The World Bank Economic Review, 36(3), 2022, 687–708
https://doi.org10.1093/wber/lhac005
Article

OXFORD

Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data

Piotr Lewandowski, Albert Park, Wojciech Hardy, Yang Du, and Saier Wu

Abstract

The shift from routine work to nonroutine cognitive work is a key feature of labor markets globally, but there is little evidence on the extent to which tasks differ among workers performing the same jobs in different countries. This paper constructs survey-based measures of routine task intensity (RTI) of jobs consistent with those based on the U.S. O*NET database for workers in 47 countries. It confirms substantial cross-country differences in the content of work within occupations. The extent to which workers' RTI is predicted by technology, supply of skills, globalization, and economic structure is assessed; and their contribution to the variation in RTI across countries is quantified. Technology is by far the most important factor. Supply of skills is next in importance, especially for workers in high-skilled occupations, while globalization is more important than skills for workers in low-skilled occupations. Occupational structure explains only about one-fifth of cross-country variation in RTI.

JEL classification: J21, J23, J24

Keywords: tasks, jobs, labor, technology, globalization

1. Introduction

In recent years, there has been an explosion of interest in how new technologies and globalization affect the nature of work. Economists have found the analysis of changes in job tasks to be a fruitful way to understand how labor market outcomes are influenced by these twin forces (Acemoglu and Autor 2011;

Piotr Lewandowski (corresponding author) is a director and economist at the Institute for Structural Research (IBS), Warsaw, Poland; his email is piotr.lewandowski@ibs.org.pl. Albert Park is chief economist of the Asian Development Bank, Manila, Philippines, and chair professor at the Hong Kong University of Science and Technology, Hong Kong; his email is afpark@adb.org. Wojciech Hardy is an assistant professor at the Faculty of Economic Sciences of the University of Warsaw; his email is whardy@wne.uw.edu.pl. Yang Du is a professor at the Institute of Population and Labor Economics of the Chinese Academy of Social Science; his email is duyang@cass.org.cn. Saier Wu is a PhD candidate at the Hong Kong University of Science and Technology, Hong Kong; her email is saier.wu@connect.ust.hk. The authors thank Peng Jia, Cheng Jie, and Zeyang Yu for their excellent research assistance, Emily Pawlowski of the American Institutes for Research provides help with using the US PIAAC restricted data. Thanks also go to the participants of ASSA2019 in Atlanta, Georgia; EALE2018 in Lyon, France; Jobs and Development Conference 2018 in Bogotá, Colombia; TASKS V in Bonn, Germany; thanks also go to participants in seminars at UCSD, The World Bank, and Princeton University, and in workshops in Beijing, Geneva, Luxembourg, and Warsaw for their insightful comments. The authors acknowledge support from the Hong Kong Research Grants Council General Research Fund, grant no. 16504217, and from International Bank for Reconstruction and Development FY2016 Development Grant Facility, grant no. 502916-05. The usual disclaimers apply. All errors are the authors' own. A supplementary online appendix is available for this article at the *World Bank Economic Review* website.

Firpo, Fortin, and Lemieux 2011; Autor 2013). In the United States and other advanced countries, the relative share of routine jobs—both cognitive and manual—has declined over time, presumably because such jobs are easily replaced by computers or automation, or can be outsourced to other countries (Autor, Levy, and Murnane 2003; Spitz-Oener 2006; Jensen and Kletzer 2010; Goos, Manning, and Salomons 2014; Michaels, Natraj, and Van Reenen 2014). However, in developing countries and emerging markets, evidence on how the nature of work is changing is mixed (World Bank 2019). For example, there is evidence that in China and some Central Eastern European countries, the role of routine-intensive occupations has actually increased since the late 1990s (Du and Park 2018; Hardy, Keister, and Lewandowski 2018).

The analysis of task demand has been facilitated by the codification of the task content of different occupations in the United States by the Department of Labor, first through the Dictionary of Occupational Titles (DOT) dating back to 1939, and since 2003 through the Occupation Information Network (O*NET). These databases provide detailed and periodically updated descriptions of the specific tasks associated with each occupation in the United States. Acemoglu and Autor (2011) used O*NET data to construct what have now become standard indices of job tasks. Because other countries have not systematically collected similar information on occupational job tasks, analyses of task demand in other countries have frequently used the US O*NET task data, requiring the assumption that the task content of occupations in those countries is identical to the content in the United States (Arias et al. 2014; Goos, Manning, and Salomons 2014; Hardy, Keister, and Lewandowski 2018; Lewandowski et al. 2020). This is almost certain to be problematic for less-developed countries, given significant differences in workers' skills, technologies, and economic activities, which leads to large labor productivity differences across countries (Hsieh and Klenow 2010; Eden and Gaggl 2020). Moreover, globalization is expected to lead to the outsourcing of routine-intensive tasks from high-wage countries to low-wage countries (Grossman and Rossi-Hansberg 2008; Hummels, Munch, and Xiang 2018). Structural changes such as industrialization and the growth of services alter the demand for goods and services, which alters the demand for different types of jobs (Bárány and Siegel 2018). Finally, the labor force in poorer countries often is much less educated, which could influence the optimal assignment of routine and nonroutine tasks (World Bank 2019).

This paper presents new evidence on the global differences in job tasks, and their associations with four fundamental forces: technology, globalization, supply of skills, and structural change.[1] The study uses microdata on job tasks collected from large-scale surveys of workers in 47 countries around the world, spanning developed and developing countries. The data come from three sources: the OECD's Programme for the International Assessment of Adult Competencies (PIAAC); the World Bank's Skills toward Employment and Productivity (STEP) surveys, conducted in middle- and low-income countries; and the China Urban Labor Survey (CULS), which included a module based on STEP. The study develops harmonized survey-based measurements of routine task intensity (RTI), which closely mirrors widely used task measurements for occupations proposed by Acemoglu and Autor (2011). However, this study's measures are worker-specific, making it possible to capture both within-occupation and cross-country differences in job tasks. Even in the United States, research has shown considerable variation in tasks among workers within the same occupation (Autor and Handel 2013). Construction of worker-specific task measures that are consistent with O*NET and cover low-, middle-, and high-income countries is the first main contribution of this study.[2]

1 This study focuses on factors that directly influence prices of outputs and factors, and firms' technology. Institutional factors are not considered, although the study recognizes their importance in shaping technology, globalization, structural change, and skills, as well as the organization of work (firm size, management structure, etc.) which may influence job tasks.

2 Other studies of tasks that use international survey data typically focus on less-diversified samples of countries: Marcolin, Miroudot, and Squicciarini (2019) and de la Rica, Gortazar, and Lewandowski (2020) used PIAAC data to study OECD countries, while Lo Bello, Sanchez Puerta, and Winkler (2019) used STEP data to cover low-income countries.

The second contribution is to document new stylized facts about cross-country differences in the task content of jobs. On average, workers in the more developed economies perform less routine-intensive work. The relationship between routine task intensity and country GDP per capita differs quite markedly for different occupation groups. In high-skilled occupations (e.g., managers, professionals), there is a sharp gradient with respect to GDP per capita, with work being more routine-intensive in poorer countries. However, for middle-skilled occupations like clerical workers, and low-skilled occupations like plant and machine operators and assemblers, the study finds a flat or an inverse-U shaped relationship between the relative routine-intensity of tasks and a country's level of development. Overall, cross-country differences in task content within the same occupations are sizable.

This article's third and most important contribution is to quantify for the first time how four fundamental forces—technology, globalization, supply of skills, and structural change—are associated with cross-country differences in the task content of jobs. Previous research has documented associations between specific factors for subsets of countries, often assuming that tasks within occupations are identical across countries.[3] The present study is the first to examine the role of all of these factors in a comprehensive framework, and for countries that span low-, middle-, and high-income countries, and using survey-based measures.

This study's assessment of the relative importance of different factors in predicting cross-country task differences starts with a regression in which workers' routine task intensity is regressed on the individual, sector, and country-level variables. In the main specification, technology is captured by country-sector computer use calculated from the survey data. Globalization is measured by the foreign share of value added in the country-sector and the foreign direct investment (FDI) share of GDP plus these shares interacted with GDP per capita. Structural change is captured by 18 sector fixed effects and GDP per capita. Skills are captured by individual education, demographics (age, sex), and a direct test of literacy proficiency. The study estimates a pooled regression for all workers, and separate task regressions for workers in high-skilled occupations (managers, professionals, and technicians), middle-skilled occupations (clerks, sales and services workers) and low-skilled occupations (craft and related trades workers, plant and machine operators and assemblers, elementary occupations).

Using the coefficients from these regressions, the study decomposes the cross-country variance in mean routine task intensity across countries, as well as the difference between countries at different development levels and the United States, into the contributions associated with each fundamental factor.

It is found that technology, the supply of skills, and globalization are all strongly associated with cross-country differences in relative routine task intensity (RTI). International differences in technology are most important, especially in accounting for cross-country variation in RTI in high-skilled occupations, consistent with complementarity between nonroutine tasks and technology (Autor, Levy, and Murnane 2003). Globalization contributes more to cross-country differences in RTI among workers in middle- and low-skilled occupations compared to high-skill occupations. This finding is in line with the view that offshoring enables countries to specialize, within industries, according to their abundant factors

3 For example, earlier research documents the importance of ICT technology for the demand for tasks in the OECD countries (Autor, Levy, and Murnane 2003; D. H. Autor, Katz, and Kearney 2006; Spitz-Oener 2006; Akerman, Gaarder, and Mogstad 2015; Deming 2017), but no studies document the relationship between ICT and tasks in a cross-country setting that includes low-income countries. Evidence also exists that offshoring contributes to the shift away from routine work in the OECD countries (Oldenski 2012; Goos, Manning, and Salomons 2014; Hummels, Munch, and Xiang 2018) and that participation in global value chains leads to a higher share of routine-intensive occupations in some developing countries (Reijnders and de Vries 2018). Regarding skill supply, a positive relationship between the supply of tertiary educated workers and nonroutine tasks has been documented by studies using O*NET data (Hardy, Keister, and Lewandowski 2018; Salvatori 2018; Montresor 2019). Structural change has been identified as relevant for polarization and shifts in tasks over time, both theoretically (Bárány and Siegel 2018) and empirically (Du, Jia, and Cheng 2017; Hardy, Keister, and Lewandowski 2018).

(Grossman and Rossi-Hansberg 2008). It is also found that the supply of skills contributes to the cross-country differences in tasks mainly through its association with the employment shares of high-, middle-, and low-skilled occupations. Moreover, in low- and middle-income countries, a lower supply of skills accounts for a large share of the difference in RTI compared to the United States. Although the complementarity of supply of skills and technology use has been acknowledged as a key factor behind cross-country differences in technology use (Eden and Gaggl 2020) it is often overlooked in the studies of tasks that focus on developed countries. This study provides evidence that in the poorer countries the skills gap predicts not only lower employment shares of high-skilled occupations but also more routine-intensive tasks performed by workers in high-skill occupations. Finally, the study shows that differences in occupational structure across countries account for a relatively small share of cross-country differences in task content. This highlights the importance of using comparable survey data to accurately estimate the extent of cross-country differences in task content and the factors associated with these differences.

The second section outlines the methodology for calculating the task content measures for the 47 countries covered by the PIAAC, STEP and CULS surveys. The third section compares the survey-based measures to those based on O*NET and presents evidence on cross-country differences in job tasks. The fourth section examines the determinants of these differences and presents the results of a decomposition analysis that explains the gap in RTI between the United States and countries at different levels of development. The fifth section concludes.

2. Data and Task Measurement

This section outlines the data and methodology used to calculate worker-specific task content measures.

Data for Measurement of Job Tasks

This study aims to create task-content measures based on PIAAC and STEP surveys, which are worker-specific but are as consistent as possible with well-established measures of job tasks. To accomplish this objective, the US PIAAC dataset is used to create measures that maximize consistency with United States O*NET occupation-specific task measures popularized by Acemoglu and Autor (2011).

The study uses survey data for 47 countries that come from three comparable surveys: OECD's Programme for the International Assessment of Adult Competencies (Survey of Adult Skills (PIAAC) 2019); the World Bank's Skills Measurement Program (The STEP Skills Measurement Program 2017); and the third wave of the China Urban Labor Survey (China Urban Labor Survey (CULS) 2017) conducted by the Institute of Population and Labor Economics of the Chinese Academy of Social Science (CASS).

In three rounds of PIAAC surveys (in 2011–2012, 2014–2015, and 2017–2018), data was collected in 37 high- or middle-income countries that made their data publicly available (the list of countries is shown in S1 of the supplementary online appendix).[4] The survey respondents were aged 16–65, with sample sizes ranging from about 4000 in Russia to 26,000 in Canada.[5] STEP surveys are available for 13 low- or middle-income countries, out of which the study uses nine (S1 in the supplementary online appendix).[6]

4 In the United States, PIAAC was supplemented by an additional wave aimed at enhancing the sample size, while retaining representativeness. The study uses this sample, which is available from the U.S. National Center for Education Statistics (NCES).

5 Individuals aged 15 years were also surveyed in Australia and Chile. Individuals aged 66–74 were surveyed in Australia.

6 The study decided against using four available STEP datasets: Yunnan (China), Sri Lanka, Ukraine, and Vietnam. For China, the CULS data are used instead of the STEP survey for the Chinese province of Yunnan, as the former contains far more observations and covers a more comprehensive area. Yunnan is one of the poorer and more rural provinces in China so it might not reflect the dominant patterns of work in Chinese urban areas. The survey of Sri Lanka includes too few observations in urban areas (about 650 workers), the Ukraine survey lacks one of the questions required for this study's task measures, and the Vietnam survey has low quality of data on skill use at work.

The surveys were conducted between 2012 and 2014 of urban residents aged 15–64, with sample sizes ranging from about 2600 (in Colombia) to about 4000 (in Kenya).[7] The study also uses the third wave of CULS, which included the "skill use at work" questionnaire of STEP and therefore is directly comparable to the STEP surveys. 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) and has a sample of 15,448 individuals.[8] Hereafter, the CULS is considered to be one of the STEP surveys.[9]

Task Measures' Definitions Based on the Survey Data

To construct survey-based task measures consistent with those based on O*NET, the study first identifies harmonized survey questions available in both PIAAC and STEP surveys whose content is similar to the questions used by Acemoglu and Autor (2011) to construct the O*NET-based task measures. Then the study systematically searches for combinations of appropriate survey questions (and best groupings of answers) for which United States PIAAC survey-based measures (averaged for each occupation) are most correlated with US O*NET-based occupation measures. Because PIAAC and STEP include only one question on physical tasks, the study applies its procedures to the cognitive tasks measures only. For methodological details, see S2 in the supplementary online appendix.

This study's procedure results in the following survey-based task definitions. The nonroutine cognitive analytical task measure is based on questions on solving problems, reading news, reading professional journals, solving problems, and programming. The nonroutine cognitive interpersonal task measure is based on supervising others and making presentations. The routine cognitive task measure is based on the ability to change the order of tasks (reversed, so not being able to change the order of tasks), filling out forms, and making speeches or giving presentations (reversed, so making no speeches and giving no presentations). 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 1.

In the United States, the survey-based measures follow closely the task measures based on O*NET. At the 3-digit occupation level, the correlations between the survey measures (occupation-level averages), and the Acemoglu and Autor (2011) measures range from 77 percent (nonroutine cognitive analytical, table 1) to 55 percent (routine cognitive).[10]

The study uses the definitions presented in table 1 to calculate worker job task content measures for all countries studied. The study also merges O*NET with PIAAC, STEP and CULS to calculate the Acemoglu and Autor (2011) task measures for each country. For both measures, the measure is standardized using the relevant mean and standard deviation in the U.S. Hence, for each task measure, 0 reflects the United States average and 1 reflects standard deviations in the United States. As the STEP surveys are urban surveys, skilled agricultural workers (ISCO 6) are omitted in all countries to improve comparability.

The study creates a synthetic measure of relative routine task intensity (RTI) at the worker level, using the formula:

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

7 Because nearly all STEP surveys were urban only, for Laos, which surveyed both urban and rural residents, the rural part of the sample is dropped in order to ensure consistency.

8 The survey sampled 260 neighborhoods, 2,581 migrant households and 3,897 local households.

9 The STEP and Indonesian data are reweighted in order to achieve representativeness of the occupational structures in urban areas. To this aim, the study retains the original shares of workers in agriculture and elementary occupations and adjusts 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, the study uses the urban occupational distribution from the 2015 Census to reweight the CULS data.

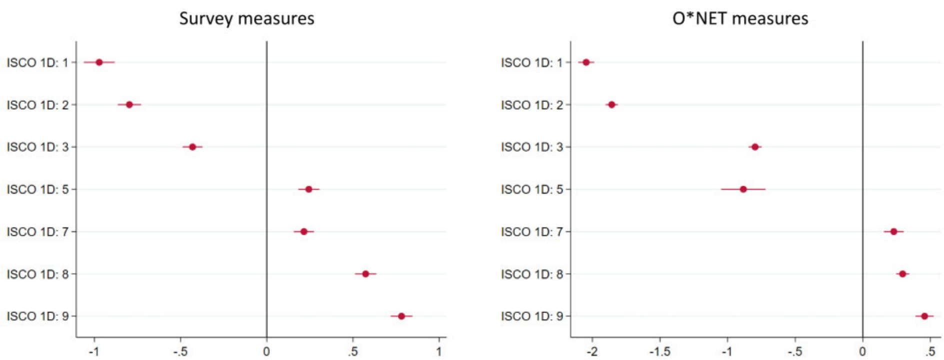
10 The highest correlations obtained at the 4-digit occupation level range from 62 percent to 79 percent.

Table 1. The Task Items Selected to Calculate Task Content Measures with the US PIAAC Data

Task content	Nonroutine cognitive analytical	Nonroutine cognitive interpersonal	Routine cognitive	Manual
Task items	Solving problems Reading news (at least once a month – answers 3,4,5) Reading professional journals (at least once a month – answers 3,4,5) Programming (any frequency –answers 2,3,4,5)	Supervising others Making speeches or giving presentations (any frequency – answers 2,3,4,5)	Changing order of tasks – reversed (not able) Filling out forms (at least once a month — answers 3,4,5) Making speeches or giving presentations – reversed (never)	Physical tasks
Correlation with O*NET-based measures	0.77	0.72	0.55	0.74

Source: Authors' elaboration based on US PIAAC and O*NET data.
Note: The cutoffs for the "yes" dummy are in brackets. The full wording of questions and definitions of cutoff are presented in S3 in the supplementary online appendix. O*NET-based measures are based on Acemoglu and Autor (2011).

Figure 1. The Differences in RTI across 1-digit ISCO Occupations According to Survey and O*NET Measures.



Source: Authors' calculations based on PIAAC, STEP, CULS, and O*NET data.
Note: Coefficients pertaining to occupation fixed effects (1-digit ISCO) estimated in a worker-level model on RTI against occupation fixed effects and country fixed effects. Manual tasks are included in the RTI based on O*NET. Sample size 168,639. Reference groups: Clerical support workers (ISCO 4), the United States.

whereby r_{cog}, $nr_{analytical}$ and $nr_{personal}$ are routine cognitive, nonroutine cognitive analytical and nonroutine cognitive personal task levels, respectively.[11] This definition follows the literature (Autor and Dorn 2009; Autor and Dorn 2013; Goos, Manning, and Salomons 2014) but the manual tasks are omitted for two reasons. First, the survey data do not allow distinguishing between routine and nonroutine manual tasks. Second, the manual measure is less comparable across countries than the other measures (for details, see S6 in the supplementary online appendix). For consistency, the RTI is standardized using its mean and standard deviation in the United States.

The survey-based RTI measure successfully captures the general routine aspect of work, despite limited information on manual tasks (fig. 1). This is because the survey question about workers being able to change the order of their tasks captures the repetitiveness of work both in occupations that require mainly cognitive tasks, and those that require mainly manual tasks. In particular, RTI among

11 To avoid nonpositive values in the logarithm, for each task, the lowest score in the sample is added to the scores of all individuals, plus 0.1.

plant and machine operators and assemblers (ISCO 8), who perform highly routine jobs according to the RTI based on O*NET, is also high according to the survey measure. The one distinction between the survey RTI and the O*NET RTI is that according to the survey measure tasks performed by sales and services workers (ISCO 5) around the world are on average slightly more routine than tasks performed by clerical support workers (ISCO 4, a reference group), which differs from the O*NET-based measure.

Methodology

After first providing descriptive evidence on how RTI of workers (overall and by broad occupational categories) is related to different levels of economic development, the study examines the factors associated with cross-country differences in routine task intensity by estimating pooled OLS regressions of the form:

$$RTT_{ijsc} = \beta_0 + \beta_1 Z_{sc} + \beta_2 G_{sc} + \beta_3 E_{ijsc} + \lambda_s + \varepsilon_{ijsc} \tag{2}$$

Here, RTI_{ijsc} is the routine task intensity of individual i in occupation j in sector s in country c; Z_{sc} is technology used in sector s in country c; G_{sc} measures globalization in sector s in country c; E_{ijsc} are the individual skills of worker I, in occupation j, in sector s, in country c; and λ_s are sector fixed effects.

The benchmark specification is also expanded by adding occupation fixed effects, τ_j:

$$RTT_{ijsc} = \beta_0 + \beta_1 Z_{sc} + \beta_2 G_{sc} + \lambda_s + \beta_3 E_{ijsc} + \tau_j + \varepsilon_{ijsc} \tag{3}$$

Because the regressions are cross-sectional, they are best thought of as characterizing equilibrium allocations of tasks rather than being interpreted causally. The technology, globalization, and structural change measures are all country-sector level measures, which are plausibly exogenous to the decisions of individual firms and workers. Skills are measured at the individual level, given that education (and literacy) are largely predetermined before entering the labor market.[12] The study has also conducted the analysis defining skill levels at the sector level and how this alters the main results is discussed.

Turning to measurements, the main technology variable is the share of workers in sector s in country c who use computers at work. PIAAC and STEP surveys include a question on individual computer use, and this variable is aggregated to the sector level due to concerns that decisions about individual computer use and tasks are made simultaneously. A quadratic specification is used to allow for a potential nonlinear relationship between computer use and RTI. Separately, the study also tests the impact of robot stock per worker by sector (International Federation of Robotics data), and country-level ICT capital stock per worker (Eden and Gaggl 2020). Adding these variables turns out not to alter the main findings in any important way, but these data are available for only 32 countries so they are excluded from the preferred specification.

Two variables are employed to measure globalization—participation in global value chains (henceforth GVC participation, Wang et al. 2017), and foreign direct investment (FDI) stock as a share of GDP.[13] The basic GVC participation variable is the backward linkage-based measure defined as the foreign value added share in the production of final goods and services (FVA share). For robustness, the forward linkage-based measure is also used (domestic value added from the production of intermediate exports or domestic factor content in intermediate exports (Wang et al. 2017). As theory (Grossman and Rossi-Hansberg 2008) predicts that globalization reduces routine tasks in rich countries and increases them in poor countries, the study allows for different effects of globalization in developed and developing countries by interacting both variables with GDP per capita (log, demeaned).

12 Recognizing that job experience could influence literacy, specifications are also estimated that do not include literacy measurements. This reduces the explanatory power of skills but does not alter any of the main findings about the relative importance of different factors. These results are available upon request.

13 Data sources and precise definitions of the technology and globalization variables are provided in S5 in the supplementary online appendix.

To measure worker skills, the study includes a test-based measure of literacy skills (four proficiency levels), an education level (primary, secondary, tertiary), age (measured by 10-year age groups), and gender. The literacy test is comprehensive and quantifies individuals' skills to understand, evaluate, use, and engage with written texts in personal, work-related, societal, and educational contexts (PIAAC Literacy Expert Group 2009).[14] In the case of worker-level variables, in particular education and literacy, indicator variables are used for different attainment levels, which makes it possible to avoid parametric assumptions about the relationship between the supply of skills and RTI.

To capture the impact of structural change, fixed effects are used for 18 of 19 sectors based on the 1-digit codes of the International Standard Industrial Classification (ISIC Rev.4), as well as their interactions with GDP per capita (log, demeaned).[15]

The study estimates the regressions for all workers and for workers in high- (ISCO 1–3), middle- (ISCO 4–5) and low-skilled (ISCO 7–9) occupations. The skill categories for occupations reflect differences in the average educational attainment of workers in each occupational group, and so are not defined in any normative way.[16] Moreover, workers in occupations ISCO 1–3 on average perform relatively nonroutine tasks, workers in occupations ISCO 4–5 perform moderately routine-intensive tasks, and workers in occupations ISCO 7–9 perform very routine-intensive tasks (fig. 1). This makes it possible to assess if the role of fundamental factors differs across occupational groups. In all worker-level regressions, standard errors are clustered at the country-sector level.[17]

To assess the relative importance of different factors in predicting cross-country differences in tasks, the estimated coefficients are used to predict the average RTI at the country level ($\overline{RTI_c}$). The variance of RTI is decomposed using a covariance-based decomposition procedure (Morduch and Sicular 2002). Formally, the contribution of a variable group, k, to the variance of RTI is defined as follows:

$$\sigma_k = \frac{cov\left(\beta_k \bar{X}_c^k,\ \overline{RTI_c}\right)}{var(\overline{RTI_c})} \tag{4}$$

The average worker characteristics in each country are used to decompose the difference in the prediction of RTI in country c, $\widehat{RTI_c}$, and the United States, $\widehat{RTI_{US}}$, to the contributions of various factors:

$$\widehat{RTI_c} - \widehat{RTI}_{US} = \beta_1(\overline{Z_{ijsc}} - \overline{Z_{ijsUS}}) + \beta_2(\overline{G_{sc}} - \overline{G_{sU}}) + \lambda(\overline{S_{sc}} - \overline{S_{sUS}}) + \beta_3(\overline{E_{ijsc}} - \overline{E_{ijsUS}}) \tag{5}$$

14 The study accounts for the fact that PIAAC and STEP include multiple plausible values of the literacy proficiency variables. To this aim, the study uses the "pv" package in Stata that implements the (Rubin 1987) combination methods, which are commonly used in the skill assessment literature. China and Laos did not collect literacy data, so the study imputes the literacy scores for those two countries using a regression estimated for other countries, controlling for education, demographic characteristics, occupation and sector of employment, and computer use at work as well as macroeconomic variables (GDP per capita, export, FDI).

15 In order to achieve a consistent sector definition across all countries, the study merges sectors D (electricity, gas, steam, and air conditioning supply) with E (water supply; sewerage, waste management and remediation activities), and M (professional, scientific, and technical activities) with N (administrative and support service activities).

16 In the sample, 66 percent of workers in ISCO 1–3 occupations, 23 percent of workers in ISCO 4–5, and only 9 percent of workers in ISCO 7–9 have tertiary education; 29 percent of workers in ISCO 1–3 occupations, 57 percent of workers in ISCO 4–5, and 56 percent of workers in ISCO 7–9 have secondary education. Only 5 percent of workers in ISCO 1–3 occupations, 20 percent of workers in ISCO 4–5, and as much as 35 percent of workers in ISCO 7–9 have primary education. The study's classification differs slightly from the ILO classification, which groups occupations ISCO 1–3 as high-skilled, occupations ISCO 4–8 as middle-skilled, and occupation ISCO 9 as low–skilled. However, in the sample occupations ISCO 7–8 are more similar to occupation ISCO 9, both in terms of workers' tasks, as well as education structure, than to occupations ISCO 4–5.

17 Macedonia is dropped from the regression sample due to lack of data on globalization variables, and the study estimates its models on a sample of 46 countries.

Table 2. Allocation of Countries To Groups Based on GDP per Capita

Low- and middle-income countries	Bottom high-income countries	Top high-income countries	Reference country
Kenya, Ghana, Lao, PDR, Bolivia, Indonesia, Ecuador, Peru, China, Armenia, Georgia, Colombia, Mexico, Kazakhstan, Russia, Serbia, Turkey	Chile, Hungary, Poland, Lithuania, Slovakia, Cyprus, Estonia, Greece, Czech Rep., Slovenia, Spain, Korea, Rep., Italy	France, Israel, Japan, New Zealand, United Kingdom, Belgium, Germany, Canada, Finland, Austria, Netherlands, Ireland, Sweden, Denmark, Norway, Singapore	United States

Source: Authors' elaboration based on World Bank data.

For presentation purposes, countries are aggregated into three groups based on their development level, and use unweighted averages of differences in RTI and all explanatory variables (table 2).

3. Descriptive Evidence on Cross-Country Differences in the Task Content of Jobs

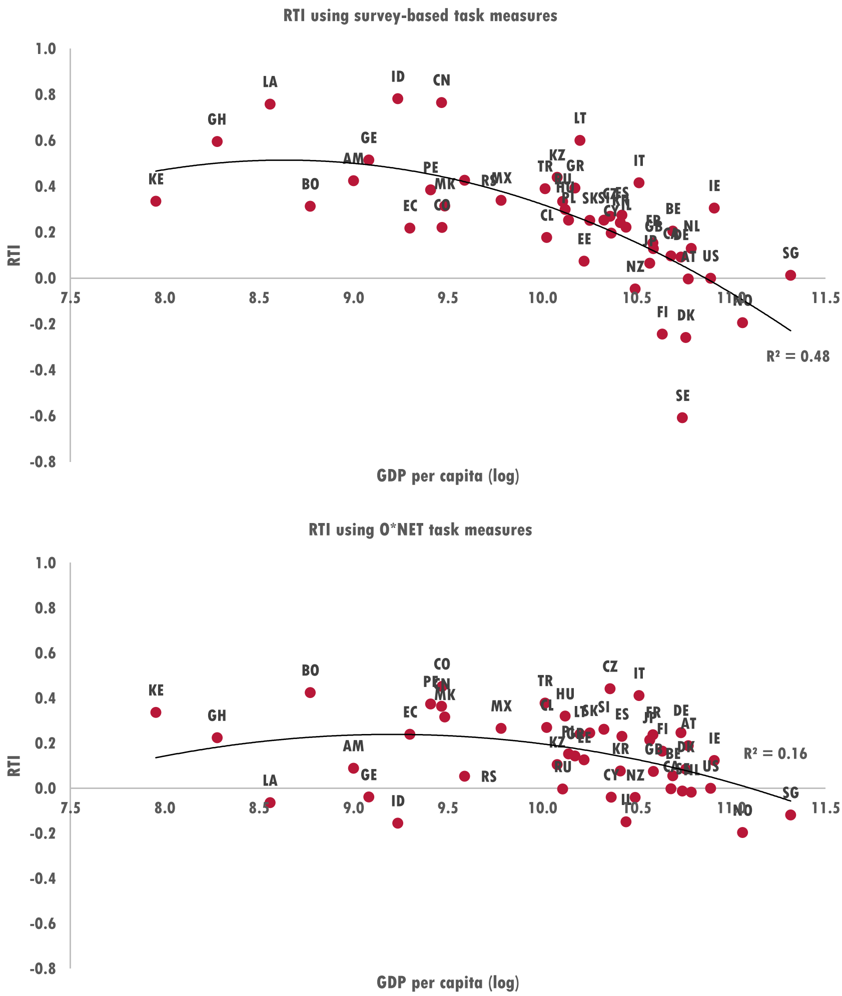
The study finds that the cross-country differences in RTI are noticeably larger using the country-specific measures (standard deviation 0.27) than using the O*NET-based measures (standard deviation 0.19).[18] Moreover, the relationship between countries' RTI and development level is stronger using the country-specific RTI measurement (fig. 2). Among the developed economies, the Nordic countries stand out with the lowest values of RTI, while most southern European and central Eastern European countries exhibit relatively higher RTI than would be expected given their development level. Moreover, the differences in RTI between low- and middle-income countries are less pronounced than the differences between middle-income and high-income countries. The results for particular tasks are shown in S6 in the supplementary online appendix.

Importantly, the survey-based measures show large cross-country differences in the relative routine intensity of tasks within specific occupation categories (fig. 3). Among workers in high-skill occupations individuals in more developed countries consistently perform less routine-intensive tasks than those in poorer countries. For those in the middle- or low-skill occupations, the relationship between GDP per capita and relative routine intensity is inconsistent. Among sales and services workers (ISCO 5), workers in richer countries do less routine work. However, among craft and related trades workers (ISCO 7), and plant and machine operators (ISCO8), there is an inverse-U shaped relationship between routine task intensity and development level of a country. Finally, among clerical workers (ISCO 4) and workers in elementary occupations (ISCO9), the cross-country differences are highly variable but are not systematically correlated with the level of GDP per capita.

Finally, the study finds that the higher is the development level of a country, the more similar are the occupational rankings based on the country-specific RTI and the O*NET RTI. The within-country rank correlations of the survey-based and O*NET RTI measures (at 2-digit ISCO occupation level) are positively correlated with GDP per capita levels (fig. 4). In the poorest countries in the sample, the rank correlations are 0.5–0.6, while in the richest countries they are 0.8–0.9.

18 The study verifies that the greater variation in RTI across countries using survey-based measures is almost entirely due to country-specific differences and not to differences in occupational mean task levels using U.S. O*NET versus U.S .PIACC survey data (results available upon request). The cross-country differences in O*NET-based measures may also be influenced by inconsistencies in coding of occupations. Indeed, the O*NET measures suggest that in many low- or middle-income countries (e.g., Bolivia, Ghana, Indonesia, Mexico) workers in middle-skilled occupations perform highly nonroutine work that on average is less routine-intensive than the work in high-skilled occupations. This implausible conclusion results from the fact that large shares of workers in these countries are classified as street sellers or services workers. These occupations require a lot of interpersonal tasks in the United States but may not require as many of them in poorer countries. Indeed, the survey measures show that work in the middle-skilled occupations in poorer countries is quite intensive in routine tasks.

Figure 2. The Average Values Of Routine Task Intensity (RTI) According to Survey-Based Measures and O*NET Measures, by Countries' Development Level (GDP per capita).



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

4. Econometric Results: Factors Associated with Task Differences Across Countries

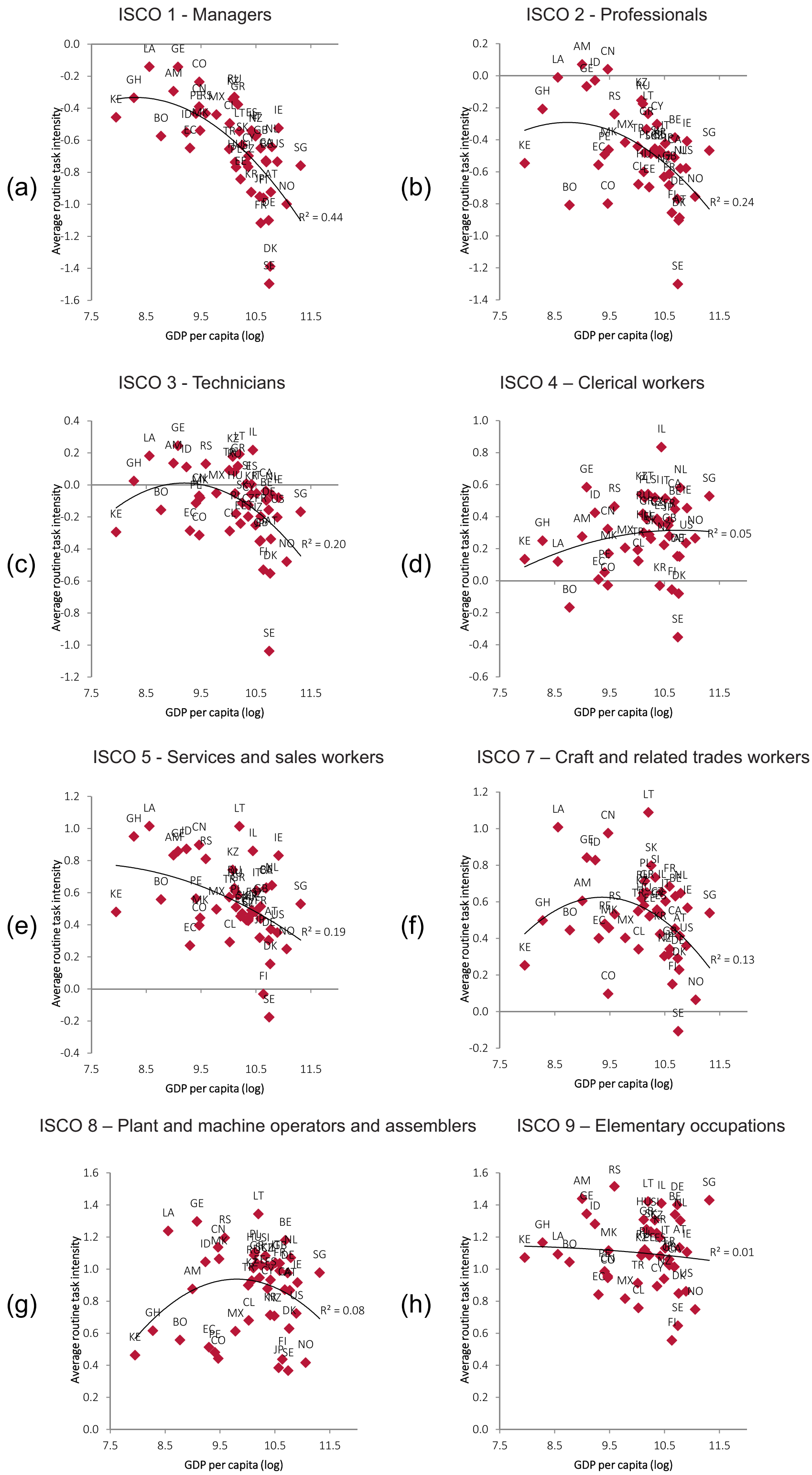
This section uses the survey-based measurement of tasks and measures of technology, globalization, supply of skills, and economic structure, to quantify the correlates of worker-level differences in RTI.

Estimation results

The study begins by discussing the results of a benchmark regression estimated for all workers, as well as for workers in high- (ISCO 1–3), middle- (ISCO 4–5) and low-skilled (ISCO 7–9) occupations, which are reported in table 3.

It is found that better access to technology is associated with the lower routine intensity of tasks performed by workers, especially in country-sectors where more than 40 percent of workers use a computer. The specification includes a quadratic term to capture nonlinearities, and the study finds that

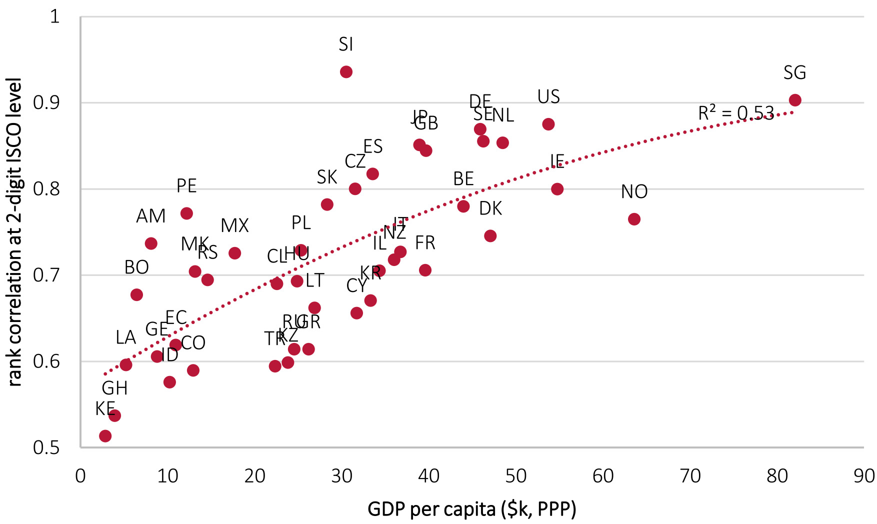
Figure 3. Average values of routine intensity of tasks (RTI) by 1-digit occupations by countries' development level.



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

Note: The horizontal axis denotes GDP per capita, PPP (international $, country averages for 2011–2016). The occupational group ISCO 6 (skilled agricultural workers) is omitted because of small sample sizes, especially in countries where surveys covered only urban areas.

Figure 4. The Rank Correlation between the RTI Based on Survey Data and the RTI based on O*NET Data, across 2-digit ISCO Occupations, against GDP per Capita.



Source: Authors' calculations based on PIAAC, STEP, CULS and O*NET data.

below 40 percent, the relationship between computer use and RTI is somewhat flat (fig. 5).[19] Above that level, the estimated effects of computer use are sizeable. A 25 pp. higher share of computer use, equivalent to the difference between the United States (75 percent) and China (50 percent) is associated with RTI being lower by 0.28 standard deviations of RTI in the United States, which is equivalent to 40 percent of the difference between average RTI in the United States and China. Evidence is also found that the negative association between computers and RTI is stronger among workers in office or services jobs that usually require more advanced cognitive skills (ISCO 1–3 and ISCO 4–5) than among workers in low-skilled occupations (ISCO 7–9, fig. 5).

To examine the predictive power of other measures of technology, the study expands the regressions with the country-level ICT stock and country-sector robot stock (both expressed in per worker terms) for a subsample of 32 countries with available data (table S7.3 in the supplementary online appendix). It is found that higher ICT stock is associated with lower RTI: an increase in ICT capital stock of 2.75 standard deviations, which is equivalent to the difference between the United States and China, is associated with a 0.08 decline in RTI, which is equivalent to 10 percent of the difference between the average worker in the United States and the average worker in China. This relationship is driven by the association between the ICT stock and RTI among workers in high-skilled occupations—in this group, the effect is stronger and significant, while it is insignificant among workers in middle- and low-skilled occupations (table S7.3). The relationship between the level of robot stock and RTI is also negative and significant for all occupational groups (table S7.3). Overall, the results show that in countries and sectors with higher levels of digital technologies and automation technologies workers perform less routine-intensive tasks than workers in comparable occupations in countries and sectors with lower levels of these technologies.

The study finds that differences in RTI are also related to globalization. In a country at the average GPD per capita level in the sample (e.g., Slovakia, Estonia, or Chile), a higher foreign value added (FVA) share in domestic production is associated with a higher RTI. Thus, workers in countries and sectors that

19 This finding is confirmed by re-estimating the baseline regressions with fixed effects for country-sector computer use share deciles instead of a continuous computer use share variable (fig. S7.1 in the Appendix S7 in the supplementary online appendix).

Table 3. The Correlates of Routine Task Intensity (RTI) at the Worker Level

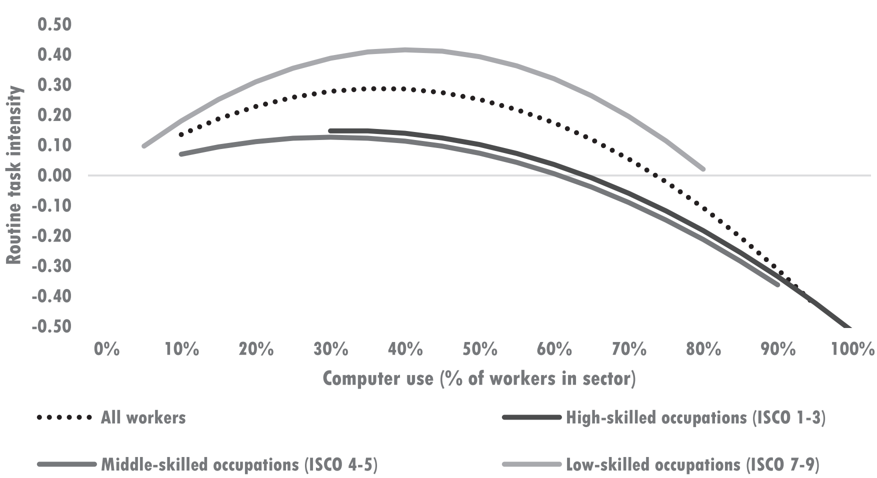
	All workers	High-skilled occupations (ISCO 1-3)	Middle-skilled occupations (ISCO 4-5)	Low-skilled occupations (ISCO 7-9)
Computer use	1.563***	0.923**	0.832*	1.858***
	(0.349)	(0.362)	(0.500)	(0.426)
Computer use ^2	−2.122***	−1.440***	−1.373***	−2.362***
	(0.294)	(0.307)	(0.419)	(0.374)
Foreign value added (FVA) share	0.226**	−0.198*	0.301*	0.673***
	(0.107)	(0.108)	(0.158)	(0.132)
FVA share * [Ln(GDP pc) –mean(Ln(GDP pc)]	−0.231**	−0.224	−0.389**	−0.022
	(0.117)	(0.138)	(0.186)	(0.130)
FDI / GDP	0.002	0.016***	−0.005	−0.022***
	(0.005)	(0.006)	(0.007)	(0.007)
FDI / GDP * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.016	0.035**	0.057***	0.021
	(0.013)	(0.014)	(0.021)	(0.017)
Ln(GDP per capita) –mean(Ln(GDP per capita))	0.041	−0.023	0.044	0.074
	(0.043)	(0.043)	(0.066)	(0.051)
Education: primary	0.281***	0.143***	0.263***	0.155***
	(0.016)	(0.027)	(0.018)	(0.021)
Education: tertiary	−0.499***	−0.278***	−0.216***	−0.169***
	(0.016)	(0.017)	(0.020)	(0.034)
Literacy skills level: 1 or lower	0.094***	0.026	0.053**	0.082***
	(0.015)	(0.022)	(0.024)	(0.021)
Literacy skills level: 3	−0.131***	−0.089***	−0.045**	−0.045**
	(0.012)	(0.014)	(0.019)	(0.022)
Literacy skills level: 4 and 5	−0.270***	−0.187***	−0.039	−0.160***
	(0.018)	(0.018)	(0.027)	(0.042)
Female	0.241***	0.226***	0.197***	0.340***
	(0.011)	(0.012)	(0.017)	(0.023)
Age: 16–24	0.202***	0.209***	0.184***	0.121***
	(0.016)	(0.025)	(0.023)	(0.020)
Age: 35–44	−0.056***	−0.056***	−0.024	−0.055***
	(0.010)	(0.013)	(0.016)	(0.019)
Age: 45–54	−0.020*	−0.055***	0.011	0.013
	(0.012)	(0.014)	(0.020)	(0.019)
Age: 55–65	0.023	−0.037**	0.101***	0.061***
	(0.015)	(0.018)	(0.023)	(0.022)
Agriculture [A]	0.081	−0.061	−0.156	0.090
	(0.065)	(0.081)	(0.108)	(0.080)
Mining [B]	−0.027	−0.012	−0.108	−0.059
	(0.081)	(0.077)	(0.131)	(0.107)
Manufacturing [C]	0.001	−0.051	−0.186***	−0.085
	(0.050)	(0.050)	(0.060)	(0.056)
Electricity & water supply [D+E]	0.083	0.053	−0.084	0.188***
	(0.053)	(0.056)	(0.123)	(0.054)
Construction [F]	−0.100**	−0.144***	−0.198***	−0.185***
	(0.051)	(0.052)	(0.075)	(0.059)
Transportation and storage [H]	0.156***	−0.068	0.000	0.074
	(0.049)	(0.053)	(0.077)	(0.058)
Accommodation and food service [I]	−0.019	−0.124*	−0.023	0.035
	(0.056)	(0.066)	(0.067)	(0.071)
Information and communication [J]	−0.010	0.059	0.127	0.342***
	(0.069)	(0.081)	(0.086)	(0.096)

Table 3. Continued

	All workers	High-skilled occupations (ISCO 1-3)	Middle-skilled occupations (ISCO 4-5)	Low-skilled occupations (ISCO 7-9)
Financial and insurance [K]	0.248***	0.324***	0.157*	0.799***
	(0.073)	(0.075)	(0.094)	(0.134)
Real estate & Professional [L]	0.074	0.135*	0.135*	0.143
	(0.062)	(0.079)	(0.082)	(0.118)
Administrative [M+N]	−0.031	−0.010	0.024	0.244***
	(0.051)	(0.055)	(0.058)	(0.062)
Public administration [O]	0.055	0.127**	0.021	0.311***
	(0.058)	(0.056)	(0.073)	(0.069)
Education [P]	−0.208***	−0.068	0.004	0.301***
	(0.051)	(0.048)	(0.087)	(0.066)
Human health [Q]	−0.003	0.207***	0.045	0.288***
	(0.047)	(0.044)	(0.057)	(0.077)
Arts [R]	−0.237***	−0.106*	−0.054	−0.013
	(0.058)	(0.058)	(0.054)	(0.098)
Other service [S]	−0.264***	−0.220***	−0.304***	−0.083
	(0.056)	(0.057)	(0.068)	(0.067)
Activities of household [T]	0.333***	0.002	0.059	0.242*
	(0.099)	(0.370)	(0.118)	(0.125)
Extraterritorial organizations [U]	0.173*	0.179	−0.150	0.682***
	(0.103)	(0.122)	(0.231)	(0.260)
No. of observations	166,495	67,986	52,902	45,607
R-squared	0.222	0.116	0.089	0.083

Source: Authors' estimations based on PIAAC, STEP, CULS World Bank, and UIBE GVC Indicators data.
Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard errors in parentheses. Standardized weights are used that give each country equal weight. The reference levels are: age 25–34, secondary education, wholesale and retail trade; repair of motor vehicles and motorcycles (ISIC G), lower medium literacy skills (level 2). The coefficients for interactions between sector fixed effects and Ln(GDP per capita) are presented in table S7.1. in the supplementary online appendix. The standard errors are clustered at a sector × country level.

Figure 5. Estimated Relationship between Computer Use and RTI, for All Workers and by Occupational Group.



Source: Authors' estimations based on PIAAC, STEP, CULS, World Bank, and UIBE GVC Indicators data.
Note: Based on the estimates presented in table 4. For each category of workers, the study selects a range of computer use, which includes 90 percent of workers in each category (the bottom and top 5 percent are omitted).

specialize in smaller segments of global value chains (e.g., assemblers of final products) tend to perform more routine-intensive tasks. This effect is particularly strong for workers in low-skilled occupations (ISCO 7–9), followed by workers in middle-skilled occupations (ISCO 4–5, table 3). Importantly, the coefficient on the interaction term between FVA share and ln(GDP per capita) is negative and marginally significant. This means that higher GDP attenuates the effect of FVA share on RTI: the effect becomes 0 for a country with GDP equal to double the average in the present sample, which is comparable to the United States. At the same time, the positive impact of FVA share on RTI is almost twice as great in countries with GDP per capita at 50 percent of the mean in the sample, e.g., Colombia or Serbia.

The second globalization measure, FDI share of GDP, also is positively associated with RTI at the average level of GDP per capita, and significantly so for workers in high-and middle-skilled occupations. However, the magnitude of the effects of FDI is much smaller than that of the FVA share. For instance, a 25 pp. higher FVA share, which is a difference between the United States and countries most specialized in smaller segments of global value chains (e.g., small central Eastern European countries) is associated with RTI in low-skilled occupations being higher by 0.16 (of the United States standard deviation), which is equivalent to about 50 percent of the RTI difference between the United States and these small CEE countries. But a 30 pp. difference in FDI share between the United States and these CEE countries is associated with RTI being lower by only 0.005 of the United States standard deviation. The association between FDI and RTI also dissipates at higher levels of development, especially among workers in low-skilled occupations: it becomes 0 in countries with GDP per capita about double the mean in the sample, but is twice as great in countries with GDP per capita at 50 percent the mean in the sample. Overall, the results are consistent with theories arguing that routine jobs are likely to be outsourced from rich countries to poor countries (Grossman and Rossi-Hansberg 2008).[20]

Next, the skill variables are examined. Workers with higher education levels and higher literacy are more likely to perform fewer routine tasks, overall and within particular occupational groups. A worker with the highest literacy proficiency (level 4–5) is expected to perform tasks with 0.27 (of the United States standard deviation) lower RTI than an otherwise identical worker with a lower medium literacy proficiency (level 2). It is also found that workers performing more routine-intensive jobs are more likely to be female[21] and young (aged 16–24). However, the relationship between age and RTI varies across occupational groups. In high-skilled occupations (ISCO 1–3), older individuals perform significantly less routine-intensive tasks, but in middle- (ISCO 4–5) and low-skilled occupations (ISCO 7–9), older workers perform more routine-intensive tasks, especially if aged over 55. This difference may suggest that experience and firm- or sector-specific knowledge can play a more important role in the allocation of workers to tasks among high-skilled occupations than among middle- and low-skilled occupations.

As an additional robustness check, the benchmark specification is re-estimated using averages of all variables at the country-sector level (table S7.4 in S7 in the supplementary online appendix). The results show a negative relationship between the probability of computer use and skills, and RTI. The results for globalization variables are also close to those found in the pooled, worker-level regression. However, the coefficients on the employment shares of educational groups are not significant at the sector level. This suggests that the significance of education in the worker-level regressions reflects the allocation of less routine-intensive tasks to better-educated workers within sectors.

20 This study's findings are also robust to the choice of the GVC participation measure—the results of the estimation with forward linkage-based measure of participation in GVCs are presented in table S7.2 in Appendix S7 in the supplementary online appendix. They are consistent with the baseline results obtained for the backward linkage-based measure (table 4).

21 Higher RTI among women is consistent with Pető and Reizer (2021) finding that women use their numeracy, literacy, and ICT skills at work less extensively than men in the same occupations.

Table 4. Decomposition of Cross-Country Variance of RTI by Fundamental Factors (% of total variance)

	Technology	Globalization	Structural change	Supply of skills	Total
All workers	40.3	8.4	−12.1	28.3	64.9
High-skilled occupations (ISCO 1-3)	39.0	6.1	−1.5	10.1	53.7
Middle-skilled occupations (ISCO 4-5)	25.7	9.0	−8.9	4.4	30.1
Low-skilled occupations (ISCO 7-9)	24.0	9.0	−0.9	0.6	32.8

Source: Authors' estimations based on PIAAC, STEP, CULS, World Bank and UIBE GVC Indicators data.

Note: The contributions of particular factors to RTI variance, σ_k, calculated in line with equation (4) using the model presented in table 3.

Decompositions of Cross-Country Differences

The study uses its estimated models to decompose the cross-country differences in RTI into the contributions of particular factors. Overall, its model accounts for 65 percent of the cross-country variance in RTI among all workers, more than 50 percent of the variance among workers in high-skilled occupations, and 30–35 percent of the variance among workers in middle- and low-skilled occupations (table 4). Most of the cross-country variance is attributed to technology (computer use): about 40 percent in the pooled sample and for high-skilled occupations, and 25 percent for middle- and low-skilled occupations. The supply of skills is the second-most-relevant factor, accounting for 28 percent of the cross-country variance of RTI for the pooled sample and 10 percent of the variance for high-skilled occupations. However, among workers in middle- and low-skilled occupations, globalization is the second-most-important factor (9 percent), and the contribution of skills is small.[22] The fact that skills account for much more of the cross-country variance when looking at all workers compared to variation within particular occupation groups suggests that the main contribution of skills is related to its association with occupational structure (this is explored further in the next subsection).[23] Finally, the contribution of structural change for all workers and for workers in high and middle-skilled occupations is negative. This may be because the employment shares of some typically nonroutine sectors (e.g., education) are virtually the same in all country groups, and the shares of some typically routine sectors (e.g., manufacturing) are lower in some low- and middle-income countries than in high-income countries.[24]

Next, the study decomposes the gaps between average RTI in different countries and the United States, which the study takes as the benchmark. The countries are divided into three groups: low- and middle-income countries (LMICs), the bottom high-income countries (HICs), (including those in southern, central and eastern Europe, as well as Chile and South Korea), and top HICs (mainly in North America, western Europe, and Australasia, plus Singapore, Japan, and Israel). Decomposition results for gaps in particular countries are reported in fig. S8.1 in the supplementary online appendix.

The average RTI scores are much higher for LMICs (0.45 United States standard deviations, table 5) and bottom HICs (0.28) than for the top high-income group and the United States (0.01 and 0). LMICs exhibit much lower shares of workers who use computers (36 percent) compared to the top HICs (76 percent) and the United States (75 percent). In terms of skill, the LMICs have fewer older workers and double the share of workers with education levels of primary school and below. Notably, 49 percent

22 These results hold if the study controls for more technology variables (robot and ICT stocks per worker) and calculates decompositions based on regression results presented in table S7.2 in S7 in the supplementary online appendix. They are available upon request.

23 Performing a variance decomposition for individual-level RTI, the study has found that explained variance is much smaller (20 percent for all workers, 8 percent to 12 percent for different occupation skill groups). Skills account for the lion's share of explained variance, which is expected, given that it is the only category for which the study employs individual data. The relative importance of technology, globalization, and structural change is similar to the results for country differences.

24 The within-sector differences in RTI between less- and more-developed countries are substantial, but this effect is of course attributed to other factors.

Table 5. Average Levels of RTI and Explanatory Variables by Country Groups

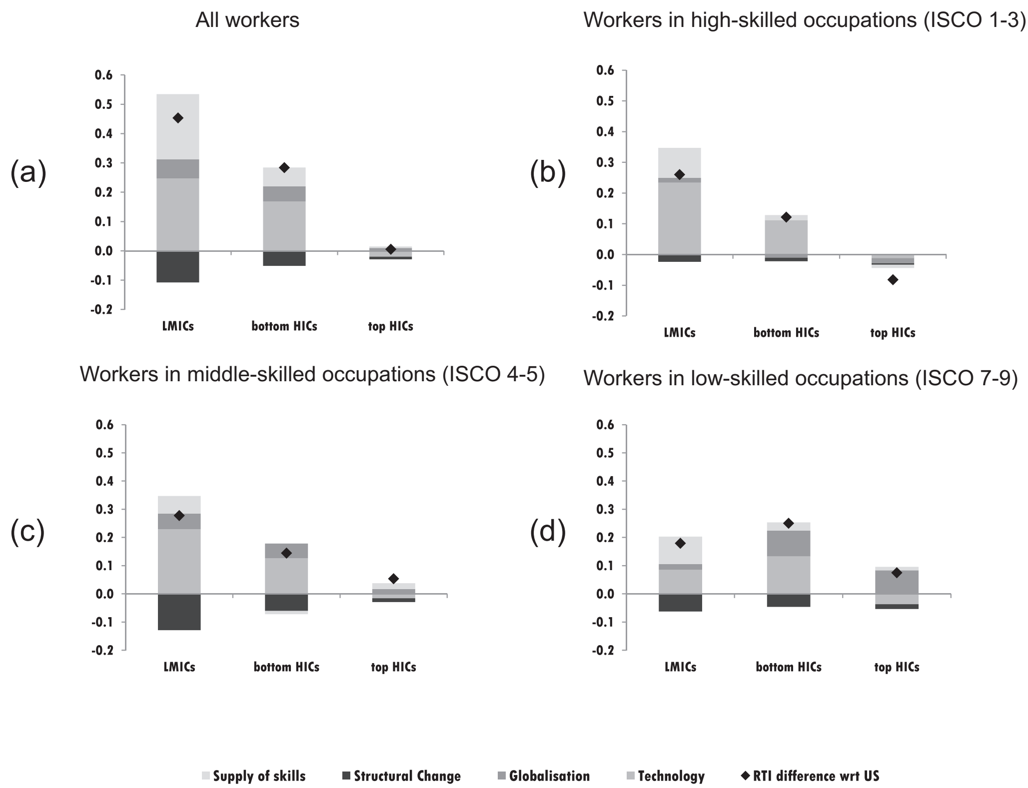
	Low- and middle-income countries	Bottom high-income countries	Top high-income countries	United States
RTI	0.45	0.28	0.01	0.00
Computer use	0.36	0.59	0.76	0.75
Log of GDP per capita (demeaned)	−1.23	0.15	1.07	1.29
FDI stock/GDP	0.44	1.19	0.79	0.35
FVA Share	0.14	0.25	0.19	0.08
Education: primary	0.34	0.17	0.15	0.10
Education: secondary	0.34	0.49	0.43	0.48
Education: tertiary	0.32	0.34	0.42	0.42
Literacy skills level: 1 or lower	0.49	0.18	0.13	0.14
Literacy skills level: 2	0.35	0.38	0.31	0.31
Literacy skills level: 3	0.14	0.37	0.41	0.40
Literacy skills level: 4 and 5	0.02	0.08	0.15	0.15
Female	0.45	0.46	0.48	0.49
Age: 16–24	0.17	0.08	0.12	0.15
Age: 25–34	0.29	0.25	0.22	0.23
Age: 35–44	0.24	0.28	0.25	0.22
Age: 45–54	0.19	0.25	0.25	0.23
Age: 55–65	0.10	0.14	0.16	0.18
Agriculture [A]	0.015	0.019	0.008	0.008
Mining [B]	0.008	0.006	0.004	0.005
Manufacturing [C]	0.167	0.193	0.140	0.112
Electricity & Water supply [D+E]	0.013	0.018	0.013	0.010
Construction [F]	0.072	0.084	0.069	0.066
Trade and repairs [G]	0.221	0.152	0.138	0.117
Transportation and storage [H]	0.065	0.058	0.054	0.043
Accommodation and food service [I]	0.062	0.055	0.050	0.072
Information and communication [J]	0.024	0.030	0.040	0.043
Financial and insurance [K]	0.020	0.029	0.037	0.048
Real estate & professional [L]	0.005	0.008	0.011	0.015
Administrative [M+N]	0.072	0.078	0.098	0.101
Public administration [O]	0.043	0.066	0.059	0.060
Education [P]	0.085	0.088	0.088	0.090
Human health [Q]	0.042	0.063	0.140	0.137
Arts [R]	0.016	0.018	0.021	0.026
Other service [S]	0.045	0.024	0.025	0.032
Activities of household [T]	0.025	0.011	0.004	0.015
Extraterritorial organizations [U]	0.001	0.001	0.000	0.000

Source: Authors' calculations based on PIAAC, STEP, CULS World Bank, and UIBE GVC Indicators data.

of workers in low- and middle-income countries are at the lowest literacy level, compared to just 13 percent and 14 percent in top HICs and the United States; and just 16 percent of workers in LMICs are at the upper-medium literacy level or above (3–5), compared to 45 percent in the bottom HICs, and 56 percent and 55 percent in top HICs and the United States, respectively. Finally, specialization in global value chains as captured by foreign value added share is the highest in the bottom high-income group (0.25) compared to just 0.14 in LMICs, 0.19 in top high-income countries, and 0.08 in the United States. The gap in GDP per capita is about 2.3 points on the log scale, implying that GDP per capita is more than 230 percent greater in the top HICs compared to the LMICs.

The decomposition results reveal that technology accounts for the largest share of the RTI gap with the United States for all country groups, but the role of other factors differs across groups (fig. 6). In LMICs,

Figure 6. Regression-Based Decomposition of Differences in RTI between Particular Countries and the United States, by Country Groups.



Source: Authors' estimations based on PIAAC, STEP, CULS, World Bank and UIBE GVC Indicators data.
Note: Results of decomposition (5) based on the estimates presented in table 3, and averaged for country groups defined in table 2. 0 is set at the U.S, average value and 1 corresponds to one standard deviation of RTI in the United States.

the contribution of skill supply (much lower in those countries than in the United States), is nearly as large as that of technology. For the bottom HICs, the contribution of skill supply is much smaller, and consequently, the RTI gaps with the United States are about half as large on average compared to LMICs. In both groups of countries, the contribution of globalization is moderate, with structural differences contributing negatively. For the top HICs, RTI gaps with the United States are negligible.

Next, the decomposition is conducted separately for high-, middle-, and low-skilled occupations. Compared to the results for all workers, for those in high-skilled occupations, RTI gaps with the United States are slightly smaller, and an even larger share of these gaps is attributable to technology (fig. 6). For LMICs, a noticeable share of the RTI difference among workers in high-skill occupations is attributable to the supply of skills, which is lower in LMICs than in the United States. For middle-skill occupations, technology has the largest contribution, followed by globalization. Again, a noticeable share of differences in RTI is associated with differences in the supply of skills only in the case of LMICs. The relatively greater importance of technology to differences in RTI of high-skill occupations is consistent with technology being complementary to nonroutine cognitive tasks that are performed relatively more often by workers in these occupations.

Finally, in low-skilled occupations, gaps with the United States in other HICs are greater than for high- and middle-skilled occupations. Globalization is the most important factor in accounting for these gaps, followed by technology. This suggests that even among HICs, the division of labor between

Table 6. Decomposition of Cross-Country Variance of RTI by Fundamental Factors, Controlling for Occupations (% of total variance)

	Technology	Globalization	Structural change	Supply of skills	Occupations	Total
With occupation fixed effects	32.4	5.6	−9.0	13.4	21.6	64.1
Without occupation fixed effects	40.3	8.4	−12.1	28.3	–	64.9

Source: Authors' estimations based on PIAAC, STEP, CULS, World Bank, and UIBE GVC Indicators data.
Note: The contributions of particular factors to RTI variance, σ_k, calculated in line with equation (4) using the model presented in table S7.5.

countries more and less narrowly specialized in GVCs is associated with noticeable differences in routine intensity of work in occupations such as assemblers, or plant and machine operators. In LMICs, however, differences with the United States among those in low-skilled occupations are smaller than in other occupational groups, and are mainly associated with a lower supply of skills and technology.

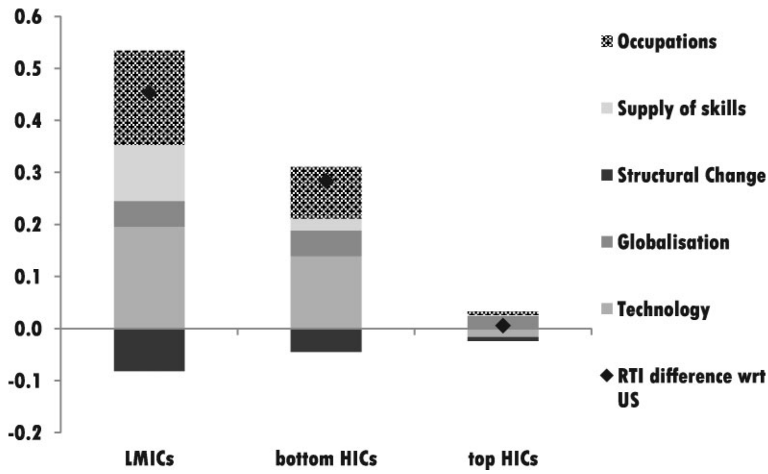
Assessing the Role of Occupations

The results thus far have shown that much of the cross-country differences in job tasks are associated with differences in technology, supply of skills, and globalization. Having individual survey data on job tasks makes it possible to study the correlates of RTI without making any assumptions about the nature of work in specific occupations. Nonetheless, given that much research on the nature of work focuses on occupations, it is of interest to investigate how much of the above-documented relationship between RTI and the four fundamental forces is explained by differences in occupational structure and how much is related to differences in tasks within occupations. To examine this question, the study estimates regression (3) which expands the benchmark specification to include occupation fixed effects, τ_o. In this specification, the coefficients on the variables for the four main factors capture their influence among workers in the same occupation. Thus, by comparing the coefficients with those estimated using the baseline specification without occupation fixed effects, it is possible to infer how much of the relationship between the four factors is captured by their impact on the occupational structure and how much is a within-occupation relationship.

The coefficients on the occupation dummies are in line with intuition: workers in high-skilled occupations (ISCO 1–3) perform less routine-intensive tasks than clerical workers (ISCO 4), while workers in low-skilled occupations (ISCO 7–9) and sales and services workers (ISCO 5) perform more routine-intensive tasks (table S7.5 in the supplementary online appendix). However, the four fundamental factors still strongly predict differences in routine intensity even after controlling for occupations. Although the absolute sizes of the coefficients on education and literacy are somewhat smaller than in the benchmark specification (table 4), none of them loses statistical significance. The coefficients on computer use and globalization variables change little and remain significant.

Next, the study conducts the cross-country variance decomposition and decomposition of gaps with the United States adding the occupational structure as an additional factor. It is found that occupations account for 22 percent of the cross-country variation in RTI for all workers. However, the total variance explained by the model (64.1 percent) is virtually the same as in the specification with no occupational fixed effects (64.9 percent, table 6). The contributions attributed to other factors, especially to the supply of skills, are lower than for the benchmark specification. Still, the contribution of technology remains noticeably larger than the contribution of occupations. When the importance of occupations is analyzed separately for high-, middle-, and low-skilled occupation groups (not reported here and available upon request), it is found that the occupation dummies have very little explanatory power. This suggests that only differences in the shares of broad occupation categories are meaningful for explaining task-content differences across countries, and that they are to a large extent related to cross-country differences in skill supply.

Figure 7. Regression-Based Decomposition of Differences in RTI between Particular Countries and the United States, Controlling for Occupations, by Country Groups.



Source: Authors' estimations based on PIAAC, STEP, CULS, World Bank and UIBE GVC Indicators data.
Note: Results of decomposition (5) based on the estimates presented in table 6, and averaged for country groups defined as in table 3. 0 is set at the United States average value, and 1 corresponds to one standard deviation of RTI in the United States.

It is found, perhaps surprisingly, that occupations are of limited importance in explaining cross-country differences in routine task intensity. Their contribution accounts for 40 percent of the total difference for LMICs—comparable to technology—and 35 percent for bottom HICs—less than technology (fig. 7). Thus, most of the association between fundamental factors and RTI appear in differences within occupation groups. This highlights the importance of collecting survey-based task data to understand the nature of work in specific countries.

5. Summary and Conclusions

This study has developed a novel dataset that measures the task content of jobs at the individual worker level for a large number of countries at different stages of economic development. The new survey-based measures are validated to be consistent with US O*NET-based task content measures that have been widely used in the existing literature on job tasks. A key advantage of the new measures is that they can distinguish between differences in task content among workers who have the same occupation but live in different country environments.

The study's results show that there are substantial cross-country differences in the routine intensity of job tasks, both at the national level and within specific occupations. The differences in tasks across countries at different stages of development are much greater than could be explained by differences in occupational structure. Not surprisingly, jobs in the most developed countries involve the most nonroutine tasks and the least routine tasks. The opposite is true for developing and emerging economies. Moreover, cross-country differences in routine task intensity are most strongly related to the differences in GDP per capita for high-skilled occupations, with no systematic correlation for middle- and low-skill occupations.

The study has estimated a regression that captures the association between the relative routine task intensity (RTI) of jobs and four fundamental forces: technology, globalization, supply of skills, and structural change. These results have been used to decompose the extent to which cross-country differences in routine task intensity are statistically associated with these different factors, both in terms of cross-country variance in mean RTI and RTI gaps between the United States and groups of countries sorted by GDP per capita. Consistent with much recent literature emphasizing the relationship between ICT and the nature of work, it is found that technology plays the largest role in explaining cross-country differences in RTI, followed by skills and globalization. Sector structures have the least explanatory power. However, interesting heterogeneities have been found in the impact of these factors for different occupation groups. Technology matters the most for high-skilled occupations, consistent with the complementarity between technology and nonroutine cognitive tasks, while globalization matters the most for low-skill occupations, which are more likely to involve routine tasks that are more easily outsourced from rich countries to poor countries. Differences in skill supply contribute a substantial share of RTI differences only in LMICs.

The present study stresses the need to quantify the country-specific task content of jobs and to identify differences between occupational task content in countries at different stages of development. It paves the way for more comprehensive research on the distribution of tasks around the world that can account for the within-occupation and between-country variation in task demand.

Data Availability Statement

The PIACC survey data used in this paper can be found at https://www.oecd.org/skills/piaac/. The STEP survey data can be found at https://microdata.worldbank.org/index.php/catalog/step/about. Relevant variables from the CULS survey is available in the replication package.

References

Acemoglu, D., and D.H. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*. Edited by D. Card and O. Ashenfelter, 4:1043–171. Amsterdam: Elsevier.

Akerman, A., I. Gaarder, and M. Mogstad. 2015. "The Skill Complementarity of Broadband Internet." *Quarterly Journal of Economics* 130 (4): 1781–824.

Arias, O.S., C. Sánchez-Páramo, M.E. Dávalos, I. Santos, E.R. Tiongson, C. Gruen, N. de Andrade Falcão, G. Saiovici, and C.A. Cancho. 2014. "Back to Work: Growing with Jobs in Europe and Central Asia | Europe and Central Asia Reports." doi:https://doi.org/10.1596/978-0-8213-9910-1.

Autor, D.H. 2013. "The 'Task Approach' to Labor Markets: An Overview." *Journal for Labour Market Research* 46 (3): 185–99.

Autor, D.H., and D. Dorn. 2009. "This Job Is 'Getting Old': Measuring Changes in Job Opportunities Using Occupational Age Structure." *American Economic Review* 99 (2): 45–51.

———. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.

Autor, D.H., and M.J. Handel. 2013. "Putting Tasks to the Test: Human Capital, Job Tasks, and Wages." *Journal of Labor Economics* 31 (S1): 59–96.

Autor, D.H., L.F. Katz, and M.S. Kearney. 2006. "The Polarization of the U.S. Labor Market." *American Economic Review* 96 (2): 189–94.

Autor, D.H., F. Levy, and R.J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–1333. doi:10.1162/003355303322552801.

Bárány, Z.L., and C. Siegel. 2018. "Job Polarization and Structural Change." *American Economic Journal: Macroeconomics* 10 (1): 57–89.

"China Urban Labor Survey (CULS)." 2017.

Deming, D.J. 2017. "The Growing Importance of Social Skills in the Labor Market." *Quarterly Journal of Economics* 132 (4): 1593–1640.

Du, Y., P. Jia, and J. Cheng. 2017. "Structural Changes in Labor Market, Job Tasks and Skill Demand." *Studies in Labor Economics* 5 (3): 30–49.

Du, Y., and A. Park. 2018. "Changing Demand for Tasks and Skills in China." Background Report for the World Bank Group (WBG)-Development Research Center under the State Council (DRC) Report on New Drivers of Growth in China, HKUST Institute for Emerging Market Studies, Hong Kong.

Eden, M., and P. Gaggl. 2020. "Do Poor Countries Really Need More IT?" *World Bank Economic Review* 34 (1): 48–62.

Firpo, S., N.M. Fortin, and T. Lemieux. 2011. "Occupational Tasks and Changes in the Wage Structure." IZA Discussion Paper5542. Institute of Labor Economics (IZA). Bonn, Germany.

Goos, M., A. Manning, and A. Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104 (8): 2509–26.

Grossman, G.M., and E. Rossi-Hansberg. 2008. "Trading Tasks: A Simple Theory of Offshoring." *American Economic Review* 98 (5): 1978–97.

Hardy, W., R. Keister, and P. Lewandowski. 2018. "Educational Upgrading, Structural Change and the Task Composition of Jobs in Europe." *Economics of Transition and Institutional Change* 26 (2): 201–31.

Hsieh, C.-T., and P.J. Klenow. 2010. "Development Accounting." *American Economic Journal: Macroeconomics* 2 (1): 207–23.

Hummels, D., J.R. Munch, and C. Xiang. 2018. "Offshoring and Labor Markets." *Journal of Economic Literature* 56 (3): 981–1028.

Jensen, J.B., and L.G. Kletzer. 2010. *Measuring Tradable Services and the Task Content of Offshorable Services Jobs*. NBER Book Chapter Series, no. c10826. National Bureau of Economic Research. Cambridge, MA.

Lewandowski, P., R. Keister, W. Hardy, and S. Górka. 2020. "Ageing of Routine Jobs in Europe." *Economic Systems* 44 (4): 100816.

Lo Bello, S., M.L. Sanchez Puerta, and H. Winkler. 2019. "From Ghana to America: The Skill Content of Jobs and Economic Development." 12259. IZA Discussion Papers. Institute of Labor Economics (IZA). Bonn, Germany. https://www.iza.org/publications/dp/12259/from-ghana-to-america-the-skill-content-of-jobs-and-economic-development.

Marcolin, L., S. Miroudot, and M. Squicciarini. 2019. "To Be (Routine) or Not to Be (Routine), That Is the Question: A Cross-Country Task-Based Answer." *Industrial and Corporate Change* 28 (3): 477–501.

Michaels, G., A. Natraj, and J. Van Reenen. 2014. "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years." *Review of Economics and Statistics* 96 (1): 60–77. doi:10.1162/REST_a_00366.

Montresor, G. 2019. "Job Polarization and Labour Supply Changes in the UK." *Labour Economics* 58 (June): 187–203.

Morduch, J., and T. Sicular. 2002. "Rethinking Inequality Decomposition, with Evidence from Rural China." *Economic Journal* 112 (476): 93–106.

Oldenski, L. 2012. "Export Versus FDI and the Communication of Complex Information." *Journal of International Economics* 87 (2): 312–22.

Pető, R., and B. Reizer. 2021. "Gender Differences in the Skill Content of Jobs." *Journal of Population Economics*, February. doi:10.1007/s00148-021-00825-6.

PIAAC Literacy Expert Group. 2009. "PIAAC Literacy: A Conceptual Framework." 34. ECD Education Working Papers. OECD Publishing, Paris. https://doi.org/10.1787/220348414075.

Reijnders, L.S.M., and G.J. de Vries. 2018. "Technology, Offshoring and the Rise of Non-Routine Jobs." *Journal of Development Economics* 135 (November): 412–32.

Rica, S. de la, L. Gortazar, and P. Lewandowski. 2020. "Job Tasks and Wages in Developed Countries: Evidence from PIAAC." *Labour Economics* 65 (August): 101845.

Rubin, D.B. 1987. *Multiple Imputation for Nonresponse in Surveys*. New York: John Wiley and Sons Inc. https://www.wiley.com/en-us/Multiple+Imputation+for+Nonresponse+in+Surveys-p-9780471655749.

Salvatori, A. 2018. "The Anatomy of Job Polarisation in the UK." *Journal for Labour Market Research* 52 (1): 8.

Spitz-Oener, A. 2006. "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure." *Journal of Labor Economics* 24 (2): 235–70.

"Survey of Adult Skills (PIAAC)." 2019. https://www.oecd.org/skills/piaac/.

"The STEP Skills Measurement Program." 2017. https://microdata.worldbank.org/index.php/catalog/step/about.

Wang, Z., S.-J. Wei, X. Yu, and K. Zhu. 2017. *Measures of Participation in Global Value Chains and Global Business Cycles*. NBER Working Paper Series, no. w23222. National Bureau of Economic Research. Cambridge, MA, USA.

World Bank. 2019. *World Development Report 2019: The Changing Nature of Work*. Washington, DC: World Bank. https://www.worldbank.org/en/publication/wdr2019.