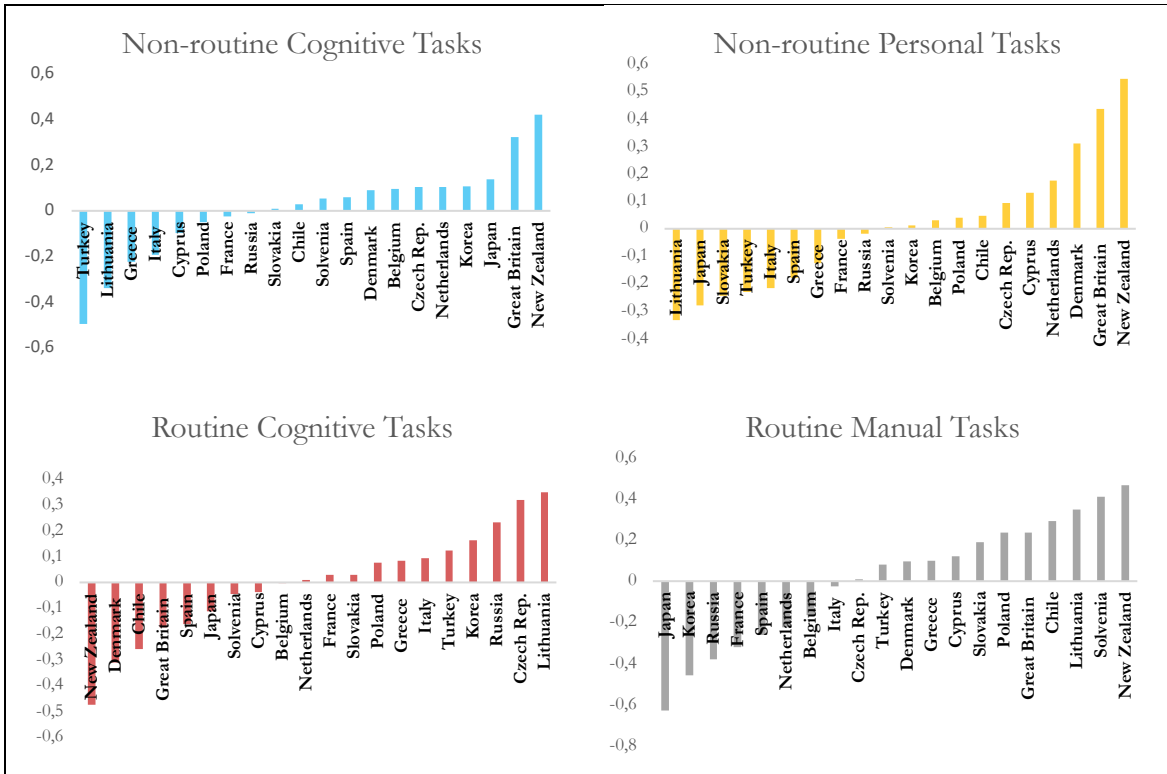
worker covariates later used in the next section. We then compute the indexes for each task. Consistent with Autor and Handel (2013), the first component of the principal component analysis for each task explains a relatively large variance – see Table A.1, being 0.55 for non-routine cognitive tasks, 0.71 for non-routine personal tasks, and 0.45 for routine cognitive tasks⁷ –. We also compute the indexes into their standardized form and compare their results at the worker level. The indexes of non-routine cognitive and personal tasks are positively correlated (0.47), while both are negatively correlated (-0.49 and -0.60) with routine cognitive tasks. Routine manual task index does not correlate with the rest of indices in any relevant way.

Job Task Descriptives around the world

In Figure 1 we depict the average values of the standardized form of the task variables explained above. In particular, we find that New Zealand, Great Britain, Denmark, Japan, South Korea and Netherlands display the largest values of non-routine cognitive tasks, while these are lowest in Turkey, Lithuania, and Greece. This is consistent with what is found for the case of routine cognitive tasks (where the order is mostly inversed), with the exception of Netherlands. Moreover, we find large values of non-routine personal tasks in New Zealand, Great Britain, Denmark and Netherlands, and low values in Japan, Lithuania, and Slovakia. Finally, Routine manual tasks are low in Japan, South Korea, France and Russia, whereas high in Lithuania, Slovenia and, surprisingly, New Zealand. The cross-country comparison between the three task indexes shows a very high and positive correlation between non-routine cognitive and personal (0.72), whereas those two display a negative correlation with routine cognitive tasks (-0.60 and -0.59 respectively). Routine manual task correlates positively with non-routine personal tasks (0.32) and negatively with routine cognitive tasks (-0.24).

⁷ Autor and Handel (2013) Abstract and Routine scales are derived from a first component of a principal component analysis which explain 41% and 56% of the total variation respectively.

Figure 1. Job Task measures by countries.



Notes: Results display values of standardized indexes for each task, with mean 0 and standard deviation 1. Observations are weighted so that countries are weighted equally. Results are also presented in **¡Error! No se encuentra el origen de la referencia.** in the **¡Error! No se encuentra el origen de la referencia.**.

*Validity of Job Task Measures: Worker level vs Occupational level (PLAAC and O*NET)*

To better understand the reliability of our measures, we compute the worker-level measurement of tasks at the occupational four-digit level and compare them with the worker-level values. In Table 2, we show a positive large correlation of worker and occupational-level task measurements.

Moreover, we can validate our individual-based task measures by comparing them with those which would be obtained when assigning job descriptors from O*NET to each of the 4-digit occupational level. For comparability reasons, we use O*NET dataset to construct measures of non-routine cognitive, non-routine personal, routine cognitive and routine manual using exactly the same task measures used in Acemoglu and Autor (2011) at the 4-digit occupation level. As Table 2 shows, we find a positive correlation of around 0.54 for non-routine cognitive tasks, 0.46 for non-routine personal tasks, 0.26 for routine cognitive tasks (which is lower than expected), and 0.30 for routine manual tasks. The fact that the PIAAC occupation-level correlation O*NET

is slightly larger compared to the PIAAC worker-level correlation (except for routine cognitive tasks) is consistent with Autor and Handel (2013)⁸.

Table 2. Correlation between worker and occupation-level task measures (PIAAC and O*NET)

	Worker-level PIAAC		Occupation-level PIAAC
	Occupation-level PIAAC	Occupation-level O*NET	Occupation-level O*NET
Non-routine cognitive	0.672	0.417	0.536
Non-routine personal	0.644	0.368	0.456
Routine cognitive	0.679	0.235	0.264
Routine manual	0.585	0.197	0.304

Notes: The sample includes employed respondents aged 20-64 currently working for which variables in section IV are well defined and have non missing values. Observations are weighted so that countries are weighted equally.

Job Tasks and Computer Adoption at Work around the world

As stated before, the implicit assumption underlying the relation between task changes and technological change is that the decline in the price of computer capital (the exogenous driver of digitalization) is expected to increase computer adoption at work. Measurement of a precise definition of computer adoption at work in a cross-country setting and its relation to job tasks is another important contribution of this paper. Previous authors have used binary indicators of computer use at work in relating technological change and the task content of jobs (Spitz-Oener, 2006) or a measure of adjusted computers-per-worker at the firm level (Autor and Dorn, 2013). To exploit further variation at the worker level, we construct a measure for the individual degree of computer use at work through four different items with frequency inputs, the same qualitative responses as of those in Table 1⁹. In particular, we use the following items: (i) use the internet to better understand issues related to work; (ii) conduct transactions on the internet, for example buying or selling products or services; (iii) use spreadsheet software; (iv) participate in real-time discussions on the internet, for example online conferences or chat groups¹⁰. We then compute

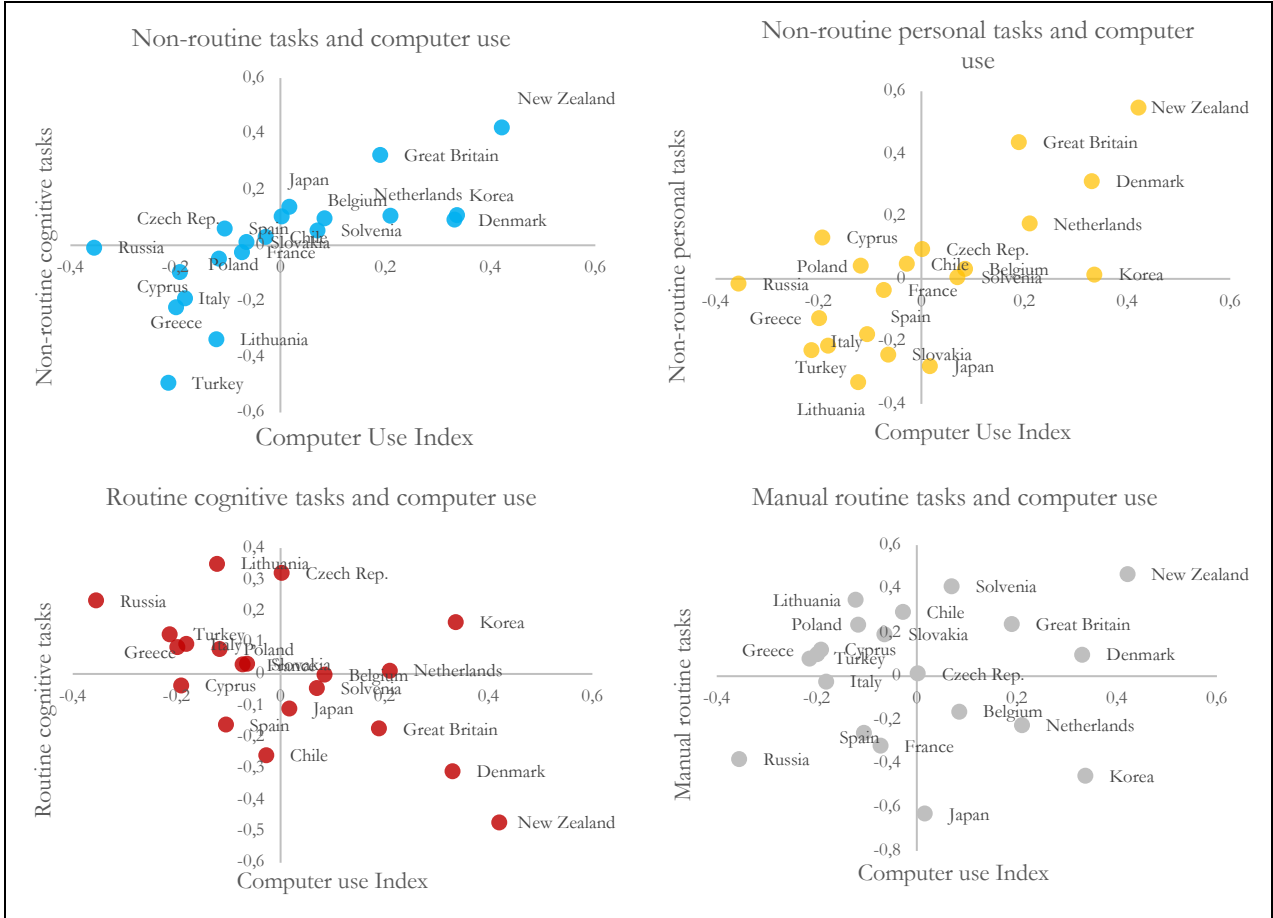
⁸ Autor and Handel find positive and high occupation-level correlation between their measures and O*NET measures for Abstract (0.65), Routine (0.48), and Manual tasks (0.63).

⁹ Again, the five item responses are (i) Every Day; (ii) At least once a week but not every day; (iii) Less than once a week; (iv) Less than once a month; (v) Never.

¹⁰ 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.

the first component of the principal component analysis of these four items (which explains 57.5% of the total variance) and present it in a standardized form¹¹.

Figure 2. Computer use and job tasks across countries



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

Figure 2 depicts such index for each of the countries under analysis, and the questionnaire items used to construct such index are detailed at the bottom of Table 1. As can be seen, New Zealand, Denmark, Korea and Great Britain display the largest values in terms of computer use, whereas the lowest values correspond to Russia, Greece, Italy and Cyprus. Moreover, the cross-country comparison shows a strong positive correlation of computer use and non-routine cognitive (0.72) and personal (0.67) tasks, whereas a negative correlation with routine cognitive (-0.55) tasks. There is no observed relevant relation between computer use at work and manual routine task at work.

¹¹ When comparing the final index with the dummy used by Spitz-Oener (2006), we find an individual correlation of 0.67. When comparing the average index at the country level with the proportion of workers responding yes to computer use dummy, the cross-country correlation is 0.83.

III. Job Tasks, occupation sorting and computer use at work

The main advantage of job task individual-level measures is that research can exploit the variance within occupations, an issue widely discussed in the literature (Spitz-Oener, 2006; AH, 2013). This section explores the potential use of job tasks measures at the individual level in order to better understand the relation between occupational sorting, education and skills and task measures. Additionally, we consider the extent to which computer use at work plays a role mostly between or within occupations in determining the relation of task measures with computerization.

Conceptually, we follow AH (2013) approach, and start by assessing the determinants of job tasks across countries, by particularly looking at the relationship between tasks at the worker-level with key covariates within occupations. To explore this relationship, we consider for a given worker i a pooled linear model with country fixed effects δ_{kj} for countries $j = 1 \dots 20$, where:

$$T_{kij} = \alpha + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_o \beta_{2o} X_{ijo}^{Job} + \beta_{k5} ICT_{ij} + \delta_{kj} + \tau_{pj} + \varepsilon_{kij} \quad (1)$$

where T_{kij} represents the intensity of k^{th} -job task for individual i in country j . In addition, X_{ij}^{Ind} is a vector of individual worker characteristics (such as gender, age, level of education or literacy and numeracy skills), X_{ij}^{Job} is a vector of job characteristics (public or private firm, firm size and on-the-job training), ICT_{ij} captures the use of computer for worker i at work. Finally, δ_{kj} and τ_{pj} represent country and occupational dummies. Country fixed effects capture the cross-country differences in the respective task measure index that cannot be explained by the model, whereas occupational dummies provide estimates net of occupational assignment. It is to be noted, once again, that this model accounts for differences in individual cognitive skills through the individual literacy and numeracy test scores. Job contents are undoubtedly driven at least partially by individual ability, which is in most instances unobservable to researchers. The possibility to account for them in an estimation of the determinants of job tasks allows to control for time invariant unobserved heterogeneity and hence, clean the relationship between job contents and other covariates from such correlation. Indeed, to our knowledge, it is the first time that cognitive skills are controlled for in an estimation of the determinants of Job Contents in a cross-country analysis.

Table 3 presents regression results for the task measures of non-routine cognitive, non-routine personal, routine cognitive and routine manual tasks. The first model of each task includes country dummies, individual characteristics, job characteristics as well as the worker-level index value of computer use. To control for occupational sorting, we include occupation fixed effects. Finally, in order to control for potential differences in elasticity of tasks with respect to computer

use across countries, we include an interaction term of country fixed effects and computer use. First, adding occupation fixed effects increases the explanatory power of the model substantially, as we might expect. Second, it is particularly interesting to see how the importance of gender, age (not for all tasks) and education levels of workers in determining job tasks decrease significantly when controlling for occupational sorting, although within occupation estimates still account for important socio-demographic marginal effects. The importance of job characteristics and the economic sector also decrease significantly. Third, computer use is a key determinant of job task and, more importantly, this relation does remain constant even when accounting for occupational sorting.

The interaction terms display some variation which is significant, but overall the positive relation between computer use and non-routine tasks, and the negative relation of computer use and routine cognitive tasks keeps the same sign for all countries. Nevertheless, for the case of manual routine tasks, the marginal term is positive, small and significant (column (11)), when we include the interaction with country fixed effects. Finally, although not reported for space brevity, there are differential effect of computer use at work for each country. The largest effects of computer use on non-routine cognitive tasks are found for the Czech Republic, Spain, France, Greece, Italy, Japan, Netherlands, Russia, Slovenia and Slovakia. Such relation is clearly smaller for Chile, Great Britain, New Zealand, and Turkey. Regarding non-routine personal tasks the effect is largest for the Czech Republic, Greece, Russia and Slovakia, while much lower for Japan, New Zealand, and Chile. With respect to routine cognitive tasks, the negative effect is stronger in the Netherlands, Slovenia, and Slovakia, and much lower in Chile and New Zealand. Finally, the relation of computer use and routine manual tasks is negative and large in France and Belgium, while positive in a large set of countries, in particular South Korea, with a very large positive relation.

Overall results show that computer use at work is a key factor in explaining differences in job contents, both between and within occupations, and that this holds even after controlling for detailed individual and job characteristics, including individual cognitive skills, usually unobservable. Although we cannot attribute this to be a causal relation, this brings suggestive evidence of the importance of technology adoption in understanding the task content of jobs across and within countries, whereas at the same time validates our measures of job content from a more policy perspective.

Table 3. Task content, Occupation sorting and computer use at work

VARIABLES	Non-routine cognitive			Non-routine personal			Routine cognitive			Routine Manual		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Computer Use (Index)	0.404*** (0.00535)	0.377*** (0.00628)	0.422*** (0.0172)	0.299*** (0.00589)	0.278*** (0.00673)	0.357*** (0.0178)	-0.268*** (0.00579)	-0.262*** (0.00672)	-0.285*** (0.0159)	-0.0578*** (0.00632)	0.0517*** (0.00742)	-0.208*** (0.0214)
Male	0.284*** (0.00982)	0.195*** (0.0109)	0.192*** (0.0109)	0.102*** (0.0108)	0.138*** (0.0118)	0.139*** (0.0118)	-0.123*** (0.0105)	-0.141*** (0.0113)	-0.142*** (0.0112)	-0.0472*** (0.0119)	-0.0360*** (0.0135)	-0.0431*** (0.0134)
Age 25-34	0.121*** (0.0183)	0.0824*** (0.0175)	0.0852*** (0.0174)	0.0404** (0.0201)	0.0586*** (0.0191)	0.0635*** (0.0191)	-0.0242 (0.0192)	-0.0246 (0.0178)	-0.0262 (0.0178)	0.0272 (0.0203)	0.0348* (0.0193)	0.0283 (0.0191)
Age 35-44	0.118*** (0.0179)	0.0683*** (0.0172)	0.0696*** (0.0172)	0.124*** (0.0198)	0.126*** (0.0188)	0.132*** (0.0188)	-0.0487*** (0.0186)	-0.0341* (0.0175)	-0.0343** (0.0175)	-0.0250 (0.0201)	0.00926 (0.0192)	0.0133 (0.0190)
Age 45-54	0.129*** (0.0182)	0.0691*** (0.0176)	0.0698*** (0.0176)	0.115*** (0.0199)	0.107*** (0.0190)	0.113*** (0.0190)	-0.0478** (0.0187)	-0.0130 (0.0176)	-0.0142 (0.0176)	-0.0763*** (0.0205)	-0.0277 (0.0196)	-0.0106 (0.0195)
Age 55-64	0.0479** (0.0198)	-0.0237 (0.0193)	-0.0237 (0.0223)	0.0965*** (0.0193)	0.0853*** (0.0215)	0.0876*** (0.0215)	0.00865 (0.0201)	0.0498** (0.0201)	0.0494** (0.0201)	-0.146*** (0.0201)	-0.0689*** (0.0222)	-0.0490** (0.0221)
High School or Sec. VET	0.138*** (0.0141)	0.0846*** (0.0138)	0.0843*** (0.0140)	0.145*** (0.0154)	0.0805*** (0.0146)	0.0853*** (0.0147)	-0.154*** (0.0150)	-0.0914*** (0.0141)	-0.0966*** (0.0143)	-0.0127 (0.0166)	-0.00196 (0.0161)	0.0143 (0.0161)
Tertiary professional	0.238*** (0.0179)	0.115*** (0.0176)	0.240*** (0.0177)	0.240*** (0.0196)	0.101*** (0.0187)	0.107*** (0.0188)	-0.301*** (0.0195)	-0.123*** (0.0188)	-0.129*** (0.0190)	-0.0235 (0.0206)	-0.0277 (0.0204)	-0.00661 (0.0204)
Tertiary college	0.362*** (0.0176)	0.208*** (0.0182)	0.207*** (0.0183)	0.531*** (0.0194)	0.133*** (0.0195)	0.136*** (0.0196)	-0.554*** (0.0194)	-0.209*** (0.0190)	-0.211*** (0.0192)	-0.222*** (0.0212)	-0.161*** (0.0217)	-0.157*** (0.0217)
Literacy Skills	-0.000382 (0.000259)	-0.000181 (0.000245)	-0.000228 (0.000245)	-0.000760** (0.000299)	-0.000466* (0.000271)	-0.000485* (0.000272)	0.000624** (0.000301)	0.000576** (0.000271)	0.000633** (0.000271)	-0.00127*** (0.000306)	-0.00102*** (0.000294)	-0.000977*** (0.000293)
Numeracy Skills	0.00207*** (0.000244)	0.00133*** (0.000232)	0.00136*** (0.000232)	0.00186*** (0.000277)	0.00121*** (0.000253)	0.00123*** (0.000253)	-0.00114*** (0.000284)	-0.000559** (0.000259)	-0.000611** (0.000259)	-0.000347 (0.000280)	-0.000170 (0.000273)	1.35e-05 (0.000271)
Private firm	-0.107*** (0.0114)	-0.00616 (0.0126)	-0.00718 (0.0125)	0.00211 (0.0129)	0.0622*** (0.0138)	0.0600*** (0.0137)	-0.0119 (0.0132)	-0.0105 (0.0135)	-0.0105 (0.0135)	0.00744 (0.0141)	-0.00583 (0.0157)	0.00147 (0.0155)
Size: 11 to 50	0.121*** (0.0119)	0.102*** (0.0116)	0.102*** (0.0116)	0.00654 (0.0134)	0.0117 (0.0127)	0.0125 (0.0127)	-0.132*** (0.0129)	-0.0978*** (0.0129)	-0.101*** (0.0120)	-0.00381 (0.0120)	0.000130 (0.0142)	-0.00194 (0.0135)
Size: 51 to 250	0.152*** (0.0135)	0.130*** (0.0132)	0.130*** (0.0132)	-0.0324** (0.0152)	-0.00364 (0.0144)	-0.000547 (0.0143)	-0.117*** (0.0146)	-0.111*** (0.0137)	-0.116*** (0.0137)	-0.0350** (0.0157)	-0.0164 (0.0153)	-0.0198 (0.0151)
Size: 251 to 1000	0.193*** (0.0164)	0.156*** (0.0165)	0.156*** (0.0165)	-0.0665*** (0.0182)	-0.00832 (0.0174)	-0.00308 (0.0174)	-0.0465*** (0.0174)	-0.105*** (0.0167)	-0.113*** (0.0167)	-0.0189 (0.0194)	-0.00697 (0.0192)	-0.0105 (0.0190)
Size: more than 1000	0.240*** (0.0203)	0.181*** (0.0198)	0.183*** (0.0198)	-0.0393* (0.0212)	0.00771 (0.0204)	0.0150 (0.0204)	-0.110*** (0.0217)	-0.171*** (0.0207)	-0.178*** (0.0206)	-0.0345 (0.0235)	-0.0489** (0.0227)	-0.0544** (0.0225)
On the job Training	0.246*** (0.0101)	0.197*** (0.00978)	0.196*** (0.00977)	0.203*** (0.0113)	0.149*** (0.0105)	0.147*** (0.0106)	-0.267*** (0.0111)	-0.215*** (0.0101)	-0.213*** (0.0101)	0.0737*** (0.0115)	0.0634*** (0.0112)	0.0590*** (0.0111)
Construction	0.139*** (0.0195)	0.0303 (0.0238)	0.0312 (0.0238)	0.150*** (0.0221)	0.116*** (0.0269)	0.118*** (0.0268)	-0.156*** (0.0205)	-0.107*** (0.0247)	-0.109*** (0.0246)	0.0565*** (0.0212)	-0.0179 (0.0267)	-0.0174 (0.0265)
Services	-0.101*** (0.0117)	-0.0686*** (0.0134)	-0.0652*** (0.0133)	0.194*** (0.0129)	0.0220 (0.0146)	0.0223 (0.0146)	-0.123*** (0.0120)	-0.00900 (0.0135)	-0.0105 (0.0135)	-0.103*** (0.0136)	-0.00961 (0.0168)	-0.00845 (0.0167)
Country Dummies	X	X	X	X	X	X	X	X	X	X	X	X
Occupation Dummies		X	X		X	X		X	X		X	X
Country Dummies*Computer Use			X			X			X			X
Constant	-0.980*** (0.0463)	-0.318*** (0.123)	-0.331*** (0.124)	-0.839*** (0.0510)	-0.410*** (0.149)	-0.460*** (0.147)	0.661*** (0.0498)	0.223* (0.114)	0.271** (0.114)	0.459*** (0.0548)	-0.373** (0.168)	-0.394** (0.166)
Observations	51,056	51,056	51,056	51,056	51,056	51,056	51,037	51,037	51,037	51,056	51,056	51,056
R-squared	0.391	0.450	0.452	0.236	0.348	0.350	0.286	0.415	0.418	0.121	0.196	0.224

Note: For country dummies, we use Belgium as country of reference. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Observations are weighted so that countries are weighted equally.

IV. The rewards to Job Tasks in the Labor Market around the world

In this section we turn to estimate the rewards to the different Job tasks in the labor market, through the empirical relation between wages and job tasks around the world. To our knowledge, there is not a single study that addresses this relationship in a cross-country framework. In particular, we are interested in computing empirically the differences in the rewards to the different job tasks, as well as differences in these rewards across different countries. We start by presenting basic empirical relationships between (log) wages and different job contents, to learn about the predictive power of job tasks for wages, both across and within occupations. As before, we “validate” our task measures by comparing our job tasks definition with those obtained from O*NET dataset.

However, to be consistent with the task approach, by which individuals decide upon which job tasks to perform on the basis of their comparative advantage, we must assess the endogeneity of job tasks for wages to obtain true job task rewards. We do that following the methodology proposed by AH (2013) to control for the self-selection of workers into different jobs based on their comparative advantage.

Wage Data

The wage data reported by PIAAC that we use corresponds to hourly earnings with bonuses for wage and salary earners. Among countries for which we have constructed task measures, there is no public data on earnings at the individual level for the case of Turkey. For this reason, we exclude the data of Turkey in the preparation of variables for wage analysis, in particular reconstructing task measures with the new sample of nineteen countries. Moreover, for consistent comparisons, we use the conversion data to \$USD, corrected in Purchasing Power Parity (PPP), constructed by OECD.

The predictive power of Job Tasks for Wages – Basic Empirical Relationship

Our basic empirical approach consists on estimating a pooled linear model for the nineteen countries described above. ($j = 1 \dots 19$).

$$\text{Log } W_{ij} = \alpha + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_o \beta_{2o} X_{ijo}^{Job} + \sum_k \beta_{3k} Task_{ijk} + \sum_k \beta_{4k} \overline{Tasks}_{jk} + \delta_j + \varepsilon_{ij} \quad (2)$$

with $\text{Log } W_{ij}$ being the hourly log-wage, X_{ij}^{Ind} individual worker characteristics: these include gender, age or level of education, but more importantly, a unique standardized measure of individual ability approximated by the individual test scores on reading and mathematical competencies. By using this last measure, rewards to task a more net of the supply component of unobserved worker ability. X_{ij}^{Job} includes a vector of job characteristics (public or private firm,

firm size and on-the-job training), and $Tasks_{ijk}$ are the intensity of non-routine cognitive, non-routine personal, routine cognitive and routine manual tasks which each worker reports to exert in her work. To net out the pure individual job task reward from the association between job tasks and occupations, we include also the average mean of each task at occupation-country level. As before, this mean is a leave-out mean, representing the average intensity of k-th task for all workers from a particular country in occupation p except for the i -th worker.

Table 4 displays several empirical specifications of the relationship between wages and each of the previously defined tasks. In particular, column 1 addresses the raw/unconditional relationship between wages and individual and job characteristics in a Mincer regression where we include country dummies. Columns 2 and 3 consider task measures, with and without controlling for worker ability measures. The first key result is that we observe a positive relation between non-routine tasks and hourly earnings, while a negative and small relation of routine cognitive and manual tasks with earnings. Returns to individual and job characteristics slightly decrease when considering job task measures. Moreover, the returns to the Index of computer use at work also decrease when considering measures of worker cognitive skills.

When including ability measures in column 3, the wage returns to tasks decrease mostly for non-routine tasks (from 3.1% of hourly wages of one standard deviation of the cognitive task measure to 2.6% and from 2.0% to 1.8% in the personal task measure) but also for manual routine tasks. In columns 4 and 5 we include variables at the occupational level: we first consider task measures of PIAAC averaged at the occupational level (column 4) and then include occupational dummies (column 5). The positive returns to tasks remain, except for non-routine cognitive tasks when considering tasks measures at the occupational level, which reveals the importance of within occupation task measures to understand wage returns in the sample of countries. The returns to task measures at the occupational level are also substantial. This indicates that heterogeneity of job tasks within and between occupations is important, and hence measuring it at the occupational level only would be greatly misleading.

Finally, it is interesting to compare the empirical relationship between tasks and wages found in this paper, where 20 OECD and non-OECD countries are used, to that found by AH (2013), who uses a similar framework but with only US data. AH (2013) finds that within occupations, a one standard deviation increase in abstract tasks is related to a 7 log point wage premium, whereas we find that the same increase in abstract tasks (non-routine cognitive and non-routine personal) predicts a 1 to 3 log point wage premium. Hence, on average, in the countries considered in this study, the rewards to abstract tasks are much lower than those found by AH (2013) for the US economy.

Table 4. Log-Wage returns to tasks, demographics and occupation variables

(1) (2) (3) (4) (5)

Male	0.186*** (0.00616)	0.168*** (0.00627)	0.156*** (0.00651)	0.147*** (0.00846)	0.121*** (0.00824)
Upper Secondary	-0.0838*** (0.00877)	-0.0650*** (0.00875)	-0.0301*** (0.00889)	-0.0204** (0.00921)	-0.0231*** (0.00884)
Post-secondary or Tertiary Professional	0.0973*** (0.00955)	0.0839*** (0.00951)	0.0708*** (0.00946)	0.0552*** (0.00997)	0.0408*** (0.00919)
Tertiary (Bachelor/Master)	0.286*** (0.00830)	0.249*** (0.00841)	0.217*** (0.00861)	0.181*** (0.0119)	0.139*** (0.0107)
25-34	0.117*** (0.0120)	0.112*** (0.0119)	0.114*** (0.0118)	0.107*** (0.0134)	0.0992*** (0.0124)
35-44	0.240*** (0.0119)	0.232*** (0.0118)	0.235*** (0.0117)	0.225*** (0.0154)	0.210*** (0.0145)
45-54	0.279*** (0.0119)	0.270*** (0.0118)	0.277*** (0.0117)	0.264*** (0.0183)	0.245*** (0.0174)
55 plus	0.298*** (0.0139)	0.293*** (0.0137)	0.310*** (0.0136)	0.292*** (0.0226)	0.274*** (0.0206)
On the Job Training	0.0725*** (0.00644)	0.0500*** (0.00645)	0.0463*** (0.00641)	0.0427*** (0.00666)	0.0401*** (0.00649)
Private sector	-0.0244*** (0.00727)	-0.00896 (0.00728)	-0.0104 (0.00720)	0.0101 (0.0106)	0.00612 (0.00995)
Firm size	-0.129*** (0.00865)	-0.119*** (0.00862)	-0.115*** (0.00858)	-0.110*** (0.0104)	-0.107*** (0.00983)
Firm size	-0.0332*** (0.00797)	-0.0339*** (0.00788)	-0.0334*** (0.00784)	-0.0328*** (0.00730)	-0.0314*** (0.00747)
Firm Size	0.0598*** (0.00995)	0.0650*** (0.00984)	0.0628*** (0.00970)	0.0631*** (0.00866)	0.0584*** (0.00886)
Firm size	0.131*** (0.0134)	0.131*** (0.0132)	0.129*** (0.0130)	0.129*** (0.0132)	0.115*** (0.0127)
Computer Use Index	0.115*** (0.00355)	0.0821*** (0.00378)	0.0716*** (0.00382)	0.0593*** (0.00564)	0.0461*** (0.00528)
Literacy Skills			-0.000169 (0.000190)	-0.000152 (0.000169)	-0.000174 (0.000167)
Numeracy Skills			0.00154*** (0.000179)	0.00137*** (0.000155)	0.00124*** (0.000153)
Non-routine cognitive (PIAAC Worker)		0.0311*** (0.00393)	0.0258*** (0.00392)	0.00216 (0.00407)	0.0126*** (0.00386)
Non-routine personal (PIAAC Worker)		0.0202*** (0.00403)	0.0177*** (0.00400)	0.0202*** (0.00421)	0.0220*** (0.00491)
Routine cognitive (PIAAC Worker)		-0.0443*** (0.00429)	-0.0450*** (0.00424)	-0.0174*** (0.00488)	-0.0228*** (0.00467)
Routine manual (PIAAC Worker)		-0.0225*** (0.00326)	-0.0194*** (0.00324)	-0.0152*** (0.00379)	-0.0159*** (0.00373)
Non-routine cognitive (PIAAC Occ.)				0.0812*** (0.0118)	
Non-routine personal (PIAAC Occ.)				-0.0285* (0.0150)	
Routine cognitive (PIAAC Occ.)				-0.0889*** (0.0156)	
Routine manual (PIAAC Occ.)				-0.00305 (0.0142)	
Worker Ability measures	No	No	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes
Occupational Dummies	No	No	No	No	Yes
Constant	2.397*** (0.0190)	2.411*** (0.0189)	2.042*** (0.0308)	2.099*** (0.0423)	2.264*** (0.0423)
Observations	46,544	46,530	46,530	46,530	46,530
R-squared	0.523	0.531	0.536	0.543	0.566

Notes: Data reflects log hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD\$. We exclude earnings below USD\$1 and above USD\$150. All regressions with occupation-level variables cluster standard errors at the occupation level.

To check the validity of our results, we also consider separate regressions for PIAAC and O*NET occupation-level tasks. In Table 5, we find positive and similar returns to non-cognitive routine tasks and modest to insignificant returns to non-routine personal tasks. First, PIAAC estimate in column 1 has (slightly) more predictive power to explain wage differences than

O*NET estimates in column 2. With respect to routine cognitive tasks, only PIAAC occupation-level data remains significant in explaining the negative wage returns to routine cognitive tasks, whereas O*NET data does not display significant results. When including tasks at the individual level (PIAAC) together with occupation-level data (using PIAAC or O*NET) in columns 3 and 4, the magnitude of returns at the occupation-level tasks remains constant, except for non-routine personal tasks, which changes to a negative (although small) effect in the case of PIAAC data at the occupation level. The individual measure estimates complement with statistically significant estimates for both measures of occupation-level tasks. Finally, including both measures at the same time (column 5) together with individual task measures shows complementarity for non-routine cognitive tasks of O*NET and PIAAC at the occupation level, but a negligible effect in the rest of O*NET task measures.

Overall, it can be said that returns to tasks are partially captured by workers' occupations, but there is still substantial heterogeneity of tasks within occupations. Hence, to capture average returns to tasks appropriately, we need to consider not only definition of job contents at occupational level, but also at individual level.

Additionally, compared to the PIAAC occupation-level measures, the O*NET measures at the occupation level are, if anything, less relevant and less precise, as the standard errors of O*NET measures are substantially higher than their counterpart from PIAAC. These results are highly consistent with those found by AH (2013).

Table 5. Log-wage returns to tasks within and between occupations comparing O*NET and PIAAC

	(1)	(2)	(3)	(4)	(5)	(6)
Non-routine cognitive (PIAAC Worker)			0.00216 (0.00407)	0.0166*** (0.00517)	0.00302 (0.00404)	0.00279 (0.00400)
Non-routine personal (PIAAC Worker)			0.0202*** (0.00421)	0.0162*** (0.00504)	0.0203*** (0.00422)	0.0199*** (0.00419)
Routine cognitive (PIAAC Worker)			-0.0174*** (0.00488)	-0.0366*** (0.00594)	-0.0177*** (0.00488)	-0.0159*** (0.00494)
Routine manual (PIAAC Worker)			-0.0152*** (0.00379)	-0.0176*** (0.00413)	-0.0158*** (0.00381)	-0.0114*** (0.00392)
Non-routine cognitive (PIAAC Occ.)	0.0766*** (0.0115)		0.0812*** (0.0118)		0.0552*** (0.0156)	0.0845*** (0.0121)
Non-routine personal (PIAAC Occ.)	-0.00867 (0.0143)		-0.0285* (0.0150)		-0.0235 (0.0162)	-0.0247* (0.0149)
Routine cognitive (PIAAC Occ.)	-0.104*** (0.0154)		-0.0889*** (0.0156)		-0.0741*** (0.0168)	-0.0799*** (0.0160)
Routine manual (PIAAC Occ.)	-0.0163 (0.0136)		-0.00305 (0.0142)		-0.00505 (0.0129)	0.00394 (0.0141)
Non-routine cognitive (O*NET Occ.)		0.0775*** (0.00896)		0.0757*** (0.00873)	0.0551*** (0.00982)	
Non-routine personal (O*NET Occ.)		0.00347 (0.00978)		-0.00765 (0.00985)	-0.00980 (0.00983)	
Routine cognitive (O*NET Occ.)		-0.0162 (0.0107)		-0.0120 (0.0101)	-0.00928 (0.00889)	
Routine manual (O*NET Occ.)		0.0105 (0.00996)		0.0147 (0.00947)	0.0206** (0.00849)	
PIAAC Non-routine cognitive (worker)*PIAAC Non-routine cognitive (occ.)						-0.0126*

PIAAC Non-routine personal (worker)*PIAAC Non-routine personal (occ.)						(0.00674)
						0.00198
PIAAC Routine cognitive (worker)*PIAAC Routine cognitive (occ.)						(0.00804)
						0.0132**
PIAAC Routine manual (worker)*PIAAC Routine manual (occ.)						(0.00605)
						0.0191***
						(0.00576)
Individual, Job and Ability measures	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.091*** (0.0424)	2.070*** (0.0446)	2.099*** (0.0423)	2.098*** (0.0429)	2.125*** (0.0422)	2.093*** (0.0431)
Observations	46,544	46,544	46,530	46,530	46,530	46,530
R-squared	0.541	0.538	0.543	0.542	0.545	0.543

Notes: Data reflects log hourly earnings, including bonuses for wage and salary earners, in PPP corrected USD\$. We exclude earnings below USD\$1 and above USD\$150. All regressions with occupation-level variables cluster standard errors at the occupation level.

Accounting for sorting of workers into occupations – Roy Model

Within the “task approach”, workers decide their job contents based on their comparative advantage. Consequently, an OLS approach of Job Tasks on Wages would not drive consistent estimates of the job task rewards. Instead, we consider, as in a Roy (1951) model, that workers are utility (wage) maximizers and hence select into those jobs/occupations where they attain the highest wage given their skills. Each job requires to perform simultaneously a different combination of different tasks.

Accounting empirically for the self-selection of workers into different jobs to estimate adequately job tasks rewards is not straightforward. One possibility is to find adequate instruments to circumvent the endogeneity of tasks due to the self-selection of workers into jobs, but unfortunately we do not have such instruments. Instead, we hypothesize, as the “task approach” does, that workers self-select into those occupations with higher returns to those tasks which they perform relatively better – i.e., have comparative advantage. From the empirical point of view, this implies that occupational level task returns must show a positive covariance with individual level task returns. Hence, and following AH (2013), we consider an augmented version of a classical mincerian regression, where in addition to the individual and occupation endowment of tasks, presented above, we include an interaction term between individual and occupation task returns. Moreover, AH (2013) shows that if all interaction terms are positive, this means that workers that are highly efficient in conducting specific tasks self-select into occupations which reward those tasks, resulting in a comparative, rather than absolute advantage. Instead, the absolute advantage hypothesis is less restrictive and requires that only one of the interaction coefficients is positive¹².

¹² The test presented by Autor and Handel does not provide dispositive evidence, but represents rather an exploratory approximation to the issue.

Results are displayed in column 6 of Table 5 and reveal that the interaction between routine (cognitive and manual) individual and occupation based measures are significantly positive, whereas such correlation is not found (at 5% level) for the non-routine (cognitive and personal) interaction between individual and occupation measures. As AH (2013) discuss, these results are consistent with absolute advantage. Additionally, when we include such interactions, individual measures of job tasks, with the exception of non routine cognitive, still show significant predictive power to explain wage differences, even within occupations. In particular, a one standard deviation increase in non-routine personal tasks predicts a 2 log point wage premium, whereas the same magnitude of increase in routine cognitive or in routine manual tasks predicts a 2 log point wage penalty.

This can be mostly extrapolated to the same argument within countries. In **¡Error! No se encuentra el origen de la referencia.** in the **¡Error! No se encuentra el origen de la referencia.**, we look at the sign and magnitude of results by countries. The results are not exactly homogenous within countries, with variation in terms of the sign of the interaction terms and the significance. It is true, at the same time, that for all countries, at least two interaction terms are positive, and for five of them (Denmark, Spain, France, Great Britain, and Greece) three out of four task interaction terms are positive, with joint significance for France, and Great Britain.

V. Conclusion

In this paper we investigate for the first time cross-country differences in the intensity of job tasks presented in the Autor, Levy and Murnane (2003) model. To do so, we use for the first time the background questionnaire items from the Programme for International Assessment of Adult Competences (PIACC) database, implemented in more than 30 countries between 2011 and 2014. The dataset provides very precise information on job contents at the worker level, which allows for job task heterogeneity within occupations when accounting for differences on the job contents, a unique feature only available in very few national surveys in the past. Additionally, the data includes novel data of an accurate measurement of cognitive skills in literacy, numeracy and problem solving skills, so that unobserved worker characteristics can be accounted for.

This allows us to have a clear picture of job tasks at the individual level and compare it across individual and job characteristics, including key variables of the ALM model such as computer use at work. The Nordic, Anglo-Saxon and East Asian advanced countries (Great Britain, Denmark, New Zealand, Japan and Korea) form the group of countries where jobs exhibit a higher intensity of non-routine task content of jobs (both cognitive and personal dimensions). On the other end stand the group of Eastern European countries, like Lithuania, Turkey Russia or the Czech Republic, which display low levels of non-routine cognitive tasks, whereas high levels of routine cognitive tasks.

Our measures derived from PIAAC data for 20 countries are consistent and display large correlation with O*NET, the other main measure used at the occupational level in the literature. In particular, relative to O*NET, the PIAAC measures shows larger consistency for the measures of non-routine tasks and for western European countries, like Belgium, Denmark France, Netherlands, or Great Britain, compared to Eastern European countries. This validity approach confirms that the task measurement followed is highly valuable for this current and future research, whenever new PIAAC waves are implemented again. It may allow for dynamic analyses of the consequences of technology adoption on job polarization or job de-routinization and the redistributive impact this may be having on the workforce population.

At the same time, when looking at the determinants of job tasks at work, we find that the task measures are relevant in explaining differences both between but also within occupation task measures, not matter if we control for individual and job characteristics. The importance and statistical significance of computer use at work is large and relevant overall, hence revealing a high predictive power of computer use at work to explain tasks determinants. We also find that within occupation task heterogeneity is relevant across and within countries, even after controlling for individual and job characteristics. Moreover, we find a positive and consistent relation of computer use at work and non-routine tasks, whereas a negative relation with routine tasks, consistent with the Autor, Levy and Murnane (2003) framework. Although this assessment has a static point of view, we observe that the relation between computer use at work and task content of jobs both across and within countries. Finally, similar to what Autor and Handel (2012) describe, we observe clear signs of self-selection of workers based on their comparative advantage to be rewarded in tasks which they more effectively perform.

Finally, results on how tasks affect earnings show clear signs for worker self-selection into jobs according to their ability to perform tasks at job. The returns to task measures at the occupational level are also substantial, but worker-level information is still key. This indicates that heterogeneity of job tasks within and between occupations is important, and hence measuring it at the occupational level only would be greatly misleading. These two findings (the comparison with O*NET and the importance of within-occupation worker level data) are highly consistent to what is found by Autor and Handel (2013) for the United States. It is to be noted that our paper goes beyond a single country approach, as it allows us to extend such results to a large set of diverse countries, hence providing external validity to the Autor and Handel approach. Finally, and as a robustness check, we show that our approach is consistent with a Roy model of self-selection.

From a policy perspective, this study is important to level the playing field of a fundamental policy discussion such as the impact of technological change and automation of the job content of workers. This will be at the core of social sciences in the coming decades. Our paper provides a consistent and promising avenue of future research on the consequences of technological

change on the labor markets from an international perspective, whenever second or third waves of PIAAC (or national longitudinal studies) data are implemented worldwide. Moreover, it confirms the importance of collecting worker level information of job activities and habits (already discussed in previous studies for the US and Germany), and hence the need to move away from occupation-level studies.

VI. References

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