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ABSTRACT

This study introduces a methodology to estimate the economy-specific task content of occupations across economies at different income levels. Combining these with employment data in 87 economies, the results show that occupations in low- and middle-income economies are more routine-intensive than in high-income economies, which is attributed to lower technology use in less-developed economies. Non-routine work continues to dominate in high-income economies while routine work remains in low-income and middle-income economies. These findings, using economy-specific estimates of occupational task content, contradict the assumption based on conventional measures that task content of occupations is converging globally. The finding of divergent trends in the relative routine intensity of work in developed and developing economies has important policy implications. Investment in skills, technology use, and participation in global value chains are key factors for work content and productivity to converge with those in high-income economies. The assumption that occupations are converging globally may also overestimate the role of routine-replacing technological change in explaining wage inequality in low- or middle-income economies.

Keywords: occupational task content, routine-task intensity, skills, jobs divergence, wage inequality

JEL codes: J24, J31, O14, O15

1. Introduction

The shift from routine-intensive jobs to non-routine work has been a critical feature of 21st-century labor markets. It has been driven by technological progress and globalization and has contributed to rising wage polarization in many economies (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 economies, the relative importance of demand and supply factors, and the consequences of these processes for wage inequality (Acemoglu and Autor 2011, Firpo et al. 2011, Autor 2013).

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 economies may perform different tasks than workers in comparable occupations in high-income economies. With globalization, poorer economies may specialize in routine tasks, and richer economies may specialize 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 economies have not systematically collected information on the task content of occupations. Hence, the majority of past studies use the United States (US) Occupation Information Network (O*NET) occupational data to analyze 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 differences in technology, economic structures, and labor force skills across economies (Hsieh and Klenow 2010, Niebel 2018, Eden and Gaggl 2020). 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 the differences of sector and economy in technology use, workers' skills, and globalization (measured by foreign value-added [FVA] share) are all related to differences across economies 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 economies are more routine intensive than in high-income economies. Even among developed economies, 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 economies, 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-routinization and wage polarization have occurred in low- and middle-income economies to an extent comparable with developed economies.

In this study, 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 economy-specific task content by occupational group in many economies where no task survey data are yet available. This enables a more accurate picture of work in low- and middle-income economies than assuming that occupational tasks are identical worldwide. Our second contribution is to establish stylized 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 occupational task measures with employment structure data for 87 economies from 2000 to 2017. Our sample includes 25 low- or lower middle-income economies, 24 upper-middle-income economies, and 38 high-income economies. In 2017, the economies in our sample jointly accounted for over 2.5 billion workers, equivalent to approximately 75% of global employment. We analyze the changing distribution of tasks over time, both by holding occupation routine-task intensity (RTI) fixed over time and by allowing the task content of occupations to evolve. Using economy-specific task measures, we show that in economies with lower economic and technological development levels, workers tend to perform more routine-intensive tasks compared to those in more advanced economies, even within the same occupations. These gaps across economies within-occupation are sizeable and are mainly attributable to differences in technology.

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

Second, we find that the gap in average RTI between low- and middle-income economies, on the one hand, and high-income economies, 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 economies has not converged to that in high-income economies, despite their increasing integration into global value chains and rising technology levels. We attribute this pattern to between-occupation effects—poorer economies exhibit higher employment shares of routine-intensive occupations— and within-occupation effects—in poorer economies, 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 economies became the dominant supplier of non-routine work. In contrast, accounting for the differences across economies within-occupation in tasks reveals that high-income economies have remained the dominant provider of non-routine work, while routine work has remained concentrated in low- and middle-income economies. 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 economies.

The remainder of the study is structured as follows. Section 2 introduces the data and methodology. Section 3 presents stylized facts regarding the global evolution and distribution of task content of jobs. Section 4 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 globalization, particularly offshoring (Autor et al. 2003, Spitz-Oener 2006). Most previous research studying the evolution of the task content of jobs focuses on developed economies (Goos et al. 2014, Hardy et al. 2018) or middle-income economies (Arias et al. 2014, Reijnders and de Vries 2018). That research assumed that occupational task demands are identical across economies 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 economy-specific, worker-level job tasks (Lo Bello et al. 2019, de la Rica et al. 2020, Caunedo et al. 2021, and Lewandowski et al. 2022). In particular, Lewandowski et al. (2022) developed survey-based, harmonized 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. They also combined them into a composite measure of RTI, which increases with the importance of routine work content and decreases with the importance of non-routine content. Previous studies on high-income economies (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 RTI using worker-level data from three large-scale surveys available for 47 economies (Table 1):

- the Programme for the International Assessment of Adult Competencies (PIAAC) of the Organisation for Economic Co-operation and Development (OECD), covering high- or middle-income economies;
- the World Bank's Skills toward Employment and Productivity (STEP) surveys, conducted in low- and middle-income economies;
- 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.

Table 1: Allocation of Economies to Income Groups

Low- and lower middle-income	Upper middle-income	Bottom high-income	Top high-income
Covered by survey data			
Armenia	People's Republic of China	Chile	Austria
Bolivia	Ecuador	Czech Republic	Belgium
Cambodia[a]	Kazakhstan	Cyprus[a]	Canada
Georgia	Mexico	Estonia	Denmark
Ghana	Peru	Greece	Estonia
Kenya	Romania	Hungary	Finland
Lao People's Democratic Republic	Türkiye	Italy	Germany
Macedonia[a]		Lithuania	Ireland
		Poland	Israel
		Republic of Korea	Japan
		Russian Federation	Netherlands
		Slovenia	New Zealand
		Spain	Norway
			Singapore
			Sweden
			United Kingdom
			United States
Covered by model-based predictions			
Bangladesh	Albania	Croatia	Australia
Egypt	Argentina	Latvia	Hong Kong, China
El Salvador	Azerbaijan	Slovak Republic	Luxembourg
Guatemala	Belarus	Uruguay	Switzerland
Honduras	Botswana		
India	Bulgaria		
Kyrgyz Republic	Brazil		
Mongolia	Dominican Republic		
Morocco	Iran		
Nigeria	Jamaica		
Pakistan	Malaysia		
Paraguay	Mauritius		
Philippines	Namibia		
Sri Lanka	South Africa		
Viet Nam	Thailand		
Zambia	Tunisia		
	Venezuela		
Share in total employment of economies in a given group (%)			
62	85	98	93

[a] Data from these economies are used only in regressions shown in Table 2 and Figure 1, as the data on occupational structure in these economies during 2000–2017 are not available for them.

Notes: The allocation of economies to low- and lower middle-, upper middle-, and high-income groups follows the World Bank Analytical Classification. The additional split of high-income economies to the bottom and top subgroups follows Lewandowski et al. (2022).

Source: Authors' elaboration based on World Bank data.

For each economy, 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 standardize 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 Lewandowski et al. (2022). They also show that managers (ISCO 1) and professionals (ISCO 2) are the least routine-intensive occupations, followed 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

[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 study, we adjusted the census weights (at the 1-digit level) to match the occupational structure in the ILOSTAT data for the US in 2000.

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 economies (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 economies.

2.2 Predicting the Economy-specific Task Content of Jobs

To predict the task content of occupations in economies 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 economy c to four key factors defined for each economy: (i) development level, measured by the gross domestic product (GDP) per capita (in purchasing power parity, natural logarithm); (ii) technology use (T), approximated by the number of internet users per 100 inhabitants; (iii) globalization (G), quantified by foreign value-added share of domestic output (FVA share); and (iv) supply of skills (S), measured by the average years of schooling. We add fixed effects, y_{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 economy'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 2011–2016 since most STEP/PIAAC/CULS survey data come from this period. We use globalization variables from 2011 as more recent data are not available.[2]

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-R^2.[3] We prioritize 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. Globalization 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 2.

Our regression results show that higher technology use is associated with lower RTI in all non-farming occupations (Table 2). 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 economies more specialized in global value chains (GVCs) perform more routine-intensive tasks, especially in less developed economies. We also

[2] The data on FVA share come from the University of International Business and Economics (Beijing) Global Value Chains (UIBE-GVC) database. Other data come from the World Development Indicators database by the World Bank.

[3] Estimation results of all specifications as well as models at the 2-digit ISCO level are available upon request.

find a negative relationship between development level and the RTI of agricultural workers (ISCO 6).

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

The predicted, economy-specific values of task content show substantial differences in RTI across economies for specific occupations, matching the patterns observed in the survey data (Lewandowski et al. 2022).[4] Work in particular occupations is generally more routine-intensive in less developed economies—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 economies perform less routine-intensive tasks than those in poorer economies. We attribute most of the variance in RTI across economies in these occupations to differences in technology, as better access to technology in the more-developed economies is associated with a lower routine intensity of tasks performed by workers.

[4] The predicted values are close to the survey results for most economies 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 economies.

Table 2: The Estimated Occupation-Specific Models of Correlates of Routine–Task Intensity

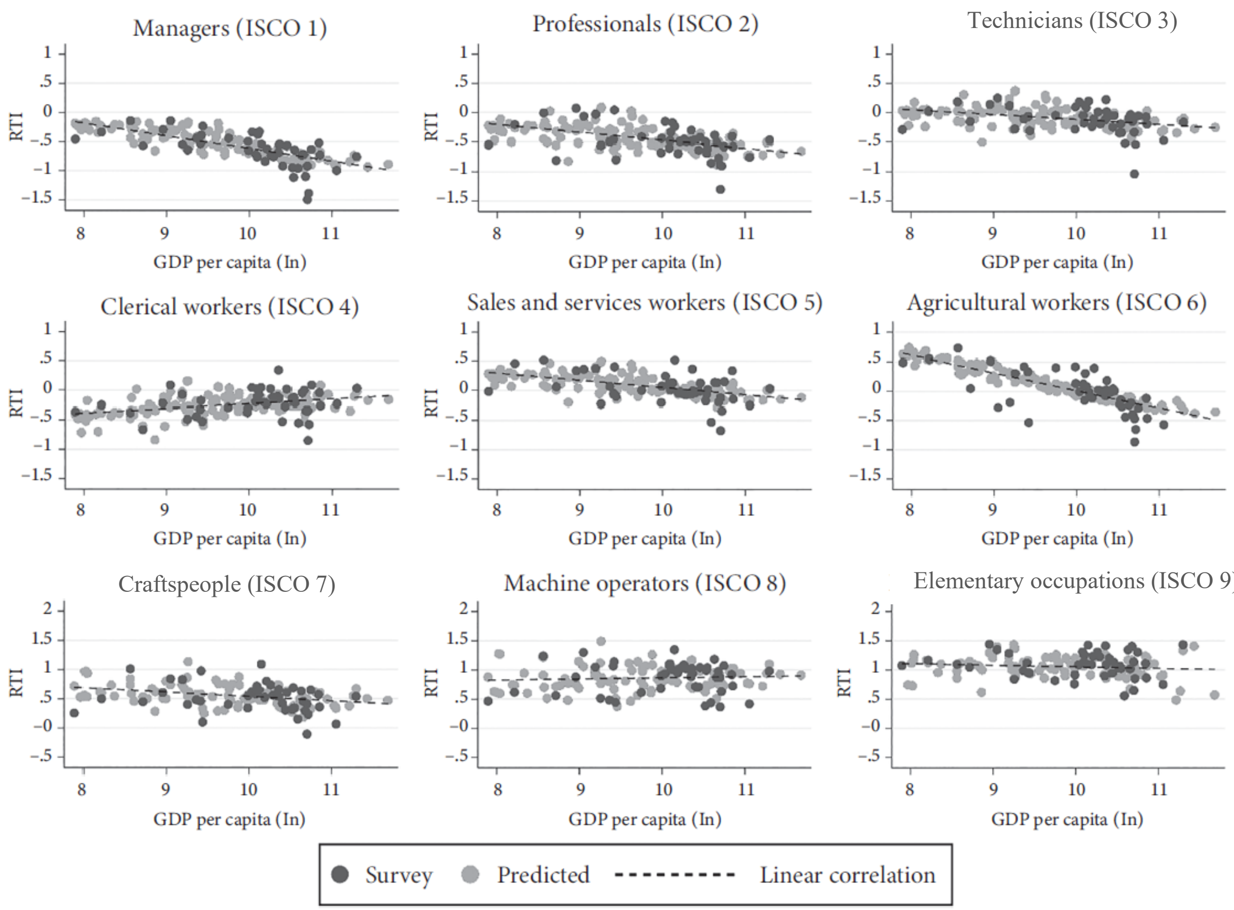
	Managers (ISCO 1)	Professionals (ISCO 2)	Technicians (ISCO 3)	Clerical workers (ISCO 4)	Sales and services workers (ISCO 5)	Agricultural workers (ISCO 6)	Craftspeople (ISCO 7)	Machine operators (ISCO 8)	Elementary occupation (ISCO 9)
GDP per capita (ln)	0.039	0.091	0.068	0.236***	0.105	−0.229***	0.266***	0.198**	−0.044
	(0.074)	(0.056)	(0.063)	(0.070)	(0.067)	(0.090)	(0.072)	(0.090)	(0.079)
FVA share (%)							1.276***	1.590***	0.621
							(0.359)	(0.457)	(0.395)
FVA share × GDP per capita (ln)							−0.604	−0.949	0.783
							(0.577)	(0.737)	(0.640)
Internet use (%)	−1.152***	−1.389***	−1.242***	−1.318***	−1.331***		−1.678***	−1.476***	−0.642*
	(0.309)	(0.236)	(0.264)	(0.294)	(0.282)		(0.304)	(0.370)	(0.332)
Average years of schooling	0.025	0.076***	0.073***	0.091***	0.064***	−0.035	0.064***	0.088***	0.075***
	(0.021)	(0.016)	(0.018)	(0.020)	(0.019)	(0.031)	(0.020)	(0.025)	(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 R^2	0.368	0.390	0.330	0.158	0.201	0.408	0.233	0.197	0.128

FVA = foreign value-added, GDP = gross domestic product, ISCO = International Standard Classification of Occupations.

Note: ***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.

Figure 1: Predicted Routine-Task Intensity Levels by 1-digit Occupations



GDP = gross domestic product, ISCO = International Standard Classification of Occupations, ln = natural logarithm, RTI = routine-task intensity.

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

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 economies. Among clerical workers (ISCO 4), there is no clear-cut relationship between the development level and RTI. However, clerical workers in the poorest economies in our sample perform less routine-intensive tasks, which may be associated with a lower supply of skills in these economies. Indeed, clerical workers are the only occupational group for which the differences in skill supply across economies make the largest contribution to international differences in RTI.

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 economies at a similar development level (Figure 1), related to differences in economies' participation in global value chains. Globalization plays the most crucial role for these occupations in predicting task differences across economies. Routine jobs are easier to offshore, so poorer economies may specialize in them (Grossman and Rossi-Hansberg 2008). Indeed, a higher FVA share in domestic production is associated with a higher RTI among less-developed economies and a lower RTI among more-developed economies. 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 specialization play a much smaller role than among plant and machine operators.

2.3 Investigating the Evolution of Task Content Over Time Across Income Groups

Having predicted the occupation-specific RTI in various economies, we investigate the evolution of task content over time. We merge the economy-specific and O*NET 2017 RTI values with ILOSTAT data on employment structures from 2000 to 2017. Our sample includes 87 economies (Table 1) comprising approximately 2.5 billion workers in 2015–2017, corresponding to 75% of global employment.[5]

Of the economies covered by the ILOSTAT data, we include those where data for all explanatory variables in equation (1) are available.[6] To avoid extrapolating beyond the range used to build the model, we omit nine economies with a GDP per capita below Kenya ($2,687 purchasing power parity [PPP], on average, between 2011 and 2016), the poorest economy 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 economies with no data available before 2005 or from 2014 on.

Based on the World Bank classifications in 2010–2011, we define four income groups (Table 1): low- or lower middle-income (25 economies), upper middle-income (24), bottom high-income (17), and top high-income (21). The economies in each income group remain fixed across years for comparability purposes.

We calculate the average RTI in a given economy and year as a weighted average of the economy-specific RTI across occupations, using occupation employment shares as weights.[7] For economies covered by the survey data, we use occupation-specific average RTIs calculated as described in Gradín (forthcoming, Section 2.1). For the

[5] Due to data availability, our sample covers a lower share of total employment in low- and lower middle-income economies (62%, Table 1) and in upper middle-income economies (85%) than in high-income economies (96%). As a result, our sample is likely to overstate the extent of non-routine work globally.

6 We omit seven oil exporting economies, and five economies classified as tax havens (according to Financial Secrecy Index for 2011).

[7] 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 economy. To convert all RTI measures to the ISCO-88 classification, we use the crosswalk prepared for the European Working Conditions Survey data.

remaining economies, we use values predicted in line with the framework presented in Gradín (forthcoming, Section 2.2). 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 ISCO 6 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 economy- and occupation-specific RTIs using averages of explanatory variables across 2001–2005, except for the globalization variable, which is available only for 2004.[8] For O*NET, we use the 2003 dataset. We then apply a weighted average. From 2000–2002, we use the RTI predicted for 2001–2005 (O*NET 2003); for any year t in 2003–2017, we assign a weight $\frac{2017-t}{14}$ to the RTI predicted for 2001–2005 (O*NET 2003), and a weight $\frac{t-2003}{14}$ to the RTI predicted for 2011–2016 (O*NET 2017). As these time-variant estimates require assuming that the estimated models across economies (2) hold over time, we treat these as complementary to our baseline results.

We apply a shift-share decomposition to analyze to what extent the differences in average RTI values across economies can be attributed to differences in occupational structures, and to what extent to differences in occupation-specific RTI values. We

[8] 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 economy 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 economies 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 information and communication technologies. Nevertheless, our estimates of changes in occupational RTI across economies can be interpreted as lower-bound estimates.

decompose the difference between the average RTI in a given income group c, RTI_c, and the average in top high-income economies, RTI, into the between-occupation, BO_c, within-occupation, WO_c, and interaction, INT_c, terms. Formally:

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

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

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

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

whereby:

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

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 economies and occupations in our sample) at the end of our study period.[9] 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

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

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 income groups in total, routine, and non-routine employment in each period. We conduct this analysis using our economy-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 economies 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 (Autor et al. 2003, Acemoglu and Autor 2011). For comparability, we also focus on the point estimates of economy-specific RTI.

3. Results

3.1 The De-routinization of Jobs has Occurred Much More Slowly in Low-Income and Middle-Income Economies than in High-Income Economies

Since 2000, occupational structures around the world have evolved away from routine-intensive occupations and towards non-routine-intensive occupations. However, accounting for differences in the task content of occupations across economies shows that the de-routinization occurred more slowly than would have been apparent under the assumption that occupations are identical worldwide. In particular, de-routinization in low-income economies and middle-income economies occurred visibly more slowly than in high-income economies.

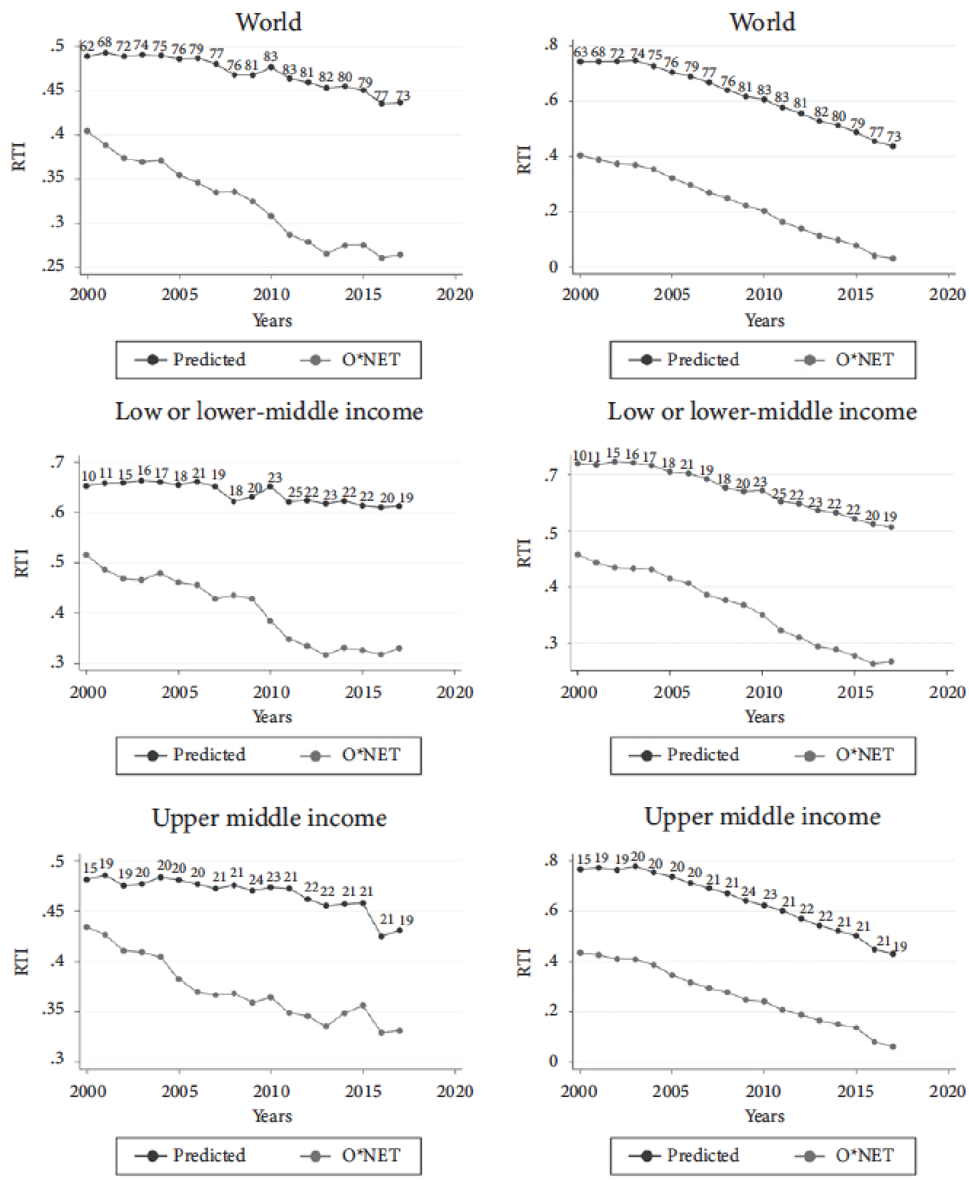
Using the economy-specific measures and holding the occupational RTI values constant over time (to focus on changes in task content attributable to shifts in occupational structures), we find evidence of diverging trends (Figure 2a). In particular, in the group of low-income or lower middle-income economies, the average RTI has barely declined, while in the high-income economies, it has declined steeply. When we allow for changes in the task content of occupations over time, the decline in RTI between 2000–2017 appears stronger. However, using the economy-specific task measures, the decrease in RTI in low-income or lower middle-income economies is still much slower than for other income groups (Figure 2b).

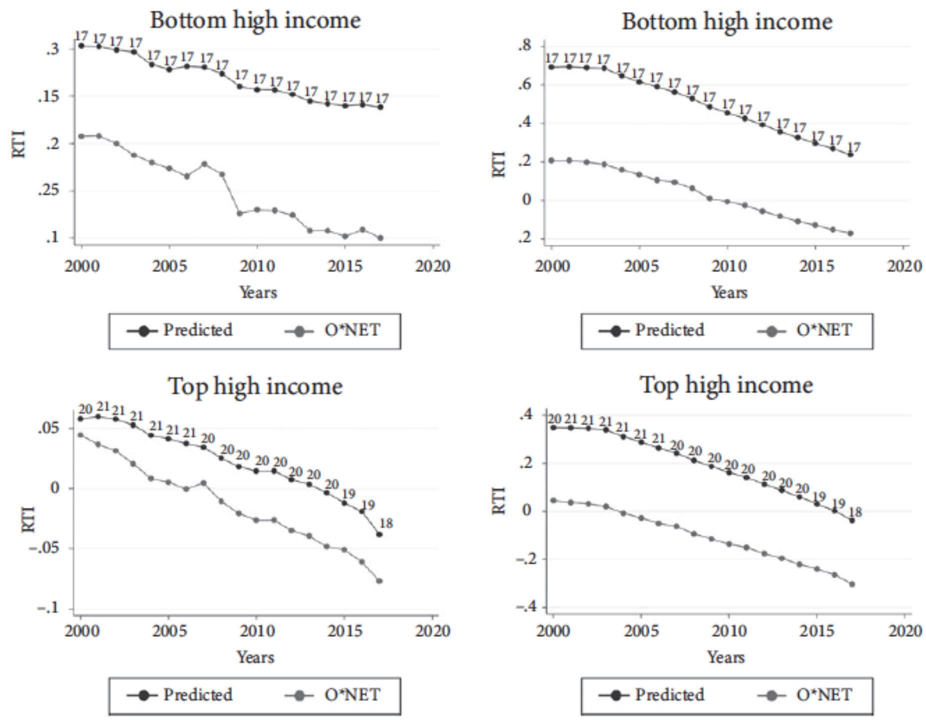
In contrast, if one assumes that occupations are identical around the world and uses the O*NET-based task measures, the routine intensity of work appears much lower on average (0.27 in 2017 compared to 0.43 using economy-specific task measures). Moreover, the trends in labor reallocation away from routine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

Figure 2: The Evolution of Average Routine-Task Intensity According to Economy-specific and O*NET Measures

a) Constant occupation task content

b) Changing occupation task content





O*NET = Occupation Information Network, RTI = routine-task intensity.

Note: 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.

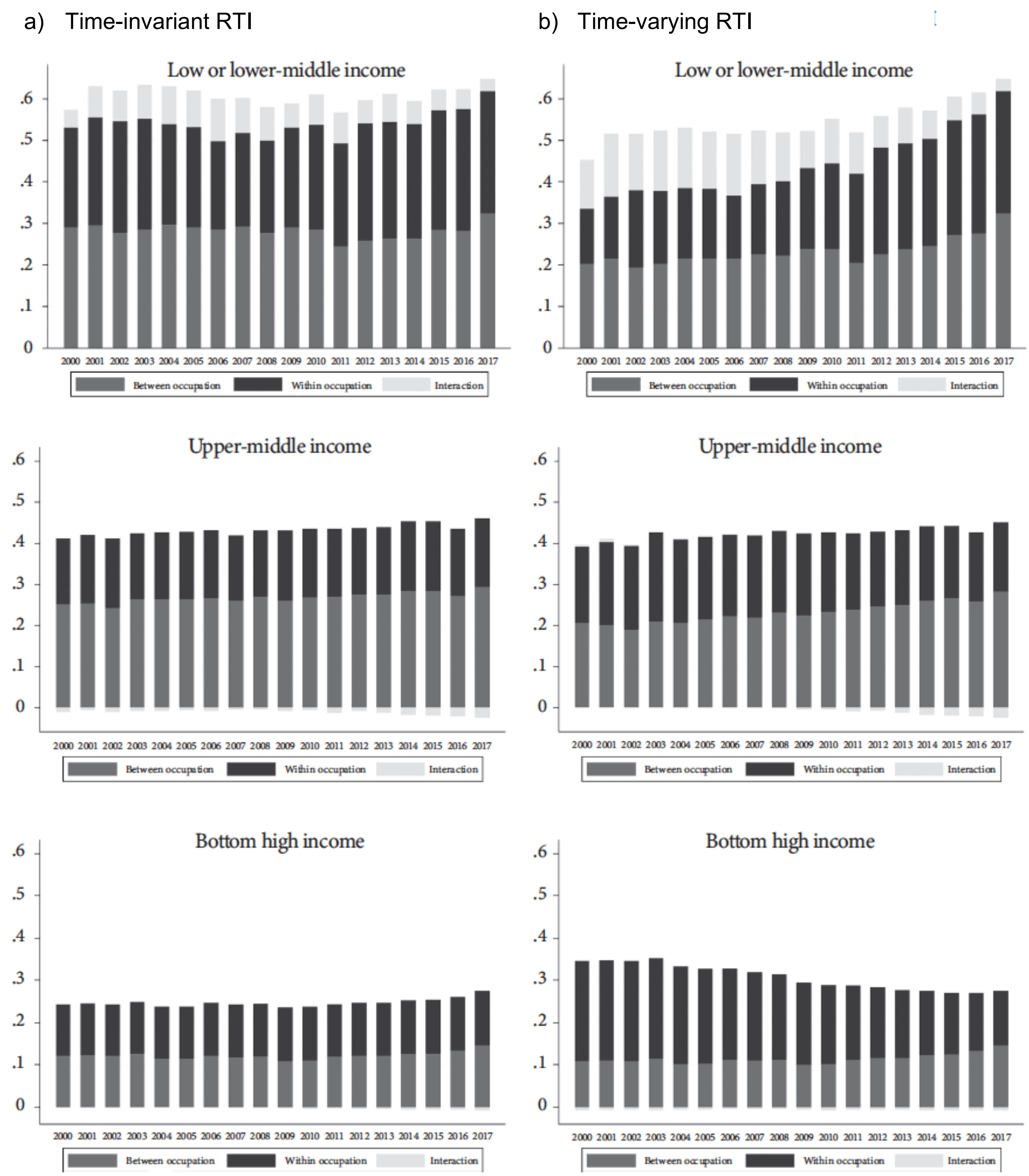
3.2 Gaps in the Routine-Task Intensity of Jobs between Low-Income and Middle-Income Economies and High-Income Economies have Increased Over Time

The unequal trends in the de-routinization of jobs have created widening gaps in the task content of work in low-income and middle-income economies as compared to high-income economies.

According to the economy-specific measures (and holding the occupational RTI values constant over time), the differences between top high-income economies and less-developed economies have increased by about 10% of the initial gap in both low-income or lower middle-income economies and upper middle-income economies (Figure 3a). But in bottom high-income economies, the distance to the top high-income economies has barely changed. The shift-share decomposition analysis shows that a substantial share of these gaps (on average, 40% for both low-income or lower middle-income economies and upper middle-income economies) is attributable to differences in the economy-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 economies. For low-income or lower middle-income economies, part of the gap in RTI with the top high-income economies (11% on average) is attributable to the interaction effect, which means that occupations that are more routine intensive than in top high-income economies also have higher employment shares. This finding aligns with theories of trade and offshoring that imply that poorer economies with a less-productive labor force might specialize 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 low-income or lower middle-income economies and top high-income economies widens even more (by 40% of the initial gap, Figure 3b). The within-occupation effect has contributed substantially to this widening, suggesting that de-routinization within identical occupations has been slower in poorer economies. In bottom high-income economies, the gaps to top high-income economies have narrowed as occupational RTI in these economies has converged (Figure 3b). In contrast, assuming that occupations are identical worldwide leads to the conclusion that the gaps in RTI between income groups have remained virtually unchanged as the gaps are entirely due to differences in occupational structures.

Figure 3: The Shift-Share Decomposition of Differences in the Average Routine-Task Intensity between Particular Income Groups and the Top High-Income Economies, According to the Time-invariant and Time-varying Economy-specific Routine-Task Intensity



RTI = routine-task intensity.

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

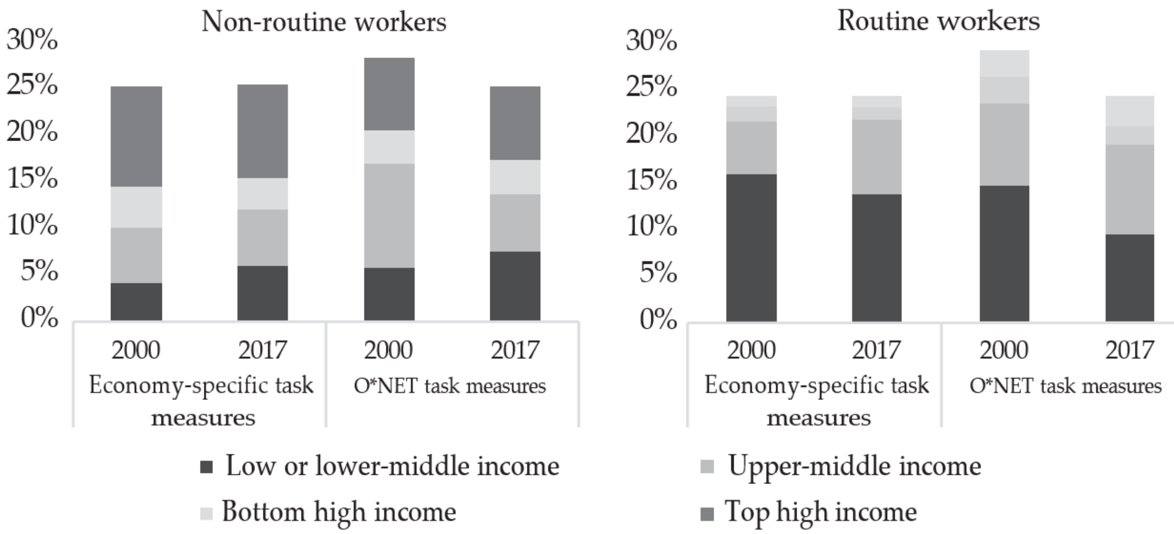
3.3 High-Income Economies Remain the Dominant Suppliers of Non-routine Work, while Low-Income and Middle-Income Economies Remain the Dominant Suppliers of Routine Work

Accounting for differences in the task content of occupations across economies, 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 economy-specific measures, non-routine workers remain concentrated in high-income economies, while routine workers remain concentrated in low-income economies and middle-income economies (Figure 4). In 2017, 53% of non-routine workers were either in the bottom or top high-income economies. However, the share of these countries in total employment in our sample was 24%. In 2000, the concentration of non-routine work in high-income economies was even stronger (60%). Although the share of low-income economies' and middle-income economies' workers in global non-routine employment increased, they remained a minority. Using O*NET, that is, assuming that high-skilled occupations such as managers and professionals in low-income economies and middle-income economies involve as many non-routine tasks as in high-income economies, implies that by 2017, low-income economies and middle-income economies became the leading suppliers of non-routine work (Figure 4).

At the same time, low-income economies and middle-income economies have consistently been the dominant suppliers of routine work: according to the economy-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 Income Groups According to Economy-Specific and O*NET Measures, Expressed as Shares in Global Employment in 2000 and 2017



O*NET = Occupation Information Network.

Note: For each economy, 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.

4. Conclusions

In this study, we have developed a methodology to predict the economy-specific task content of occupations in a wide range of economies at all development levels. We have combined these measures with employment data in 87 economies representing more than 2.5 billion workers, or 75% of global employment before the coronavirus disease (COVID-19) pandemic. We have shown that occupations in low- and middle-income economies are more routine-intensive than in high-income economies, 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 economies.

On this basis, we have established three new stylized facts about the evolution of occupational task content in countries at different stages of development, spanning the period 2000–2017. First, the gross reallocation of labor away from routine work and toward non-routine work has occurred much more slowly in low-income economies and middle-income economies than in high-income economies. Second, as a consequence, the gap between these income groups in work content, as measured with RTI, has widened. Finally, high-income economies have remained the dominant supplier of non-routine work, while low-income economies and middle-income economies have remained the dominant supplier of routine work.

These stylized facts derived using our economy-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 income groups at a similar pace. The assumption that occupations are identical has also led to an implausible conclusion that by 2017, low-income economies and middle-income economies 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 economies has important policy implications. First, the differences in the content of work across economies are much larger than would be implied by differences in the supply of skills. Investment in skills in developing and emerging economies are most likely necessary for the convergence of work content and productivity to high-income economies (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 an overestimation of the role of routine-replacing technological change, embodied in information and communication and automation technologies, in explaining the evolution of wage inequality in low- or middle-income economies.

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Global Divergence in the De-routinization of Jobs

This study introduces a methodology to estimate the economy-specific task content of occupations across economies at different income levels. The results show that occupations in low- and middle-income economies are more routine-intensive than in high-income economies and the gap continues to widen. Investment in skills, technology use, and participation in global value chains are key factors for work content and productivity to converge with those in high-income economies.

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