ibs instytut badań strukturalnych

IBS WORKING PAPER 08/2022
NOVEMBER 2022

GLOBAL DIVERGENCE IN THE DE-ROUTINIZATION OF JOBS

Piotr Lewandowski
Albert F. Park
Simone Schotte

ibs working paper 08/2022

november 2022

GLOBAL DIVERGENCE IN THE DE-ROUTINISATION OF JOBS•

Piotr Lewandowski♦

Albert Park♥

Simone Schotte♠

Abstract

We establish new stylised facts about the global evolution and distribution of routine and non-routine work, relaxing the common assumption that occupations are identical globally. We combine survey data and regression models to predict the country-specific routine-task intensity of occupations in 87 countries employing over 2.5 billion workers, equivalent to 75% of global employment. From 2000 to 2017, the shift away from routine work was much slower in low- and middle-income countries than in high-income countries, widening gaps in the nature of work. Low– and middle-income countries remained the dominant provider of routine work. Not accounting for differences in occupation-specific job tasks across countries leads to a significant overestimation of the role of non-routine tasks in less developed countries.

Keywords: non-routine, labour, tasks, jobs, cross-country

JEL: J21, J23, J24

• We thank Adam Bielski and Karol Madoń for excellent research assistance. We also thank participants of the LISER-IAB Conference on Digital Transformation and the Future of Work for their insightful comments. We acknowledge support from UNU-WIDER, and the Hong Kong Research Grants Council General Research Fund [16504217]. This study is reproduced here with full acknowledgement of UNU-WIDER, Helsinki. The study was originally published under the UNU-WIDER project *The changing nature of work and inequality*, which is part of a larger research project on *Inequalities – measurement, implications, and influencing change*. The usual disclaimers apply. All errors are our own.

♦ Institute for Structural Research (IBS), and IZA. Warsaw, Poland. e-mail: piotr.lewandowski@ibs.org.pl, corresponding author.

♥ Asian Development Bank, Department of Economics, HKUST, CEPR, and IZA. Manila, Philippines. e-mail: afpark@adb.org.

♠ United Nations University World Institute for Development Economics Research (UNU-WIDER). Helsinki, Finland. e-mail: schotte@wider.unu.edu.

ISSN 2451-4373 | IBS ®

1 Introduction

The shift from routine-intensive jobs to non-routine work has been a critical feature of 21st-century labour markets. It has been driven by technological progress and globalisation and has contributed to rising wage polarisation in many countries (Autor et al., 2003; Goos et al., 2014). Over the past decade, a growing body of research has studied the evolution of the task content of jobs. It investigated patterns over time and across countries, the relative importance of demand and supply factors, and the consequences of these processes for wage inequality (Acemoglu and Autor, 2011; Autor, 2013; Firpo et al., 2011).

Theory suggests that employers endogenously assign tasks based on the demand and supply of different skills given available technologies (Acemoglu and Autor, 2011; Autor and Handel, 2013). As a consequence, workers in a specific occupation in low- and middle-income countries may perform different tasks than workers in comparable occupations in high-income countries. With globalisation, poorer countries may specialise in routine tasks, and richer countries may specialise in non-routine tasks (Grossman and Rossi-Hansberg, 2008). In previous research, the task content of jobs, namely the role of routine vs non-routine and cognitive vs manual tasks, has been typically measured at the occupation level. However, most countries have not systematically collected information on the task content of occupations. Hence, the majority of past studies use the US Occupation Information Network (O*NET) occupational data to analyse task demand around the world (Arias et al., 2014; Fonseca et al., 2018; Hardy et al., 2018; Reijnders and de Vries, 2018) or to assess the suitability of jobs to working from home (Dingel and Neiman, 2020). This approach requires assuming that the task content of each occupation everywhere in the world is the same as in the US. It may be problematic given the large cross-country differences in technology, economic structures, and labour force skills (Eden and Gaggl, 2020; Hsieh and Klenow, 2010; Niebel, 2018).

Corroborating this concern, Lewandowski et al. (2022) presented evidence of substantial differences in the task content of work within occupations across countries. They found that sector and country differences in technology use, workers' skills, and globalisation (measured by foreign value-added (FVA) share) are all related to cross-country differences in the task content of jobs, both across and within particular occupations. Lo Bello et al. (2019) also showed that jobs in low- and middle-income countries are more routine intensive than in high-income countries. Even among developed countries, there are differences in the task content of occupations and wage premia associated with performing less routine-intensive tasks (de la Rica et al., 2020). Lewandowski et al. (2022) relied on adult skill use surveys collected in 47 countries, including low-, middle-, and high-income economies. However, such data are (as yet) unavailable for several large emerging economies such as Argentina, Brazil, Bangladesh, India, Nigeria, and South Africa. As a result, they are insufficient to quantify the global allocation of routine and non-routine work fully, nor to test whether de-routinisation and wage polarisation have occurred in low- and middle-income countries to an extent comparable with developed economies.

In this paper, we relax the assumption that occupations are identical worldwide. We study the global evolution and distribution of routine and non-routine work from 2000 to 2017, making two main contributions. First, building upon earlier work (Lewandowski et al., 2022), we develop a regression-based methodology to predict the country-specific task content by occupational group in many countries where no task survey data are yet available. This enables a more accurate picture of work in low- and middle-income countries than assuming that occupational tasks are identical worldwide. Our second contribution is to establish stylised facts on the patterns and evolution of the global distribution of routine and non-routine work since the early 2000s. To this end, we merge country-specific occupational task measures with employment structure data for 87 countries from 2000 to 2017. Our country sample includes 25 low- or lower-middle-income countries, 24 upper-middle-income countries, and 38 high-income countries. In 2017, the countries in our sample jointly accounted for over 2.5 billion workers, equivalent to approximately 75% of global employment. We analyse the changing distribution of tasks over time, both by holding country-occupation routine task intensity (henceforth RTI) fixed over time and by allowing the task content of occupations to evolve. Using country-specific task measures, we show that in countries with lower economic and technological development levels, workers tend to perform more routine-intensive tasks compared to those in more advanced countries, even within the same occupations. These cross-country within-occupation gaps are sizeable and are mainly attributable to differences in technology.

Three key stylised facts emerge. First, accounting for cross-country differences in RTI, the de-routinisation of work has occurred much slower in low- and middle-income countries compared to high-income countries. In contrast, the assumption that occupations are identical worldwide leads to an improbable result that the reallocation of labour away from routine and toward non-routine work has occurred at a similar pace in all country groups.

Second, we find that the gap in average RTI between low- and middle-income countries, on the one hand, and high-income countries, on the other, is much larger than suggested using O*NET. Moreover, this gap has widened over time, so the nature of work in poorer countries has not converged to that in high-income countries, despite their increasing integration into global value chains and rising technology level. We attribute this pattern to between-occupation effects—poorer countries exhibit higher employment shares of routine-intensive occupations—and within-occupation effects—in poorer countries, occupations require more routine tasks.

Third, we show that the assumption that occupations are identical worldwide leads to the finding that, between the early 2000s and the middle 2010s, low- and middle-income countries became the dominant supplier of non-routine work. In contrast, accounting for cross-country within-occupation differences in tasks reveals that high-income countries have remained the dominant provider of non-routine work, while routine work has remained concentrated in low- and middle-income countries. Overall, our findings corroborate theories of allocation of tasks that suggest that a higher level of technology and a more sophisticated role in global value chains is associated with less routine intensive work. They also show that ignoring this property and assuming that occupations are identical around the world would underestimate the role of routine work in low- and middle-income countries.

The remainder of the paper is structured as follows. Section II introduces the data and methodology. Section III presents stylised facts regarding the global evolution and distribution of task content of jobs. Section IV concludes.

2 Data and methodology

2.1 Measuring the task content of jobs using survey data

Economists have studied the changes in the task content of jobs – within and between occupations – as a key method to track changes in the nature of work attributed to technological progress and globalisation, particularly offshoring (Autor et al., 2003; Spitz-Oener, 2006). Most previous research studying the evolution of the task content of jobs focuses on developed countries (Goos et al., 2014; Hardy et al., 2018) or middle-income countries (Arias et al., 2014; Reijnders and de Vries, 2018). That research assumed that occupational task demands are identical across countries and can be quantified using the task content measures proposed by Autor et al. (2003) and Acemoglu and Autor (2011) based on the US O*NET data.

The increasing availability of surveys collecting information on tasks performed by individual workers has facilitated more detailed studies of occupational task demand (Arntz et al., 2017). Using these new data, researchers developed several approaches to measure country-specific, worker-level job tasks (Caunedo et al., 2021; de la Rica et al., 2020; Lewandowski et al., 2022; Lo Bello et al., 2019; Marcolin et al., 2019). In particular, Lewandowski et al. (2022) developed survey-based, harmonised task measures of non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, and manual tasks. These measures were consistent with the widely used Acemoglu and Autor (2011) measures based on the O*NET data (definitions shown in Table S1 in Supplementary Material). They also combined them into a composite measure of routine task intensity (RTI), which increases with the importance of routine work content and decreases with the importance of non-routine content. Previous studies on high-income countries (Autor and Dorn, 2013; Goos et al., 2014) often used RTI. It captures the differences in the task demand across occupations, and quantifies the potential substitutability of human work in various jobs with routine-replacing technologies based on algorithms.

Applying the methodology proposed by Lewandowski et al. (2022), we calculate country-specific RTI using worker-level data from three large-scale surveys available for 47 countries (Table S2 in Supplementary Material):

- the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), covering high- or middle-income countries,
- the World Bank's Skills toward Employment and Productivity (STEP) surveys, conducted in the middle- and low-income countries,
- the China Urban Labor Survey (CULS), collected by the Institute of Population and Labor Economics of the Chinese Academy of Social Science; CULS included a module based on STEP.

For each country, we calculate the average RTI by 1- and 2-digit occupations according to the International Standard Classification of Occupations (ISCO-08) classification. We also use the 2017 release of O*NET and Acemoglu and Autor's (2011) methodology to define task content and RTI values under the assumption that occupations are identical worldwide. We standardise all task variables, including the RTI, using relevant means and standard deviations in the US. The final measures refer to the US average and standard deviations in 2000.[1]

In the US, the correlation between the survey-based RTI and the O*NET RTI is very high, so the survey measure successfully captures the variation in the routine intensity of work across occupations (Lewandowski et al., 2022). First, the survey questions on the repetitive and structured component of work – used to calculate the routine cognitive measure – successfully capture the general routine aspect of work. Second, the survey questions on solving problems at work, programming, or supervising others – used to create the non-routine cognitive measures – successfully capture this aspect of work. Both approaches – survey and O*NET – identify plant and machine operators and assemblers (ISCO 8), and elementary occupations (ISCO 9) as the most routine-intensive occupations, followed by craft and related trades workers (ISCO 7) – see Figure S1 in Supplementary Material. They also show that managers (ISCO 1) and professionals (ISCO 2) are the least routine-intensive occupations, followed

[1] Following Acemoglu and Autor (2011), we use survey weights (at the 3-digit ISCO level) from the US 2000 census for the standardization of O*NET tasks. However, to ensure consistency with the ILOSTAT data we use in our cross-country study, we adjusted the census weights (at the 1-digit level) to match the occupational structure in the ILOSTAT data for the USA in 2000.

by technicians (ISCO 3). Clerical workers (ISCO 4) and sales and services workers (ISCO 5) are in the middle of the RTI distribution: O*NET suggests that clerical jobs are slightly more routine-intensive than sales and service jobs. In contrast, the survey-based measure finds the opposite.

Achieving the distribution of the survey RTI across occupations in the US that is consistent with the distribution of O*NET RTI in the US ensures that the concept of the routine intensity of work as measured with survey data is in line with the idea used in the literature on developed countries (Acemoglu and Autor, 2011; Autor and Handel, 2013). However, the critical difference between the O*NET and the survey-based measures is that the latter allows measuring differences in occupational task demand across countries.

2.2 Predicting the country-specific task content of jobs

To predict the task content of occupations in countries with no available survey data on tasks, we estimate a set of ordinary least squares (OLS) regressions that relate the RTI of occupation j in country c to four key factors defined for each country: (1) development level, measured by the gross domestic product (GDP) per capita (in purchasing power parity, natural logarithm); (2) technology use (T), approximated by the number of internet users per 100 inhabitants; (3) globalisation (G), quantified by foreign value added share of domestic output (FVA share); and (4) supply of skills (S), measured by the average years of schooling. We add fixed effects, γ_{kj}, for 2-digit ISCO sub-occupations k that belong to a given 1-digit occupation j. Formally:

$$RTI_{kjc} = \beta_{j0} + \beta_{j1}GDP_c + \beta_{j2}T_c + \beta_{j3}G_c + \beta_{j4}S_c + \gamma_{kj} + \varepsilon_{kjc}. \quad (1)$$

The task content of occupations can change over time depending on the country's overall endowments (Autor et al., 2003; Spitz-Oener, 2006) and will likely not be reactive to short-term business cycle fluctuations. Therefore, to fit the regression model, we take averages of the explanatory variables for 2011–16 since most STEP/PIAAC/CULS survey data come from this period. We use globalisation variables from 2011 as more recent data are not available.[2] We use a covariance-based decomposition procedure to assess the relative role of particular factors in predicting the cross-country variance in occupational RTI (Morduch and Sicular, 2002).

For each occupation, we select the model that fits the data best from a set of seven alternatives that differ in explanatory variables. We use leave-one-out cross-validation, and select models that exhibit the lowest root mean square errors, the lowest mean absolute errors, and (with two exceptions) the highest pseudo-R2 (see Table S3 in Supplementary Material). We prioritise specifications consistent with the findings of worker-level regressions in Lewandowski et al. (2022). They found that technology and skills are significant correlates of workers' routine intensity of tasks in all occupations. Globalisation is particularly relevant for the content of work in occupations predominantly employed in tradable sectors, such as plant and machine operators. For agricultural workers (ISCO 6), we condition RTI on development level and average years of schooling. The estimation results are reported in Table 1. The fixed effects estimated for 2-digit sub-occupations are shown in Figure S2 in Supplementary Material.

[2] The data on FVA share come from the UIBE-GVC database. Other data come from the World Development Indicators database by the World Bank.

Our regression results show that higher technology use is associated with lower RTI in all non-farming occupations (Table 1). A higher supply of skills and a higher level of development partly mediate this effect. In occupations typical for tradable sectors (ISCO 7-9), workers in countries more specialised in GVCs perform more routine-intensive tasks, especially in less developed countries. We also find a negative relationship between development level and the RTI of agricultural workers (ISCO 6).

Table 1: The estimated occupation-specific models of correlates of RTI

	Managers (ISCO 1)	Profes-sionals (ISCO 2)	Tech-nicians (ISCO 3)	Clerical workers (ISCO 4)	Sales and services workers (ISCO 5)	Agricul-tural workers (ISCO 6)	Crafts-men (ISCO 7)	Machine operators (ISCO 8)	Elemen-tary occ. (ISCO 9)
GDP per capita (ln)	0.039 (0.074)	0.091 (0.056)	0.068 (0.063)	0.236*** (0.070)	0.105 (0.067)	-0.229*** (0.090)	0.266*** (0.072)	0.198** (0.090)	-0.044 (0.079)
FVA share (%)							1.276*** (0.359)	1.590*** (0.457)	0.621 (0.395)
FVA share x GDP per capita (ln)							-0.604 (0.577)	-0.949 (0.737)	0.783 (0.640)
Internet use (%)	-1.152*** (0.309)	-1.389*** (0.236)	-1.242*** (0.264)	-1.318*** (0.294)	-1.331*** (0.282)		-1.678*** (0.304)	-1.476*** (0.370)	-0.642* (0.332)
Average years of schooling	0.025 (0.021)	0.076*** (0.016)	0.073*** (0.018)	0.091*** (0.020)	0.064*** (0.019)	-0.035 (0.031)	0.064*** (0.020)	0.088*** (0.025)	0.075*** (0.022)
Fixed-effects 2-digit level	YES	YES	YES	YES	YES	NO	YES	YES	YES
Observations	164	246	205	164	164	44	200	112	227
Adjusted R2	0.368	0.390	0.330	0.158	0.201	0.408	0.233	0.197	0.128

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Constant not shown.
Source: authors' estimations based on PIAAC, STEP, CULS, World Bank, and UIBE-GVC data.

Next, we use the estimated coefficients to predict the RTI by 1- and 2-digit occupations for each country, conditional on the level of economic development, skill supply, technology endowment, and participation in GVCs.

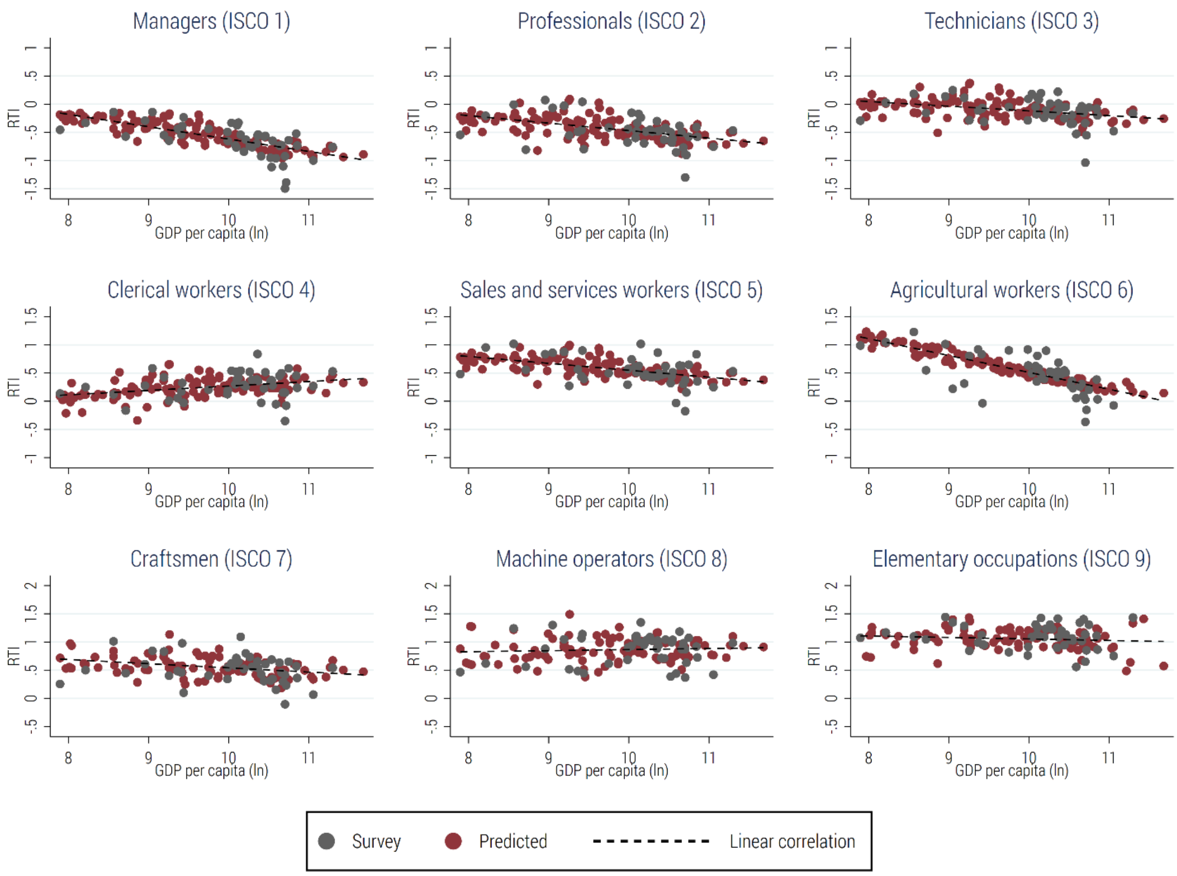
The predicted, country-specific values of task content show substantial cross-country differences in RTI for specific occupations, matching the patterns observed in the survey data (Lewandowski et al., 2022).[3] Work in particular occupations is generally more routine-intensive in less developed countries – a negative relationship exists between development level and occupational RTI (Figure 1). It is most pronounced in high-skilled occupations (ISCO 1—managers, ISCO 2—professionals, ISCO 3—technicians): skilled workers in richer countries perform less routine-intensive tasks than those in poorer countries. We attribute most of the cross-country variance in RTI in these occupations to differences in technology (see Figure S3 in Supplementary Material), as better access to technology in the more-developed countries is associated with a lower routine intensity of tasks performed by workers.

[3] The predicted values are close to the survey results for most countries covered by PIAAC/STEP/CULS but show a narrower range. Our predictions thus provide a conservative estimate of the within-occupation differences in RTI levels across countries.

The relationship between GDP per capita and RTI is mixed for occupations typical for service sectors. Among sales and services workers (ISCO 5), those in more affluent countries do less routine-intensive work. Again, we attribute these differences mainly to lower technology use in less-developed countries (Figure S3). Among clerical workers (ISCO 4), there is no clear-cut relationship between the development level and RTI. However, clerical workers in the poorest countries in our sample perform less routine-intensive tasks, which may be associated with a lower supply of skills in these countries. Indeed, clerical workers are the only occupational group for which the cross-country differences in skill supply make the largest contribution to international differences in RTI (Figure S3).

There is no clear-cut relationship between development level and RTI among workers in occupations typical for manufacturing and other tradable sectors (ISCO 8—plant and machine operators, ISCO 7—craft and related trades workers). However, compared to other occupations, we find a larger dispersion of RTI among countries at a similar development level (Figure 1), related to differences in countries' participation in global value chains. Globalisation plays the most crucial role for these occupations in predicting cross-country task differences (Figure S3). Routine jobs are easier to offshore, so poorer countries may specialise in them (Grossman and Rossi-Hansberg 2008). Indeed, a higher FVA share in domestic production is associated with a higher RTI among less-developed countries and a lower RTI among more-developed countries. Among workers in elementary occupations (ISCO 9), which are more often demanded in non-tradable sectors, the dispersion of RTI at a given development level is less pronounced (Figure 1). Differences in skills play a much greater role, while differences in GVC specialisation play a much smaller role than among plant and machine operators (Figure S3).

Figure 1: Predicted routine task intensity levels by 1-digit occupations.



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

2.3 Investigating the evolution of task content over time across country groups

Having predicted the occupation-specific RTI in various countries, we investigate the evolution of task content over time. We merge the country-specific and O*NET 2017 RTI values with ILOSTAT data on employment structures from 2000–17. Our sample includes 87 countries comprising approximately 2.5 billion workers in 2015–17, corresponding to 75% of global employment.[4]

Of the countries covered by the ILOSTAT data, we include those where data for all explanatory variables in equation (1) are available. [5] To avoid extrapolating beyond the range used to build the model, we omit nine economies with a GDP per capita below Kenya ($2687 PPP, on average, between 2011 and 2016), the poorest country in the PIAAC/STEP/CULS sample. The starting point is 2000, or the earliest available employment data. The end point is 2017, or the most recent available data. We omit countries with no data available before 2005 or from 2014 on.

Based on the World Bank classifications in 2010-2011, we define four income groups: low- and lower-middle-income countries, LIC-LMICs (25 countries), upper-middle-income countries, UMICs (24), bottom high-income countries, bottom-HICs (17), and top high-income countries, top-HICs (21, Table S2 in Supplementary Material). The countries in each income group remain fixed across years for comparability purposes.

We calculate the average RTI in a given country and year as a weighted average of the country-specific RTI across occupations, using occupation employment shares as weights. [6] For countries covered by the survey data, we use occupation-specific average RTIs calculated as described in section II.A. For the remaining countries, we use values predicted in line with the framework presented in section II.B. For skilled agricultural, forestry, and fishery workers (ISCO 6), we use predicted RTI values at the 1-digit level for all countries because the sample sizes in ISCO6 are small in some countries covered by STEP, which is an urban survey.

First, we hold the occupational RTI constant over time so that shifts in the employment structure are the only drivers of change. Second, we allow for intertemporal changes in occupational task content. We predict the country- and occupation-specific RTIs using averages of explanatory variables across 2001–05, except for the globalisation

---

[4] Due to data availability, our sample covers a lower share of total employment in low- and lower-middle income countries (62%, see Table S2 in Supplementary Material) and in upper-middle income countries (85%) than in high-income countries (96%). As a result, our sample is likely to overstate the extent of non-routine work globally.

[5] We omit seven oil exporting countries, and five countries classified as tax havens (according to Financial Secrecy Index for 2011).

[6] Whenever possible, we use data at the 2-digit occupation level. However, we use 1-digit level data if the employment structure at the 2-digit level is not available in the survey data or in the ILOSTAT data, or if the share of workers unclassified at the 2-digit occupation level exceeds 5% in a given year. If the share of workers unclassified at the 1-digit occupation level exceeds 5%, we omit such year. We use a linear interpolation to fill other gaps in the ILOSTAT data. We use either ISCO-08 or ISCO-88, depending on the classification available in the ILOSTAT data for a given year and country. In order to convert all RTI measures to the ISCO-88 classification, we use the crosswalk prepared for the European Working Conditions Survey data.

variable, which is available only for 2004.[7] For O*NET, we use the 2003 dataset. We then apply a weighted average. From 2000–02, we use the RTI predicted for 2001–05 (O*NET 2003); for any year t in 2003–17, we assign a weight $\frac{2017-t}{14}$ to the RTI predicted for 2001–05 (O*NET 2003), and a weight $\frac{t-2003}{14}$ to the RTI predicted for 2011–16 (O*NET 2017). As these time-variant estimates require assuming that the estimated cross-country models (2) hold over time, we treat these as complementary to our baseline results.

We apply a shift-share decomposition to analyse to what extent the cross-country differences in average RTI values can be attributed to differences in occupational structures, and to what extent to differences in occupation-specific RTI values. We decompose the difference between the average RTI in a given country group c, RTI_c, and the average in top high-income countries, RTI, into the between-occupation, BO_c, within-occupation, WO_c, and interaction, INT_c, terms. Formally:

$$RTI_c - RTI = \sum_{j \in ISCO} \alpha_{j,c} rti_{j,c} - \sum_{j \in ISCO} \alpha_j rti_j = BO_c + WO_c + INT_c \tag{2}$$

$$BO_c = \sum_{j \in ISCO} rti_j (\alpha_{j,c} - \alpha_j) \tag{3}$$

$$WO_c = \sum_{j \in ISCO} \alpha_j (rti_{j,c} - rti_j) \tag{4}$$

$$INT_c = \sum_{j \in ISCO} (\alpha_{j,c} - \alpha_j)(rti_{j,c} - rti_j) \tag{5}$$

whereby:

- $rti_{j,c}$ and rti_j are the average values of RTI for workers in occupation j in country group c, and top high-income countries, respectively;
- $\alpha_{j,c}$ and α_j are the shares of workers in occupation j in total employment in country group c, and top high-income countries, respectively; and
- $ISCO$ is the set of 1-digit ISCO-08 occupations.

[7] We have to predict the past levels of RTI as the survey data on the task content of jobs has so far been collected only once per country so direct measurement of changes in occupational RTI is not possible. An additional assumption behind our prediction is the independence of right-hand side variables, in particular technology adoption and participation in global value chains. There is some evidence for developing countries that participation in global value chains facilitates the adoption of advanced technologies, like Industry 4.0 (Delera et al., 2022). However, we are focused on basic ICT technologies. Nevertheless, our estimates of country-specific changes in occupational RTI can be interpreted as lower-bound estimates.

Finally, we use the task measures merged with employment data to quantify the global allocation of routine and non-routine work. To this aim, we calculate the global distribution of RTI (weighted by total employment across all countries and occupations in our sample) at the end of our study period.[8] We define the threshold for the non-routine jobs as the 25th percentile of that distribution and classify all jobs with the RTI value below it as non-routine. We define the threshold for the routine jobs as the 75th percentile of that distribution and classify all jobs with the RTI value above it as routine. We apply the same thresholds at the beginning and end of our study period. This ensures that the definitions of routine and non-routine jobs are consistent over time.

Next, we calculate the shares of particular country groups in total, routine, and non-routine employment in each period. We conduct this analysis using our country-specific occupational task and O*NET task measures. This allows us to quantify how much the role of non-routine tasks in low- and middle-income countries is overestimated under the assumption that occupations are identical worldwide. The O*NET task content data are provided as point estimates and have been presented as such in previous research (Acemoglu and Autor, 2011; Autor et al., 2003). For comparability, we also focus on the point estimates of country-specific RTI.

3 Results

3.1 The de-routinisation of jobs has occurred much slower in LICs and MICs than in HICs

Since 2000, occupational structures around the world have evolved away from routine-intensive occupations and towards non-routine-intensive occupations. However, accounting for cross-country differences in the task content of occupations shows that the de-routinisation occurred slower than would have been apparent under the assumption that occupations are identical worldwide. In particular, de-routinisation in LICs and MICs occurred visibly slower than in HICs.

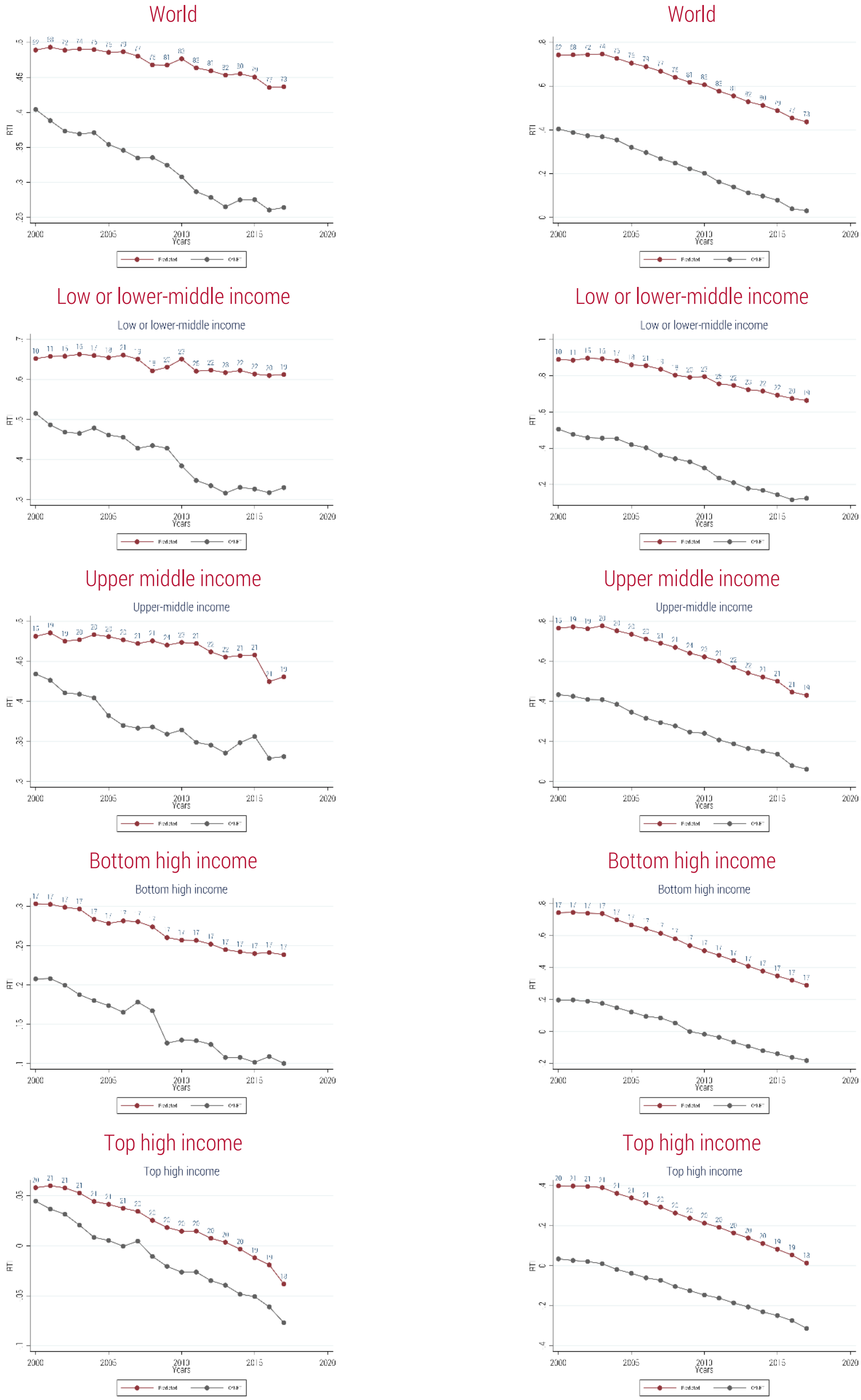
Using the country-specific measures and holding the occupational RTI values constant over time (to focus on changes in task content attributable to shifts in occupational structures), we find evidence of diverging trends (Figure 2a). In particular, in the group of LIC-LMICs, the average RTI has barely declined, while in the HICs, it has declined steeply. When we allow for changes in the task content of occupations over time, the decline in RTI between 2000–17 appears stronger. However, using the country-specific task measures, the decrease in RTI in LIC-LMICs is still much slower than for other country groups (Figure 2b).

In contrast, if one assumes that occupations are identical around the world and uses the O*NET-based task measures, the routine intensity of work appears much lower on average (0.27 in 2017 compared to 0.43 using country-specific task measures). Moreover, the trends in labour reallocation away from routine and toward non-routine tasks seem parallel across all country groups (Figure 2a). Assuming that occupations are identical worldwide leads to a substantial overestimation of the role of non-routine tasks in less developed countries and their growth over time.

[8] As a starting point, we use the 2000 employment data, and for countries lacking 2000 data, we use the earliest available data. The end point is 2017, and for countries lacking 2017 employment data, we use the most recent available data. If a country has no data available before 2005, or from 2014 on, we do not include it in this analysis.

Figure 2: The evolution of average routine task intensity according to country-specific and O*NET measures.

a) Constant occupational task content, by country groups b) Changing occupational task content, by country groups



Notes: Labels indicate the number of countries per group with data available in a given year.
Source: authors' estimations based on PIAAC, STEP, CULS, O*NET, World Bank, UIBE-GVC, and ILOSTAT data.

3.2 Gaps in the routine-task intensity of jobs between LICs/MICs and HICs have increased over time

The unequal trends in the de-routinisation of jobs have created widening gaps in the task content of work in LICs and MICS as compared to HICs.

According to the country-specific measures (and holding the occupational RTI values constant over time), the differences between top-HICs and less developed countries have increased by about 10% of the initial gap in both LIC-LMICs and UMICs (Figure 3a). But in bottom HICs, the distance to the top HICs has barely changed. The shift-share decomposition analysis shows that a substantial share of these gaps (on average, 40% for both LIC-LMICs and UMICs) is attributable to differences in the country-specific task content of comparable occupations (the within-occupation effect, Figure 3a). In our regression-based approach, we attribute most of these within-occupation differences to lower technology use in less developed countries (Figure S3 in Supplementary Material). For LIC-LMICs, part of the gap in RTI with the top-HICs (11% on average) is attributable to the interaction effect, which means that occupations that are more routine intensive than in top-HICs also have higher employment shares. This finding aligns with theories of trade and offshoring that imply that poorer countries with a less-productive labour force might specialise in more routine-intensive activities (Grossman and Rossi-Hansberg, 2008; Reijnders and de Vries, 2018).

Accounting for task content changes within occupations over time, we find that the gap in average RTI between LIC-LMICs and top-HICs widens even more (by 40% of the initial gap, Figure 3b). The within-occupation effect has contributed substantially to this widening, suggesting that de-routinisation within identical occupations has been slower in poorer countries. In bottom-HICs, the gaps to top-HICs have narrowed as occupational RTI in these countries has converged (Figure 3b). In contrast, assuming that occupations are identical worldwide leads to the conclusion that the gaps in RTI between country groups have remained virtually unchanged (Figure S4 in Supplementary Material).

Figure 3: The shift-share decomposition of differences in the average routine task intensity between particular country groups and the top-HICs, according to the time-invariant and time-varying country-specific RTI.

a) Time-invariant country-specific RTI

b) Time-varying country-specific RTI

Source: authors' estimations based on PIAAC, STEP, CULS, World Bank, UIBE-GVC, and ILOSTAT data.

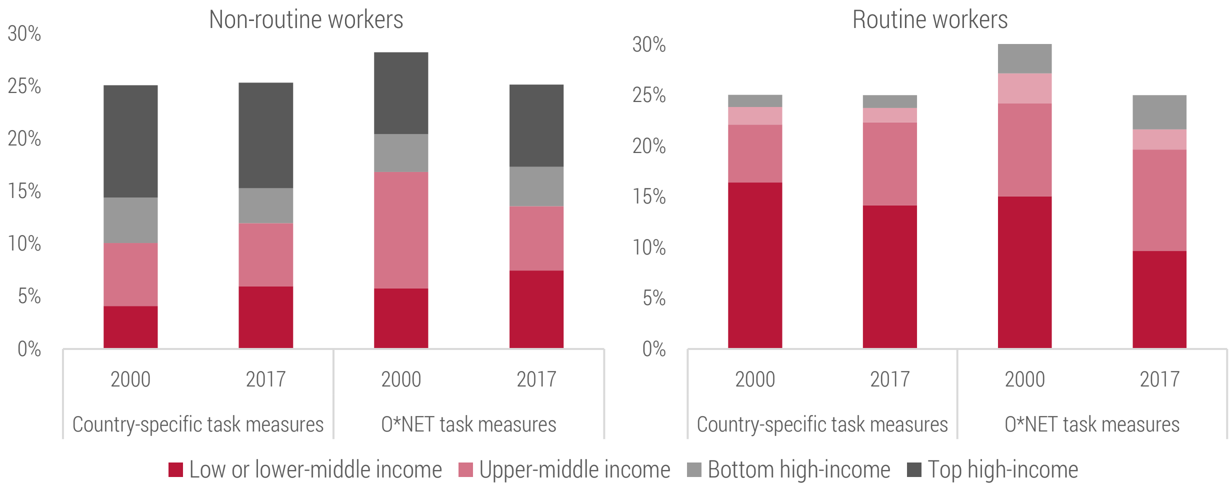
3.3 HICs remain the dominant suppliers of non-routine work, while LICs and MICs remain the dominant suppliers of routine work

Accounting for cross-country differences in the task content of occupations, we find that the global allocation of routine and non-routine work has been much more stable than it would appear if occupations were identical worldwide.

According to the country-specific measures, non-routine workers remain concentrated in HICs, while routine workers remain concentrated in LICs and MICs (Figure 4). In 2017, 53% of non-routine workers were either in the bottom or top HICs. However, the share of these countries in total employment in our sample was 24%. In 2000, the concentration of non-routine work in HICs was even stronger (60%). Although the share of LICs' and MICs' workers in global non-routine employment increased, they remained a minority. Using O*NET, i.e. assuming that high-skilled occupations such as managers and professionals in LICs and MICs involve as many non-routine tasks as in HICs, implies that by 2017 LICs and MICs became the leading suppliers of non-routine work (Figure 4).

At the same time, LICs and MICs have consistently been the dominant suppliers of routine work: according to the country-specific measures, their share of routine work has remained stable at almost 90%. According to the O*NET measures, the LICs and MICs' share in global pool routine work was noticeably lower (80%).

Figure 4: The distribution of routine and non-routine workers across country groups according to country-specific and O*NET measures, expressed as shares in global employment in 2000 and 2017 (in %).



Note: for each country, we use data from 2000, or the earliest available, and 2017, or the most recent available.
Source: authors' estimations based on PIAAC, STEP, CULS, O*NET, World Bank, UIBE-GVC, and ILOSTAT data.

Finally, both approaches to measuring occupational job content show that between 2000 and 2017, the global distribution of RTI has changed much more strongly below the global median than above it (Table S4 in Supplementary material). The country-specific RTI shows that the strongest de-routinisation occurred in jobs with moderately low routine intensity (around the 25th percentile). The O*NET RTI, however, suggests that the strongest de-routinisation occurred among the least routine intensive jobs – because the use of O*NET assumes that all occupations, including the highly skilled professional and managerial positions, are identical in all countries no matter their development level.

4 Conclusions

In this paper, we have developed a methodology to predict the country-specific task content of occupations in a wide range of countries at all development levels. We have combined these measures with employment data in 87 countries representing more than 2.5 billion workers, or 75% of global employment before the COVID-19 pandemic. We have shown that occupations in low- and middle-income countries are more routine intensive than in high-income countries, especially in high-skilled occupations (ISCO 1-3). These international differences in the RTI of occupations are mainly attributable to lower technology use in less-developed countries.

On this basis, we have established three new stylised facts about the evolution of occupational task content in countries at different stages of development, spanning the period 2000–17. First, the gross reallocation of labour away from routine work and toward non-routine work has occurred much slower in LICs and MICs than in HICs. Second, as a consequence, the gap between these country groups in work content, as measured with routine task intensity, has widened. Finally, HICs have remained the dominant supplier of non-routine work, while LICs and MICs have remained the dominant supplier of routine work.

These stylised facts derived using our country-specific estimates of occupational task content contrast with the findings obtained using conventional O*NET task measures that assume that the task content of occupations is identical around the world. Analysis based on the latter has suggested that average RTI has declined in all country groups at a similar pace. The assumption that occupations are identical has also led to an implausible conclusion that by 2017 LICs and MICs became the dominant global supplier of non-routine work.

These new insights deepen our understanding of how the nature of work has evolved globally since the early 2000s. The finding of divergent trends in the relative routine intensity of work in developed and developing countries has important policy implications. First, the cross-country differences in the work content are much larger than would be implied by the cross-country differences in the supply of skills. Investments in skills in developing and emerging countries are most likely necessary for the convergence of work content and productivity to high-income countries (World Bank, 2019). However, they are unlikely to be sufficient, considering that technology use and participation in global value chains are key factors behind differences in the task content of work. Second, assuming that occupations are identical worldwide may lead to the overestimation of the role of routine-replacing technological change, embodied in ICT and automation technologies, in explaining the evolution of wage inequality in low- or middle-income countries.

These insights also raise important questions. First, what factors prevent convergence in job tasks across countries, even within the same occupations? Second, whether the divergence portends future difficulty in achieving more global convergence in labour productivity and incomes? Future research might focus on studying whether policies aimed at increasing technology use or raising skill supply can be conducive to reducing within-occupation gaps in the content of work. It may also investigate the extent to which globalisation contributes to the global divergence in the de-routinisation of work. It may also apply the task approach to shed new light on the implications of so-called pre-mature deindustrialisation (Rodrik, 2016) for labour market outcomes. The task approach that accounts for cross-country differences can also help understand how the nature of work in developing and emerging countries is associated with new patterns of structural change that involve service-led growth (Atolia et al., 2020).

5 References

Acemoglu, D., Autor, D.H., 2011. Skills, Tasks and Technologies: Implications for Employment and Earnings, in: Card, D., Ashenfelter, O. (Eds.), Handbook of Labor Economics. Elsevier, pp. 1043–1171. https://doi.org/10.1016/S0169-7218(11)02410-5

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

Arntz, M., Gregory, T., Zierahn, U., 2017. Revisiting the risk of automation. Economics Letters 159, 157–160. https://doi.org/10.1016/j.econlet.2017.07.001

Atolia, M., Loungani, P., Marquis, M., Papageorgiou, C., 2020. Rethinking development policy: What remains of structural transformation? World Development 128, 104834. https://doi.org/10.1016/j.worlddev.2019.104834

Autor, D.H., 2013. The "task approach" to labor markets: an overview. J Labour Market Res 46, 185–199. https://doi.org/10.1007/s12651-013-0128-z

Autor, D.H., Dorn, D., 2013. The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. American Economic Review 103, 1553–1597. https://doi.org/10.1257/aer.103.5.1553

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

Autor, D.H., Levy, F., Murnane, R.J., 2003. The Skill Content of Recent Technological Change: An Empirical Exploration. Q J Econ 118, 1279–1333. https://doi.org/10.1162/003355303322552801

Caunedo, J., Keller, E., Shin, Y., 2021. Technology and the Task Content of Jobs across the Development Spectrum (No. w28681). National Bureau of Economic Research. https://doi.org/10.3386/w28681

de la Rica, S., Gortazar, L., Lewandowski, P., 2020. Job Tasks and Wages in Developed Countries: Evidence from PIAAC. Labour Economics 65, 101845. https://doi.org/10.1016/j.labeco.2020.101845

Delera, M., Pietrobelli, C., Calza, E., Lavopa, A., 2022. Does value chain participation facilitate the adoption of Industry 4.0 technologies in developing countries? World Development 152, 105788. https://doi.org/10.1016/j.worlddev.2021.105788

Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? Journal of Public Economics 189, 104235. https://doi.org/10.1016/j.jpubeco.2020.104235

Eden, M., Gaggl, P., 2020. Do Poor Countries Really Need More IT? World Bank Econ Rev 34, 48–62. https://doi.org/10.1093/wber/lhy022

Firpo, S., Fortin, N.M., Lemieux, T., 2011. Occupational Tasks and Changes in the Wage Structure (No. 5542), IZA Discussion Papers. Institute of Labor Economics (IZA).

Fonseca, T., Lima, F., Pereira, S.C., 2018. Job polarization, technological change and routinization: Evidence for Portugal. Labour Economics 51, 317–339. https://doi.org/10.1016/j.labeco.2018.02.003

Goos, M., Manning, A., Salomons, A., 2014. Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. American Economic Review 104, 2509–2526. https://doi.org/10.1257/aer.104.8.2509

Grossman, G.M., Rossi-Hansberg, E., 2008. Trading Tasks: A Simple Theory of Offshoring. American Economic Review 98, 1978–1997. https://doi.org/10.1257/aer.98.5.1978

Hardy, W., Keister, R., Lewandowski, P., 2018. Educational upgrading, structural change and the task composition of jobs in Europe. Economics of Transition and Institutional Change 26, 201–231. https://doi.org/10.1111/ecot.12145

Hsieh, C.-T., Klenow, P.J., 2010. Development Accounting. American Economic Journal: Macroeconomics 2, 207–223. https://doi.org/10.1257/mac.2.1.207

Lewandowski, P., Park, A., Hardy, W., Du, Y., Wu, S., 2022. Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work Using Survey Data. The World Bank Economic Review lhac005. https://doi.org/10.1093/wber/lhac005

Lo Bello, S., Sanchez Puerta, M.L., Winkler, H., 2019. From Ghana to America: The Skill Content of Jobs and Economic Development (No. 12259), IZA Discussion Papers. Institute of Labor Economics (IZA).

Marcolin, L., Miroudot, S., Squicciarini, M., 2019. To be (routine) or not to be (routine), that is the question: a cross-country task-based answer. Industrial and Corporate Change 28, 477–501. https://doi.org/10.1093/icc/dty020

Morduch, J., Sicular, T., 2002. Rethinking Inequality Decomposition, with Evidence from Rural China. The Economic Journal 112, 93–106. https://doi.org/10.1111/1468-0297.0j674

Niebel, T., 2018. ICT and economic growth – Comparing developing, emerging and developed countries. World Development 104, 197–211. https://doi.org/10.1016/j.worlddev.2017.11.024

Reijnders, L.S.M., de Vries, G.J., 2018. Technology, offshoring and the rise of non-routine jobs. Journal of Development Economics 135, 412–432. https://doi.org/10.1016/j.jdeveco.2018.08.009

Rodrik, D., 2016. Premature deindustrialization. J Econ Growth 21, 1–33. https://doi.org/10.1007/s10887-015-9122-3

Spitz-Oener, A., 2006. Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure. Journal of Labor Economics 24, 235–270. https://doi.org/10.1086/499972

World Bank, 2019. World Development Report 2019: The Changing Nature of Work. World Bank, Washington, DC.

6 Supplementary material

Table S1: Survey task items from PIAAC selected to calculate task content measures consistent with O*NET occupation task measures

Task content	Non-routine cognitive analytical	Non-routine cognitive interpersonal	Routine cognitive	Manual
Task items	Solving problems Reading news (at least once a month) Reading professional journals (at least once a month) Programming (any frequency)	Supervising others Making speeches or giving presentations (any frequency)	Changing order of tasks – reversed (not able) Filling out forms (at least once a month) Making speeches or giving presentations – reversed (never)	Physical tasks

Notes: the cut-offs for the 'yes' dummy are in parentheses. See Lewandowski et al. (2022) for more detail on the full wording of questions, the definitions of cut-offs, and the criteria for selecting task items.
Source: authors' illustration based on Lewandowski et al. (2022).

We also define a composite measure of routine task intensity (RTI), which increases with the importance of routine content of work, and decreases with the importance of non-routine content of work, using the formula:

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

where r_{cog}, $nr_{analytical}$ and $nr_{personal}$ are routine cognitive, non-routine cognitive analytical, and non-routine cognitive personal task levels, respectively.[9]

[9] For each task, the lowest score in the sample is added to the scores of all individuals, plus 0.1, to avoid non-positive values in the logarithm.

Table S2: Allocation of countries to income groups

Low- and Lower Middle-Income Countries	Upper Middle-Income Countries	Bottom High-Income Countries	Top High-Income Countries
	Covered by survey data		
Armenia	China	Chile	Austria
Bolivia	Ecuador	Czechia	Belgium
Cambodia	Kazakhstan	Cyprus*	Canada
Colombia*	Mexico	Estonia	Denmark
Georgia	Peru	Greece	Estonia
Ghana	Romania	Hungary	Finland
Indonesia	Turkey	Italy	France
Kenya		Lithuania	Germany
Laos		Poland	Ireland
Macedonia*		Russia	Israel
		Slovenia	Japan
		South Korea	Netherlands
		Spain	New Zealand
			Norway
			Singapore
			Sweden
			United Kingdom
			United States
	Covered by model-based predictions		
Bangladesh	Albania	Croatia	Australia
Egypt, Arab Rep.	Argentina	Latvia	Hong Kong SAR, China
El Salvador	Azerbaijan	Portugal	Luxembourg
Guatemala	Belarus	Slovakia	Switzerland
Honduras	Botswana	Uruguay	
India	Bulgaria		
Kyrgyz Republic	Brazil		
Mongolia	Dominican Republic		
Morocco	Iran, Islamic Rep.		
Nigeria	Jamaica		
Pakistan	Malaysia		
Paraguay	Mauritius		
Philippines	Namibia		
Sri Lanka	South Africa		
Vietnam	Thailand		
Zambia	Tunisia		
	Venezuela		
	Share in total employment of countries in a given group (in %)		
62	85	98	93

Notes: the allocation of countries to low- and lower middle-, upper middle-, and high-income groups follows the World Bank Analytical Classification. The additional split of high-income countries to the bottom and top subgroups follows Lewandowski et al. (2022). Data from countries marked with * are used only in regressions shown in Table 1 and Figure 1, as the data on occupational structure in these countries between 2000-2017 are not available for them.

Source: authors' elaboration based on World Bank data.

Table S3: Specification of regression model and model fit measures based on the leave-one-out cross-validation procedure at the 1-digit ISCO level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln (GDP per capita)	x	x	x	x	x	x	x
FVA (%)				x	x	x	x
FVA share x Ln (GDP per capita)				x	x	x	x
Internet use (%)	x		x		x		x
Average years of schooling		x	x			x	x
ISCO 1							
RMSE	0.239	**0.226**	0.230	0.236	0.242	0.233	0.238
MAE	0.193	**0.179**	0.186	0.189	0.194	0.186	0.191
Pseudo-R2	0.308	**0.383**	0.363	0.339	0.309	0.361	0.342
ISCO 2							
RMSE	0.264	0.240	**0.236**	0.267	0.276	0.256	0.250
MAE	0.204	0.186	**0.182**	0.207	0.215	0.198	0.193
Pseudo-R2	0.069	0.212	**0.245**	0.082	0.048	0.155	0.195
ISCO 3							
RMSE	0.238	0.222	**0.214**	0.243	0.247	0.233	0.224
MAE	0.182	0.169	**0.171**	0.184	0.190	0.174	0.180
Pseudo-R2	0.020	0.124	**0.189**	0.020	0.009	0.095	0.162
ISCO 4							
RMSE	0.231	0.225	**0.210**	0.236	0.237	0.228	0.215
MAE	0.179	0.177	**0.161**	0.186	0.185	0.185	0.167
Pseudo-R2	0.003	0.038	**0.160**	0.000	0.000	0.042	0.149
ISCO 5							
RMSE	0.241	0.226	**0.224**	0.239	0.244	0.234	0.234
MAE	0.187	0.176	**0.175**	0.186	0.191	0.188	0.191
Pseudo-R2	0.076	0.178	**0.195**	0.114	0.086	0.151	0.164
ISCO 6							
RMSE	**0.288**	0.290	0.298	0.293	0.301	0.301	0.313
MAE	**0.221**	0.223	0.228	0.233	0.234	0.237	0.242
Pseudo-R2	**0.337**	0.330	0.299	0.318	0.294	0.292	0.254
ISCO 7							
RMSE	0.254	0.235	0.235	0.252	0.259	0.239	**0.240**
MAE	0.203	0.187	0.181	0.194	0.199	0.187	**0.185**
Pseudo-R2	0.010	0.061	0.079	0.017	0.004	0.097	**0.104**
ISCO 8							
RMSE	0.280	0.272	0.270	0.267	0.276	0.259	**0.257**
MAE	0.234	0.228	0.218	0.222	0.227	0.215	**0.207**
Pseudo-R2	0.105	0.022	0.006	0.025	0.008	0.080	**0.111**
ISCO 9							
RMSE	0.213	0.225	0.208	0.209	0.199	0.214	**0.194**
MAE	0.169	0.179	0.164	0.170	0.158	0.175	**0.154**
Pseudo-R2	0.022	0.229	0.069	0.062	0.153	0.037	**0.202**

Notes: RMSE, MAE and pseudo-R2 calculated with the leave-one-out cross-validation method. Bold numbers indicate the models we chose for the predictions.
Source: authors' estimations based on PIAAC, STEP, CULS, World Bank, and RIGVC UIBE (2016) data.

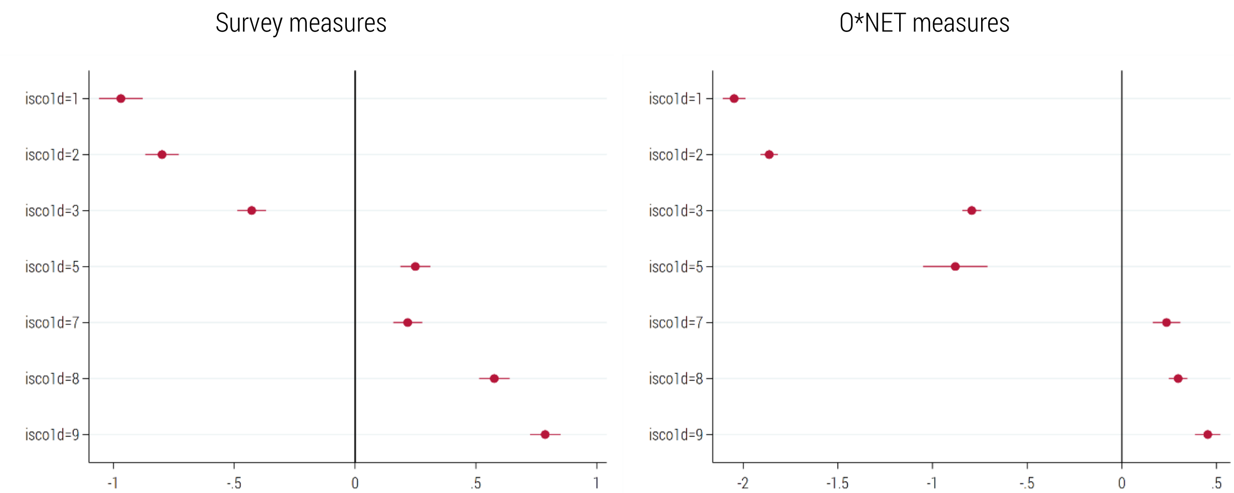
Table S4: Percentiles of the global distribution of RTI

	p10	p25	p50	p75	p90
Country-specific task content (constant over time at the occupational level)					
2000	-0.20	0.47	0.73	0.92	1.08
2017	-0.33	0.32	0.73	0.92	1.08
Country-specific task content (time-varying at the occupational level)					
2000	0.09	0.65	0.98	1.20	1.28
2017	-0.33	0.32	0.73	0.92	1.08
O*NET task content (constant over time at the occupational level)					
2000	-0.70	0.16	0.30	0.74	1.59
2017	-0.90	0.10	0.30	0.74	1.57
O*NET task content (time-varying at the occupational level)					
2000	-0.70	0.16	0.30	0.74	1.59
2017	-1.20	-0.03	0.31	0.45	0.89

Note: for each country, we use data from 2000, or the earliest available, and 2017, or the most recent available.

Source: authors' estimations based on PIAAC, STEP, CULS, O*NET, World Bank, UIBE-GVC, and ILOSTAT data.

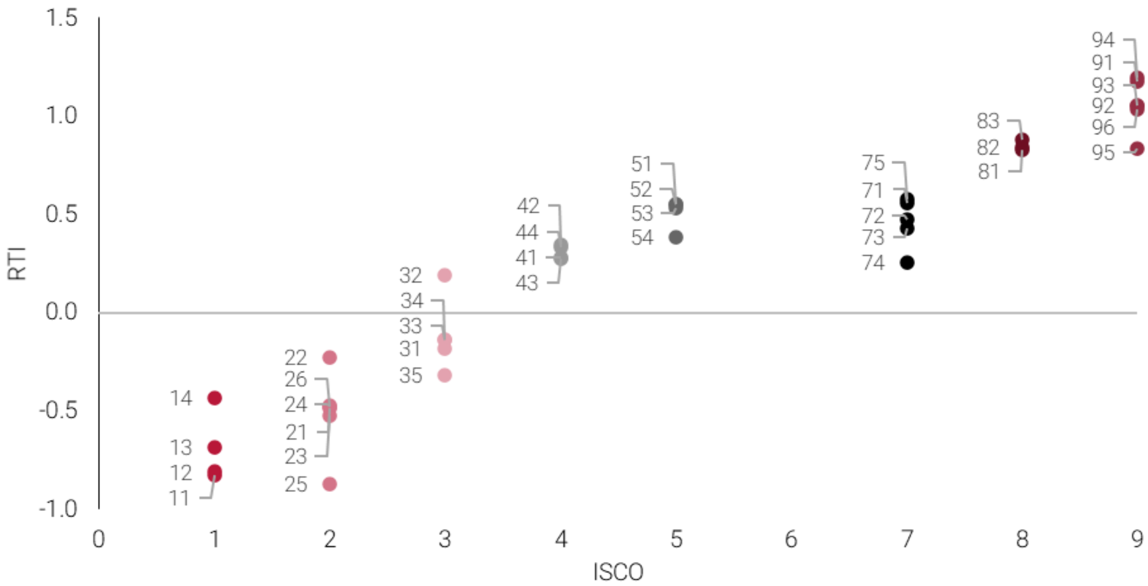
Figure S1. The differences in RTI across 1-digit ISCO occupations according to survey- and O*NET measures.



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.

Source: Lewandowski et al. (2022).

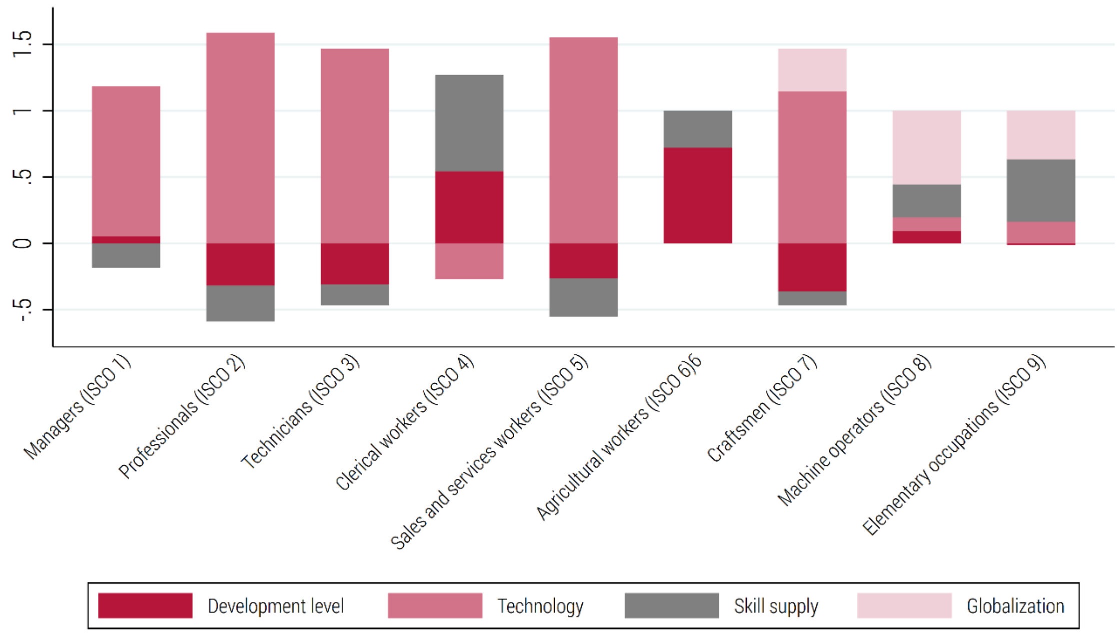
Figure S2: Estimated differences in RTI across 2-digit ISCO occupations



Note: coefficients pertaining to occupation fixed effects (2-digit ISCO) estimated in a country-level model on RTI against occupation fixed effects and country variables presented in Table 1.

Source: authors' estimations based on PIAAC, STEP, CULS, World Bank, and RIGVC UIBE (2016) data.

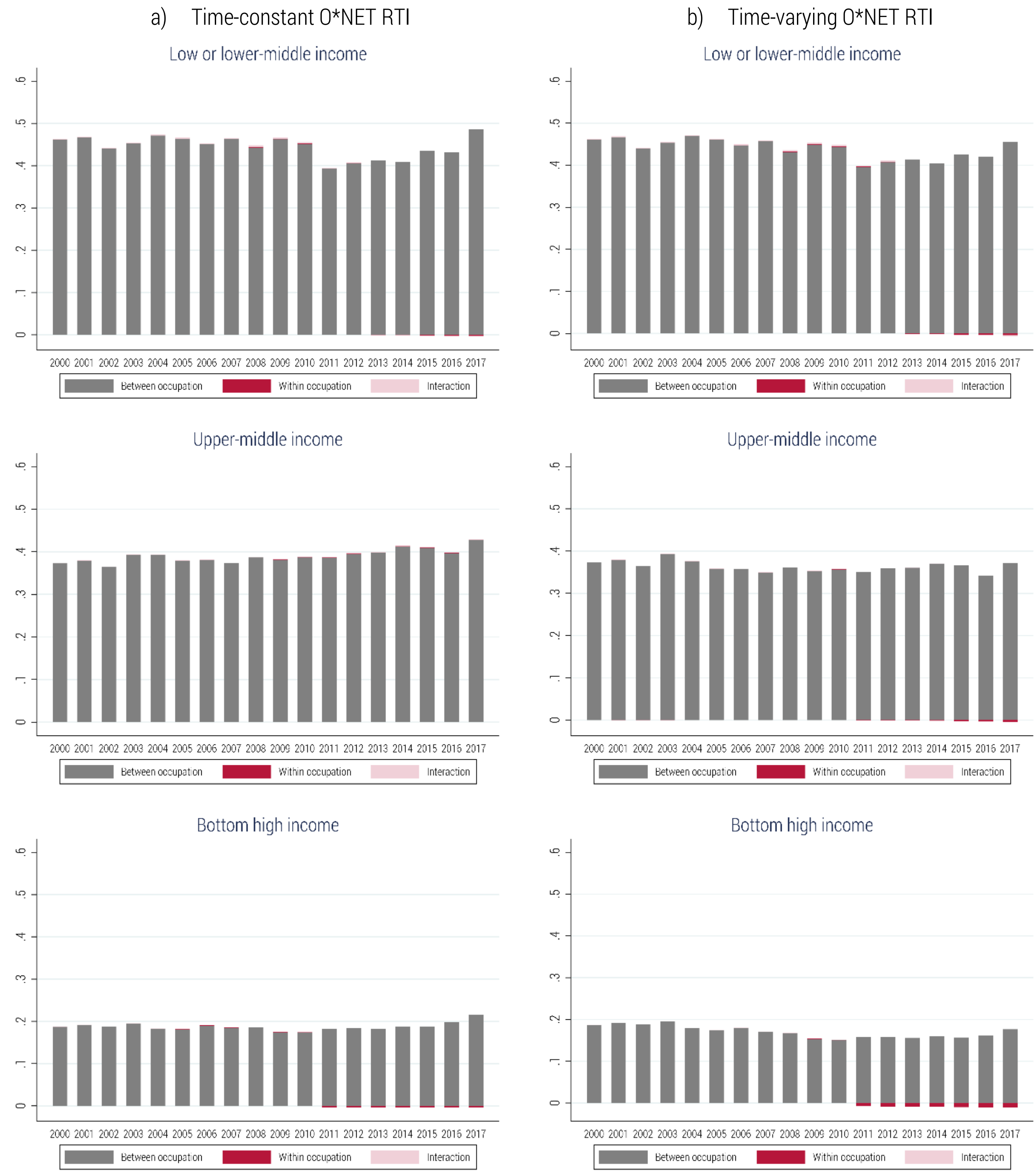
Figure S3: Decomposition of cross-country variance of predicted routine task intensity (share of total variance)



Note: the contributions of particular factors to RTI variance, calculated using the covariance-based decomposition proposed by Morduch and Sicular (2002) applied to the models presented in Table 1.

Source: authors' estimations based on PIAAC, STEP, CULS, World Bank, and RIGVC UIBE (2016) data.

Figure S4: The shift-share decomposition of differences in the average routine task intensity between particular country groups and the top-HICs, according to the time-constant and time-variant O*NET RTI.



Source: authors' estimations based on PIAAC, STEP, CULS, O*NET, World Bank, and RIGVC UIBE (2016) data.

instytut
badań
strukturalnych

www.ibs.org.pl