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THE GLOBAL DISTRIBUTION OF ROUTINE AND NON-ROUTINE WORK[•]

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Abstract

The shift away from manual and routine cognitive task, and towards non-routine cognitive tasks changes the nature of work. Using the US PIAAC data, we develop measures of non-routine cognitive analytical and personal, routine cognitive and manual task content that are consistent with measures based on O*NET, but are country-specific and worker-specific. We apply them to 42 countries covered by PIAAC, STEP and CULS surveys. We find that the relationship between relative routine task intensity 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. In most countries, structure of worker and job characteristics is more conducive to routine-intensive work than in the US, but these differences cannot fully explain cross-country differences in routine task intensity. The higher is the ICT capital stock per worker or the position in the global value chain, the lower is the routine task intensity, especially among, respectively, high-skilled and low-skilled occupations. The use of robots within an industry is negatively related to the routine task intensity, though it does not contribute much to the differences with regards to the US.

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. The literature found that 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; Autor & Price, 2013, Goos et al. 2014). The demands of particular occupations have also changed accordingly (Autor et al., 2003; Spitz-Oener, 2006). Similar patterns have been identified in the middle-income or newly established high income countries, although routine cognitive employment, has either 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 which started in 2003, and following methodologies proposed by Autor et al. (2003) and Acemoglu and Autor (2011). The O*NET task measures are often merged with country-specific data sources, usually labour force surveys, and used to calculated task content of jobs in countries other than the US (Arias et al., 2014, Goos et al., 2009, 2014, Dicarlo et al., 2016, Hardy et al., 2018, Lewandowski et al., 2017). Researchers using O*NET have to make two key assumptions. First, that the occupational demand in the US and other countries are identical. Second, that the task content of jobs is uniform within occupations. These assumptions are not necessarily wrong as Handel (2012) showed that O*NET measures and measures based on skill surveys in European countries provide very similar outcomes. Cedefop (2013) confirmed that it is methodologically valid to use O*NET data to construct occupational measures in European countries. Nevertheless, the use of O*NET in research on countries other than the US stems rather from necessity than will – no other data sources on occupations are as rich and detailed as O*NET.

The emergence of synchronised surveys of skills and skill use at work, such as the OECD’s Programme for the International Assessment of Adult Competencies (PIAAC) and the World Bank’s Skills Measurement Program (STEP), offers an opportunity to measure both the country-specific occupational demands and the within-occupation heterogeneity of tasks performed by workers. De la Rica & Gortazar (2016) used PIAAC data to create measures of “de-routinisation”, Marcolin et al. (2016a, 2016b) – to classify workers into non-, low-, medium- and high-routine intensive occupations. Dicarlo et al. (2016) attempted to create the task content measures with STEP data. These measures, however, have not been validated with O*NET, so it is unclear to what extent the terms “routine” and “non-routine” mean the same as in previous literature. It is also unclear to what extent potential 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 is especially relevant as researchers have mapped O*NET items to PIAAC or STEP questions in a rather arbitrary way. Moreover, some O*NET items used by Acemoglu and Autor (2011) do not have counterparts in PIAAC or STEP surveys.

In this paper 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, and what is the resulting distribution of non-routine and routine work around the world? Second, which labour supply and labour demand factors contribute to these differences?

To this aim, we create new measures of task content of jobs which are (i) consistent with O*NET and validated on the US data to make sure that the interpretation of routine and non-routine contents is as similar to the established literature (Acemoglu and Autor, 2011) as possible, (ii) country specific, and (iii) observed at a worker level which translates into a within-occupation heterogeneity of task contents. We use both PIAAC and STEP surveys, as well as China Urban Labor Survey (CULS) which includes the same "skill use at work" questionnaire as STEP. This allows us to analyse more countries than one survey would enable, and to cover developing, emerging and developed countries in a consistent manner.

The paper is structured as follows. In the second section we outline our methodology of creating the task content measures with PIAAC, STEP and CULS, and present their properties. In the third section we discuss the properties of our measures, and in the fourth section we analyse the cross-country and individual level results. 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.

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

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.

We reweight the STEP and Indonesian[4] 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.

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

[3] Yunnan province of China 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. Dicarlo et al. (2016) also omitted the Yunnan dataset.

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

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]

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

[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.

[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).

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]. PIAAC uses the ISCO classification of occupations, but the level of detail varies between countries. US PIAAC data with 3-digit ISCO occupations are available from the NCES and 4-digit ISCO occupations are indirectly accessible for analysis available. We apply our procedure at both levels separately. We use the methodology of Acemoglu and Autor (2011), although we 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 & Autor (2011). We standardise the measures within the US dataset.

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 task item contributions to the task content measures.

The chosen combinations and correlations between our tasks and the Acemoglu and Autor (2011) tasks based on O*NET are presented in Table 2. The outcomes of both methodologies at the 3-digit occupation level using the US PIAAC data are shown on Figure 1. Our measures follow the Acemoglu and Autor (2011) tasks based on O*NET quite closely. 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).[8] 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

[7] See: www.ibs.org.pl/resources [accessed: 2017-05-04].
[8] The highest correlations obtained at the 4-digit occupation level range from 62% to 79%.

analytical) while the standard deviations of the O*NET-based tasks range from 1.02 (non-routine cognitive personal) to 1.23 (routine cognitive).[9]

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

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

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.*

We use the chosen combinations to calculate task content measures in all countries studied. We also merge O*NET with PIAAC, STEP and CULS and calculate the Acemoglu and Autor (2011) tasks. In both cases, we standardise the task content values using the relevant mean and standard deviation in the US. Hence, the US serves as the reference level for each task measure and the unit value of task content can be interpreted as one standard deviation of the task content value in the US. In order to have one synthetic measure of relative routine intensity of jobs, for each individual we construct the routine task intensity (RTI), using the formula:

[9] 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 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.

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

whereby r_{cog}, $nr_{analytical}$ and $nr_{personal}$ are routine cognitive, non-routine cognitive analytical and non-routine cognitive personal task levels, respectively. For all tasks, we add the absolute value of the lowest score in the sample to the scores of all individuals and an additional 1 to eliminate negative and zero scores from the logarithm. Our definition follows the literature and the definitions previously used by Autor & Dorn (2009, 2013) and Goos et al. (2014). However, we do not include the manual tasks as we cannot distinguish between routine and non-routine tasks. Hence, our RTI measure reflects mainly the relative importance of routine cognitive and non-routine cognitive tasks.

2.4 Other data

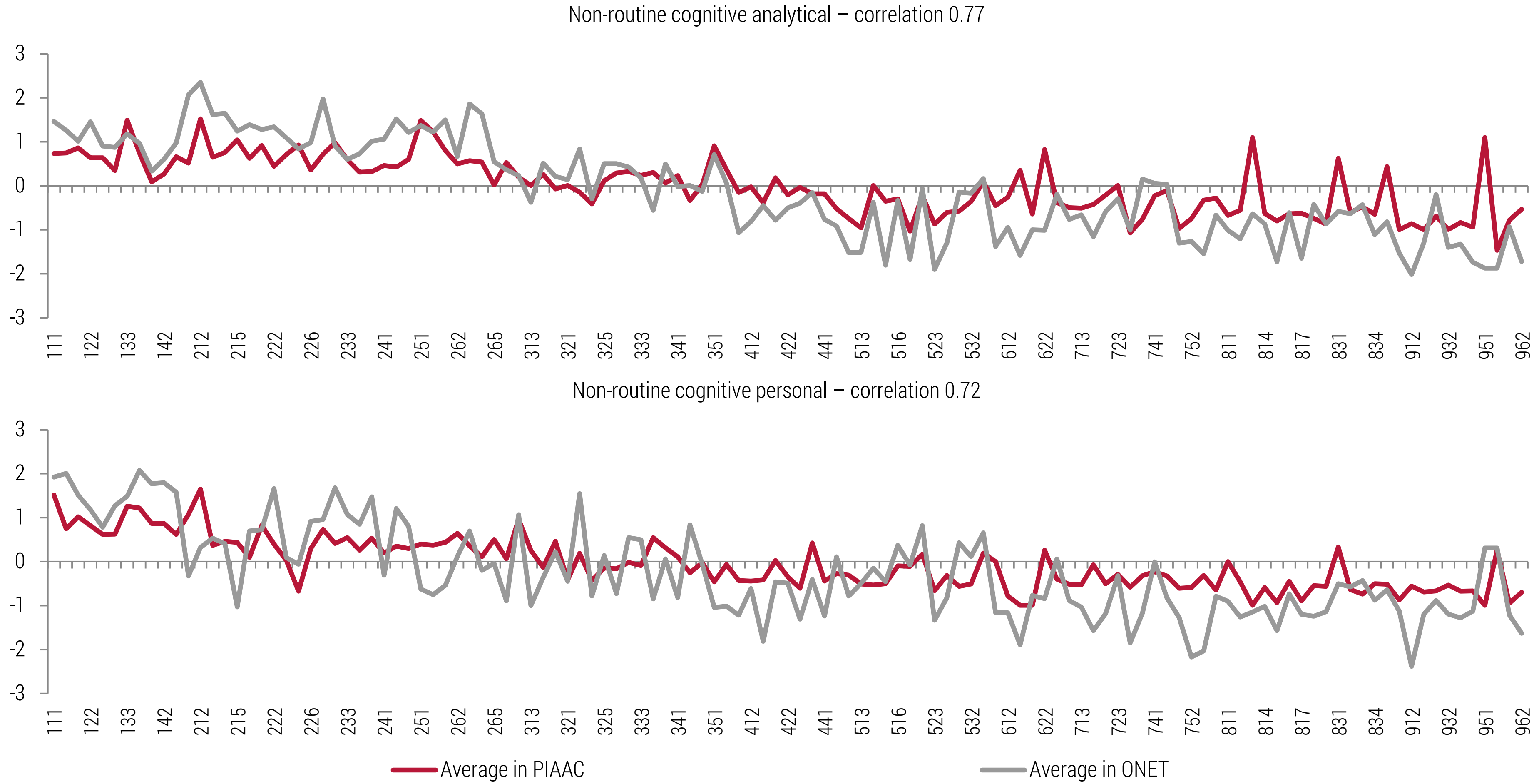
We complement our data with three additional variables: ICT stock per worker, foreign value added share in production of final goods and services and the number of robots per worker within country sectors.

The data on ICT capital stock comes from Eden & Gaggl (2015). The latest year available is 2011 and we merge it with our STEP-PIAAC-CULS by country. The ICT data is, however, unavailable for seven countries in our sample: Armenia, Cyprus, Georgia, Ghana, Estonia, Laos and Macedonia.

The foreign value comes from the data compiled by RIGVC UIBE (2016). The latest year available is 2011. We merge the data with our STEP-PIAAC-CULS at a country-industry level. The FVA data has broader industry categories than the STEP-PIAAC-CULS data, so for the matching we include the following, broader ISIC 4 categories: D+E+R+S+T+U, G+I, J+L+M+N and O+P+Q, with the other industries at a more detailed level. The FVA data is unavailable for Macedonia.

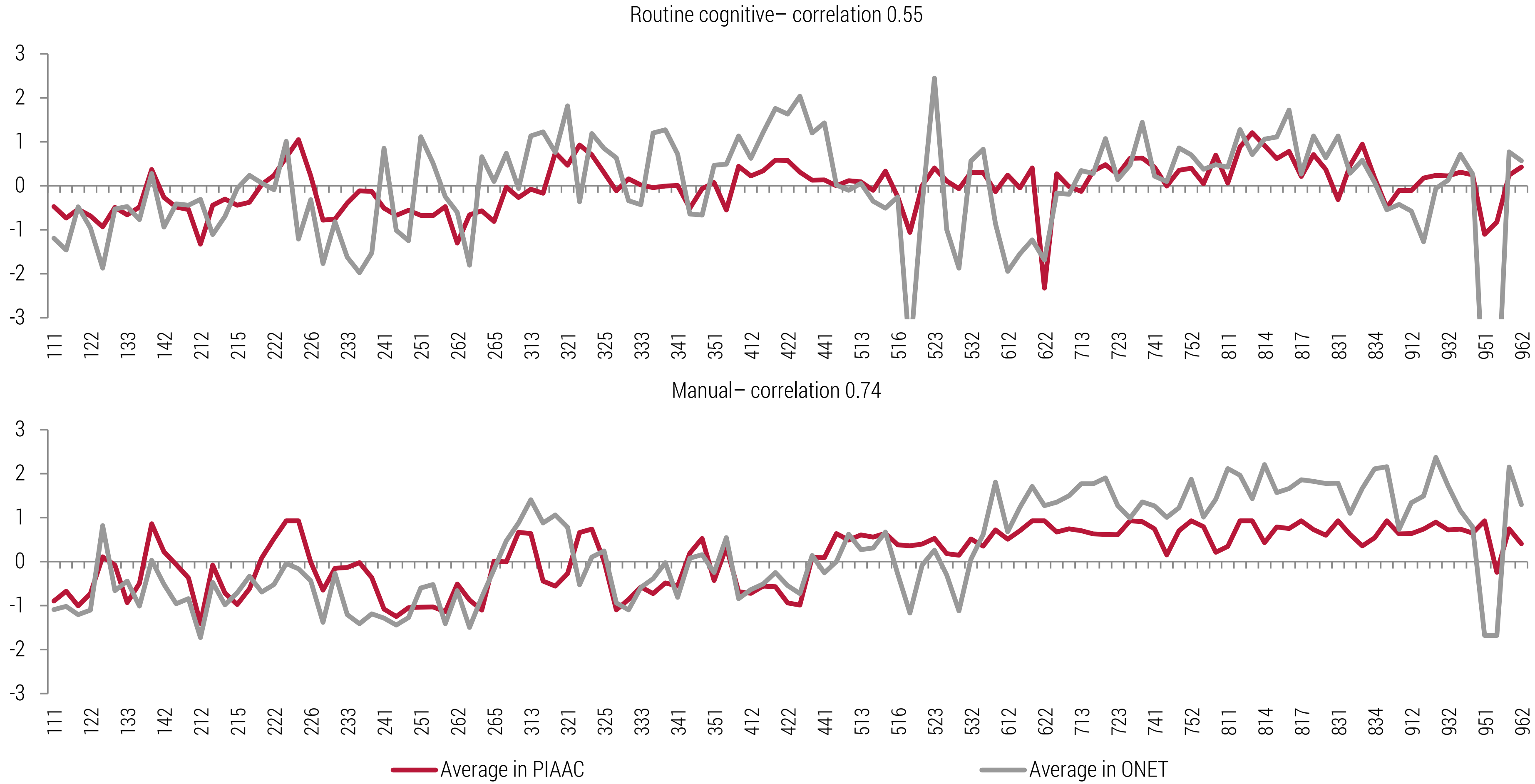
The robots data comes from the International Federation of Robotics [IFR] (2017). The latest data available comes from 2016 – we used the average yearly numbers from the period 2011-2016, since our STEP-PIAAC-CULS data covers this period. The IFR data is available for ISIC 4 sectors: A, B, C, D, E, F and P, with an aggregate number for sectors D and E. We aggregate these numbers further to three broad categories: Agriculture, Industry and Services and use them to derive the number of robots per workers in each of them. The robots data is unavailable for 8 countries: Armenia, Bolivia, Cyprus, Georgia, Ghana, Kenya, Laos and Macedonia.

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 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 initial 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 STEP survey. We find that 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,[10] the difference between STEP and PIAAC in non-routine cognitive analytical tasks becomes insignificant.[11] When we additionally control for the log of GDP per capita (level and squared), this difference becomes insignificant also for routine cognitive tasks. The difference in values of cognitive tasks between countries covered by STEP and countries covered by PIAAC can be explained by personal characteristics and cross-country differences in the development level. Hence, our measures of cognitive tasks seem consistent and comparable between the two surveys.

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.

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

[11] The STEP dummy is significant in the base model re-estimated on the subsample of 39 countries which have literacy assessment data (Table 3). Hence, it is the inclusion of literacy skills rather than limiting the sample which explains the change in the significance of the STEP dummy.

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. Hence, 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.

The occupational patterns of our task content measures are consistent with those identified by O*NET, although they differ in two important aspects. First, the average values of task content in particular occupations vary between countries at any level of occupational aggregation. At the 1-digit ISCO level, the cross-country standard deviation of our task values is consistently higher than the cross-country standard deviation of O*NET task (which is driven entirely by cross-country differences in employment structures at a finer ISCO levels). Second, the average values of our measures are less diverse across occupations (1-digit ISCO) than the O*NET values (similarly to patterns found for the US at the 3-digit occupation level, see Figure 1).

Table 4. Cross-country averages and standard deviations of values of tasks, by 1-digit ISCO occupations

	ISCO	1	2	3	4	5	6	7	8	9
Non-routine cognitive analytical										
Our measure	Average	0.38	0.42	0.08	-0.23	-0.60	-0.50	-0.58	-0.80	-1.06
	Std.	0.28	0.26	0.25	0.20	0.23	0.45	0.26	0.20	0.13
O*NET	Average	0.99	1.17	0.19	-0.68	-0.64	-1.28	-0.66	-0.74	-1.48
	Std.	0.09	0.10	0.10	0.10	0.21	0.39	0.18	0.13	0.14
Non-routine cognitive personal										
Our measure	Average	0.72	0.24	0.06	-0.31	-0.49	-0.64	-0.52	-0.66	-0.76
	Std.	0.33	0.19	0.18	0.23	0.17	0.23	0.16	0.14	0.10
O*NET	Average	1.63	0.55	-0.09	-0.95	0.02	-1.20	-0.99	-0.79	-1.24
	Std.	0.10	0.16	0.18	0.11	0.18	0.35	0.23	0.14	0.15
Routine cognitive										
Our measure	Average	-0.53	-0.36	0.00	0.33	0.08	-0.20	0.10	0.49	0.16
	Std.	0.28	0.33	0.31	0.30	0.27	0.35	0.29	0.34	0.24
O*NET	Average	-0.77	-0.62	0.45	1.43	-0.29	-1.25	0.29	0.59	-0.22
	Std.	0.14	0.20	0.20	0.09	0.54	0.32	0.14	0.15	0.34
Manual										
Our measure	Average	-0.60	-0.71	-0.52	-0.71	0.08	0.52	0.43	0.25	0.46
	Std.	0.21	0.21	0.22	0.17	0.23	0.32	0.26	0.20	0.27
O*NET	Average	-0.79	-0.97	-0.10	-0.40	-0.04	1.35	1.36	1.67	1.16
	Std.	0.14	0.08	0.19	0.13	0.18	0.33	0.14	0.14	0.21

Note: 1 – Managers, 2 – Professionals, 3 – Technicians, 4 – Clerical workers, 5 – Services and sales workers, 6 – Skilled agricultural workers, 7 – Craft and related trades workers, 8 – Plant and machine operators & assemblers, 9 – Elementary occupations.
*Source: own calculations based on PIAAC, STEP, CULS and O*NET.*

Table 4 shows that on average, the values of non-routine cognitive (both analytical and personal) tasks are positive among occupations 1-3 (managers, professionals, technicians), close to zero or slightly negative among in occupation 4 (clerks), and negative among occupations 5-9 (services and sales workers, skilled agricultural workers, craft and related trades workers, plant machine operators and assemblers, elementary occupations). According to our measure, the values of routine cognitive tasks are on average negative among managers, professionals and technicians (1-3) and skilled agricultural workers (6) and negative among other occupational groups. The average values of manual tasks are negative in occupations 1-4 (in all countries covered), close to zero in occupation 5 (services and sales workers) and positive in occupations 6-9. O*NET displays the same patterns, with few exceptions – it implies that, on average, the values of non-routine cognitive personal tasks are negative among technicians and positive among sales and services workers, while our measures show the opposite (also in terms of the median). It also shows that the average (and median) values of routine cognitive tasks among sales and services workers are negative while our measure shows they are slightly positive. In absolute terms, the average values of O*NET non-routine cognitive tasks are higher than the values of our tasks. Overall, the values of our task measures are more diverse between countries than O*NET tasks, but less diverse between occupations.

In the next section we analyse in detail the results of our measures, focusing on the measures of cognitive tasks.

4. Results

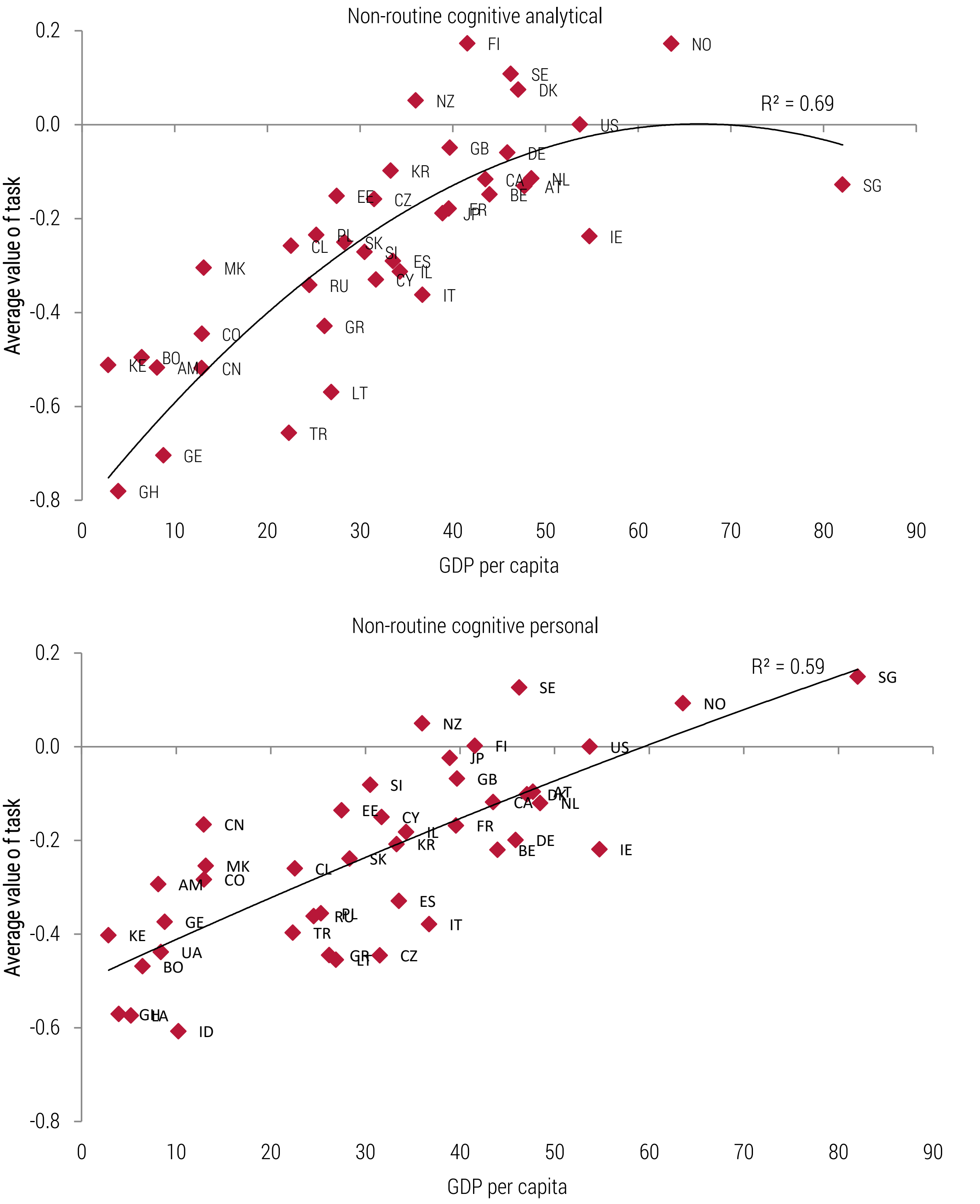
4.1 Descriptive results

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 4). 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 2). 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.

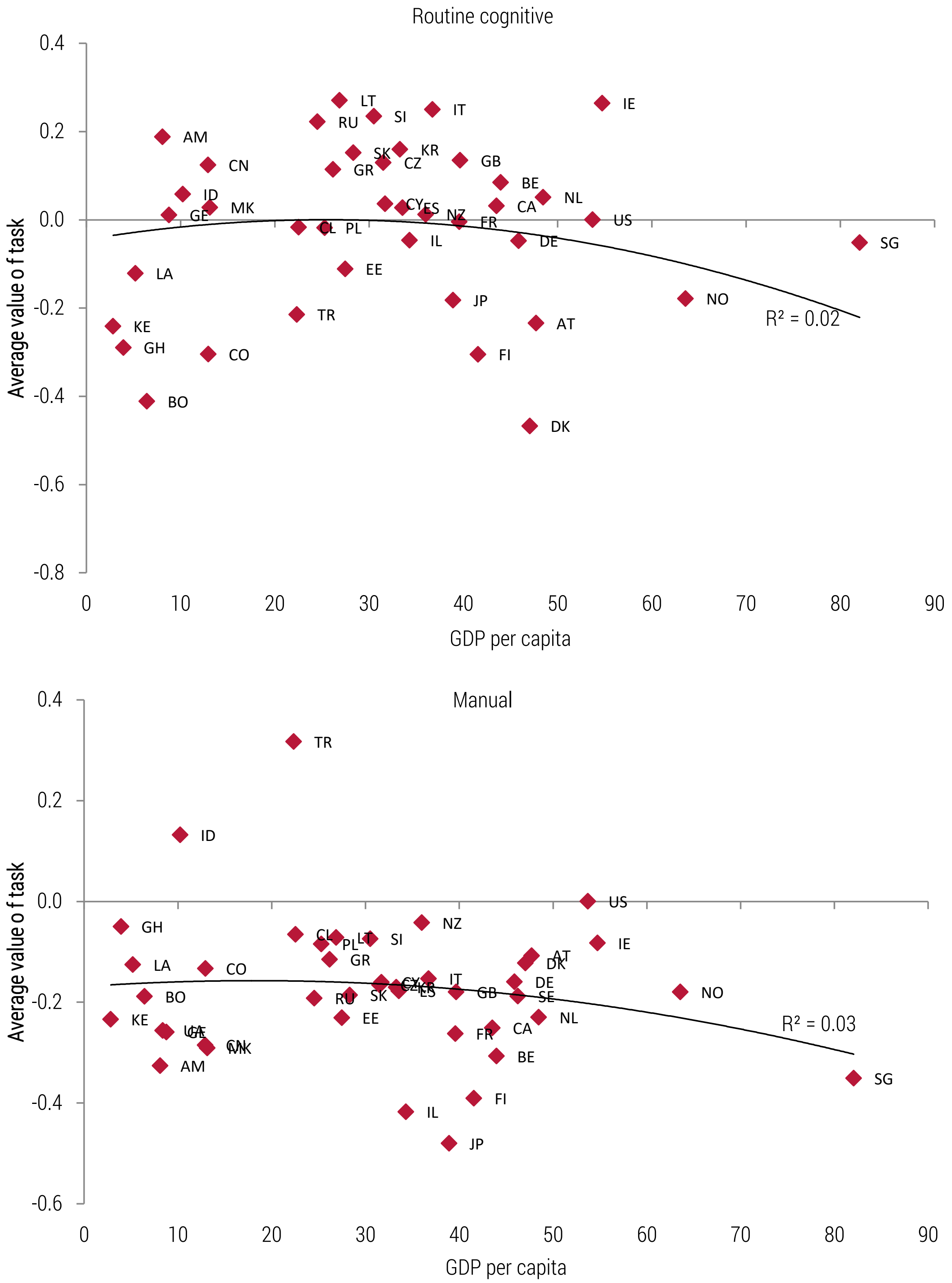
The average values of manual tasks do not show any clear-cut relationship with the level of development. For instance, Indonesia and Turkey evidence the highest manual task levels, but Armenia, Macedonia, Ukraine and Georgia are among the countries with the lowest levels. United States and New Zealand 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.

Figure 2. The average values of tasks against GDP per capita.



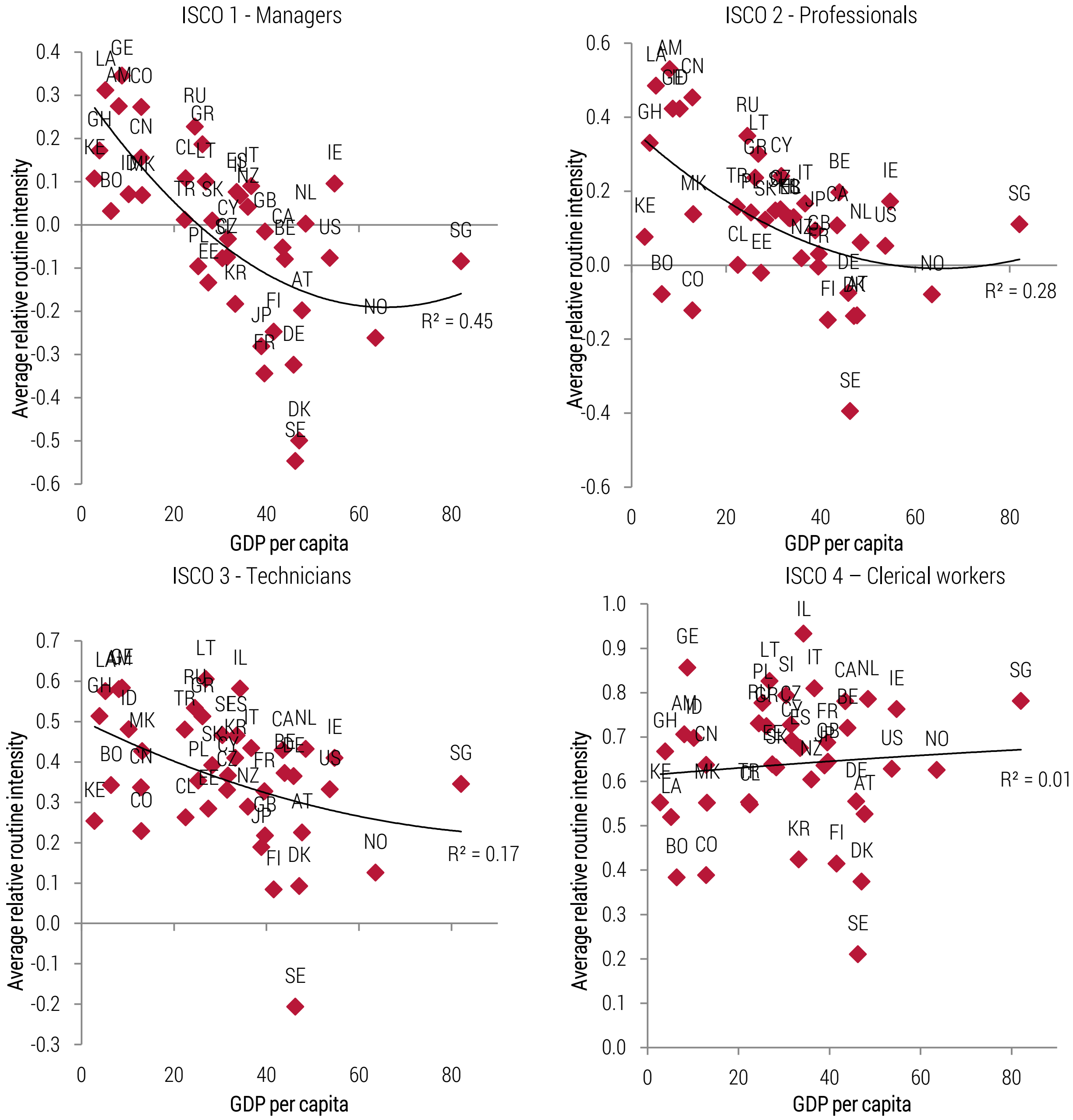
Note: for each task content, the 0 is set at the US average value and 1 corresponds to one standard deviation of this particular task content value in the US. GDP per capita in PPP, current international $, country averages for 2011-2016.
Source: own calculations based on PIAAC, STEP, CULS (tasks), and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

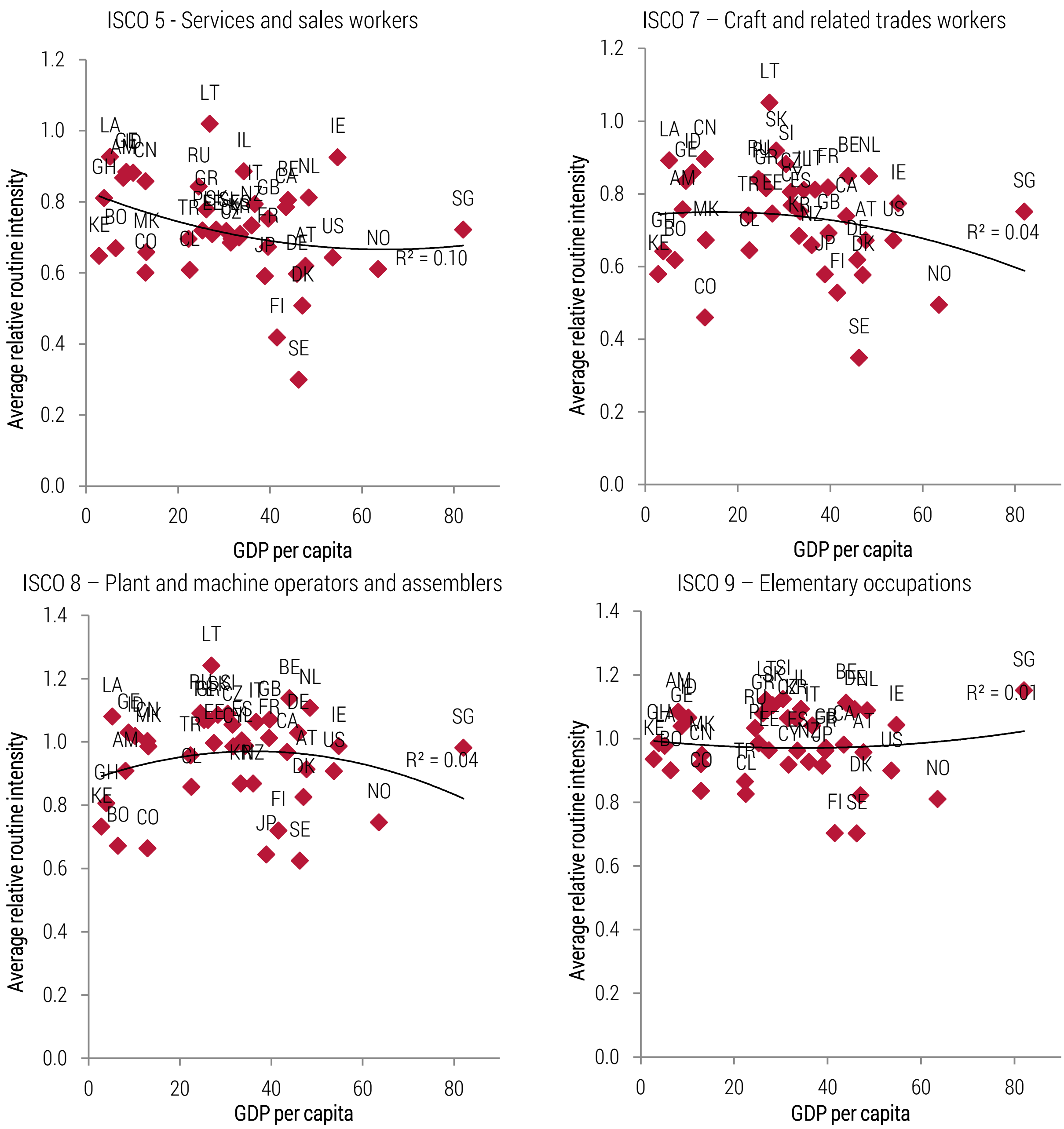
Figure 2. The average values of tasks against GDP per capita. (cont'd)



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 3. 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.*

Regarding particular occupations, the differences in relative importance of routine and non-routine tasks, as proxied by the RTI measure, are been to largest extent related to the differences in the development level in case of high-skilled occupations 1-3 (Managers, Professionals, Technicians). In the case of other occupations, the cross-country variance was slightly smaller,[12] but most importantly, the cross-country differences were not related systematically to the level of GDP per capita (Figure 3). In the case of occupations concentrated in manufacturing (Craft and related trades – ISCO-7, Plant & Machine Operators & Assemblers – ISCO-8), we find a moderate, inverse-U shaped relationship between the relative routine intensity of tasks and the development level. 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.

4.2 Worker-level correlates of relative routine task intensity

In order to shed light on factors which may contribute to the cross-country differences in the task intensity, we identify individual, workplace, industry and country characteristics which correlate with the relative routine intensity of jobs. To this end, we estimate OLS regressions on the RTI in a pooled sample. We include individual characteristics (gender, age and education) in all regressions. We subsequently add sets of control variables to check if the within-country labour characteristics can explain the between-country differences in the RTI levels. Finally, we add country and industry-level indicators. Previous literature has related the deroutinisation of jobs to the complexity of computer use (Almeida et al., 2017), access to broadband internet (Akerman et al. 2013), the position of a country and/or sector in the global value chains (Marcolin et al., 2016a) or the use of robots (Graetz & Michaels, 2015). We account for three factors: ICT capital stock, the global value chain position proxied by the foreign value added share in production of final goods and services, and robots stock (see section 2.4 for more information on the data). The robots stock and ICT stock are first related to the number of workers and then standardised (together with FVA) using the whole data sample to have the mean of 0 and the standard deviation of 1. Results of the estimations are presented in Table 5.

In the base model, we explain the RTI with individual characteristics. We find that the workers performing more routine-intensive jobs are more likely to be female workers, workers who are young (aged 16-24) or workers with lower education. Workers aged 35-65 are likely to perform less routine-intensive jobs than workers in both the younger and older age groups. Once we control for occupations, the coefficients on education levels decline and workers aged 55-65 evidence RTI levels higher than workers aged 35-54. Moreover, once we control for computer use the difference between the primary and secondary educated workers is no longer significant.

Workers in the low-skilled occupations (the craft and related trades workers, plant and machine operators and assemblers and workers of elementary occupations) are more likely to perform more routine-intensive jobs than the service and sales workers (the reference group). On the other hand, workers in the high-skilled occupations (managers, professionals, technicians and associate professionals) and armed forces are more likely to perform less routine-intensive jobs than the service and sales workers. Interestingly, once we control for computer use,

[12] Among the high-skilled occupations, the cross-country standard deviation of country-average RTI ranges from 0.16 (Technicians) to 0.20 (Managers), while among the remaining occupations it ranges from 0.11 (Elementary occupations) to 0.15 (Plant & Machine Operators & Assemblers). We omit the occupational group ISCO 6 (Skilled agricultural workers) because of small sample sizes, especially in countries where surveys covered only urban areas.

the clerical workers evidence higher RTI values than the service and sales workers. The inclusion of sectors does not affect any of the results for occupations and contributes little to the explanatory power of the model.

Table 5. Individual, workplace and aggregate correlates of routine task intensity (RTI - OLS regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.14***	0.17***	0.17***	0.15***	0.15***	0.15***	0.16***	0.16***
Age: 16-24	0.12***	0.11***	0.11***	0.10***	0.11***	0.11***	0.11***	0.12***
Age: 35-44	-0.06***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***
Age: 45-54	-0.04***	-0.02**	-0.02**	-0.03***	-0.04***	-0.03***	-0.03***	-0.03***
Age: 55-65	-0.04**	-0.00	-0.00	-0.02	-0.02	-0.02	-0.01	-0.01
Education: primary	0.20***	0.10***	0.10***	0.03	0.01	0.01	0.01	0.01
Education: tertiary	-0.37***	-0.13***	-0.12***	-0.10***	-0.08***	-0.08***	-0.09***	-0.10***
ISCO: 0. Armed forces occupations		-0.35***	-0.28***	-0.23***	-0.22***	-0.22***	-0.22***	-0.23***
ISCO: 1. Managers		-0.61***	-0.59***	-0.48***	-0.47***	-0.47***	-0.47***	-0.47***
ISCO: 2. Professionals		-0.46***	-0.43***	-0.33***	-0.32***	-0.32***	-0.32***	-0.32***
ISCO: 3. Technicians and associate professionals		-0.26***	-0.24***	-0.15***	-0.14***	-0.14***	-0.14***	-0.14***
ISCO: 4. Clerical support workers		-0.04	-0.01	0.10***	0.11***	0.11***	0.10***	0.10***
ISCO: 6. Skilled agricultural, forestry and fishery workers		-0.01	-0.02	-0.05	-0.04	-0.04	-0.03	-0.03
ISCO: 7. Craft and related trades workers		0.11***	0.12***	0.09***	0.10***	0.10***	0.11***	0.10***
ISCO: 8. Plant and machine operators and assemblers		0.33***	0.32***	0.27***	0.28***	0.28***	0.29***	0.29***
ISCO: 9. Elementary occupations		0.25***	0.25***	0.18***	0.20***	0.20***	0.20***	0.20***
Sectors included	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Uses computer				-0.32***	-0.31***	-0.31***	-0.29***	-0.29***
Literacy skills level: 1 and below					-0.01	-0.01	-0.01	-0.00
Literacy skills level: 3					-0.03***	-0.03**	-0.02**	-0.02**
Literacy skills level: 4 and 5					-0.09***	-0.09***	-0.08***	-0.08***
FVA share in production of final goods and services						0.02	0.01	0.01
ICT stock per worker							-0.03	-0.04*
Robots per worker								-0.04***
Constant	0.59***	0.60***	0.62***	0.82***	0.82***	0.82***	0.80***	0.79***
Observations	157,806	156,151	154,890	154,888	143,970	143,970	128,586	124,418
Countries	42	42	42	42	39	39	34	32
R-squared	0.14	0.29	0.29	0.33	0.33	0.33	0.34	0.34

*Note: *** p<0.01, ** p<0.05, * p<0.1. The reference level for age is 25-34. The reference level for education is secondary. The reference level for ISCO is 5 (i.e. service and sales workers). We do not include the coefficients for all sector dummies for brevity. They are available from the authors on request. China, Laos and Macedonia are dropped in models (5)-(8); Armenia, Cyprus, Georgia, Ghana and Estonia are dropped in models (7)-(8) and Bolivia and Kenya are dropped in model (8), due to data constraints (see section 2.4).*
Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

Computer use at work is highly and negatively correlated with routine task intensity and the coefficient is very robust to addition of further variables. Controlling for computer use makes the difference between workers with primary education and workers with secondary education insignificant. This suggests that secondary educated workers perform less routine intensive work than workers with primary education, mainly in connection to the use of computers. Moreover, the absolute sizes of coefficients on occupations decline once we control for computer use, showing that part of differences between occupations can be attributed to differences in computer use by workers in different occupations. The exception pertains to the clerical support workers who seem to perform more routine intensive jobs than service and sales workers when we factor out computer use.

Once we control for literacy skills, industry and country-level variables we need to remove some of the countries from our sample. However, the coefficients on the previously analysed variables do not change much when we do so. Literacy skills are negatively related to the RTI which means that workers with lower skills are more likely to perform more routine intensive jobs.

Moreover, once we add the share of foreign value added in the production of final goods and services, ICT stock per worker, and robots per worker, we observe a negative relationship between ICT stock and RTI as well as between robots and RTI.

4.3 Factors contributing to the cross-country differences in routine intensity of jobs

In the next step, we re-estimate the model (8) from Table 5 and calculate predicted values of routine intensity of jobs for each individual. We then derive the contributions of particular variables to the RTI values and aggregate the information to country-levels by calculating weighted averages. Finally, we use this data to decompose the differences between the US and any other country in the sample in terms of contributions of specific factors. 3 countries lack information on literacy skills: Macedonia, China and Laos. Moreover, further 7 countries lack information on FVA, ICT stock or robot stock. For these 10 countries we recalculate model (8) on the whole country sample but without the missing variables. We then use these specific predictions for the respective countries. Figure 7 presents differences between each of the countries in the sample and the US.

Individual characteristics do not contribute much to the differences in RTI levels. The differences in gender and age structures typically contributed negatively to the RTI, relative to the levels in US. On the other hand, the differences in educational attainment and literacy skills typically contributed positively to the RTI, relative to the levels in US. These four factors partially balanced each other out in most of the countries. Differences in occupational structures contributed much to the differences between countries, with the poorer countries generally evidencing higher shares of more routine-intensive occupations and sectors.

Differences in computer usage and in the ICT stock per worker contribute most to the differences between the country-levels of RTI. Notably, most countries evidenced higher RTI levels relative to the US due to lower levels of computer usage and of ICT stock per worker. The level of computer usage contributed negatively to the RTI levels, relative to the US, in Denmark, Finland, Norway, Netherlands and Sweden, while Norway also evidenced higher levels of ICT stock per worker. Finally, FVA and robots contribute positively to the RTI levels in most of the countries, relative to the US, though the contribution is not very large.

In the next step we repeat the model estimation and calculate the contributions for three occupational groups: the high-skilled occupations (ISCO 1-3), the middle-skilled occupations (ISCO 4-5) and the low-skilled occupations (ISCO 7-9). This approach allows us to further inspect if the any of the factors contributes mainly within specific groups of occupations, but does not differentiate much for others. Figures 5-7 show the decompositions within specific occupational groups (the regression coefficients are available upon request from the authors).

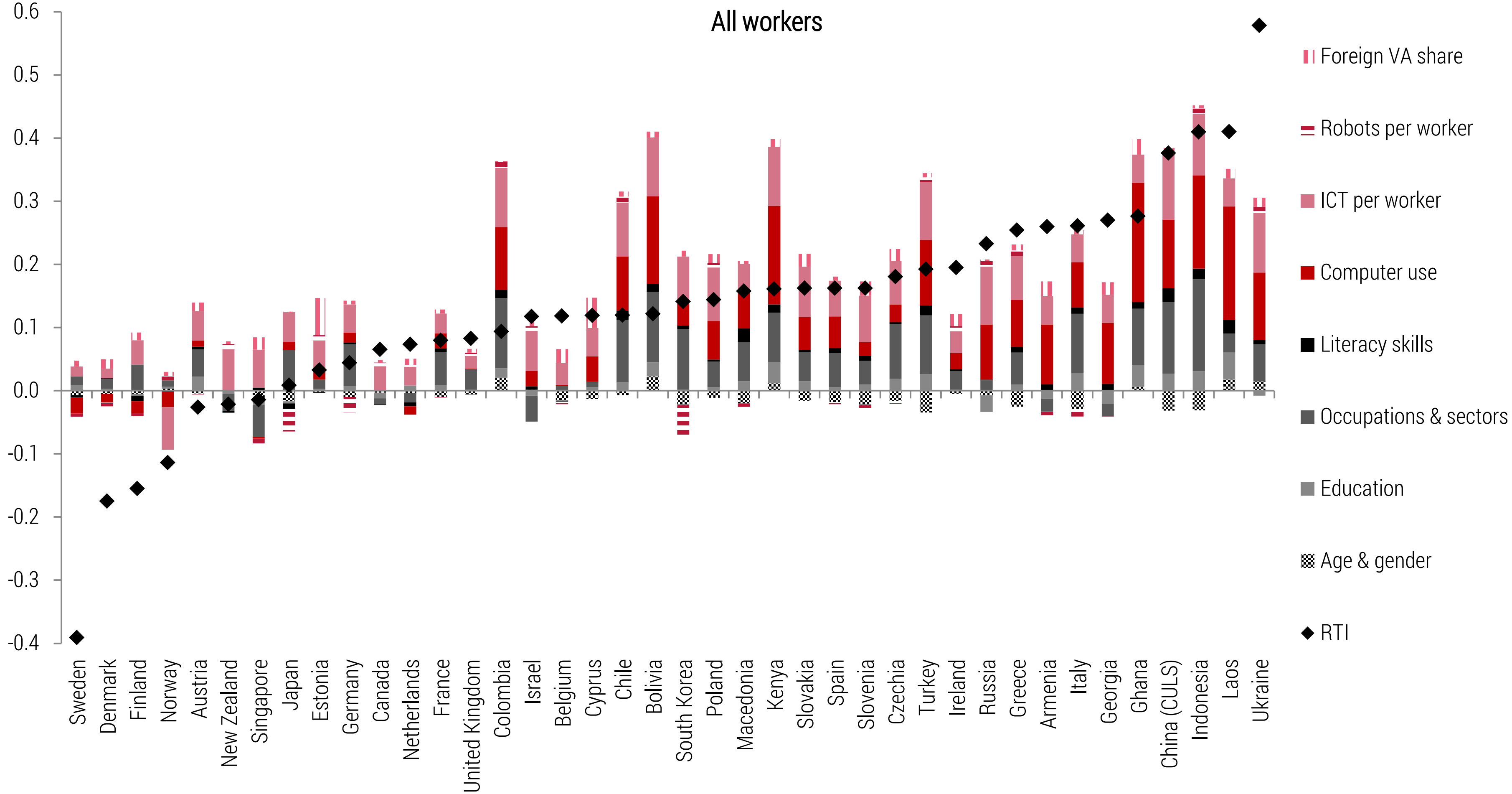
The contributions of job and worker characteristics to the cross-country differences in routine task intensity among the occupation groups is smaller than in the call of total differences. It is not surprising as the differences in occupational structures are the key contributor to the total differences. However, it also shows that only a small fraction of cross-country differences in routine intensity of tasks within particular occupations can be attributed to differences in observable individual characteristics such as the education structure of workers or differences in computer use.

For the high-skilled occupations (ISCO 1-3, Figure 5) the ICT stock per worker contributes most to the routine task intensity of work. Moreover, differences in literacy skills contribute positively to the differences in RTI levels with regards to the US. Interestingly, the shares of FVA contribute negatively to the country levels of RTI, relative to the US. For the medium-skilled occupations (ISCO 4-5, Figure 6), computer usage dominates in terms of contribution to the differences, while the ICT stock per worker contribution becomes much smaller. Moreover, the shares of FVA contribute positively to the country levels of RTI, relative to the US, while the differences in age and gender composition within these occupations contribute negatively to the differences with regards to the US. Finally, computer use contributes most to the differences in RTI levels within low-skilled occupations (ISCO 7-9, Figure 7), but the share of FVA also contributes positively and much to the differences relative with regards to the US.

In summary, the occupational structure contributes much to the differences in RTI levels across countries, but the RTI levels are also very different at the level of occupational groups. ICT stock per worker is highly correlated with the way work is performed in the high-skilled occupations (when controlling for computer use). However, computer usage contributes more to the differences in the way middle-skilled and low-skilled occupations are performed. These suggest that the relationship between the development level and the RTI differences partly operates through higher ICT stocks and computer usage in the more developed countries. However, our results might suggest that different types of technologies affect the way high-skilled and middle or low-skilled jobs are performed. On the other hand, our results might also suggest that the work in high-skilled occupations (such as managers or professionals) is more strongly related to the way other workers within the industry do their jobs and general access to ICT equipment.

The share of foreign value added in the production of final goods and services contributes differently to different types of occupations. Specifically it contributes slightly negatively to the differences in RTI with regards to the US in high-skilled occupations, but positively in the middle-skilled occupations and highly positively in the low-skilled occupations. This suggests that workers in countries located lower in the global value chains tend to perform more routine tasks, in particular in non-managerial manufacturing jobs. This finding is consistent with previous research showing that routine jobs are easier to offshore (Grossman & Rossi-Hansberg, 2008; Oldenski, 2012).

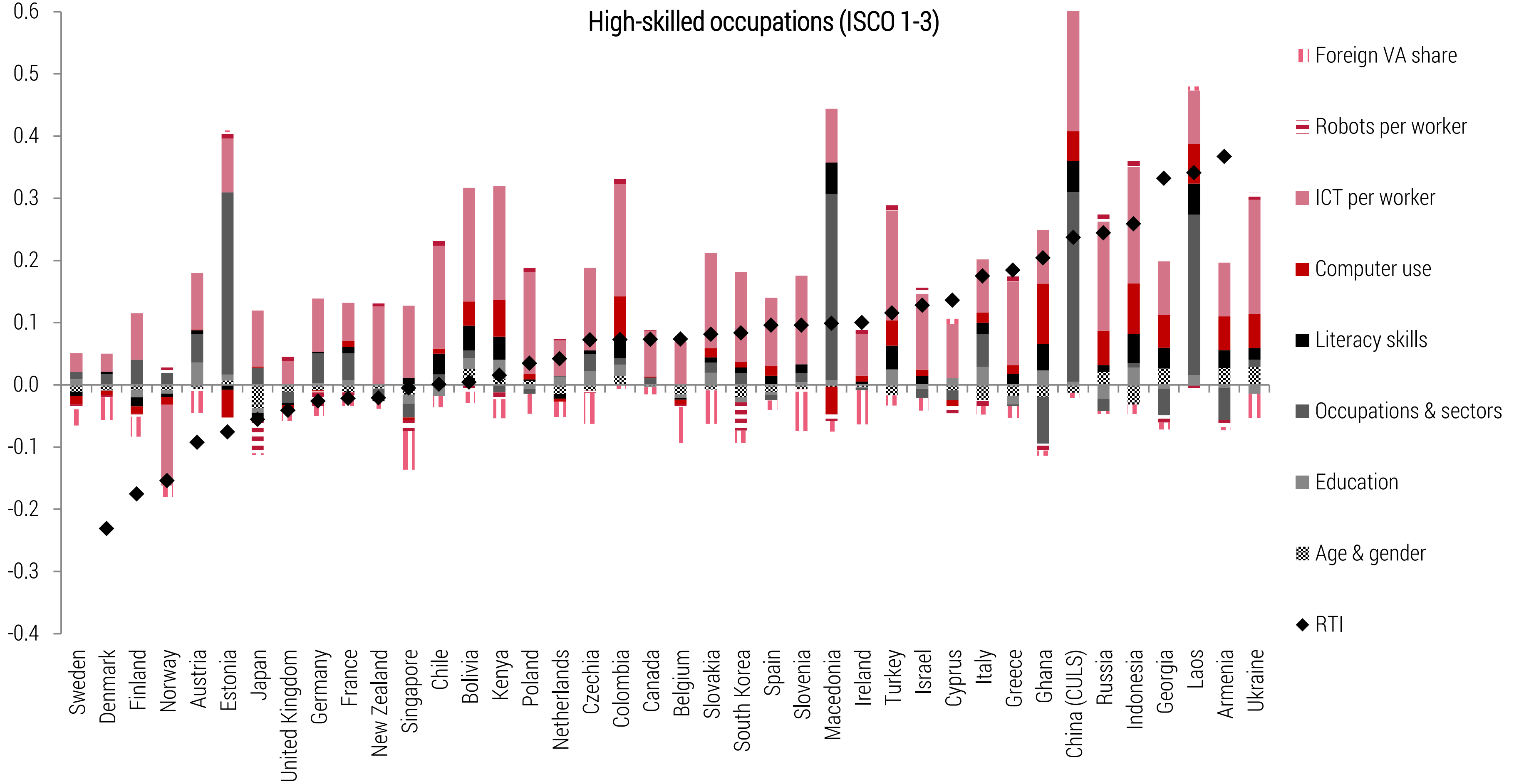
Figure 4. Contributions of various factors to the differences in routine task intensity (RTI) between a particular country and the United States, derived from predictions from model (8) in Table 5.



Note: The decomposition is based on OLS regressions with same control variables as the regression model (6) from 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.

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

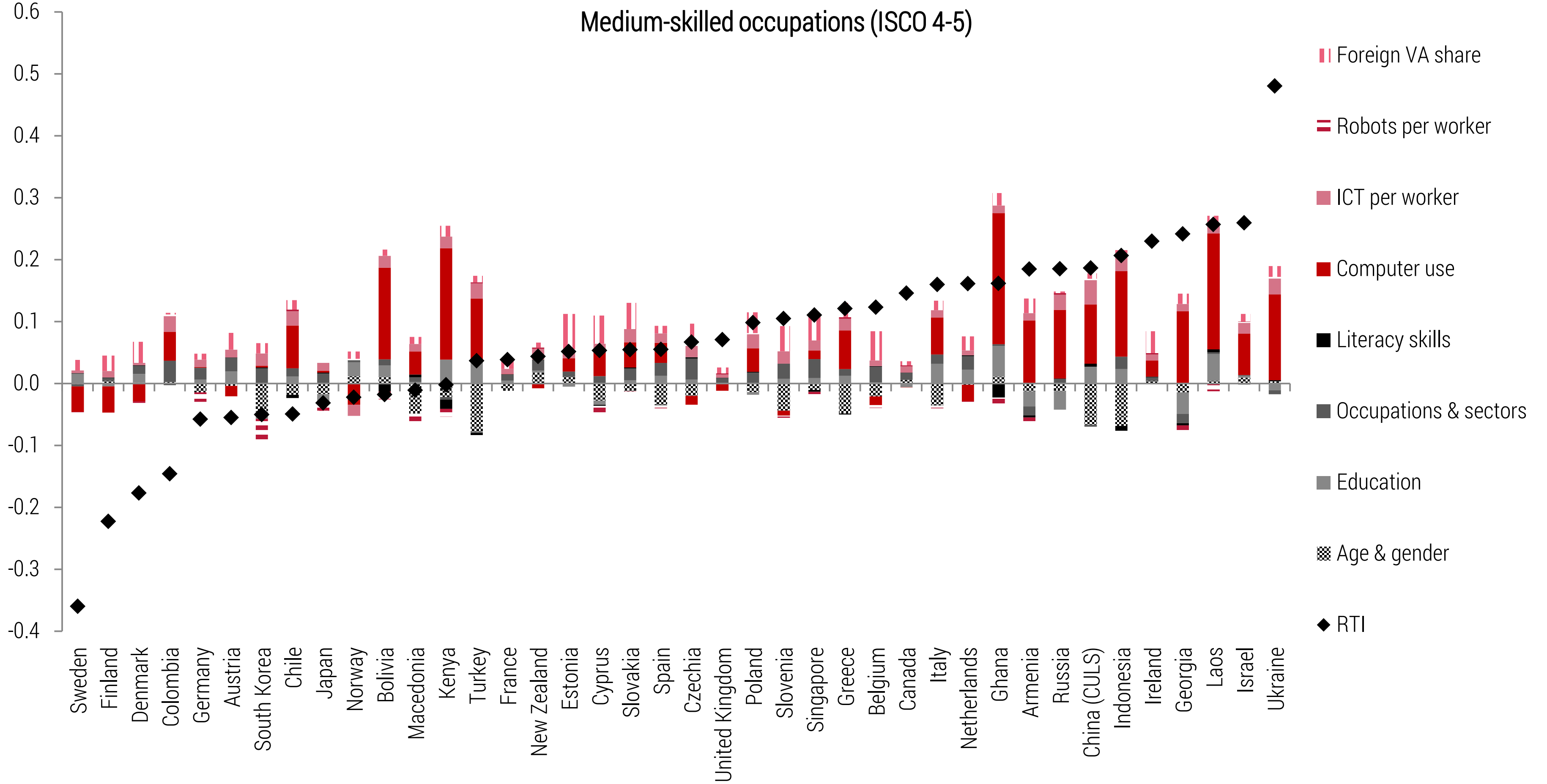
Figure 5 Contributions of various factors to the differences in routine task intensity (RTI) between a particular country and the United States, derived from predictions from model for high-skilled occupations (ISCO1-ISCO3), analogous to model 8 in Table 5.



Note: The decomposition is based on OLS regressions with same control variables as the regression model (6) from 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. The RTI values for Sweden and Ukraine are equal to -0.47 and 0.61, respectively. They are omitted here to hold the same scale for Figures 4-7.

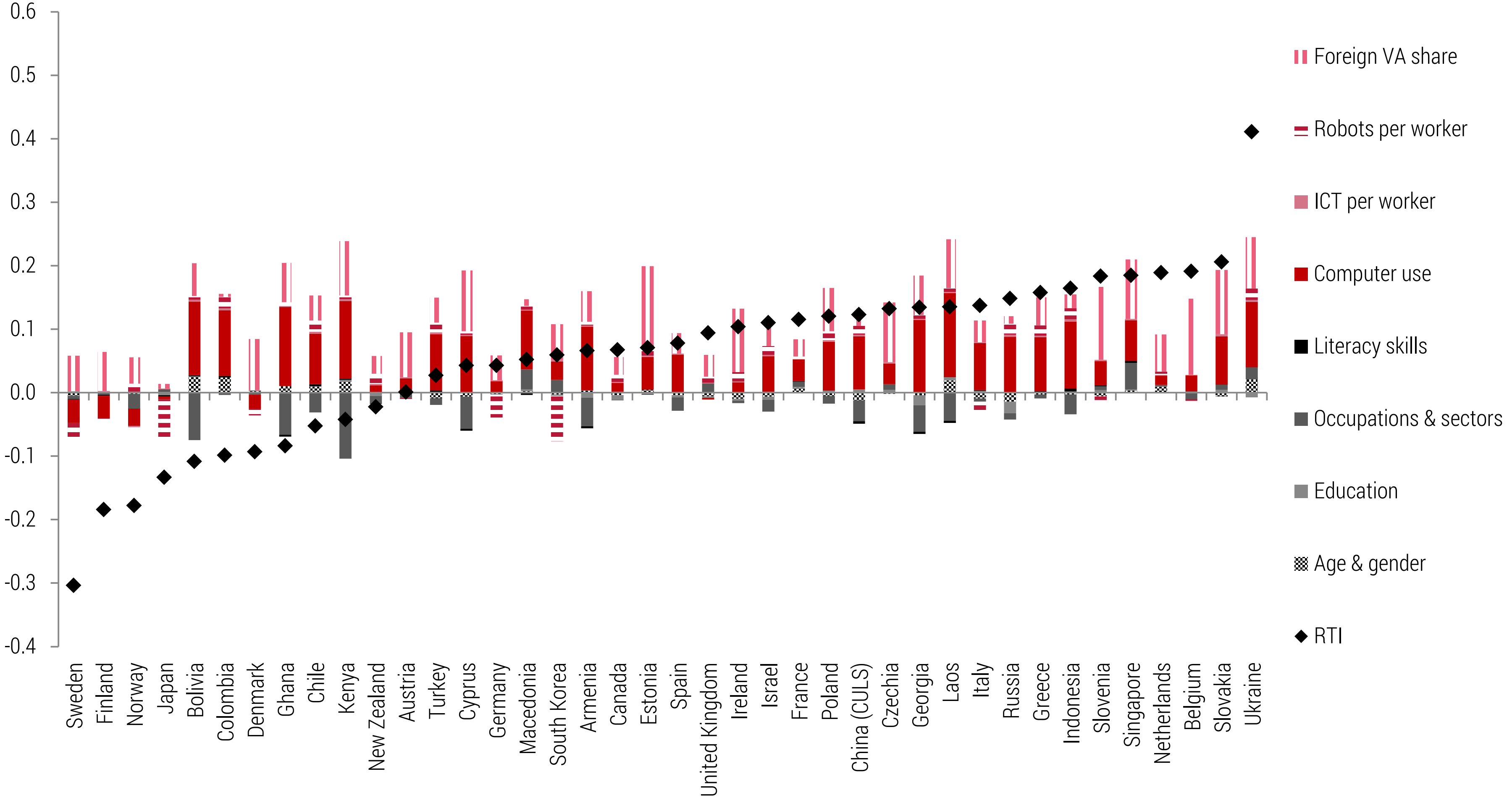
Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

Figure 6. Contributions of various factors to the differences in routine task intensity (RTI) between a particular country and the United States, derived from predictions from model for medium-skilled occupations (ISCO4-ISCO5), analogous to model 8 in Table 5.



Note: The decomposition is based on OLS regressions with same control variables as the regression model (6) from 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.
Source: own estimations based on PIAAC, STEP, CULS, Eden & Gaggl (2015), IFR and RIGVC UIBE (2016) data.

Figure 7. Contributions of various factors to the differences in routine task intensity (RTI) between a particular country and the United States, derived from predictions from model for high-skilled occupations (ISCO7-ISCO9), analogous to model 8 in Table 5.



Note: The decomposition is based on OLS regressions with same control variables as the regression model (6) from 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.

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 framework to analyse the task structure of jobs in 42 countries around the world, including emerging economies. Our approach utilises PIAAC, STEP and CULS data and it contributes to previous literature by overcoming several problems related to the measurement of task content of jobs. First, our measures are country-specific and defined at a worker level. Second, they are validated with the US PIAAC data against the established O*NET definitions of task content, ensuring that they indeed describe the same types of tasks as in previous studies. Third, our approach produces comprehensive measures for a larger set of countries than any of the previous studies which were either focused on the developed or on the developing economies.

Our results show that there are substantial cross-country differences in the average values of particular tasks, not only at the country level, but also among the high-skilled (ISCO 1 – ISCO 3), the middle-skilled (ISCO 4 – ISCO 6) and the low-skilled occupations (ISCO 7 – ISCO 9). 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 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 the development level. Interestingly, we find that cross-country differences in the intensity of routine task are to the strongest extent related to the differences in GDP per capita level in the case of high-skilled occupations.

Workers with tertiary education, workers in professional or managerial jobs, workers with higher literacy skills and workers who use computer at work are significantly more likely to perform less (cognitive) routine work. 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.

Most of differences in the average values of tasks between particular countries and the US can be attributed to the differences in country-specific task intensity of jobs performed by workers with similar individual characteristics, including literacy skills and computer use, in different countries. Slightly different factors contribute to these cross-country differences in the routine task intensity among various occupations. The cross-country differences in the ICT capital stocks per worker are strongly related to the differences in routine task intensity among the high-skilled occupations, and to a lesser extent among the middle- and low-skilled occupations. The cross-country differences in the position in the global value chains are strongly related to the differences in routine task intensity among the low-skilled occupations, but they are insignificant in the case of high-skilled occupations. The size of the robots stock within industries is related negatively to the routine task intensity of workers, but it contributes little to the overall country differences relative to the US and mostly within the low-skilled occupations.

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. Next steps may include the analysis of the interplay between the country-specific task content of jobs, especially the relative role of non-routine and routine tasks, and exposure to international trade, off-shoring, robots and ICT technology adoption at the sectoral or even individual level.

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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?	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?	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?	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.[13] 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.[14]

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

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

Appendix C. Different task measures using STEP and PIAAC data

Table C1. Different task measures using STEP and PIAAC data

Our measures; PIAAC and STEP	
Task content	Items
Non-routine cognitive analytical	Reading news
	Reading professional titles
	Solving problems
	Programming
Non-routine cognitive personal	Supervising
	Presenting
Routine cognitive	Changing order of tasks (reversed)
	Filling forms
	Presenting (reversed)
Manual	Physical tasks
Methods: uniform coding in STEP and PIAAC; standardisation (means and standard deviations); averages	

Dicarlo et al. (2016); STEP	
Task content	Items
Non-routine analytical	No. of types of documents read
	Length of longest documents typically read
	Length of longest document typically written
	Solving problems
	Advanced math
	Any of the basic mathematical tasks
	Learning new things
Non-routine interpersonal	Supervising
	Presenting
	Contact with clients
	Collaborating
Routine & Manual	Changing order of tasks (reversed)
	Repetitiveness
	Operate machines or equipment
	Driving
	Repair electronic equipment
	Physical tasks
Methods: standardisation (means and standard deviations); summation	

de la Rica and Gortazar (2016); PIAAC	
Task content	Items
Abstract	Read diagrams, maps or schematics
	Write reports
	Solving problems
	Persuading/influencing people
	Negotiating with people
Routine	Changing order of tasks
	Change how to do work
	Change speed of work
	Change working hours
	Learn work-related things from co-workers
	Learning-by-doing from tasks performed
	Keeping up to date with new products/services
	Hand/Finger Accuracy
Manual	Physical tasks
Methods: principal component analysis	

Marcolin et al. (2016b); PIAAC; Routine Intensity Index only
Items
Planning own activities
Changing order of tasks
Change how to do work
Organising own time
Methods: averages.

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

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