

TECHNOLOGY, SKILLS, AND GLOBALISATION: EXPLAINING INTERNATIONAL DIFFERENCES IN ROUTINE AND NONROUTINE WORK USING SURVEY DATA*

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Abstract

Technology and globalisation drive the shift away from manual and routine cognitive work, and towards non-routine cognitive work. Studies on the task content of work usually use the US database O*NET, and it is still unknown how the task content of occupations differs between countries. We create measures of non-routine cognitive analytical and personal, routine cognitive and manual task contents that are consistent with Acemoglu & Autor (2011) measures based on O*NET, but are worker-specific. We apply them to 42 countries at various development level that are covered by PIAAC, STEP and CULS surveys. We find that the relationship between routine intensity of tasks and development level is inverse-U shaped. Tertiary education, computer use, literacy skills, and work in professional or managerial jobs are negatively related to the routine task intensity. The higher is the ICT capital stock per worker, the number of robots per worker, and the participation in global value chains, the lower is the routine task intensity, especially in high-skilled occupations. In most countries, the structure of worker and job characteristics is more conducive to routine work than in the US. However, most of cross-country differences routine task intensity can be attributed to differences in computer use in the workplace.

Keywords: task content of jobs, deroutinisation, global division of labour, PIAAC, STEP, CULS.

JEL: J21, J23, J24

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1. Introduction and motivation

The shift away from manual and routine cognitive work, and towards non-routine cognitive work has been changing the nature of work around the world. Since the 1970s the employment shares of high-skilled workers performing non-routine work have grown while those of middle-skilled workers performing routine work have declined in the US and other OECD countries (Autor et al., 2003; Goos et al. 2014). The demands of particular occupations have also changed accordingly (Autor et al., 2003; Spitz-Oener, 2006). The middle-income or newly established high-income countries have experienced similar changes, although the routine cognitive work has remained stable or even increased in the emerging South (Aedo et al., 2013), in Russia (Gimpelson & Kapeliushnikov, 2016), and in the transition economies of Central and Eastern Europe (Hardy et al., 2018).

The measurement of task content of jobs is usually done on the basis of Occupational Information Network (O*NET) data, the US survey of occupational demands, and following the methodologies proposed by Autor et al. (2003) and Acemoglu & Autor (2011). The O*NET task measures are often merged with country-specific data sources, usually labour force surveys, and used to calculate the task content of jobs in countries other than the US (Arias et al., 2014, Goos et al., 2009, 2014, Dicarolo et al., 2016, Lewandowski et al., 2017, Hardy et al., 2018). This approach is common because no other sources offer as rich and detailed data on occupations as O*NET. However, it requires assuming that the occupational demands in the US and other countries are identical. This assumption is not necessarily wrong because Handel (2012) and Cedefop (2013) showed that it is methodologically valid to use O*NET to construct occupational measures in the developed countries. On the other hand, World Bank (2016) applied the occupational typologies based on O*NET to all countries in the world which implied that agricultural workers were classified as middle-skilled workers also in the developing countries.

It can be presumed that the tasks performed by workers in a given occupation around the world differ to some extent, although it has not been quantified yet how large these differences are. Understanding this differences is of both scientific and policy-making relevance, as the projections of shares of automatable jobs are usually based on the estimates of task structures (Arntz et al., 2017, Frey & Osborne, 2017).

In this paper we create task content measures that are consistent with the Acemoglu & Autor (2011) measures based on O*NET, but are worker-specific and can be calculated for a range of countries. We aim at answering two main questions. First, how different are the country-specific task structures of jobs in various countries, in particular in emerging and developed economies? Second, which labour supply, labour demand and technological factors contribute to these differences?

We propose a novel methodology by using the US dataset of the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) survey to create individual-level task content measures, and validating them with the Acemoglu & Autor (2011) O*NET-based measures for the US. As a result, the interpretation of our task content measures and the occupational characteristics identified for the US are consistent with those in the established literature (Autor et al., 2003; Acemoglu & Autor, 2011; Goos et al., 2014). As our measures are worker-specific, they can be calculated for any country with available data. We apply our methodology to 42 countries covered by PIAAC, as well as World Bank's Skills Measurement Program (STEP) and China Urban Labor Survey (CULS) surveys which include the "skill use at work" questionnaire comparable with the one in PIAAC. The sample includes the OECD countries, as well as low- and middle-income countries so our results provide a comprehensive picture of the cross-country differences in the task content of jobs.

The use of US data to validate the methodology with the Acemoglu & Autor (2011) measures distinguishes our paper from previous studies that used PIAAC or STEP to measure the country-specific occupational demands. De la Rica & Gortazar (2016) used PIAAC to create measures of “de-routinisation”, Marcolin et al. (2016b) – to classify workers in the OECD countries into non-, low-, medium- and high-routine intensive occupations. Dicarolo et al. (2016) attempted to create task content measures with the STEP data. However, the measures proposed in those papers were somewhat arbitrary. It is unclear how similar is their meaning of “routine” and “non-routine” to the meaning established in the literature based on O*NET, and to what extent the differences with respect to the O*NET-based results stem from the use of country-specific data, and to what extent from differences in definitions and coverage of different surveys. The latter caveat is especially relevant as some of the O*NET items used by Acemoglu & Autor (2011) do not have counterparts in PIAAC or STEP surveys. By merging O*NET with the US PIAAC, however, we are able to find the best possible proxies of O*NET among the PIAAC questions.

Applying our methodology to countries around the world we find that occupations are indeed different. Workers in the more developed economies perform more non-routine tasks, both cognitive and analytical. This pattern is the strongest for managerial and professional occupations. At the same time, the relationship between development level (GDP per capita) and the level of routine cognitive tasks is inverse U-shaped.

In order to shed light on factors which may contribute to the cross-country differences in the task content of jobs, we use regression-based decomposition and we distinguish between demand- and supply-side factors.

Among the demand side factors, we focus on technology and participation in the global value chains, in particular off-shoring. Technological progress, especially automation and computerisation, reduces demand for workers to perform routine tasks and increases demand for non-routine tasks, both analytical and interpersonal (Autor et al., 2003; Autor et al., 2006; Acemoglu & Autor, 2011; Brynjolfsson & McAfee, 2014; Deming, 2018; Spitz-Oener, 2006). Therefore, workers in countries differing with respect to the adoption of routine-replacing technologies and the incidence of ICT use in the workplace, may perform varying proportions of routine and non-routine tasks. Indeed, we find that about $\frac{1}{4}$ of cross-country differences in the relative role of routine and non-routine tasks can be attributed to the differences in the ICT capital stocks (per worker) and in the incidence of computer use at work. Differences in robot stocks (per worker) turn out quantitatively less important. Offshoring is the second important factor contributing to the shift away from routine tasks, particularly in the OECD countries (Goos et al., 2014, Hummels et al., 2016). As the routine jobs are easier to offshore (Grossman & Rossi-Hansberg, 2008; Oldenski, 2012), it can be presumed that workers in the countries which receive the offshored jobs may perform more routine tasks. Indeed, we find such correlations, but we attribute only a small share of the cross-country differences in task contents to the differences in participation in global value chains. Moreover, a comparable share of these differences can be attributed to differences in sectoral structures of employment.

The relative importance of routine and non-routine tasks is also related to education and skills – the higher is the share of tertiary graduates, the higher is the relative role of non-routine tasks (Oesch, 2013; Salvatori, 2015; Hardy et al., 2018, Montresor, 2018). We also find that education and skills are a key supply-side factor contributing to the differences in the task content of jobs, especially in the less developed countries.

In the second section we outline our methodology of creating the task content measures with PIAAC, STEP and CULS, and validating them with O*NET based measures. In the third section we discuss the properties of our measures. In the fourth section we present the cross-country differences in task structures and their regression-based decompositions. The fifth section concludes.

2. Methodology

2.1 Data – PIAAC, STEP and CULS surveys

Our main goal is to analyse the task content of jobs in a sample of countries that participated either in the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) or in the World Bank's Skills Measurement Program (STEP). We supplement these two cross-country surveys with the third wave of China Urban Labor Survey (CULS) conducted by the Institute of Population and Labor Economics of the Chinese Academy of Social Science (CASS). The country coverage of PIAAC and STEP does not overlap, so in total the data are available for 44 countries from around the world.

So far, two rounds of PIAAC were conducted and the third one is ongoing at the time of writing. The first round encompassed 24 countries, of which 23 made their data publically available (see Appendix A for the full list of countries in PIAAC and STEP), while the second round encompassed 9 countries. The data collection for the first round took place between 2011 and 2012, and for the second round between 2014 and 2015. All of the studied countries were either OECD or OECD Partners, with sample sizes ranging from approx. 4000 (in Russia) to approx. 9 400 in Poland and more than 26 000 in Canada, of adults aged 16-65.¹ Moreover, the PIAAC survey in the US was supplemented by an additional wave in order to enhance the sample size, while retaining or improving representativeness. The enhanced sample is available from the US National Center for Education Statistics (NCES) and we use it instead of the smaller OECD PUF sample.

At the time of writing, the STEP study has been conducted in and made available for 12 low-income countries. The data collection took place between 2012 and 2014. The sample sizes for the countries we include range from approx. 2 400 (in Ukraine) to approx. 4 000 (in Macedonia), of urban residents aged 15-64. In principle, STEP is an urban survey, so we drop the rural part of sample in Laos, in order to ensure comparability with other countries. Finally, we remove Sri Lanka and Vietnam from the analysis as the former contains too few observations in urban areas for a meaningful analysis (about 650 workers) and the latter delivers skewed results, potentially because it covered only the two largest cities.

We also use the third wave of CULS which included the "skill use at work" questionnaire of STEP and therefore it is directly comparable to STEP. The survey was conducted in 2016 in six large cities in China (Guangzhou, Shanghai, and Fuzhou on the coast, Shenyang in the northeast, Xian in the northwest, and Wuhan in central China).² We use the CULS data instead the STEP survey for the Chinese Yunnan province, as it contains far more observations (almost 15 500) and covers a more comprehensive area.³ For convenience, we will refer to CULS as one of the STEP countries, as the data on skill are comparable and we processed them in the same way.

¹ Individuals aged 15-year were also surveyed in Australia and Chile. Individuals aged 66-74 were surveyed in Australia.

² The survey sampled 260 neighbourhoods, 2 581 migrant households and 3 897 local households, including 15 448 individuals in total.

³ Yunnan is one of the poorer and more rural provinces in China. The urban STEP survey conducted in Yunnan might not reflect the dominant patterns of work in Chinese urban areas. Dicarolo et al. (2016) also omitted the Yunnan dataset.

We reweight the STEP and Indonesian⁴ data in order to achieve representativeness of the occupational structures in urban areas. To this aim, we retain the original shares of workers in agriculture and elementary occupations and adjust the distribution of other 1-digit ISCO occupations in line with occupational distributions reported in the International Labour Organization Database (ILOSTAT). In the case of China, we use the urban occupational distribution from the 2015 Census to reweight the CULS data and achieve the same distribution of in our sample.

2.2 Selection of task items in PIAAC and STEP

PIAAC and STEP surveyed the tasks performed by responders on-the-job, although the questionnaires in these surveys are slightly different. Out of the large number of questions available, we pick a set of items that appeared in the same or close form in both surveys. The list of comparable items from both surveys, along with their full wording, can be found in Appendix B.

Table 1. Task items from PIAAC and STEP surveys, considered for the calculation of final task content measures.

Task content	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
Task items	Reading bills Reading news Reading professional titles Advanced math Solving problems Calculating prices Calculating fractions Programming	Supervising Collaborating Presenting	Changing order of tasks (reversed) Reading bills Filling forms Calculating fractions Solving problems (reversed) Presenting (reversed)	Physical tasks
No. of item / cut-off combinations	156 250	24	5 000	1

Notes: The number of cutoff combinations refers to the number of all possible task item combinations for the construction of final indices. See section 2.3 for further details.

Source: Own elaboration.

We aim to calculate task content measures as categorised in the previous literature that utilised O*NET, namely: non-routine cognitive analytical, non-routine cognitive personal, routine cognitive and manual (Acemoglu and Autor, 2011, Autor & Price, 2013). For each task content measure we identified between three and nine items that could potentially be used to derive each of the task measures (see Table 1), except the manual content for which only one item (the frequency of performing physical tasks) is available in both STEP and PIAAC. Therefore, we define only one measure of manual tasks. Previous studies on the US (Autor & Price, 2013) and European countries (Lewandowski et al., 2017) found that routine and non-routine manual tasks are correlated and follow similar trends so having only one measure of manual tasks is not a serious limitation.⁵

⁴ Indonesia is the only urban areas survey in PIAAC (Jakarta).

⁵ As a double-check, we merged the US PIAAC data with the O*NET measures used by Acemoglu and Autor (2011) used for the calculation of non-routine and routine manual tasks. The resulting correlation between the non-routine and routine manual tasks was 85% across 3-digit ISCO occupations and 88% across 2-digit occupations.

To ensure comparability between STEP and PIAAC data, we rescale the answers from both surveys to achieve common levels of answers for all questions (see Appendix B for the differences in possible answers in PIAAC and STEP). The main difference between STEP and PIAAC items is that the PIAAC questions typically refer to the frequency of performing a task (five levels ranging from 'never' to 'every day'), while many STEP questions refer to whether the responders normally perform a specific task as part of their job or not. Out of 16 task items we consider, 10 have five possible answers in PIAAC but a 'Yes/No' answer in STEP; two have five possible answers in both PIAAC and STEP (though one had different descriptions for the answers); two have 'Yes/No' answers in both PIAAC and STEP; and two have five possible answers in PIAAC but answers on a scale from 1 to 10 in STEP. For those with 'Yes/No' answers in STEP, we looked for appropriate cutoff points to reduce them into dummy variables in PIAAC as well. For those with the same numbers of possible answers in both surveys we used the original variables. For those with higher variability in STEP, we reduced the scale from 1-10 to 1-5 (1-2 became 1; 3-4 became 2; etc.). We also corrected the item indicating supervising other workers in the STEP data so that only individuals with co-workers are allowed to supervise others.⁶ In the PIAAC data all of the self-employed responders who had no other workers in their jobs indicated they did not supervise anyone. Since this item has a very similar wording in both surveys, our correction of values in STEP ensures consistency with PIAAC data. There are no variables in CULS survey allowing for a similar check of this item, but the values for supervising seem consistent with the corrected STEP item.

2.3 Calculation of task content measures

To construct our task content measures, we use the US PIAAC and (US) O*NET data. Much of the previous research on tasks exploited the O*NET database which contains extensive information on the occupations in the US (Acemoglu & Autor, 2011; Autor et al., 2003; Autor & Price, 2013). We aim at ensuring that our measures calculated on the US PIAAC are as consistent as possible with task content measures calculated with O*NET data mapped to PIAAC. In the next step, we apply the same definitions of task measures to other countries in PIAAC and STEP. This approach allows us to construct task content measures which are comparable to those established in the literature and which are defined consistently across all countries in our sample, but which also provide country-specific and worker-level results.

In the first step, we map the O*NET task item data to the PIAAC data using the occupational crosswalks from the O*NET Resource Center, the U.S. Bureau of Labor Statistics and the National Crosswalk Service Center, as compiled and prepared by Hardy et al. (2018)⁷. The ISCO classification of occupations is used in PIAAC, but the level of detail varies between countries. 3-digit and 4-digit codes are available in the US PIAAC.⁸ We apply our procedure separately at both levels. We use the methodology of Acemoglu and Autor (2011), although we

⁶ Some respondents in STEP indicated supervising other workers despite declaring that they worked alone. Our change corrects this in cases where respondents indicated any of the following combinations: a) being self-employed with no hired workers, b) being self-employed with no unpaid or paid workers, c) being the only paid worker at the current job or that the total number of people working at the organization equals one (the respondent).

⁷ See: www.ibs.org.pl/resources [accessed: 2017-05-04].

⁸ The dataset with 3-digit ISCO codes is available for researchers from National Center for Education Statistics. The 4-digit ISCO codes are included in the restricted dataset at the American Institutes for Research who have kindly run our code.

calculate one manual task content measure that aggregates all O*NET task items which define routine and non-routine manual task content measures in Acemoglu and Autor (2011).

In the second step, we consider every combination of the cutoff points for every subset of the task items which we selected as potential variables to calculate particular task content measures (Table 1). For each combination, we adapt the Acemoglu and Autor (2011) approach and calculate the task content measures in the same way as with the O*NET items – (i) we standardise every PIAAC item within the US dataset, (ii) sum the standardised items into relevant task content measures and (iii) standardise them again within the US dataset. Then we calculate the average task content values for all 3-digit and 4-digit occupations in the US PIAAC dataset and their correlations with the relevant O*NET-based task content measures at the same occupation level.

For each task measure, we use the following criteria to select the combination of PIAAC items:

- We consider five combinations with the highest correlation with the relevant O*NET-based measure at the 3-digit level of ISCO, and at the 4-digit level of ISCO.
- A particular combination can be preferred over the combination with the highest correlation with O*NET-based measures at the 4-digit level only if it has a higher correlation at the 3-digit level.
- The measure has to consist of at least two task items.
- A change in the cutoff level within a chosen item set is preferred over the combination indicated by previous steps when two conditions are met: first, the combination with the new cutoff point has a comparable correlation at the 3-digit level and second, the new cutoff point offers better consistency across PIAAC and STEP countries in terms of the contribution of a given task to the task content measure.

This procedure results in the following definitions. The non-routine cognitive analytical task measure is measured based on reading news, reading professional titles, solving problems and programming. The non-routine cognitive interpersonal task measure is based on supervising people and presenting. The routine cognitive task measure is based on the ability to change the order of tasks (reversed, so we assign higher score the lack of this ability), filling forms and presenting (reversed). The manual task measure is based on the item describing if a job usually involves working physically for a long period. The cutoffs for each item are presented in Table 2.

In the US, our measures follow the Acemoglu and Autor (2011) tasks based on O*NET quite closely (Table 2). At the 3-digit occupation level, the correlations of our measures with the Acemoglu and Autor (2011) measures range from 55% (routine cognitive) to 77% (non-routine cognitive analytical, manual).⁹ However, our measures are less diversified between occupations than measures based on O*NET. At the 3-digit occupation level, the standard deviations of tasks range from 0.50 (routine cognitive) to 0.67 (non-routine cognitive analytical) while the standard deviations of the O*NET-based tasks range from 1.02 (non-routine cognitive personal) to 1.23 (routine cognitive).¹⁰ This is visually illustrated on Figure 1 which shows the average task content at the 3-digit occupation level according to both Acemoglu and Autor (2011) and our methodology.

⁹ The highest correlations obtained at the 4-digit occupation level range from 62% to 79%.

¹⁰ High standard deviation of routine cognitive tasks based on O*NET is driven by negative outliers: occupations 521 (Street and Market Salespersons), 951 (Street and Related Services Workers) and 952 (Street Vendors, excluding food). If these

Table 2. The task items used for the construction of aggregate task content measures

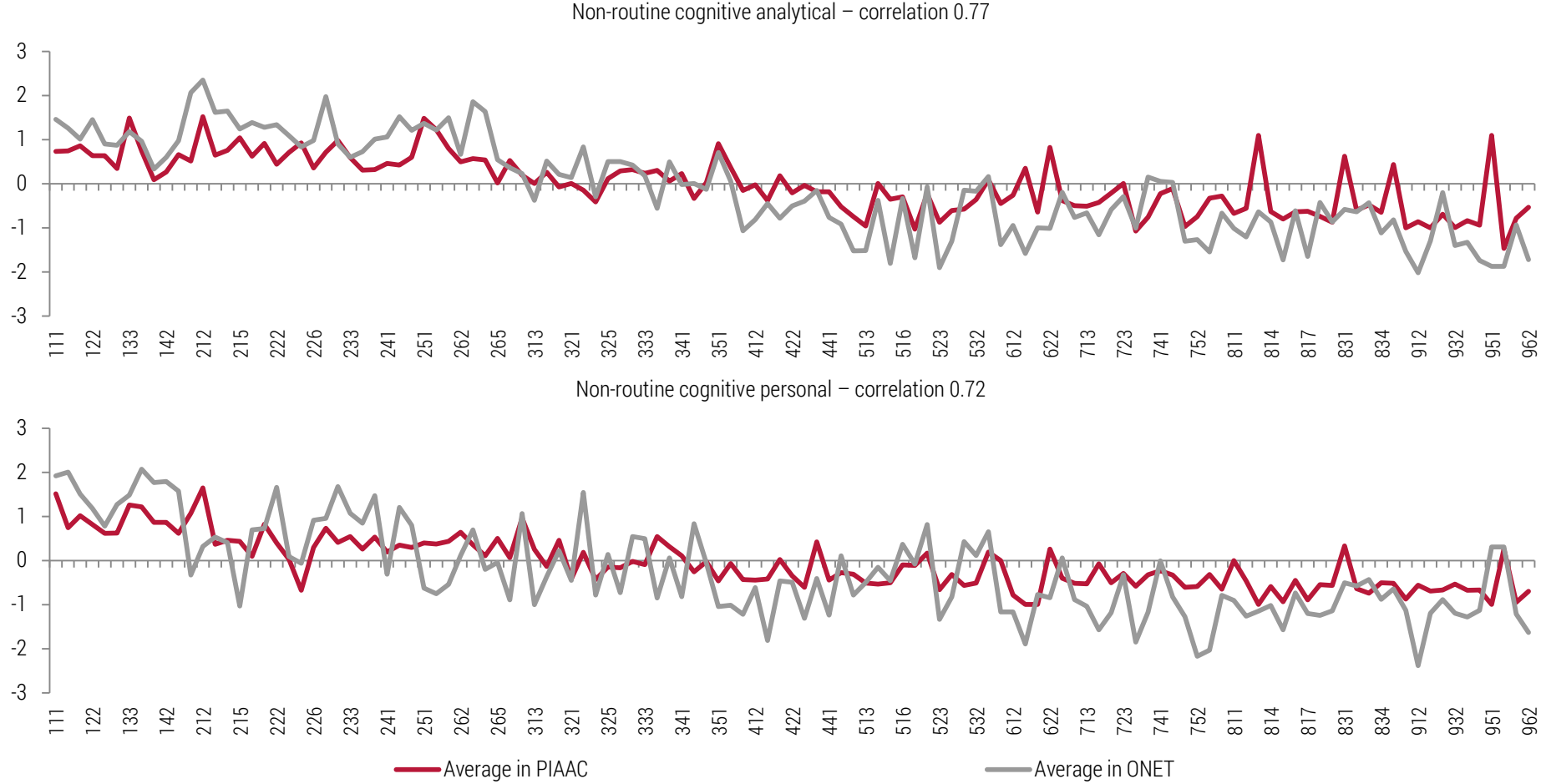
Task content	Chosen task items	Cutoff for “Yes” in PIAAC	Correlations with O*NET measures across occupations in the US			
			Highest available in mapping at 4-digit level	Highest available in mapping at 3-digit level	Final measures calculated at 4-digit level	Final measures calculated at 3-digit level
Non-routine cognitive analytical	Reading news	At least once a month (answers 3,4,5)	0.61	0.74	0.61	0.77
	Reading professional titles	At least once a month (answers 3,4,5)				
	Solving problems	No cutoff				
	Programming	All other than “Never” (answers 2,3,4,5)				
Non-routine cognitive personal	Supervising	No cutoff	0.51	0.72	0.51	0.72
	Presenting	All other than “Never” (answers 2,3,4,5)				
Routine cognitive	Changing order of tasks (reversed)	No cutoff	0.38	0.48	0.33	0.55
	Filling forms	At least once a month (answers 3,4,5)				
	Presenting (reversed)	See ‘Presenting’ above				
Manual	Physical tasks	No cutoff	0.65	0.74	0.65	0.74

Note: The “Highest at 4 digits” correlations refer to the highest possible correlations achieved during the calibration. The “Highest at 3 digits” correlations are correlations calculated at a 3-digit ISCO level, but using the combinations used for the “Highest at 4 digits” column. The “Final at 3 digits” correlations are for the final choice sets of cutoffs and items. For the full wording of the task items and the definition of cutoff points see Table B1 in Appendix B.

*Source: own calculations based on US PIAAC and O*NET.*

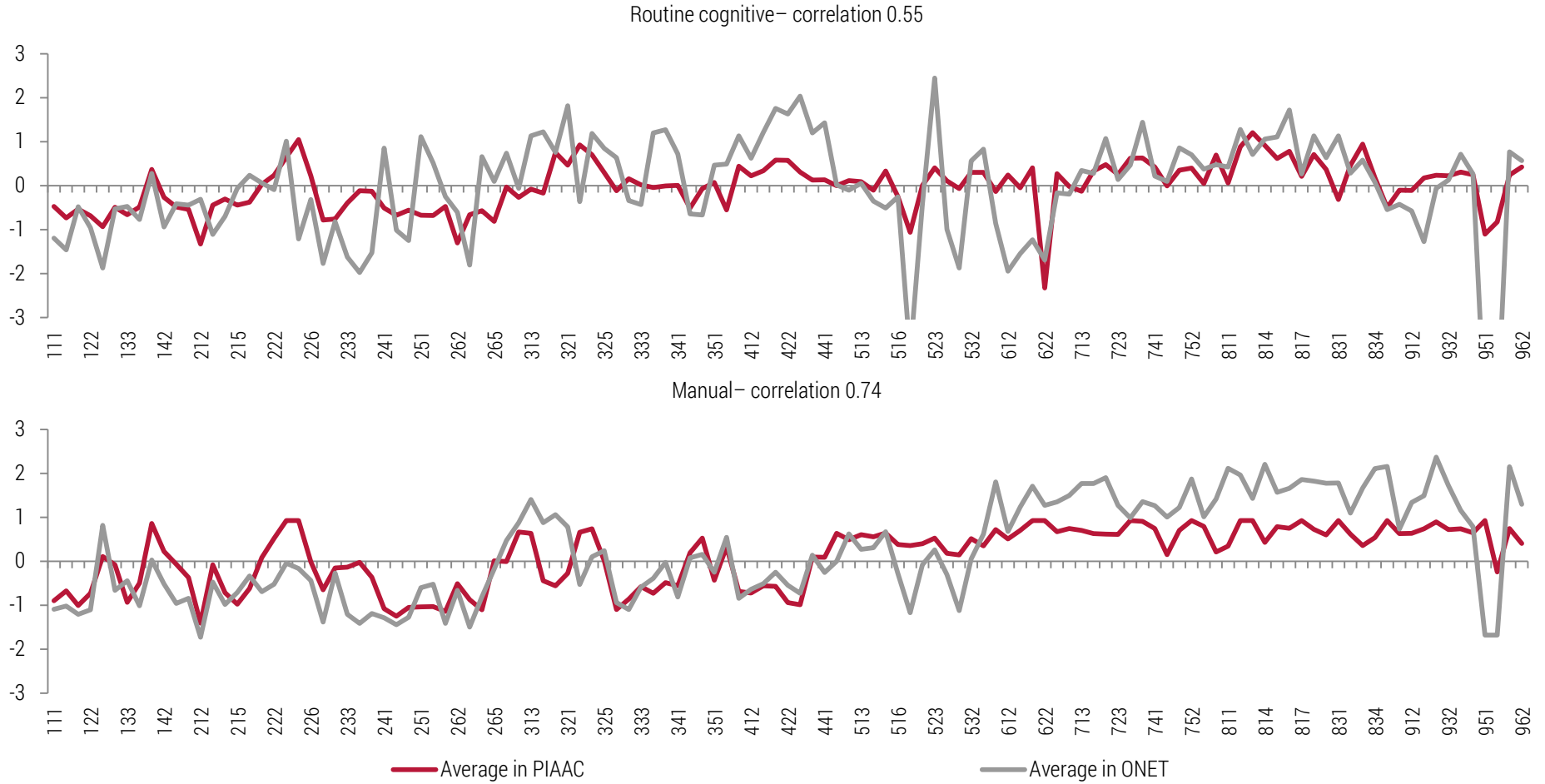
outliers are ignored, the standard deviation of routine cognitive tasks turns out the lowest among the O*NET based measures (0.97), similarly to our measures.

Figure 1. Values of task contents across 3-digit ISCO occupations in the United States.



Note: The horizontal axis shows selected 3-digit ISCO occupation codes.
 Source: Own calculations using O*NET and PIAAC data.

Figure 1. Values of task contents across 3-digit ISCO occupations in the United States (cont'd).



Note: The horizontal axis shows selected 3-digit ISCO occupation codes. In order to use the same range for all tasks, the negative outliers in the O*NET routine cognitive tasks are truncated at -3: occupation 521 (Street and Market Salespersons) which has the value of -3.86, and occupation 951 (Street and Related Services Workers) and 952 (Street Vendors, excluding food) which both have the value of -5.29.

Source: Own calculations using O*NET and US PIAAC data.

3. Properties of task content measures based on PIAAC, STEP and CULS

We use the chosen combinations to calculate task content measures in all countries studied. We also merge O*NET with PIAAC, STEP and CULS in order to calculate the Acemoglu and Autor (2011) task measures for each country. In both cases, we standardise each measure using the relevant mean and standard deviation in the US. Hence, for each task measure, zero reflects the US average and 1 reflects the standard deviation in the US. As STEP and CULS are urban surveys, we omit skilled agricultural workers (ISCO 6).¹¹

We find that the values of task content do not depend on the data source (PIAAC or STEP) and can be explained by individual worker characteristics and country development level, except for the manual tasks where the results from STEP are biased down. In order to verify whether the source of data matters for results, we estimate a range of OLS regressions. In a base model, we run OLS regressions for each task content measure with control variables including individual characteristics (gender, 10-year age groups, education, 1-digit occupations, sectors) and a dummy indicating the STEP survey. The values of all tasks except non-routine cognitive personal are significantly lower in STEP (Table 3). However, when we control for the level of literacy skills,¹² the difference between STEP and PIAAC in non-routine cognitive analytical tasks becomes insignificant.¹³ When we additionally control for the log of GDP per capita (level and squared), this difference becomes insignificant also for routine cognitive tasks. Hence, our measures of cognitive tasks seem consistent and comparable between the two surveys.

In the base model for manual tasks, the STEP dummy is negative and significant at a 1% level. When we control for literacy skills and the GDP per capita level, the estimated coefficient declines by more than half, but it remains significant. We cannot define the manual tasks measure in any other way because there is only one item on physical tasks in both STEP and PIAAC surveys. In order to achieve consistency of the manual task content measure, we deduct the coefficient on the STEP dummy estimated in the relevant regression presented in Table 3 from the initial manual task scores in STEP (in other words, we add 0.17 to the manual task scores of each individual in STEP countries). Any following calculations include this correction.

We create a synthetic measure of routine task intensity (RTI) at a worker-level, using the formula:

$$RTI = \ln(r_{cog}) - \ln\left(\frac{nr_{analytical} + nr_{personal}}{2}\right), \quad (1)$$

whereby r_{cog} , $nr_{analytical}$ and $nr_{personal}$ are routine cognitive, non-routine cognitive analytical and non-routine cognitive personal task levels, respectively.¹⁴ For each task, we add the lowest score in the sample to the scores of all individuals, plus 0.1, to avoid non-positive values in the logarithm. Our definition follows the literature (Autor & Dorn, 2009, 2013, Goos et al., 2014) but we skip the manual tasks as we cannot distinguish between routine and non-routine tasks. For consistency, we standardise the RTI using its mean and standard deviation in the US.

¹¹ We are unable to calculate the non-routine cognitive analytical task measure for Ukraine because the Ukrainian STEP does not include the question about reading of professional items.

¹² The literacy skills tests follow the same methodology in both STEP and PIAAC and are comparable.

¹³ Reducing the sample by three countries does not matter as the STEP dummy is also significant in the base model re-estimated on the subsample of 39 countries which have literacy assessment data (Table 3).

¹⁴ In the case of Ukraine, we add only the log of non-routine cognitive personal task measure (see footnote 11).

Table 3. OLS regressions of task measures on sets of control variables and a STEP dummy

	Non-routine cognitive analytical	Non-routine cognitive personal	Routine cognitive	Manual
Base model, total sample of 42 countries				
STEP dummy	-0.22***	-0.03	-0.05	-0.38***
Base model, subsample of 39 countries with literacy assessment data				
STEP dummy	-0.17**	-0.08	-0.17	-0.39***
Base model + control for literacy skills, subsample of 39 countries with literacy assessment data				
Literacy skills level: 0 and 1	-0.11***	-0.05***	-0.03	-0.00
Literacy skills level: 3	0.09***	0.06***	-0.09***	-0.13***
Literacy skills level: 4 and 5	0.17***	0.13***	-0.23***	-0.29***
STEP dummy	-0.11	-0.04	-0.20	-0.44***
Base model + controls for literacy skills and for GDP per capita, subsample of 39 countries with literacy assessment data				
Literacy skills level: 0 and 1	-0.10***	-0.04***	-0.02	0.02
Literacy skills level: 3	0.08***	0.05***	-0.09***	-0.14***
Literacy skills level: 4 and 5	0.16***	0.11***	-0.22***	-0.30***
GDP per capita	-0.95	-1.51***	1.41	0.27
GDP per capita squared	0.05	0.08***	-0.07	-0.01
STEP dummy	-0.00	0.06	-0.07	-0.18***

Note: the base regressions include dummies for gender, 10-year age groups, education, 1-digit occupations and sectors. To save space, we report only the coefficients for the STEP dummy, literacy skills and GDP per capita (in 1000s, in PPP, current international \$, country averages for 2011-2016). The regressions with literacy scores exclude China (CULS), Laos and Macedonia due to lack of literacy skills assessment in these countries. The total number of observations equals around 155,500 for the base model regression with all countries and around 144,500 for the specifications without China (CULS), Laos and Macedonia. The standard errors are clustered at a country level.

Source: own estimations based on PIAAC, STEP, CULS and World Bank data.

The occupational patterns of our task content measures are consistent with those resulting from O*NET, although they differ in important aspects. They are consistent as both measures show that better skilled workers perform less routine tasks (Figure 2).¹⁵ They differ as the cross-country differences in task contents within particular occupations are noticeably higher according to our measures than according to task measures based on O*NET. The cross-country standard deviation of RTI according to our measure is for each category higher than according to the O*NET based measure (0.37 vs. 0.04 among high-skilled workers, 0.38 vs. 0.24 among middle-skilled workers, 0.33 vs. 0.05 among low-skilled workers). In the case of O*NET measures, the cross-country differences within occupations are driven entirely by cross-country differences in employment structures at finer ISCO levels. In the case of our measures, these differences result from worker-level, country-specific measurement. To highlight this point, we map our measures calculated for the US with PIAAC data to other countries at the same occupational level that we map O*NET measures. The resulting task measures based on the assumption that occupations are identical across the world (but quantified using our methodology on PIAAC) follow the measures based on O*NET more closely than they follow country-specific measures based on PIAAC, STEP and CULS surveys.

¹⁵ For brevity, we use routine task intensity and aggregate occupations into three categories: high-skilled (ISCO 1-3), middle-skilled (ISCO 4-5) and low-skilled (ISCO 7-9).

Figure 2. The average values of relative routine intensity (RTI) by occupational categories.



Note: Countries are ranked according to the GDP per capita level.

Source: own calculations based on PIAAC, STEP, CULS, O*NET (tasks), and World Bank data (GDP).

4. Cross-country differences in the task content of jobs

4.1 Descriptive results

We find substantial cross-country differences in the average values of particular task content measures. In general, the more developed countries exhibit higher average values of both non-routine tasks than the less developed countries (Figure 3). The Nordic countries (Denmark, Sweden, Norway, Finland), most of the English-speaking countries (Canada, New Zealand, the UK and the US) and Singapore stand out with the highest levels of both non-routine cognitive tasks. The less developed countries – both covered by STEP (Georgia, Ghana, Laos, Colombia) and by PIAAC (Lithuania, Turkey, Indonesia, Greece) – have the lowest average values of non-routine cognitive tasks. Our results show that the average value of non-routine cognitive tasks, especially of analytical tasks, is also low in Chinese cities covered by CULS. The difference between the averages values of task in the highest-scoring and the lowest-scoring countries is of magnitude comparable to one standard deviation of particular task content values among the US workers.

The relationship between routine cognitive tasks and the level of development is inverse U-shaped (Figure 3). The least developed countries and the Nordic countries exhibit the lowest values of routine cognitive tasks. On the other hand, Central Eastern and Eastern European countries (Ukraine, Lithuania, Czechia, Russia, Slovakia, Slovenia) have the highest average values of the routine cognitive tasks. The values of routine cognitive tasks are also high in Southern European countries (Greece, Italy), the United Kingdom and Ireland.

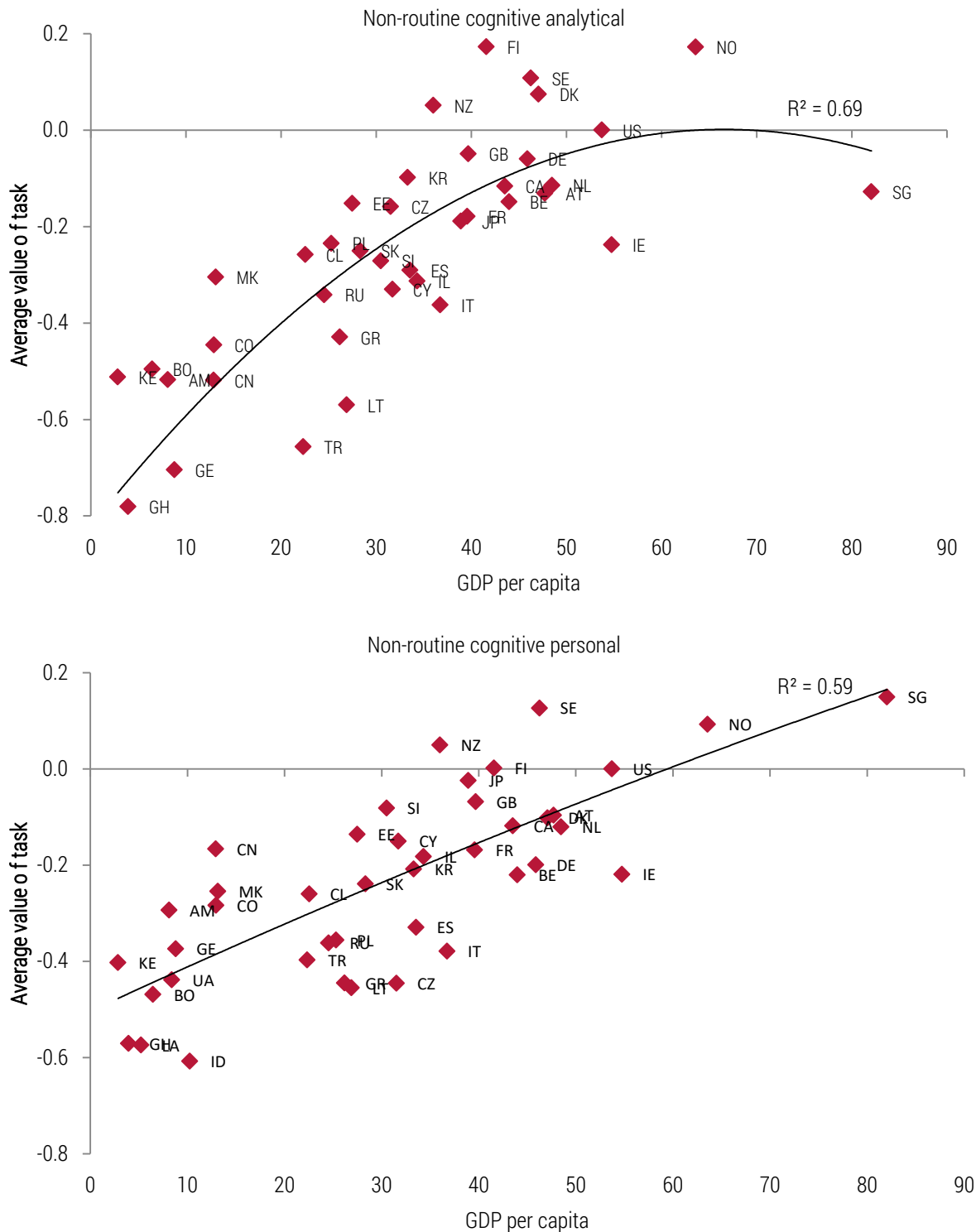
The average values of manual tasks do not show any clear-cut relationship with the level of development. For instance, Indonesia and Turkey evidence the highest manual task levels, but Armenia, Macedonia, Ukraine and Georgia are among the countries with the lowest levels. United States and New Zealand are among the countries with highest manual levels, while Japan, Finland and Belgium among the lowest. However, these differences should be interpreted with caution as we are able to use only one task item for the manual task content measure.

Our survey-based measures show large cross-country differences in the task content of jobs in particular occupations. The standard deviation of country-specific average routine task intensity ranges from 0.24 (elementary occupations) to 0.32 (professionals).¹⁶ Importantly, in high-skilled occupations (ISCO1-ISCO3: managers, professionals, technicians) and among sales and services workers (ISCO 5), workers in the more developed countries perform visibly less routine intensive work (Figure 4). To a lesser extent, it is also the case among craft and related trades workers (ISCO 7). Among the clerical workers (ISCO 4) and workers in low-skilled occupations ISCO8-ISCO9 (plant and machine operators, elementary occupations), the cross-country differences are not related systematically to the level of GDP per capita.

Overall, our results show that the higher is the GDP per capita of a country, the higher is the relative role of non-routine content of jobs, in particular among the high-skilled occupations.

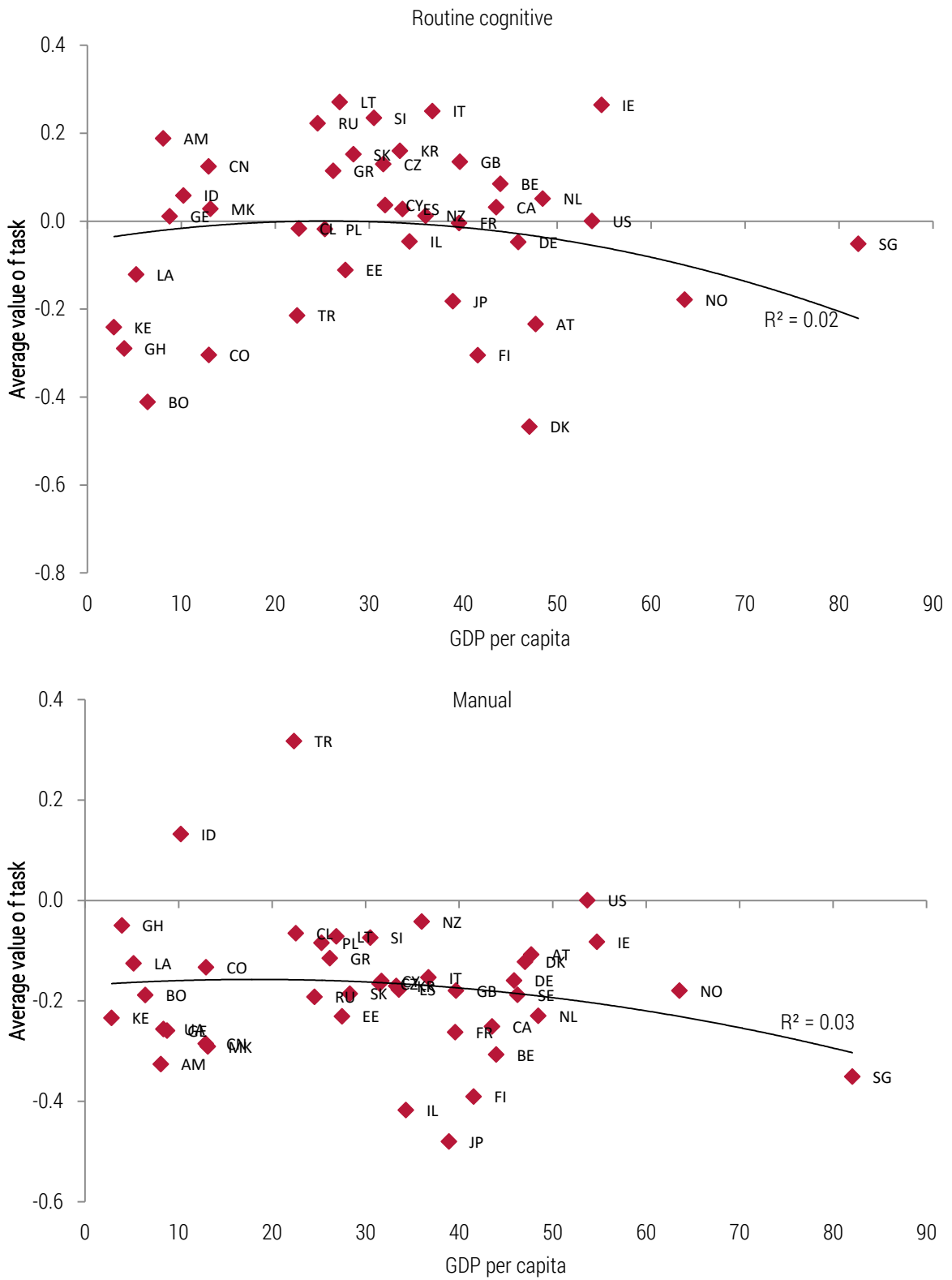
¹⁶ We omit the occupational group ISCO 6 (Skilled agricultural workers) because of small sample sizes, especially in countries where surveys covered only urban areas.

Figure 3. The average values of tasks against GDP per capita.



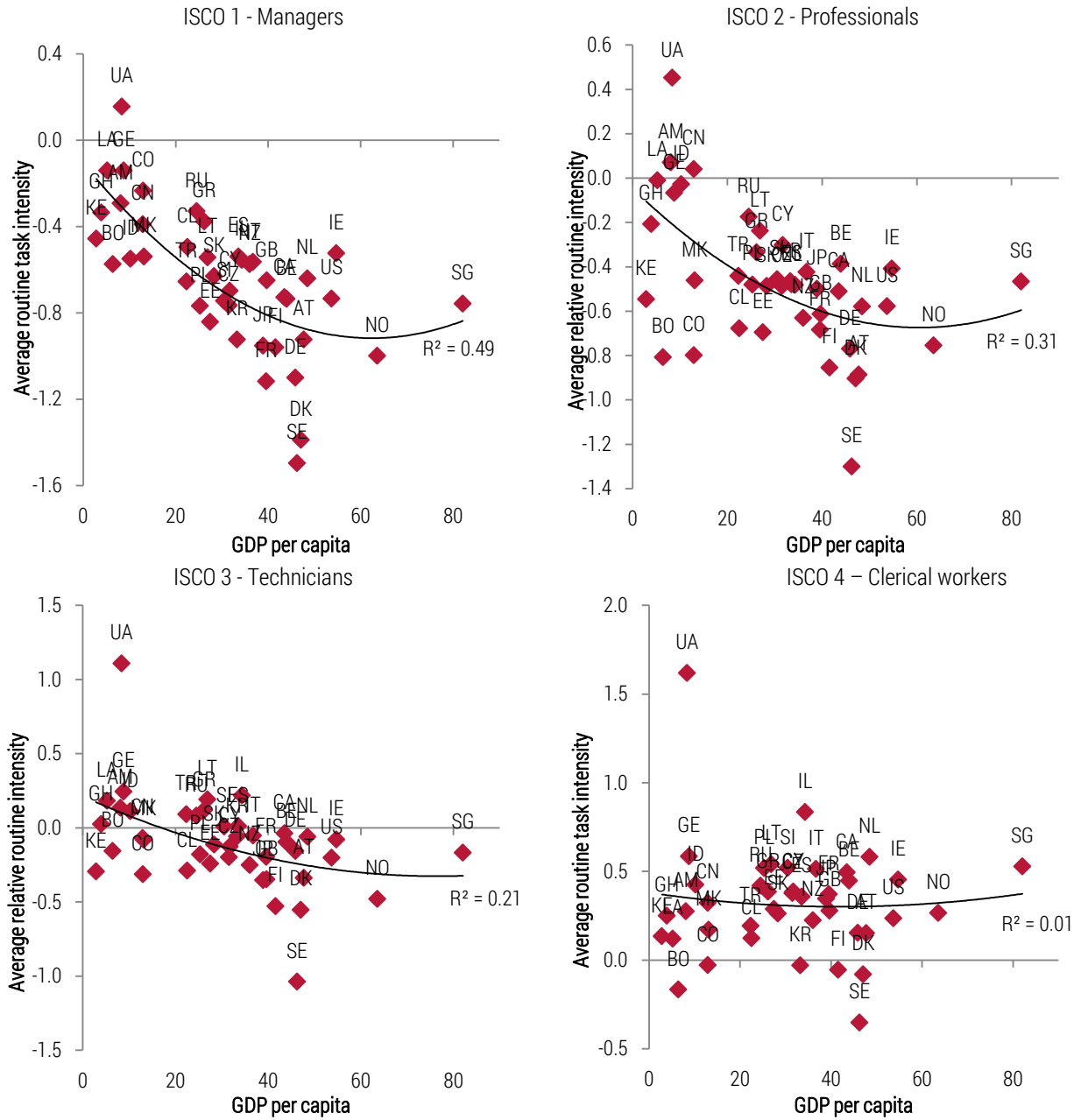
Note: for each task content, the 0 is set at the US average value and 1 corresponds to one standard deviation of this particular task content value in the US. GDP per capita in PPP, current international \$, country averages for 2011-2016. Source: own calculations based on PIAAC, STEP, CULS (tasks), and World Bank data (GDP).

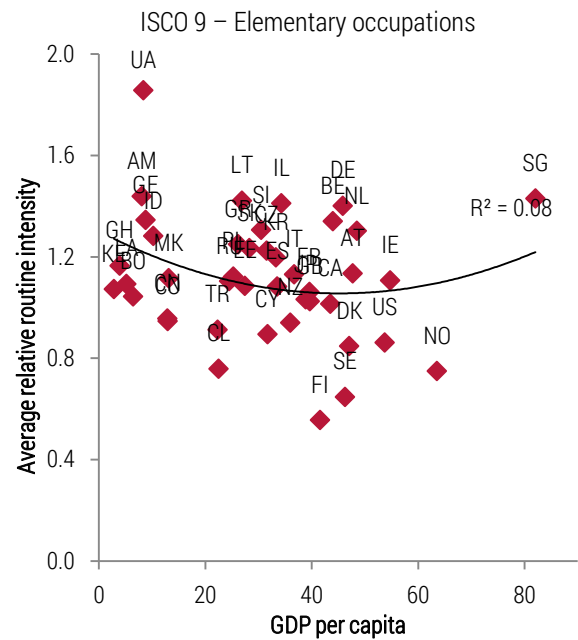
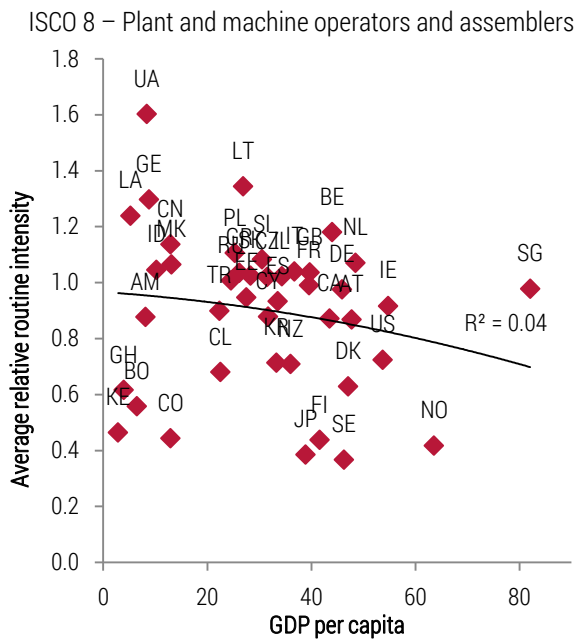
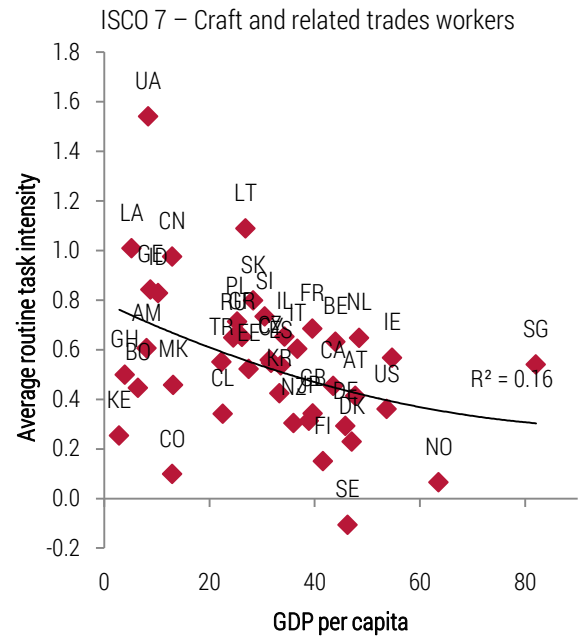
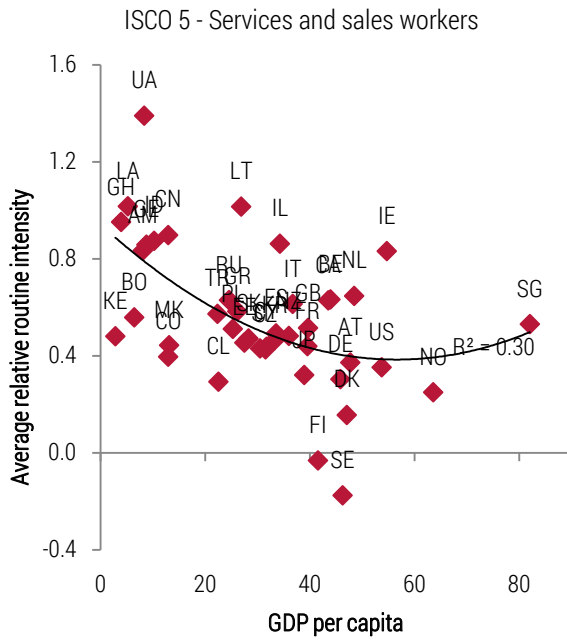
Figure 2. The average values of tasks against GDP per capita. (cont'd)



Note: for each task content, the 0 is set at the US average value and 1 corresponds to one standard deviation of this particular task content value in the US. GDP per capita in PPP, current international \$, country averages for 2011-2016. Source: own calculations based on PIAAC, STEP, CULS (tasks), and World Bank data (GDP).

Figure 4. Average values of routine intensity of tasks (RTI) by 1-digit occupations against GDP per capita.





Note: the horizontal axis denotes GDP per capita, PPP (international \$, country averages for 2011-2016). We omit the occupational group ISCO 6 (Skilled agricultural workers) because of small sample sizes, especially in countries where surveys covered only urban areas.

Source: own calculations based on PIAAC, STEP, CULS, O*NET and World Bank data.

4.2 Worker-level correlates of relative routine task intensity

To shed light on factors contributing to the cross-country differences in the routine task intensity, we estimate pooled, OLS regressions. Previous studies found that the routine intensity of jobs is related to education and skills (de la Rica & Gortazar, 2016), the complexity of computer use (Almeida et al., 2017), access to broadband internet (Akerman et al. 2013), the participation in the global value chains (Marcolin et al., 2016a), and the use of robots (Graetz & Michaels, 2015). We use individual, workplace, industry and country characteristics as explanatory variables and estimate the following regression:

$$RTI = \beta_0 + \beta_{ind}X_{ind} + \beta_{occ}X_{occ} + \beta_{sec}X_{sec} + \beta_{tech}X_{tech} + \beta_{int}X_{int} + \varepsilon, \quad (2)$$

Where RTI is routine task intensity measured at the worker-level (we omit worker subscripts), X_{ind} stands for socio-demographic controls and skills (age, gender, education level, literacy skills), X_{occ} stands for occupational categories (high-skilled, ISCO 1-3; middle-skilled, ISCO 4-5; low-skilled, ISCO 7-9), and X_{sec} for sectors (19 ISIC sectors). X_{tech} includes variables related to technology and globalisation: computer use at work (worker-level dummy), ICT capital stock per worker measured at the country level (Eden & Gaggl, 2015), robot stock per worker measured at the country-sector level (Acemoglu & Restrepo, 2017), and participation in global value chains (henceforth GVC participation, Wang et al., 2017) measured at the country-sector level – see Appendix D for details on the data. Our basic GVC participation variable is the backward linkage-based measure defined as the foreign value added share in production of final goods and services (FVA share), and for robustness check we also use the forward linkage-based measure (domestic value added from production of intermediate exports or domestic factor content in intermediate exports, Wang et al., 2017). X_{int} stands for interactions between the X_{tech} variables and occupational groups that we use to account for potentially different relations between particular structural factors and routine intensity of jobs among blue-collar and white-collar workers. Initially we include only individual characteristics (gender, age and education), and subsequently add sets of worker characteristics, and country- and industry-level variables. Results are presented in Table 5.

We find that the workers performing more routine-intensive jobs are more likely to be female workers, workers who are young (aged 16-24), and workers with lower education (column 1 of Table 5). Workers aged over 35 are likely to perform less routine-intensive jobs than workers aged up to 34. Once we control for occupational categories, workers aged 55-65 are not significantly different from workers aged 25-34 (column 2). Moreover, the differences attributed to education decline. When we also account for computer use, the difference between the primary and secondary educated workers is no longer significant (column 4). This suggests that the lower routine intensity of jobs performed by secondary educated workers in comparison to primary educated workers can be related to the more prevalent computer use among the former. Moreover, the higher is the literacy skill level of a worker, the lower is the routine task intensity (column 5). Workers in the low-skilled occupations (the craft and related trades workers, plant and machine operators and assemblers and workers of elementary occupations – ISCO 7-9) are more likely to perform more routine tasks than the clerical workers and service and sales workers (ISCO 4-5, the reference group, column 2). The opposite is true for workers in the high-skilled occupations (managers, professionals, technicians and associate professionals – ISCO 1-3). These occupational effects are not related to sectoral differences (column 3), but they are mediated by computer use and exposure to technology: their size decreases when we control for computer use (column 4) and further declines when we account for interactions between occupational categories and structural variables (column 8).

Workers who use computer at work perform significantly less routine tasks than workers who do not (column 4). This effect is robust to the addition of further variables. The relationship between the RTI and other technological variables is also negative: the higher is the ICT stock per worker or the number of robots per worker, the lower is the routine intensity of tasks performed by workers (columns 6 and 7). This relationship is particularly pronounced for workers in the high-skilled occupations (column 8). The GVC participation is not significantly related to the routine task intensity of an average worker (column 6). However, it is negatively and significantly related to the RTI in the high-skilled occupations, and positively and significantly related to the RTI in the low-skilled occupations (column 8). The results are robust to the choice of the GVC participation measure.

The technological and structural factors may also influence the occupational structures and thus indirectly contribute to the cross-country differences in task content of jobs. To account for this possibility, we estimate a two-stage multinomial treatment effects model (Deb, 2009), explaining selection into low-skilled, middle-skilled and high-skilled occupations in the first stage (equation 3), and the RTI in the second stage (equation 4).

$$OCC_j = \gamma_{0,j} + \gamma_{ind,j}X_{ind} + \gamma_{sec,j}X_{sec} + \gamma_{tech,j}X_{tech} + \varepsilon_{1,j}, \quad (3)$$

$$RTI = \theta_0 + \theta_{ind}X_{ind} + \theta_{occ}X_{occ} + \theta_{tech}X_{tech} + \theta_{int}X_{int} + \varepsilon_2, \quad (4)$$

Where $j \in \{ISCO1 - 3, ISCO7 - 9\}$ defines treatments. In the second stage, we use the most elaborate specification of regression (2), although we do not control for sectors which are only used in the first stage estimation. We use the FVA share as the GVC participation proxy. Results are presented in Table 6.

We find that both individual and structural factors influence the occupational structures. Women are most likely to work in the middle-skilled occupations and least likely in the low-skilled occupations. Age also matters as the older a worker is, the more likely a worker is to work in a high-skilled occupation. The higher the education level attained by a worker, the higher the likelihood of working in a high-skilled occupation and the lower the likelihood of working in a low-skilled occupation. The same applies to literacy skills. Using computer at work is positively related to working in a high-skilled occupation and negatively related to working in a low-skilled occupation. Finally, higher ICT stock levels are associated with job polarization – a higher probability of working in a high-skilled or a low-skilled occupation. On the other hand, a higher robot stock is associated with a lower share of high-skilled occupations across countries and sectors.

Accounting for selection into occupations does not change the associations between particular variables and RTI described above on the basis of OLS regressions. However, it lowers the absolute value of some coefficients, in particular those on tertiary education and computer use which suggests that these factors contribute to RTI differences indirectly through occupational structure. The differences between literacy levels are also less pronounced than in the OLS estimation, except for the stronger, negative effect of the highest skill level. Interestingly, the coefficient on being female does not change, which suggests that the higher RTI levels among female workers are not driven by selection to more routine intensive occupations (at least at the studied level of occupation aggregation). The interaction between high-skilled occupations (ISCO 1-3) and FVA share is no longer significant. This suggests that the significance in the OLS regression was likely due to its relationship with shares of high-skilled occupations. On the other hand, the interaction between FVA share and low-skilled occupations (ISCO 7-9) remains significant and positive, and the interaction between ICT stock and high-skilled occupations significant and negative, despite accounting for selections into occupations.

Table 4. Individual, workplace and structural correlates of routine task intensity (RTI - OLS regressions)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8a) ^x	(8b) ^x
Female	0.21***	0.29***	0.28***	0.27***	0.27***	0.27***	0.28***	0.27***	0.27***
Age: 16-24	0.19***	0.17***	0.17***	0.17***	0.17***	0.18***	0.18***	0.18***	0.18***
Age: 35-44	-0.09***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***
Age: 45-54	-0.06***	-0.04**	-0.04***	-0.06***	-0.07***	-0.06***	-0.06***	-0.06***	-0.06***
Age: 55-65	-0.06**	-0.01	-0.01	-0.04*	-0.04**	-0.03	-0.03	-0.02	-0.02
Education: primary	0.31***	0.15***	0.15***	0.03*	0.01	0.01	0.01	0.02	0.02
Education: tertiary	-0.59***	-0.25***	-0.23***	-0.19***	-0.17***	-0.18***	-0.19***	-0.18***	-0.18***
High-skilled occupation (ISCO 1-3)		-0.62***	-0.59***	-0.50***	-0.48***	-0.48***	-0.49***	-0.42***	-0.43***
Low-skilled occupation (ISCO 7-9)		0.35***	0.35***	0.22***	0.23***	0.24***	0.24***	0.22***	0.22***
Sectors included	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Computer use				-0.49***	-0.48***	-0.45***	-0.44***	-0.43***	-0.43***
Literacy skills level: 1 or lower					-0.02	-0.02	-0.01	-0.01	-0.01
Literacy skills level: 3					-0.05***	-0.04**	-0.04**	-0.04**	-0.04**
Literacy skills level: 4 and 5					-0.17***	-0.15***	-0.14***	-0.13***	-0.13***
Global Value Chain participation						0.02	0.02	0.02	0.02
ICT stock per worker						-0.05***	-0.06***	-0.03*	-0.03*
Robots per worker							-0.05***	-0.06***	-0.06***
Uses computer # high-skilled occ. (ISCO 1-3)								-0.07*	-0.06
Uses computer # low-skilled occ. (ISCO 7-9)								-0.02	-0.02
GVC participation # high-skilled occ. (ISCO 1-3)								-0.05**	-0.05***
GVC participation # low -skilled occ. (ISCO 7-9)								0.03*	0.03
ICT stock per worker # high-skilled occ. (ISCO 1-3)								-0.07***	-0.07***
ICT stock per worker # low -skilled occ. (ISCO 7-9)								0.02	0.02
Robots per worker # high-skilled occ. (ISCO 1-3)								-0.02	-0.01
Robots per worker # low -skilled occ. (ISCO 7-9)								0.01	0.01
Constant	0.11*	0.10**	0.12**	0.47***	0.48***	0.45***	0.44***	0.43***	0.43***
Observations	151,624	151,624	150,393	150,391	140,071	125,206	121,109	121,109	121,109
Countries	42	42	42	42	39	34	32	32	32
R-squared	0.14	0.27	0.28	0.31	0.31	0.32	0.32	0.32	0.32

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ^x Columns (8a) and (8b) differ in the GVC participation variable used: the foreign value added share in the production of final goods and services (8a) and to the GVC participation based on forward industrial linkage (8b). The reference levels are: age 25-34, secondary education, middle-skilled occupations (ISCO 4-5), wholesale and retail trade; repair of motor vehicles and motorcycles (ISIC G), lower medium literacy skills (level 2). The coefficients for sector dummies are not presented in order to save space and are available on request. RTI, ICT stock per worker, robots per worker and GVC participation variables are standardised in our sample. China, Laos and Macedonia are dropped in models (5)-(8); Armenia, Cyprus, Georgia, Ghana and Estonia are dropped in models (6)-(8) and Bolivia and Kenya are dropped in models (7)-(8), due to missing data (see section 2.1 and Appendix D). The results for regressions presented in columns 1-4 but estimated on a smaller samples as in columns 5-8 are available upon request.

Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

Table 5. Individual, workplace and structural correlates of routine task intensity (RTI - multinomial treatment effects model with selection to occupations)

	1st step: selection to occupations		2nd step:
	high-skilled (ISCO 1-3)	low-skilled (ISCO 7-9)	RTI
Female	-0.82***	-1.45***	0.27***
Age: 16-24	-0.49***	-0.09	0.16***
Age: 35-44	0.19***	0.08	-0.06***
Age: 45-54	0.44***	0.13**	-0.05***
Age: 55-65	0.44***	-0.09	-0.01
Education: primary	-0.20*	0.40***	0.00
Education: tertiary	1.43***	-0.45***	-0.13***
Uses computer	1.35***	-1.54***	-0.37***
Literacy skills level: 1 or lower	-0.21*	0.12	-0.04
Literacy skills level: 3	0.28***	-0.31***	-0.03
Literacy skills level: 4 and 5	0.70***	-0.59***	-0.19***
Global Value Chain participation	0.08	0.00	0.01
ICT stock per worker	0.07	0.13*	-0.03
Robots per worker	-0.35***	-0.12	-0.04**
High-skilled occupation (ISCO 1-3)			-0.62***
Low-skilled occupation (ISCO 7-9)			0.28***
Uses computer # high-skilled occ. (ISCO 1-3)			-0.06
Uses computer # low-skilled occ. (ISCO 7-9)			0.00
GVC participation # high-skilled occ. (ISCO 1-3)			-0.03
GVC participation # low -skilled occ. (ISCO 7-9)			0.06***
ICT stock per worker # high-skilled occ. (ISCO 1-3)			-0.06***
ICT stock per worker # low -skilled occ. (ISCO 7-9)			0.03
Robots per worker # high-skilled occ. (ISCO 1-3)			-0.02
Robots per worker # low -skilled occ. (ISCO 7-9)			-0.01
Sectors included	Yes	Yes	No
Constant	-2.68***	0.35***	0.42***
Observations	121,109		
Countries	32		
R-squared			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The reference levels are: age 25-34, secondary education, middle-skilled occupations (ISCO 4-5), wholesale and retail trade; repair of motor vehicles and motorcycles (ISIC G), lower medium literacy skills (level 2). The coefficients for sector dummies are not presented in order to save space and are available on request. RTI, ICT stock per worker, robots per worker and FVA share are standardised in our sample. The sample does not include Armenia, Bolivia, China, Cyprus, Estonia, Georgia, Ghana, Kenya, Laos and Macedonia due to missing data (see section 2.1 and Appendix D).

Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

4.3 Decomposition of the cross-country differences in routine intensity of jobs

We use the estimated models to decompose the differences between average routine task intensity, \overline{RTI}^c , in country, c , and the US. First we use the most elaborate OLS specification (column 8 in Table 5), and then the model accounting for selection to occupations (Table 6).

We calculate the linear prediction of the RTI, \widehat{RTI}_{ols}^c , using the average worker characteristics in each country (denoted by dashed symbols), and apply the following formula:

$$\begin{aligned} \widehat{RTI}_{ols}^c - \widehat{RTI}_{ols}^{US} = & \beta_{ind}(\bar{X}_{ind}^c - \bar{X}_{ind}^{US}) + \beta_{occ}(\bar{X}_{occ}^c - \bar{X}_{occ}^{US}) + \beta_{sec}(\bar{X}_{sec}^c - \bar{X}_{sec}^{US}) + \\ & + \beta_{tech}(\bar{X}_{tech}^c - \bar{X}_{tech}^{US}) + \beta_{int}(\bar{X}_{int}^c - \bar{X}_{int}^{US}), \quad (5) \end{aligned}$$

This allows us to disentangle the contribution of particular variables to the overall differences in routine task intensities. In the case of technology-related variables and FVA share we aggregate their direct contributions with the contributions of their interactions across occupation groups. For each variable (or variable set), k , we also define σ_k^{ols} , a synthetic measure of k 's contribution to the cross-country differences in routine task intensity:

$$\sigma_k^{ols} = \frac{cov(\beta_j(\bar{X}_j^c - \bar{X}_j^{US}), \overline{RTI}^c - \overline{RTI}^{US})}{var(\overline{RTI}^c - \overline{RTI}^{US})}, \quad (6)$$

Results for particular countries are presented in Figure 4, and synthetic measures are shown in Table 7.

Overall, the model explains about half of the cross-country differences in RTI (Table 7). Two groups of factors that contribute the most to the cross-country differences in routine task intensity are information and communication technologies, and occupational structures.

About 1/3 of cross-country differences in RTI with respect to the US can be attributed to differences in the incidence of computer use in the workplace and in the aggregate ICT capital stock (per worker). In the majority of countries that exhibit lower routine task intensity than the US (Denmark, Finland, Norway, Netherlands, New Zealand and Sweden), it can be attributed to higher incidence of computer use, and in Norway also to a higher ICT stock per worker. At the same time, the contribution of these technological factors is also pronounced in countries which exhibit noticeably higher routine task intensity than the US. The contribution of robot intensity is much smaller than those of ICT stock and computer use, and it is noticeable only in the case of few countries with high robot intensity (Germany, Japan, South Korea). The contribution of differences in FVA shares are noticeable and positive only in the developing countries and small Central and Eastern European economies which are located relatively low in global value chains (e.g. Estonia, Slovakia, Slovenia).

About 1/8 of differences in RTI can be attributed to the differences in occupational structures. In 35 out of 40 analysed countries, the occupational structures are more conducive to routine work than in the US (their contribution is positive).¹⁷ Once the contribution of occupations is factored out, differences in sectoral structure contribute very little.

Education and literacy skills have a noticeable contribution only in low- and middle-income countries where the workforce is have noticeably less educated and possesses lower literacy skills than the workforce in US, which

¹⁷ Canada, Israel, Netherlands, New Zealand and Singapore constitute the only exceptions.

contributes to a higher routine intensity of jobs. On the other hand, the cross-country differences in demographic structures of the workforce (age and gender) are of minor importance.

As the occupational structures are related to workforce characteristics and structural variables, each variable might contribute to the RTI differences both directly, and indirectly via its contribution to the difference in occupational structures in a given country and the US. To quantify these channels we use the model that accounts for selection to occupations and apply the decomposition to the predicted values of RTI, \widehat{RTI}_{mt}^c , using both the first stage and the second stage regressions (equation 7).

The direct contribution is calculated as in the OLS estimation (equation 8), but using the estimates of equation (4) presented in Table 6 (column 3) and ignoring the θ_{occ} coefficients pertaining to occupational groups.

To calculate the indirect contribution, for each country we construct an 'average' worker whose characteristics reflect weighted country-specific means of the variables used in the selection regression (3). Then, we use the relevant coefficients from Table 6 to calculate the predicted probabilities that the average worker in a particular country belongs to specific occupation group. By the law of large numbers, these probabilities are equivalent to the expected employment shares of occupational groups in each country (equation 10). Next, for each variable set¹⁸ we substitute the country-specific averages with the US averages and calculate the hypothetical, expected employment shares of each occupational group in a given country (equation 11). The difference between these hypothetical shares conditional on a given variable set being equal to the US averages, and the country-specific expected.¹⁹ Finally, we multiply these contributions to the share of a particular occupational groups by the country-specific RTI average levels in the relevant occupational groups. The sum these products across occupational groups constitutes the indirect contribution of a given variable to the RTI (equation 8). Formally:

$$\widehat{RTI}_{mt}^c - \widehat{RTI}_{mt}^{US} = direct^c + indirect^c, \quad (7)$$

$$direct^c = \sum_k \theta_k * (\bar{X}_k^c - \bar{X}_k^{US}), \quad (8)$$

$$indirect^c = \sum_k \sum_j (Share_j^c - Share_{j,k}^c) * \overline{RTI}_j^c, \quad (9)$$

$$Share_j^c = \frac{Exp(\sum_k \gamma_{k,j} * \bar{X}_k^c)}{\sum_j^J Exp(\sum_k \gamma_{k,j} * \bar{X}_k^c)}, \quad (10)$$

$$Share_{j,k}^c = \frac{Exp(\sum_{k'} \gamma_{k',j} * \bar{X}_{k'}^c + \gamma_{k,j} * \bar{X}_k^{US})}{\sum_j^J Exp(\sum_{k'} \gamma_{k',j} * \bar{X}_{k'}^c + \gamma_{k,j} * \bar{X}_k^{US})}, \quad (11)$$

¹⁸ By variable set we mean sets of connected variables like the dummies for levels of literacy skills, education or sectors. We substitute the average values for whole such sets simultaneously, rather than for single variables from these sets.

¹⁹ The sums of these contributions are an approximation of the actual differences in predicted shares, because in a multinomial logistic regression the predicted probabilities are not a linear function of the independent variables. However, the approximation is highly accurate and correlates well with the actual differences in country predicted shares – at the level of 96% for shares in high-skilled occupations, 34% for shares in middle-skilled occupations and 99% for shares in low-skilled occupations. For the middle-skilled occupations, the correlation is sensitive to few outlying lower-income countries (it increases to 69% after excluding Bolivia, Ghana, Indonesia, Kenya and Laos).

Whereby set $k \in \{ind, sec, tech, int\}$ is a set of explanatory variables (excluding occupations), $Share_j^c$ is the share of occupation j (from the occupation set $J = \{ISCO1 - 3, ISCO7 - 9\}$) in country c , $Share_{j,k}^c$ is the share of occupation j in country c if the average of variable k was equal to that in the US, k' is the set of all variables excluding k , and \bar{X}_k^c is the vector of average values of variables k' . $\gamma_{j,k'}$ is the vector of coefficients from the multinomial regression for occupation j , excluding the coefficient for variable k . For the reference occupation category (middle-skilled) the coefficients $\gamma_{j,k}$ are all equal to 0. Please note that we omit the direct contribution of occupations as estimated in regression (4). Results are presented in Figure 5.

For each variable (or variable set), the direct and indirect contributions are added, and the synthetic measure of contributions to the cross-country differences in RTI, σ_k^{ols} , is defined as:

$$\sigma_k^{mt} = \frac{cov(\theta_k * (\bar{X}_k^c - \bar{X}_k^{US}) + \sum_j (Share_j^c - Share_{j,k}^c) * \bar{RTI}_j^c, \bar{RTI}^c - \bar{RTI}^{US})}{var(\bar{RTI}^c - \bar{RTI}^{US})}, \quad (12)$$

The model accounting for selection to occupations explains a higher share (almost 60%) of differences in average routine task intensity in various countries than the OLS (Table 7). Moreover, a higher share of cross-country differences in average RTI is attributed to technological factors (45% of the total variance, out of 58% that is attributed to any factor, compared with 34% out of 50% in the case of OLS). In particular, the contributions of computer use, literacy skills, sectors and GVC participation are larger. This suggests that these factors partially contribute to routine task intensity through their relationship with occupational distributions within countries. The finding related to GVC participation is consistent with previous research showing that routine jobs are easier to offshore (Grossman & Rossi-Hansberg, 2008; Oldenski, 2012), although the contribution of GVC participation is quantitatively small even if we account for the selection to occupations. On the other hand, the contribution of ICT stock and robots per worker are lower than in the decomposition based on OLS. This means that although these technological variables contribute to lower RTI for any worker, they also contribute to higher shares of more routine intensive occupations.

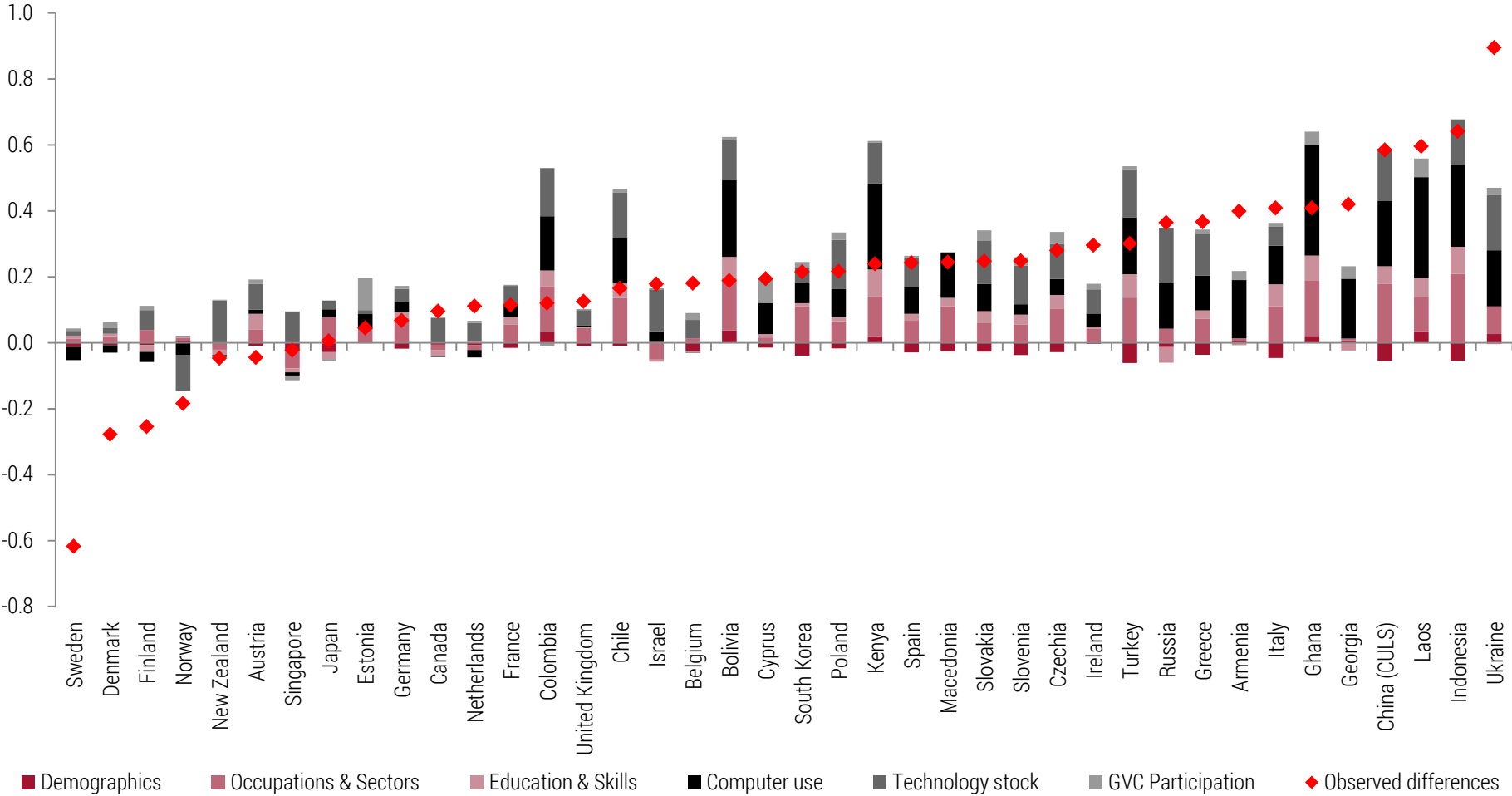
Table 6. Contributions of particular factors to cross-country variance of routine task intensity (in % the cross-country variance of average RTI)

	Occupations	Demo-graphics	Sectors	Educa-tion	Literacy	Computer use	ICT per worker	Robots per worker	GVC Partici-pation	Total
σ_k^{ols}	11.8	-0.4	-0.7	1.8	2.0	26.0	6.8	1.5	1.3	50.1
σ_k^{mt}	na	0.6	6.1	2.3	5.0	39.0	5.2	0.3	2.2	58.5

Note: the contributions of particular variables (variable groups) to cross-country differences in average RTI according to the OLS model, σ_k^{ols} , are calculated in line with equation (6), and the contributions according to the two-stage multinomial treatment effects model which accounts for the selection to occupations, σ_k^{mt} , are calculated in line with equation (12).

Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

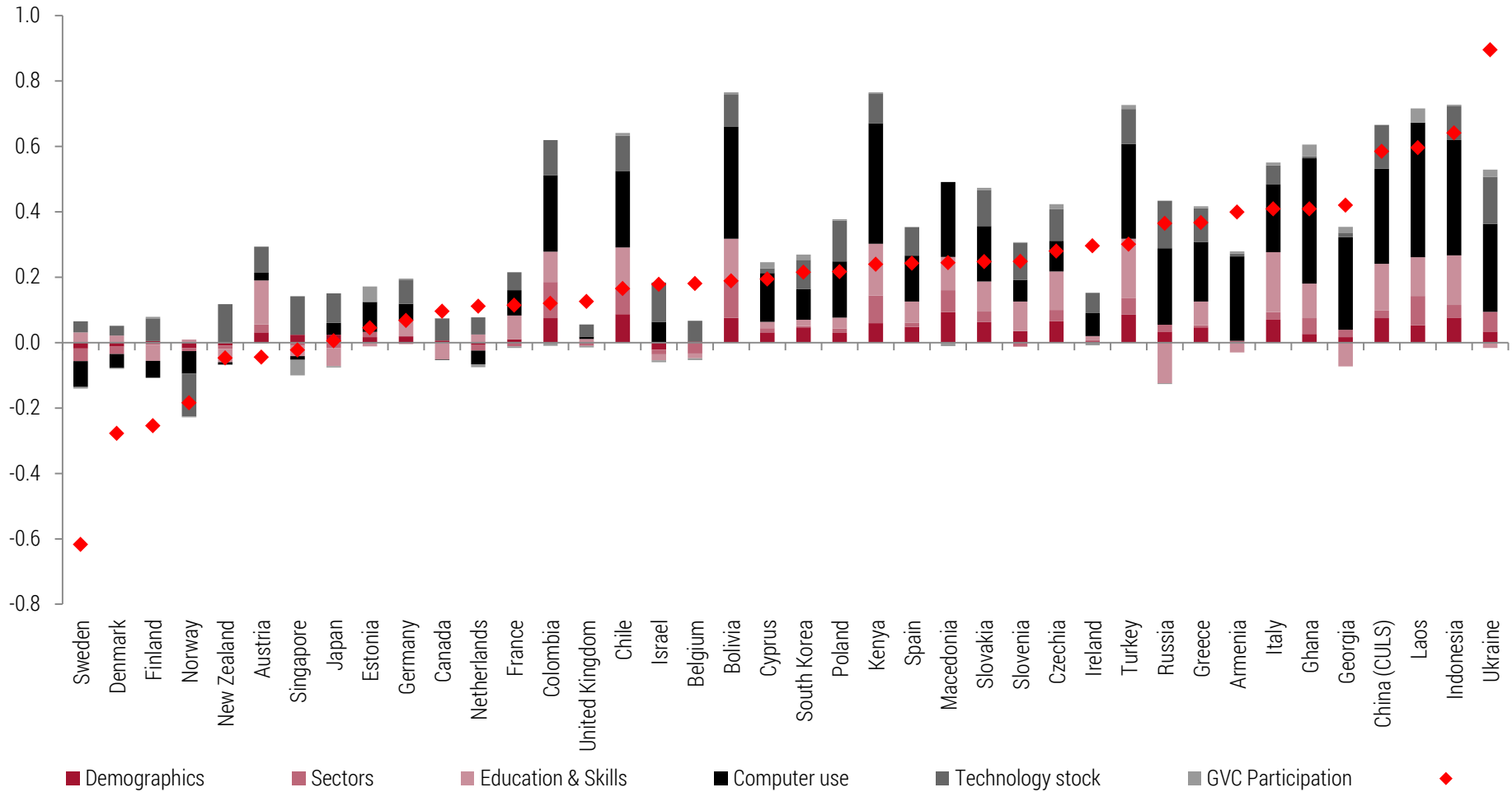
Figure 5. Decomposition of differences in routine task intensity (RTI) between a particular country and the United States, based on the OLS regression (column 8 in Table 5).



Note: The decomposition is based on OLS regression presented in column 8a in Table 5, except for: Macedonia based on a model without literacy skills, ICT stock, FVA and robots; China (CULS) based on a model without literacy skills; Armenia, Cyprus, Georgia and Ghana based on a model without ICT stock and robots; Bolivia and Kenya based on a model without robots and Estonia based on a model without ICT stock. For clarity, we combine contributions of occupations and sectors, education and literacy skills, ICT capital stock and robots per worker.

Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

Figure 6 Decomposition of differences in routine task intensity (RTI) between a particular country and the United States, based on the model accounting for selection to occupations (Table 6).



Note: The decomposition is based on the multinomial treatment regression presented in Table 6, except for: Macedonia based on a model without literacy skills, ICT stock, FVA and robots; China (CULS) based on a model without literacy skills; Armenia, Cyprus, Georgia and Ghana based on a model without ICT stock and robots; Bolivia and Kenya based on a model without robots and Estonia based on a model without ICT stock. For clarity, we combine contributions of occupations and sectors, education and literacy skills, ICT capital stock and robots per worker.

Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

5. Summary and conclusions

We have developed a novel framework to measure the task content of jobs at a worker-level. Our measures are constructed using the US PIAAC data and validated with the O*NET-based Acemoglu & Autor (2011) task content measures, to ensure that the interpretation of our measures is consistent with that in the established literature. Our measures can be applied to 42 countries covered by PIAAC, STEP and CULS surveys which results in country-specific values of task content of jobs within particular occupations.

Our results show that there are substantial cross-country differences in the average values of particular tasks, both at the national level and in particular occupations. The most developed countries are characterised by the highest average values of non-routine cognitive analytical and non-routine cognitive personal tasks, and many of them exhibit the lowest average values of manual tasks. The opposite is true for the developing and emerging economies. The average values of routine cognitive task are the lowest in the least and the most developed countries, and are the highest in Central Eastern and Eastern European countries and Southern European countries, suggesting an inverse U-shaped relationship between the role of routine cognitive work and development level. Moreover, the cross-country differences in the routine task intensity are most strongly related to the differences in GDP per capita in the case of high-skilled occupations.

Differences in the routine intensity of tasks performed by workers around the world are related to both individual characteristics, and features of particular economies. Workers with tertiary education, workers in professional or managerial jobs, workers with higher literacy skills and workers who use computer at work perform significantly less (cognitive) routine work. Moreover, the higher is the ICT capital stock per worker or the number of robots per worker in a given country and sector, the less routine intensive is the work performed by humans. Although our findings in a cross-country setting are only descriptive, they are consistent with the routine-replacing technological change hypothesis (Autor et al., 2003, Goos et al., 2014).

In the majority of countries the structure of individual and workplace characteristics is conducive to a more routine-intensive task structure than in the US. However, only a small share of these differences in the average values of tasks between particular countries and the US can be attributed to differences in individual characteristics, such as education and skills. Most of these differences can be attributed to the differences in the ICT capital stock per worker and in the incidence of computer use in the workplace. Because these technological variables also affect the country-specific occupational structure – the higher is the technology stock and use, the higher is the share of high-skilled occupations (ISCO 1-3) that tend to perform especially low amounts of routine tasks – their contribution is higher when we account for selection of workers to occupations. We also find that workers in countries which exhibit high shares of foreign value added in the domestic production, which are countries presumably receiving offshored jobs, perform more routine tasks, in line with the Grossman & Rossi-Hansberg (2008) model. However, we find that this factor contributes much less than the technological variables to the cross-country differences in routine task intensity.

Our work stresses the need to quantify the country-specific task content of jobs and identify differences between occupational demands in countries at various stage of development. It paves the way for a more comprehensive research on the distribution of tasks around the world that can account for the within-occupation and between-country variation in the task demand.

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Appendix

Appendix A. List of countries in PIAAC, STEP and CULS

PIAAC surveys include publically available data representative of 32 countries. 23 in Round I: Austria, Belgium (Flanders), Canada, Cyprus (the area under the effective control of the Government of the Republic of Cyprus), Czechia, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, South Korea, Netherlands, Norway, Poland, Russia (w/o Moscow municipal area), Slovakia, Spain, Sweden, UK (England and Northern Ireland), United States. 9 in Round II: Chile, Greece, Indonesia (Jakarta), Israel, Lithuania, New Zealand, Singapore (only permanent residents), Slovenia and Turkey. Moreover, a dataset with supplementary 2nd round is available for the United States via the US National Center for Education Statistics (NCES).

STEP surveys include data on individuals in 12 countries: Armenia, Bolivia (four main capital cities – La Paz, El Alto, Cochabamba and Santa Cruz de la Sierra), China (Yunnan province), Colombia (13 main metropolitan areas), Georgia (w/o Abkhazia and South Ossetia), Ghana, Kenya, Lao PDR (both urban and rural areas), Macedonia, Sri Lanka (both urban and rural areas), Ukraine, Vietnam (Ha Noi and Ho Chi Minh). In our final sample we exclude the China (Yunnan), Sri Lanka and Vietnam datasets (see the main text).

The 3rd wave of the CULS survey includes data on individuals in six large cities in China: Guangzhou, Shanghai, and Fuzhou on the coast, Shenyang in the northeast, Xian in the northwest, and Wuhan in central China.

Appendix B. Relevant task items in PIAAC and STEP surveys

Table B1. The considered task items, their exact wordings and possible answers in PIAAC and STEP surveys.

Task item name	PIAAC		STEP		
	Question	Answers	Question	Answers	
	In your job, how often do you usually...	1. Never 2. Less than once a month 3. Less than once a week but at least once a month 4. At least once a week but not every day 5. Every day	As a regular part of this work, do you have to read the following...?	Yes / No	
Reading bills	- Read bills, invoices, bank statements or other financial statements?		- Bills or financial statements		
Reading news	- Read articles in newspapers, magazines or newsletters?		- Newspapers or magazines		
Reading professional titles	- Read articles in professional journals or scholarly publications?		- Reports		
Reading manuals	- Read manuals or reference materials?		- Instruction manuals/operating manuals		
Filling forms	- Fill in forms?		As part of this work, do you fill out bills or forms?		
	In your job, how often do you usually...	As above	As a normal part of this work, do you do any of the following...?	As above	
Advanced math	- Use more advanced math or statistics such as calculus, complex algebra, trigonometry or use of regression techniques?				- Use more advanced math, such as algebra, geometry, trigonometry, etc.
Calculating prices	- Calculate prices, costs or budgets?				- Calculate prices or costs
Calculating fractions	- Use or calculate fractions, decimals or percentages?		- Use or calculate fractions, decimals or percentages		
Programming	In your job, how often do you usually use a programming language to program or write computer code?	As above	Does your work as [OCCUPATION] require the use of software programming?	As above	
Presenting	How often does your job usually involve making speeches or presentations in front of five or more people?	As above	As part of this work, do you have to make formal presentations to clients or colleagues to provide information or persuade them of your point of view?	As above	
Solving problems	And how often are you usually confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to THINK of a solution, not the time needed to carry it out.	As above	Some tasks are pretty easy and can be done right away or after getting a little help from others. Other tasks require more thinking to figure out how they should be done. As part of this work as [OCCUPATION], how often do you have to undertake tasks that require at least 30 minutes of thinking (examples: mechanic figuring out a car problem, budgeting for a business, teacher making a lesson plan, restaurant owner creating a new menu/dish for restaurant, dress maker designing a new dress)	1. Never 2. Less than once a month 3. Less than once a week but at least once a month 4. At least once a week but not every day 5. Every day	

Physical tasks	How often does your job usually involve working physically for a long period?	As above	Using any number from 1 to 10 where 1 is not at all physically demanding (such as sitting at a desk answering a telephone) and 10 is extremely physically demanding (such as carrying heavy loads, construction worker, etc.), what number would you use to rate how physically demanding your work is?	1-10
Supervising	Do you manage or supervise other employees?	Yes / No	As a normal part of this work do you direct and check the work of other workers (supervise)?	Yes / No
Using computer	Do you use a computer in your job?	Yes / No	As a part of your work do you use a computer?	Yes / No
Collaborating	In your job what proportion of your time do you usually spend cooperating or collaborating with co-workers?	<ol style="list-style-type: none"> 1. None of the time 2. Up to a quarter of the time 3. Up to half of the time 4. More than half of the time 5. All the time 	As part of this work, how frequently do you spend time co-operating or collaborating with co-workers?	<ol style="list-style-type: none"> 1. Never 2. Less than once a month 3. Less than once a week but at least once a month 4. At least once a week but not every day 5. Every day
Changing order of tasks	The next few questions are about the amount of flexibility you have in deciding how you do your job: To what extent can you choose or change the sequence of your tasks?	<ol style="list-style-type: none"> 1. Not at all 2. Very little 3. To some extent 4. To a high extent 5. To a very high extent 	Still thinking of your work as [OCCUPATION] how much freedom do you have to decide how to do your work in your own way, rather than following a fixed procedure or a supervisor's instructions? Use any number from 1 to 10 where 1 is no freedom and 10 is complete freedom.	1-10

Note: the PIAAC questions wordings in this table come from the International Master Questionnaire, available at the OECD website.²⁰ The STEP questions wordings in this table come from the English version of the Armenia STEP Skills Measurement Survey, available at the World Bank's microdata website.²¹

²⁰ See www.oecd.org/skills/piaac/BQ_MASTER.HTM [accessed: 2017-05-02].

²¹ See microdata.worldbank.org/index.php/catalog/2010 [accessed: 2017-05-04].

Appendix C. Comparison of task measures based on STEP and PIAAC data

Table C1. Comparison of task measures based on STEP and PIAAC data

Our measures; PIAAC and STEP		Dicarlo et al. (2016); STEP		de la Rica and Gortazar (2016); PIAAC		Marcolin et al. (2016b); PIAAC; Routine Intensity Index only			
Task content	Items	Task content	Items	Task content	Items	Items			
Non-routine cognitive analytical	Reading news	Non-routine analytical	No. of types of documents read	Abstract	Read diagrams, maps or schematics	Planning own activities			
			Length of longest documents typically read						
	Reading professional titles		Length of longest document typically written						
	Solving problems		Solving problems						
	Programming		Advanced math						
			Any of the basic mathematical tasks						
			Learning new things						
Non-routine cognitive personal	Supervising	Non-routine interpersonal	Supervising	Routine	Negotiating with people				
	Presenting		Presenting						
Routine cognitive	Changing order of tasks (reversed)		Routine & Manual			Changing order of tasks (reversed)	Routine	Changing order of tasks	Changing order of tasks
						Repetitiveness		Change how to do work	Change how to do work
	Filling forms	Operate machines or equipment		Change speed of work	Organising own time				
		Driving		Change working hours					
	Presenting (reversed)	Repair electronic equipment		Learn work-related things from co-workers					
Physical tasks		Learning-by-doing from tasks performed							
Manual	Physical tasks	Manual	Physical tasks	Hand/Finger Accuracy		Keeping up to date with new products/services			
Methods: uniform coding in STEP and PIAAC; standardisation (means and standard deviations); averages		Methods: standardisation (means and standard deviations); summation		Methods: principal component analysis		Methods: averages.			

Source: own elaboration based on Dicarlo et al. (2016), de la Rica and Gortazar (2016) and Marcolin et al. (2016b).

Appendix D. Other data sources

In order to estimate cross-country regressions (sections 4.2-4.3) we merge the PIAAC, STEP and CULS data with three additional variables: ICT stock per worker, number of robots per worker, and the global value chain participation

The data on ICT capital stock come from Eden & Gaggl (2015). The data are available at the country level, except seven countries in our sample: Armenia, Cyprus, Georgia, Ghana, Estonia, Laos and Macedonia. The latest year available is 2011.

The data on robots come from the International Federation of Robotics [IFR] (2017). The latest data available are from 2016 but we use the average for 2011-2016 since the STEP-PIAAC-CULS data cover this period. The IFR data are available for ISIC 4 sectors: A, B, C, D & E (jointly), F and P. We aggregate these numbers further to three broad categories: Agriculture, Industry and Services and calculate the number of robots per worker in each country / sector cell. The IFR data are unavailable for eight countries in our sample: Armenia, Bolivia, Cyprus, Georgia, Ghana, Kenya, Laos and Macedonia.

The data on global value chain participation are sourced from the RIGVC UIBE (2016) database. We use the backward linkage-based measure, defined as the foreign value added share in production of final goods and services, and as a robustness check we use the forward-linkage measure, defined as the domestic value added from production of intermediate exports or domestic factor content in intermediate exports (Wang et al., 2017). We use the variables based on GTAP. The latest year available is 2011. We merge the GVC data with our data at the country-industry level. However, as the two classifications are not fully compatible, we aggregate some of the ISIC 4 categories to broader groups for the matching: "E+O+P+Q+U" (water supply; sewerage, waste management and remediation activities; public administration and defence; compulsory social security; education; human health and social work activities; activities of extraterritorial organizations and bodies). In the case of China (CULS) this group also includes category D (electricity, gas, steam and air conditioning supply). "G+I" (wholesale and retail trade, repair of motor vehicles and motorcycles; accommodation and food service activities); "L+M+N" (real estate activities; professional, scientific and technical activities; administrative and support service activities); and "R+S+T" (arts, entertainment and recreation; other service activities; activities of households as employers; undifferentiated goods- and services-producing activities of households for own use). The RIGVC UIBE (2016) data are not available for Macedonia.