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Technology and the Task Content of Jobs across the Development Spectrum*

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Abstract

The tasks workers perform on the job are informative about the direction and the impact of technological change. We harmonize occupational task content measures between two worker-level surveys, which separately cover developing and developed countries. Developing countries use routine-cognitive tasks and routine-manual tasks more intensively than developed countries, but less intensively use non-routine analytical tasks and non-routine interpersonal tasks. This is partly because developing countries have more workers in occupations with high routine contents and fewer workers in occupations with high non-routine contents. More important, a given occupation has more routine contents and less non-routine contents in developing countries than in developed countries. Since 2006, occupations with high non-routine contents gained employment relative to those with high routine contents in most countries, regardless of their income level or initial task intensity, indicating the global reaches of the technological change that reduces the demand for occupations with high routine contents.

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1 Introduction

Most developed countries underwent a similar arc of structural change, or the reallocation of economic activity from agriculture to manufacturing and then to services. There is some evidence that this pattern may have shifted for developing countries—for example, Rodrik (2016) documents a pattern of "premature de-industrialization" among many developing countries. One possible explanation is that the availability and adoption of new technology, automation in particular, may reduce the demand for low-skill manufacturing jobs that used to be gateways for workers leaving agriculture (Hallward-Driemeier and Nayyar, 2017).

The vast literature on the evolution of labor markets in developed countries has shown that the tasks workers perform on the job and the allocation of workers across occupations are crucial for understanding the direction and the impact of technological change—see Acemoglu and Autor (2011) for a review. However, not much is known about developing countries. There is little data on worker tasks in developing countries, and the little that is available is not directly comparable to the task data in developed countries. In this paper, we fill this gap. This is the first step towards characterizing how the technology being operated and also workers' exposure to technological change vary across the development spectrum.

We overcome the data challenge by harmonizing task content measures between two worker-level surveys, one for developing countries (STEP from the World Bank) and the other mostly for developed countries (PIAAC from OECD), utilizing the questions that are exactly the same in both surveys, which are about computer use at work.[1] Combining the harmonized country-specific task content measures by occupation and the occupational employment data, we construct an index of country-level task intensity for five task categories: routine cognitive, routine manual, non-routine analytical, non-routine interpersonal, and non-routine manual. We only consider non-agricultural workers in all countries, because the developing country survey we use focuses on urban workers, and also because the broader literature on tasks and occupations excludes agriculture (Autor and Dorn, 2013). As a result, our findings are not driven by the difference in the importance of agriculture between developing and developed countries.

We document systematic differences in task intensity across countries. Developing countries use routine-cognitive tasks and routine-manual tasks more intensively but use non-routine analytical tasks and non-routine interpersonal tasks less intensively than developed countries. This result is partly driven by the occupational employment difference: develop-

[1] Ours is not the only attempt at harmonizing STEP and PIAAC. In our discussion of the literature below, we explain the relative merit of our procedure.

ing countries have more workers in occupations with high routine contents and fewer workers in those with high non-routine contents. In addition, a given occupation has more routine contents and less non-routine contents in developing countries than in developed countries. This is especially true for managers, professionals, and technicians, which are the occupations with the least routine contents and the most non-routine contents in any given country. These differences in occupational task content across countries explain a larger share of the cross-country patterns in task intensities than occupational employment differences do, which challenges the often-used assumption that a given occupation's task contents are the same across countries.

Next, we find that, since 2006, occupations with high non-routine contents gained employment relative to those with high routine contents by similar magnitudes in nearly all countries, regardless of their income level or initial task intensity. The fact that the direction and the magnitude of task intensity changes were similar across countries implies that the task intensities across countries have not converged at least since 2006. In addition, the common trend, especially the fall of the routine-manual task intensity, suggests that the development path of developing countries may have deviated from the path most developed countries have taken. If developing countries had followed the typical structural change pattern, manufacturing would have expanded or at least contracted more slowly in developing countries, implying a rise or a slower decline of the routine-manual intensity, as had been reported by earlier work in the literature (Maloney and Molina, 2016; Das and Hilgenstock, 2018; Lewandowski et al., 2019). The common trend we find points to the global reaches of the technological change that reduces the demand for occupations with high routine contents, drowning out the effect of offshoring that may reallocate such jobs from developed to developing countries.

Finally, employment changes across sectors account for only a small fraction of the shift in occupational employment, implying that sector-specific technological change had only a minor impact on the evolution of countries' task intensity during this period.

Contribution to the Literature. Researchers have recently begun to look at differences in the occupational composition of the labor force across countries. For example, Vizcaino (2019) documented that developed countries have disproportionately more workers in skill-intensive occupations, and Gottlieb et al. (2020) showed that workers in developing countries tend to be employed in occupations that are less compatible with remote work.

Less is known about systematic differences in task contents of the same occupations across countries and, accordingly, about the country-level task intensities and their change over time across the development spectrum.

The main contribution of our paper is to construct harmonized measures of the task contents of occupations that are country specific but comparable across countries in different stages of economic development. To this end, we combine PIAAC and STEP. These two surveys have similar but different questions and response scales and, between them, span a broad development spectrum.

Lewandowski et al. (2019) also used both PIAAC and STEP and hence merits more discussion. They started with the common questions in PIAAC and STEP, including those that have different response scales, and picked the combination of a subset of those questions and response cutoffs that made the occupational task content measures for the US in PIAAC closest to those constructed from Occupation Information Network (O*NET) of the US. For comparability between PIAAC and STEP, they project task content measures reported by survey respondents on individual characteristics, countries' GDP per capita, and a fixed effect for the STEP survey.

There are several reasons why we do not follow this harmonizing procedure. First, O*NET task measures are based on experts' descriptions of each occupation, whereas PIAAC and STEP ask workers about their tasks and competencies on the job. Given this fundamental difference, instead of maximizing the comparability between PIAAC-based and O*NET-based measures for the US, we use all questions in PIAAC and focus on the comparability between PIAAC and STEP. Second, any re-scaling is inherently arbitrary and may introduce biases whose sign cannot be easily determined. In fact, Lewandowski et al. (2019) reports that the STEP survey fixed effect in their projection is significant across many specifications and therefore some task content measures in STEP need to be further re-scaled. Third, when one of the outcome variables of interest is the correlation between the projected content measures and GDP per capita, we find it undesirable that the content measures are projected on GDP per capita in the first place. Last but not least, the non-response rates for questions on analytical tasks can be quite high in STEP, especially among the countries in the lower end of the development spectrum.

We take a different tack. We address these challenges by utilizing the identical questions in both surveys on computer use at work, which also happen to have the fewest missing responses in both surveys.

In addition to the methodological differences, there are substantive differences between Lewandowski et al. (2019) and our paper. Lewandowski et al. (2019) dropped manual tasks from their analysis and focused on their own version of the routine task intensity (RTI), defined as routine cognitive tasks minus the average of non-routine analytical and interpersonal tasks.[2] By using all the questions in PIAAC and STEP, we calculate measures for routine manual and non-routine manual tasks (in addition to routine cognitive, non-routine analytical and non-routine interpersonal tasks), and we consider these tasks separately, rather than a reduced measure like RTI. One benefit, for example, is our discovery that the high RTI of developing countries is driven at least as much by their lower non-routine task contents as by their higher routine task contents.

Unsurprisingly, some of our main findings are different from those of Lewandowski et al. (2019). First, we find a monotonically declining relationship between a country's routine task intensity (both cognitive and manual) and its income level, while Lewandowski et al. (2019) found an inverted U shape. Second, Lewandowski et al. (2019) found that the RTI in developing countries has fallen more slowly than in developed countries, possibly because offshoring shifted routine jobs from developed to developing countries.[3] By contrast, we find that, since 2006, routine task intensity has fallen by similar magnitudes in nearly all countries, independently of their income level or initial task intensity.

2 Task Intensity across Countries

We first describe the data and our procedure of harmonizing between PIAAC and STEP. We then construct an index of task intensity for each country and document the cross-country pattern. We separate the role of the tasks performed by workers in a given occupation from that of the distribution of workers across occupations in shaping the cross-country pattern.

2.1 Data

We construct the task content measures of occupations by combining the Survey of Adult Skills within the OECD's Programe for the International Assessment of Adult Competencies (PIAAC) and the World Bank's STEP Skills Measurement Program (STEP).

PIAAC is designed to measure adults' proficiency in information-processing skills at work,

[2]The original RTI of Autor and Dorn (2013) is defined as routine tasks minus the average of manual and abstract tasks.

[3]Related, Maloney and Molina (2016) and Das and Hilgenstock (2018) tested the "routinization" hypothesis (or the disappearance of middle-skill jobs with high routine task contents, a phenomenon well established in many developed countries) for a large set of countries, with the assumption that the task contents of a given occupation are the same in all countries. They found that, in developing countries, the employment share of the occupations with high routine contents was small in 1990 but grew over the years, the opposite of what the literature had found in developed countries.

such as literacy, numeracy and problem solving. The survey asks individual workers how intensively and how often they perform broad categories of tasks in the workplace. These categories are: cognitive skills, interaction and social skills, physical skills, and learning skills. It covers 41 countries at different levels of development, of which 33 have task information and the occupational categories that can be merged with the occupational employment data from the International Labour Organization (ILO). The poorest country in this sample is Ecuador (20 percent of the US GDP per capita) and the richest is Singapore.[4]

STEP is designed to measure skill requirements in the labor markets of poor and middle-income countries. It surveys workers in urban areas in 16 countries of which nine have full information on occupational task contents and occupational categories. The poorest country in this sample is Ghana (8 percent of the US GDP per capita) and the richest is Macedonia (26 percent of the US GDP per capita).[5]

The PIAAC and STEP questionnaires are similar, but they have different integer scales for answers. These disparities in scale could generate systematic differences in answers through extreme responding behaviors—i.e., respondents tend to choose the extremes of the options, which make the surveys incomparable even after a simple re-scaling.[6] Another serious challenge is that the non-response rates for some questions can be quite high in STEP, especially among the countries in the lower end of the development spectrum. For example, the non-response rate for questions about reading is 63 percent in Ghana and 56 percent in Sri Lanka, likely introducing substantial biases. The average non-response rate for reading questions is 38 percent in STEP countries, while the non-response rates for other categories are at least an order of magnitude lower. Non-response rates are even lower (less than 1 percent) in PIACC countries.[7]

To overcome this hurdle, we exploit the questions on computer use at work, because they are posed in the exact same manner in both surveys with the same response scale. These questions also have the lowest non-response rates in both surveys (less than 0.1 percent). Furthermore, incidentally, the larger literature on tasks and occupations has pointed to computer capital or information and communications technology (ICT) more broadly as the main driver of job task changes over time in the US (Autor et al., 2003; Aum et al., 2018).

[4]The majority of the 33 PIAAC countries in our sample was surveyed during the first round, in 2011–12, and the rest were surveyed in either 2014–15 or 2017. The online appendix has more details on PIAAC.

[5]Of the nine STEP countries in our sample, eight were surveyed in 2012–13. The exception is the Philippines in 2015–16. The online appendix provides more details on STEP.

[6]For most questions, STEP answers are binary choices, rather than a full scale as in PIAAC or O*NET. Harmonizing individual answers would require choosing a threshold to turn PIAAC responses into binaries. Lewandowski et al. (2019) entertained this method.

[7]A detailed tabulation of the non-response rates is in the online appendix.

For these reasons, we find it natural to center the harmonization between PIAAC and STEP on the computer use question.

For this procedure, we aggregate 21 questions in PIAAC into seven task categories using the mean of responses to the corresponding questions: Read, think creatively, personal interactions, guiding/coaching, structure/repetition, controlling machines, and hands/manual.We then aggregate these content measures and the computer use variable to the occupation level, using sample weights.[8]

The harmonization between PIAAC and STEP is as follows. For each occupation, we estimate the linear relationship between the task content measures and the answers to the computer use questions in PIAAC, and then use this estimated relationship and the actual answers to the computer use questions in STEP to predict the content measures for a STEP country. Consider the detailed task category "Read" for an example. We estimate from PIAAC

$$READ_{oc} = \alpha_o + \beta_o COMP_{oc} + \epsilon_{oc}, \tag{1}$$

where o indexes (one-digit) occupations and c countries. We then use the estimated $\hat{\alpha}_o$, $\hat{\beta}_o$, and the actual $COMP_{oc}$ in STEP to predict the $READ_{oc}$ in the STEP sample for occupation o and country c. We do this for the other six detailed task categories: $THINK$, $PERSON$, $GUIDE$, $STRUC$, $CONTRO$, and $OPER$.

The validity of the harmonization procedure presupposes that the relationship between a given task content measure and computer use at work within a given occupation in the middle- and high-income countries in PIAAC applies to the poorer economies in STEP. We directly test this assumption. When we include an interaction term between computer use and GDP per capita in the estimating equation (1), the coefficients on the interactions often come out statistically significant, seemingly suggesting that the relationship between computer use and tasks at the occupation level is affected by countries's income level. However, this does not invalidate out harmonization, because these interaction terms turn out to be economically insignificant. The predicted task content measures in STEP, which is what we are after, remain nearly unchanged even when the interaction term is included.[9] Furthermore, even the statistical significance of the interaction term is fragile. When we also include the interaction term between computer use and a measure of human capital (the fraction of population with post-secondary education), with the idea that the relationship between

[8] We favor using the variation at the occupation level rather than at the individual level. The results are robust to using individual responses.

[9] Our harmonization is a prediction problem, not one of inference.

computer use and tasks at the occupation level may be affected by the supply of human capital, in most cases both interaction terms are statistically insignificant.

Several other diagnostic analyses support the validity of the harmonization procedure. First, for STEP countries, we confirm that the predicted task content measures are strongly correlated with the task content measures constructed from the raw survey data.[10] Second, the correlation between a predicted task content measure and a country's log GDP per capita in STEP is similar to the correlation between the same task measure and log GDP per capita among PIAAC countries, even though GDP per capita is not used when predicting the STEP task content measures.

In addition, since the unit of observation for the projection step is an occupation-country pair, we also worked out a version with two-digit occupational classification (rather than one-digit) and obtain similar results.

With the full, harmonized sample in hand, we further aggregate the above seven task categories into five along their routineness and the nature of the skills required following Autor et al. (2003): non-routine analytical (NRA), non-routine interpersonal (NRI), non-routine manual (NRM), routine cognitive (RC), and routine manual (RM). These task content measures are aggregated across occupations and countries, standardized by the mean and the variance of the respective task measures across occupations in the US in PIAAC.

To construct country-level task intensities from the occupation-level task contents, we need occupational employment shares for each country. PIAAC and STEP occupation classification is at the three-digit level, but the in-sample occupational employment distribution is not representative. For this reason, we use each country's occupational employment shares provided by the ILO at the one-digit occupation level, the highest degree of disaggregation for ISCO-08. There are two important caveats. First, because STEP is a survey of urban workers, we exclude agricultural workers from all countries, which is also consistent with the common practice of excluding agriculture in the tasks/occupations literature. Second, for many countries, the ILO occupational employment time series have abrupt jumps in the late 1990s and the early 2000s. To avoid this problem while maximizing the number of countries in the sample, we only use the employment data from 2006 or later, which explains why our time span is shorter than similar studies in the literature.[11]

[10] One exception is the hands/manual category, but this is a component of the non-routine manual task category, which is not the focus of our analysis.

[11] The ILO data does not have the occupational employment in 2006 for the following countries, so we use adjacent years instead: 2008 for Armenia, 2004 for Mexico, and 2007 for Vietnam.

2.2 Task Intensity

We document the distribution of the task intensities across countries using the occupational task content measures from PIAAC and the harmonized STEP and the occupational employment data from the ILO.[12] The employment shares are from 2015, the latest available year, except for Canada, from 2014. For each task category i, occupation o, and country c, we have a standardized task content measure: τ_{ioc}. Denoting the share of workers in occupation o in country c by s_{oc}, we define the country-level task intensity τ_{ic} for each task i as follows:

$$\tau_{ic} := \sum_{o} s_{oc}\tau_{ioc}. \tag{2}$$

By construction, a country's task i intensity can be high either because they have more workers in occupations with high task i contents or because occupations in that country have higher task i contents than the same occupations in other countries.

We first show how countries' task intensities vary with their income level. In the analysis that follows, we focus on the non-routine analytical (NRA) and the non-routine interpersonal (NRI) tasks, as well as the routine cognitive (RC) and the routine manual (RM) tasks. The NRA and the NRI task intensities are positively correlated with income per capita across countries (first and second columns, panel A of Table 1). On the other hand, the RC and the RM task intensities are negatively correlated with income per capita. The table also shows that the non-routine manual intensity is strongly negatively correlated with income level (fifth column). Finally, computer use at work, the variable that we use to harmonize STEP and PIAAC, is strongly positively correlated with a country's income level (last column). Quantitatively, a one log point increase in income per capita is associated with a 0.46 standard deviation increase in the NRA intensity and a 0.51 standard deviation increase in the NRI intensity.[13] It is also associated with a 0.25 standard deviation decrease in the RC intensity and a 0.42 standard deviation decrease in the RM intensity. These results are also graphically represented in Figure 1 with solid lines.[14]

Typically, educated workers choose occupations with high NRA and NRI task contents, while less educated workers choose occupations with high routine task contents. Therefore, the correlation between task intensities and income per capita across countries may be mirroring the cross-country differences in educational attainment. However, the cross-country correlation between task intensities and income persists even when we control for countries'

[12]For comparison, we also report results using the raw STEP data in the online appendix.

[13]The unit is the standard deviation of occupational task contents across occupations in the US.

[14]These correlations are also robust to aggregating occupations to the two-digit level in the projection step, which we report in Figure 3 in the appendix.

Table 1: Task Intensity and GDP per Capita

	NRA (1)	NRI (2)	RC (3)	RM (4)	NRM (5)	CU (6)
Panel A						
GDP Per Capita	0.461***	0.505***	-0.253***	-0.416***	-0.694***	0.719***
	(0.0419)	(0.0546)	(0.0595)	(0.0424)	(0.223)	(0.0535)
N	42	42	42	42	42	42
R^2	0.752	0.681	0.311	0.706	0.195	0.819
GDP Per Capita	0.814***	0.874***	-0.235*	-0.657***	-1.449**	1.405***
	(0.0877)	(0.124)	(0.132)	(0.0920)	(0.527)	(0.115)
N	28	28	28	28	28	28
R^2	0.768	0.658	0.108	0.663	0.225	0.852
Panel B						
GDP Per Capita	0.477***	0.501***	-0.226**	-0.346***	-0.924**	0.771***
	(0.0522)	(0.0758)	(0.0867)	(0.0567)	(0.353)	(0.0632)
Post Secondary Education	-0.000326	0.00307	0.00912	-0.00435	-0.00567	0.0134**
	(0.00421)	(0.00611)	(0.00699)	(0.00457)	(0.0284)	(0.00510)
N	28	28	28	28	28	28
R^2	0.789	0.675	0.219	0.653	0.246	0.888

Note: Panel A shows the regression results of a country's task intensity on its log GDP per capita in 2015 across 42 countries. Panel B controls for the share of workers with post secondary education in 2015 (WDI). Education information is available for the following 28 countries only: Armenia, Austria, Belgium, Bolivia, Chile, Czech Republic, Denmark, Ecuador, Finland, France, Germany, Greece, Hungary, Israel, Italy, Korea, Lithuania, Mexico, the Netherlands, Norway, Peru, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey, USA.

average schooling level, as measured by the fraction of the population with post-secondary education (Table 1, Panel B).[15] That is, the cross-country pattern of task intensities reflects the cross-country differences in the occupational composition and the occupational task contents, rather than the differences in the skill composition of the labor force as measured by educational attainment.

A widely used measure of occupational task contents is the one available from O*NET in the US (Autor and Dorn, 2013). If the task contents of a given occupation are similar across countries, one can construct countries' task intensities as in equation (2) but with τ_{io} from O*NET instead of τ_{ioc} on the right-hand side. For many European countries, Handel (2012) showed that country-specific measures of occupational task contents are similar to those in O*NET. However, we find that this is not true for a broader set of countries. Figure 1 compares the task intensity of each country based on our country-specific occupational task contents (τ_{ioc}, solid lines) to the intensity based on O*NET (τ_{io}, dashed lines). By construction, the variation across countries in the latter is only due to the difference in the occupational composition of the labor force.

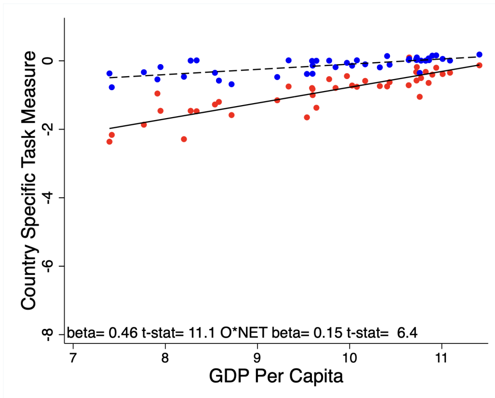
In panels (a) and (b) of Figure 1, we first see that the NRA and NRI intensities of countries based on the common O*NET measures are higher (in levels) than the ones based on our country-specific task measures, across all countries in our sample. Second, the positive slopes of the dashed lines imply that developing countries have fewer workers in occupations with high NRA and NRI contents (according to O*NET) than developed countries, since for the dashed lines the task contents of a given occupation are the same across countries. Third, the NRA and NRI intensities are more strongly correlated with income when our country-specific occupational task content measures are used (solid lines). In fact, for both NRA and NRI, the solid lines are more than three times steeper than the dashed lines. This shows that a given occupation in developing countries has *less* NRA and NRI task contents than the same occupation in developed countries.

For the routine cognitive intensity in panel (c), when we use the O*NET-based occupational task content measures, countries' RC intensity and income are nearly uncorrelated (flat dashed line). However, with the country-specific occupational task content measures, this correlation is significantly negative (solid line). For the routine manual intensity in panel (d), although the dashed line has a negative slope, the solid line is more than twice steeper.

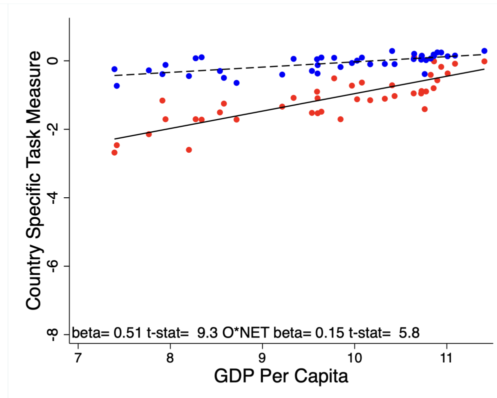
[15] For panel B, we only consider the 28 countries for which we have educational attainment data (two out of nine STEP countries and 26 out of 33 PIAAC countries). The regression without the education variable for the 28 countries gives similar coefficients as those in panel B (not reported); if anything, the relationship comes out marginally stronger.

Figure 1: Task Intensity and Development

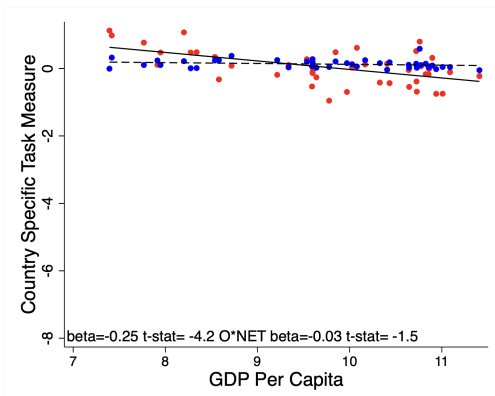
(a) NRA



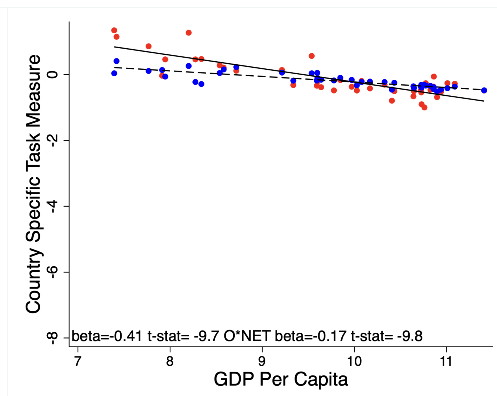
(b) NRI



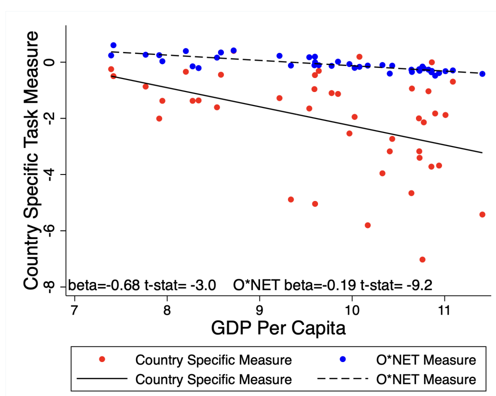
(c) RC



(d) RM



(e) NRM



Note: This figure plots a country's task intensity based on country-specific (red dots, solid lines) and O*NET-based (blue dots, dashed lines) measures of occupational task contents against GDP per capita (PPP in log).

Overall, developing countries do have more workers in the occupations with high RC and RM contents (according to O*NET) than developed countries, but the crucial difference across countries is that a given occupation in developing countries has *more* RC and RM task contents than the same occupation in developed countries.

We can further characterize the occupational task content differences across countries. For each occupation, we calculate the average task contents among the bottom quartile of countries and among the top quartile of countries ordered by income per capita. Consistent with the results above, occupations in the low-income countries have less NRA and NRI contents than the same occupations in the high-income countries. This gap between the high-income and the low-income countries is largest for managers, professionals, and technicians, which are the occupations with the most NRA and NRI contents in all countries. On the other hand, occupations in the low-income countries have more RC and RM contents than the same occupations in the high-income countries. This gap is again largest for managers, professionals, and technicians, which are the occupations with the least RC and RM contents in all countries. The details of these comparisons are in the online appendix.

We can further decompose the differences in the task intensity across countries as follows. Let the average task-i contents of occupation o across countries be $\bar{\tau}_{io}$ and the average employment share of occupation o across countries be $\bar{s}_o$. The difference between country c's intensity of task i and the cross-country mean, $\sum_o(\tau_{ico}s_{co} - \bar{\tau}_{io}\bar{s}_o)$, can be decomposed into the difference in occupational task contents between country c and the cross-country mean (*task effect*), the difference in the occupational employment shares (*employment effect*), and the correlation between the two (*cross effect*):

$$\sum_o(\tau_{ico}s_{co} - \bar{\tau}_{io}\bar{s}_o) = \underbrace{\sum_o(\tau_{ico} - \bar{\tau}_{io})\bar{s}_o}_{\text{task effect}} + \underbrace{\sum_o \bar{\tau}_{io}(s_{co} - \bar{s}_o)}_{\text{employment effect}} + \underbrace{\sum_o(\tau_{ico} - \bar{\tau}_{io})(s_{co} - \bar{s}_o)}_{\text{cross effect}}. \quad (3)$$

For each task category i and each country c, we compute the task intensity deviation from the mean (the left-hand side of equation 3) and the three effects on the right-hand side. We correlate these terms with countries' income per capita, and report the results in Table 2. The reported coefficients are broadly consistent with what we saw in Figure 1. Developing countries have fewer workers in the occupations with high NRA and NRI contents than developed countries (positive employment effect coefficient), and a given occupation in developing countries has less NRA and NRI contents than the same occupation in developed countries (positive task effect coefficient). The magnitudes of the coefficients show that occupational task content differences (task effects) are more important than employment share differences (employment effects) for the cross-country variation in the NRA and the NRI task intensities.

Table 2: Task Intensity Decomposition and Development

	Total	Task Effect	Employment Effect	Cross Effect
NON-ROUTINE ANALYTIC:				
log(GDP Per Capita)	0.448***	0.266***	0.189***	-0.00650
	(0.0418)	(0.0406)	(0.0260)	(0.00903)
R^2	0.742	0.517	0.568	0.013
NON-ROUTINE INTERPERSONAL:				
log(GDP Per Capita)	0.510***	0.318***	0.187***	0.00612
	(0.0551)	(0.0519)	(0.0275)	(0.0102)
R^2	0.682	0.483	0.535	0.009
ROUTINE COGNITIVE:				
log(GDP Per Capita)	-0.193***	-0.0673	-0.131***	0.00547
	(0.0573)	(0.0587)	(0.0188)	(0.00800)
R^2	0.221	0.032	0.548	0.012
ROUTINE MANUAL:				
log(GDP Per Capita)	-0.439***	-0.262***	-0.197***	0.0202*
	(0.0433)	(0.0417)	(0.0207)	(0.0118)
R^2	0.720	0.497	0.693	0.068
NON-ROUTINE MANUAL:				
log(GDP Per Capita)	-0.705***	-0.489**	-0.200***	-0.0159
	(0.223)	(0.217)	(0.0244)	(0.0233)
R^2	0.200	0.113	0.626	0.012

For RM, also consistent with Figure 1(d), developing countries have more workers in occupations with high RM contents (negative employment effect coefficient), and a given occupation in developing countries has more RM contents that the same occupation in developed countries (negative task effect coefficient). The two coefficients are similar, but the task effect is more important for the cross-country variation in the RM task intensity.

However, the coefficients for RC are quite different from what we inferred from Figure 1(c). The employment effect coefficient is significantly negative—that is, developing countries have significantly more workers in occupations with high RC contents than developed countries, which contrasts with the nearly flat dashed line in Figure 1(c). At the same time, the task effect coefficient is insignificant, implying that there is no difference in RC contents of occupations between developing and developed countries, which again contrasts with the slope of the solid line in Figure 1(c). This seemingly contradictory results can be reconciled, because Figure 1 is a comparison between country-specific occupational task contents and the O*NET-based task contents, while the decomposition here is about deviations from the cross-country mean.

Finally, the coefficients on the cross effect are not significant at the 5 percent level and their magnitudes are much smaller than the other coefficients.

3 Changes in Task Intensity over Time

Technological change can replace workers with machines in certain tasks and reallocate workers to other tasks, including new ones. The disappearance of jobs that have high routine task contents in developed countries since the 1980s is a well-established fact (e.g. Autor and Dorn, 2013), and our finding that the RC and the RM intensities nowadays are lower in developed countries may be the result of this trend. The natural question is then whether the higher RC and RM intensities of developing countries mean they had been subjected to a different trend. We now examine the changes in task intensities and their relationship with countries' income level and initial employment structure. We consider the allocation of labor across both occupations and sectors.

3.1 Role of Occupational Employment Changes

We saw how the task intensity of a country, as defined by equation (2), varies across the development spectrum at a point in time, year 2015, to be exact. We now construct the task-i intensity of country c in 2006 and see how it changed between 2006 and 2015. The country-specific occupational task contents τ_{ioc} are fixed over time, so any change in country-level task intensity comes from the shifts in the occupational employment (s_{oc}).

Table 3: Changes in Task Intensity

	NRA	NRI	RC	RM	NRM	CU
Avg. change in task intensity	0.04	0.05	-0.04	-0.05	-0.05	0.06
GDP per capita (2016)	0.004	0.004	-0.008	-0.004	-0.010	0.003
	(0.011)	(0.013)	(0.009)	(0.011)	(0.021)	(0.014)
N	42	42	42	42	42	42

Note: The first row is the average change across countries in the task intensity and computer usage (last column) between 2006 and 2015. The lower panel shows the coefficients from regressing the change in countries' task intensity between 2006 and 2015 on log GDP per capita in 2006, with standard errors in parentheses. GDP per capita is in PPP from the World Development Indicators (WDI).

The first row of Table 3 shows the average change in the respective task intensity across countries between 2006 and 2015, together with the average change in the index of computer use at work in the last column. On average, countries' NRA and NRI intensities rose, but their RC and RM intensities fell.[16] This means that in most countries the occupations that have high NRA and NRI contents gained employment relative to those occupations that have high RC and RM contents. The lower panel reports the coefficients from regressing the task intensity changes on countries' GDP per capita (PPP in log) in 2006. For all five task categories, there is no correlation between a country's income level and the change in its task intensity between 2006 and 2015. Although not shown here, the task intensity changes are not correlated with the initial level of the respective task intensity in 2006 either.

Our finding that the RC and the RM intensities fell by similar magnitudes across countries contrasts with earlier papers that reported smaller decreases of the routine task intensity or RTI defined by Autor and Dorn (2013) in developing countries, as discussed in our literature review. The following explanations have been given for this perceived difference in the decline in RTI. First, the higher price of capital relative to consumption (Hsieh and Klenow, 2007) and the scarcity of skilled labor in developing countries (Caselli and Coleman, 2006) may have deterred the adoption of the technology that substitutes for jobs that have high routine contents. Second, as suggested by Das and Hilgenstock (2018) and Lo Bello et al. (2019), the offshoring of routine jobs from developed countries may have shored up the routine intensities of developing countries. Nevertheless, our finding points to the global reaches of the technological change that replaced routine jobs and complemented analytical and interpersonal jobs in all countries.[17]

The fact that the direction and the magnitude of task intensity changes are similar across developing and developed countries has two implications. First, the task intensities across countries has not converged at least since 2006, given that the magnitude of the changes is not correlated with the initial task intensity levels. Second, the common trend, especially the fall of the routine-manual task intensity, suggests that the development path of developing countries may have deviated from the path most developed countries have taken: If developing countries had followed the typical structural change pattern of agriculture to manufacturing to services, the rise of manufacturing jobs with high RM contents in developing countries

[16] The unit is the standard deviation of occupational task contents across occupations in the US. The average changes are all significant at the 5 percent level.

[17] This is consistent with the evidence in Lo Bello et al. (2019) that the adoption of ICT in developing countries correlated with a decline in routine-cognitive jobs, and consistent with what happened with computerization in the US and Western Europe. Of course, not all ICT replaces routine jobs and complements abstract/interpersonal jobs. Software in particular can have the effect of reducing the demand for workers performing abstract tasks, as shown in the US by Aum (2017) and in Chile by Almeida et al. (2017). More generally, technological change in a large set of equipment categories and capital deepening may increase or decrease the demand for workers, as documented by Caunedo et al. (2019).

would have shown a rise or at least a slower decline of the RM intensity. The common trend in the task intensities we find supports the evidence on premature de-industrialization (Rodrik, 2016).

3.2 Role of Sectoral Employment Changes

It is possible that the occupational employment changes above are driven by sector-specific technological change that reallocates workers across sectors: the occupations over-represented in expanding sectors will gain employment and those over-represented in shrinking sectors will lose employment.[18]

We assess the relative importance of occupation-specific and sector-specific technological change for occupational employment changes using the following decomposition. First, the employment share of occupation o in period t can be written as, following Aum et al. (2017):

$$s_{ot} = \sum_{j \in J} \frac{l_{ojt}}{l_{jt}} \times \frac{l_{jt}}{l_t},$$

where l_{ojt} is the number of workers in occupation o in sector j in year t, l_{jt} is the number of workers in sector j in year t, and J is the set of sectors (we are omitting the country index c). The employment share change of occupation o from year t' to t can be written as

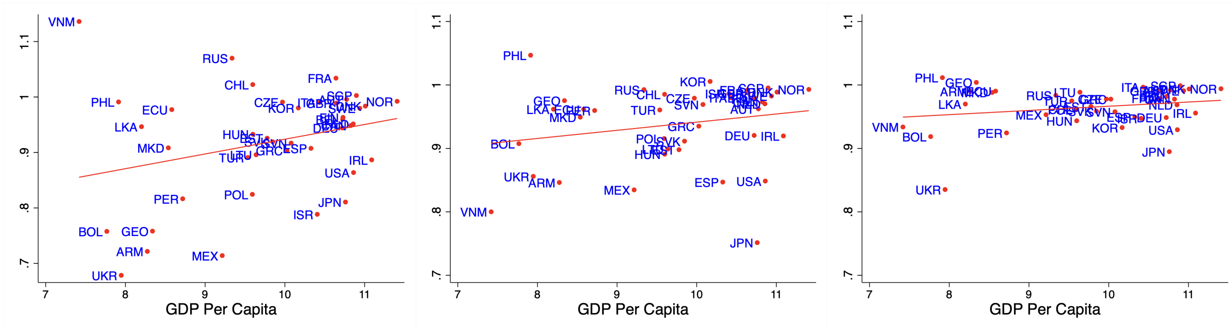
$$\Delta s_{ot} = \underbrace{\sum_{j \in J} \Delta \left(\frac{l_{ojt}}{l_{jt}} \right) \times \overline{\left(\frac{l_j}{l} \right)}}_{\text{within sector}} + \underbrace{\sum_{j \in J} \Delta \left(\frac{l_{jt}}{l_t} \right) \times \overline{\left(\frac{l_{oj}}{l_j} \right)}}_{\text{between sector}}, \tag{4}$$

where $\Delta(x_t) \equiv (x_t - x_{t'})/(t - t')$ and $\overline{(x)} \equiv (x_t + x_{t'})/2$. The first term on the right-hand side is the change in the occupational employment *within* each sector, weighted by the average employment share of the sector over the two years and then summed across all sectors. The second term is the change in the employment share of each sector, multiplied by the average employment share of occupation o in the sector over the two years and then summed over all sectors. This is the *between*-sector term that captures the change in occupational employment caused by changing employment across sectors. A large between-sector term implies that technological change is at the sector level rather than the occupation level. On the other hand, a large within-sector term implies that the occupational employment changes are primarily driven by occupation-specific technological change.

[18] This compositional link between occupations and structural change accords with Lee and Shin (2017) but differs from Duernecker and Herrendorf (2016), who assign occupations to sectors.

Figure 2: Decomposition of Occupational Employment Change: Within-industry Component

(a) 1-digit Industry (b) 2 Sectors (c) 3 Sectors



Note: This figure shows the contribution of the within-sector component to the changes in occupational employment share between 2006 and 2015 for each country. There are nine 1-digit occupations. In the left panel, we use 19 industries in the 1-digit industry classification. In the center panel, we have two sectors: manufacturing and service. In the right panel, we have three sectors: manufacturing, low-skill service, and high-skill service. The x-axis is GDP per capita in 2006 (PPP in log).

Our data allows us to consistently use nine occupations at the 1-digit level, excluding agricultural occupations. For sectors, we consider three different classifications, again excluding agriculture. First, we use the 19 industries in the 1-digit industry classification. Second, we consider a simple manufacturing vs. service dichotomy, and finally divide service into high-skill and low-skill service to have three sectors. We compute the contribution of the within-sector component for each occupation in a given country, and then average the within component across the 9 occupations using occupational employment shares as weights.

The results are shown in Figure 2. We first note that the within-sector component explains over 90 percent of the occupational employment changes in the vast majority of countries, in all three classifications, but especially with the 3-sector classification in the right panel. In other words, occupational employment has changed significantly within any given sector, implying that technological change at the occupation level is the dominant driver of overall occupational employment and hence task intensity changes in most countries. Second, the within-sector component is more important in richer countries. One interpretation is that technological change at the sector level and hence structural change play a larger role in developing countries than in developed ones, although they are still much less important than technological change at the occupation level.

4 Concluding Remarks

The tasks workers perform on the job are at the center of the large and growing literature on technological change and its effect on the labor market, as reviewed in Acemoglu and Autor (2011), for example. The literature has shown that workers' tasks and the shifting occupational employment structure are informative about the patterns of technological change. Because of data availability, this literature has almost exclusively focused on developed economies, the US in particular. Our paper contributes to the literature by constructing and analyzing country-specific task measures of occupations that can be compared across developing and developed countries. We find robust differences in task intensities across countries, which imply that developing countries and developed countries are differentially exposed to technological change. However, since 2006, the direction and the magnitude of task intensity changes have been similar across all countries. Our analysis shows the importance of measuring occupational task contents country by country for uncovering these cross-country patterns.

One implication is that the question of why occupational task contents vary across countries should be addressed together with the question of why occupational employment structure varies across countries. Another open question is whether our findings on task intensities predict a development path for developing countries that is different from the one developed countries have taken. More broadly, it would be important to find out the implications that task intensity differences and technological change have for cross-country income differences and also for inequality within a developing country. We expect that the task measures we constructed will aid future research on these compelling questions.

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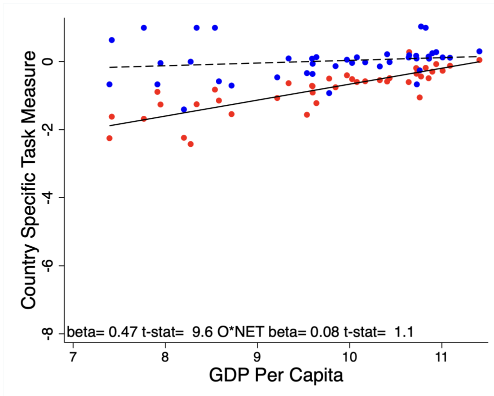
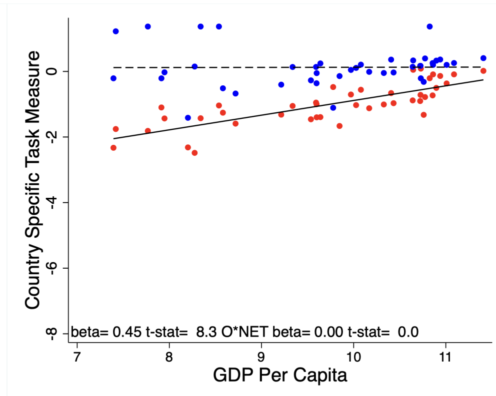
Figure 3: Task Intensity Decomposition and Development, 2 digit projection

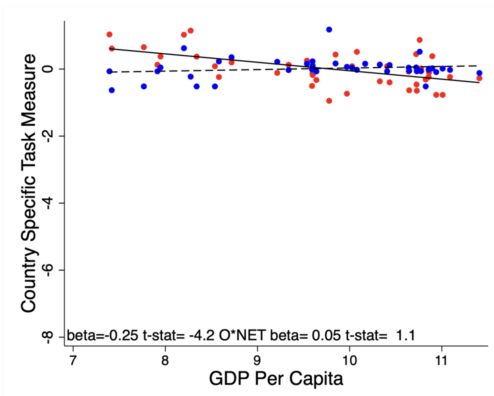
(a) NRA



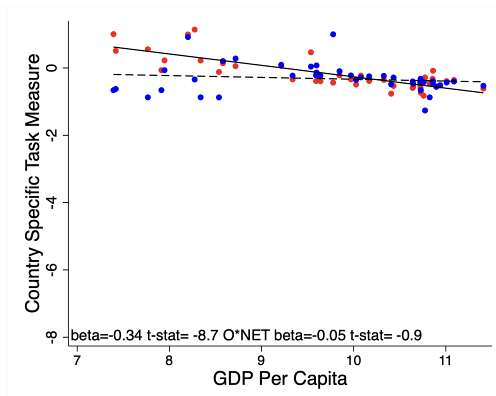
(b) NRI



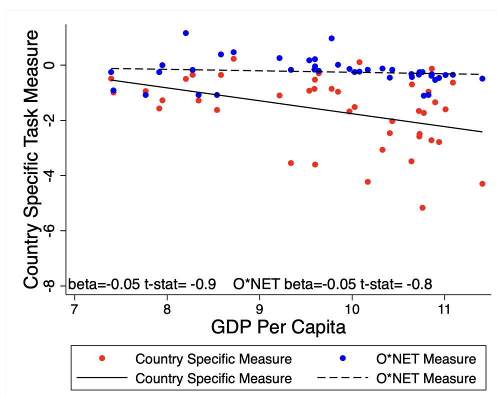
(c) RC



(d) RM



(e) NRM



Note: This figure plots a country's task intensity based on country-specific (red) and O*NET-based (blue) measures of occupational task intensity against GDP per capita (PPP in log). The solid line is the correlation between GDP and task intensity based on country-specific occupational task intensity. The dashed line is the correlation between GDP and task intensity based on O*NET. Task intensity in STEP countries is predicted at the 2-digit level.