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.

JEL Codes: E24, J24, O14
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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 today's 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. This paper fills the gap. It is the first step toward characterizing how the technology being operated and also workers' exposure to technological change vary across the development spectrum.

The analysis in this paper overcomes 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 the Organisation for Economic Co-operation and Development or 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 from the International Labour Organization (ILO), 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. Only non-agricultural workers are considered 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, the findings in this paper are not driven by the difference in the importance of agriculture between developing and developed countries.

This paper documents systematic differences in task intensity across countries. Developing countries use routine-cognitive tasks and routine-manual tasks more intensively but

[1] This paper is not the only attempt at harmonizing STEP and PIAAC. The discussion of the literature below explains the relative merit of the procedure in this paper.

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: developing 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 cautions against 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.[2] 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 had taken in the past. 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 that this paper reports 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-

[2] The occupational task contents are held fixed over time, so the task intensity changes only reflect the changing occupational composition over time.

intensive occupations, and Gottlieb et al. (2021) showed that workers in developing countries tend to be employed in occupations that are less compatible with remote work. These studies document how the occupational composition of the labor force varies across countries rather than how the nature of work for a given occupation varies across countries.[3] Indeed, much less is known about the latter and, accordingly, about the country-level task intensities and their change over time across the development spectrum.

The main contribution of this 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 and selected the combination of a subset of those questions and response thresholds 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. Because most STEP answers are binary choices, rather than a full scale as in PIAAC, one needs to choose a threshold for each question to turn PIAAC responses into binaries.

There are several reasons why we propose another harmonizing procedure. First, O*NET task measures are mostly 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.[4] Third, Lewandowski et al. thoughtfully explained their procedure, but the process of selecting the combination of questions and response thresholds may prove cumbersome for other researchers wanting to modify or experiment with their procedure. Last but not least, the non-response rates for questions on analytical tasks is quite high in STEP, especially among the countries in the lower end of the development spectrum.

This paper takes a different, complementary tack. We address these challenges by utilizing the identical questions in both surveys on computer use at work, which also happen to

[3] Gottlieb et al. (2021) does show the within-occupation difference in remote work across countries.

[4] Lewandowski et al. ran diagnostic regressions on their harmonized data and further rescale STEP task measures.

have the fewest missing responses in both surveys.

In addition to the methodological differences, there are substantive differences. 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.[5] By using all relevant questions in PIAAC and STEP, this paper on the other hand calculates measures for routine manual tasks and non-routine manual tasks (in addition to routine cognitive, non-routine analytical and non-routine interpersonal tasks), and considers these tasks separately. 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 (both manual and cognitive) task contents.

Unsurprisingly, some of the main findings are different. First, a country's routine task intensity (both manual and cognitive) monotonically declines with its income level, while Lewandowski et al. (2019) found an inverted U shape.[6] Second, Lewandowski et al. found that their RTI in developing countries has fallen more slowly than in developed countries, possibly because offshoring shifted routine jobs from developed to developing countries.[7] By contrast, this paper finds 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

The first step is to describe the data and our procedure of harmonizing between PIAAC and STEP. This is followed by the construction of an index of task intensity for each country and the documentation of cross-country patterns. 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.

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

[6]Note that Lewandowski et al. do not utilize routine manual task measures.

[7]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.

2.1 Data and Harmonization

Constructing the task content measures of occupations involves 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, 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 ILO. The poorest country in this sample is Ecuador (20 percent of the US GDP per capita) and the richest is Singapore.[8]

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).[9]

The PIAAC and STEP questionnaires are similar. However, whereas most STEP questions have a binary response scale, PIAAC has a finer integer scale. 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. 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 among STEP countries, while the non-response rates for other categories are at least an order of magnitude smaller. Non-response rates are even lower (less than 1 percent) in PIACC countries. See Table S2 of the online appendix for a detailed tabulation of the non-response rates.

To overcome this hurdle, we exploit the questions on computer use at work, because they

[8]The majority of the 33 PIAAC countries in our sample were surveyed during the first round, in 2011–12, and the rest were surveyed in either 2014–15 or 2017. Section S2.1.1 of the online appendix, available with this article at *The World Bank Economic Review* website, has more details on PIAAC.

[9]Of the nine STEP countries in our sample, eight were surveyed in 2012–13. The exception is the Philippines in 2015–16. Section S2.1.2 of the online appendix provides more details on STEP.

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 (for example, Autor, Levy, and Murnane, 2003; Aum, Lee, and Shin, 2018). For these reasons, we find it natural to center the harmonization between PIAAC and STEP on the computer use question.

We aggregate 21 questions in PIAAC into seven detailed task categories using the mean of responses to the corresponding questions: Read, think creatively, personal interactions, guiding and coaching, structure and repetition, controlling machines, and hands/manual. We then aggregate these content measures and the computer use variable to the occupation level, using sample weights.[10]

The harmonization between PIAAC and STEP is as follows. For each of the seven detailed task categories, we estimate the linear relationship between the task content measures and the answers to the computer use questions in PIAAC across occupations and countries, 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. For example, for the detailed task category "Read," we estimate from PIAAC:

$$READ_{oc} = \alpha_{READ} + \beta_{READ} COMP_{oc} + \epsilon_{oc}, \tag{1}$$

where o indexes one-digit occupations and c countries. We then use the estimated $\hat{\alpha}_{READ}$, $\hat{\beta}_{READ}$, 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 PIAAC estimation results are in Section S3.3 of the online appendix.

The underlying idea is that an occupation is a combination of these detailed task categories, whose relationship with the computer use at work question is common across occupations and across the STEP and PIAAC countries. One may find these assumptions restrictive, so we address this concern in several ways.

First, in an alternative specification, we allow the relationship between computer use and a given detailed task to vary across occupations. That is, the coefficients in equation (1) become occupation-specific and are estimated from the variation across the PIAAC countries within an occupation. The predictions for the STEP countries and the main results from

[10]That is, we use the variation at the occupation level rather than at the individual level. Results were similar when we used individual responses as a robustness check.

this alternative specification remain close to those using equation (1).[11] We prefer the specification in equation (1), because it allows us to check whether the relationship between computer use and detailed tasks varies with countries' income level, as we discuss below.

Second, it is possible that the relationship between detailed tasks and computer use in the middle- and high-income countries in PIAAC differs from the relationship in the poorer countries in STEP. However, the correlation between the predicted task content measures and countries' income levels among the STEP countries is not statistically different from the correlation between the task measures and countries' income levels among the PIAAC countries, even though GDP per capita is not used when either estimating the relationship in equation (1) for the PIAAC countries or predicting the task content measures for the STEP countries. Furthermore, another alternative specification includes the interaction term between computer use and log GDP per capita when estimating equation (1) for the PIAAC countries and when predicting for the STEP countries. The coefficient on the interaction comes out statistically significant for most of the seven detailed task categories, showing that the relationship between computer use and a given task varies with countries's income level in PIAAC (Section S3.3 of the online appendix). However, this does not invalidate our harmonization procedure, because these interaction terms turn out to be economically insignificant. The predicted task content measures for the STEP countries, which is what we are after, remain nearly unchanged even when the interaction term is included. Accordingly, our results change little, as reported in Figure S3 of the online appendix.[12] Given this result, we prefer equation (1) without the interaction term, because we consider it undesirable to predict the STEP countries' task content measures using their income level, when the key outcome variable of interest is the relationship between countries' task intensities and their income levels.

Other diagnostic analyses support our harmonization procedure. First, for the STEP countries, we confirm that the predicted task content measures are strongly correlated with the task content measures constructed from the raw survey data.[13] In addition, when we do

[11] Because of the reduced number of observations when estimating occupation-specific coefficients, the standard errors become larger and most coefficients are not significantly different from those in equation (1). This result is reported in Section S3.1 of the online appendix.

[12] In addition, the statistical significance of the interaction terms is not robust. When we also include the interaction term between computer use and a measure of human capital (the fraction of workers with post-secondary education), with the idea that the relationship between computer use and tasks may be affected by the supply of human capital, for the vast majority of the detailed task categories, both interaction terms become statistically insignificant. See Table S6 of the online appendix.

[13] See Section S3.6 of the online appendix. One exception is the hands/manual (OPER) category, but this is a component of the non-routine manual task, which is not a focus of our analysis. One reason is that the OPER question is materially different between PIAAC and STEP.

the estimation and prediction at the two-digit occupation level, rather than at the one-digit occupation level, the results remain unchanged for the most part.[14]

With the full harmonized sample in hand, we further aggregate the above seven task categories into five along routineness and the nature of the skills required, following Autor, Levy, and Murnane (2003): non-routine analytical (NRA), non-routine interpersonal (NRI), routine cognitive (RC), routine manual (RM), and non-routine manual (NRM). NRA is the sum of read and think task contents, and NRI the sum of personal and guide task contents. RC corresponds to structure and RM to control, while NRM corresponds to operations. These task content measures are aggregated to the level of occupation for each country, standardized by the mean and the variance of the respective task content measures across occupations in the US in PIAAC.

Constructing country-level task intensities from the occupation-level task contents requires 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.[15] 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.[16]

2.2 Task Intensity

The occupational task content measures from the harmonized PIAAC and STEP and the occupational employment data from the ILO generate the distribution of task intensities across countries. The employment shares are from 2015, the latest available year, except

[14] After working with two-digit occupations in the harmonization step, we aggregate task measures to the one-digit occupation level using the sample weights in PIAAC and STEP. This alternative result is in Section S3.5 of the online appendix.

[15] PIACC and STEP sampling weights are not representative of the occupational composition of a country, because the samples are not stratified by occupation. To make our measures representative of the occupation composition, we use the ILO employment shares.

[16] 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.

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}, the country-level task intensity τ_{ic} for each task i is defined 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.

The analysis that follows focuses on non-routine analytical (NRA) and non-routine interpersonal (NRI) tasks, as well as routine cognitive (RC) and routine manual (RM) tasks. The NRA and the NRI task intensities are positively correlated with income per capita across countries (first and second columns, upper half of panel A, 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). Computer use at work, the variable that harmonizes 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.[17] 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.

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' average schooling level, as measured by the fraction of the population with post-secondary education (Table 1, Panel B).[18] 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.

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

[18] Panel B only considers the 28 countries for which educational attainment data are available (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 (lower half of panel A); if anything, the relationship between task intensity and income comes out marginally stronger.

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.[19] 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 workforce.

In panels (a) and (b) of Figure 1, one sees 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 show 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 three times as steep as 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 two and a half times as steep. 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.

One 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

[19]Note that the subscripts i, o, c correspond to task, occupation, and country, respectively.

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 Section S3.7 of the online appendix.[20]

One can further decompose the differences in the task intensities across countries as follows. Let the average task-i content 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, the task intensity deviation from the mean (the left-hand side of equation 3) and the three effects on the right-hand side are computed. These terms are then correlated with countries' income per capita, which is reported 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 strongly correlated with income than employment share differences (employment effects), and hence are more important for

[20] One related question is whether the ranking of occupations in terms of a given task intensity within a country varies with countries' income level. We find that, for the most part, such rankings are the same between the two income groups of countries. For all five tasks, the ranking of occupations in the low-income group and the high-income group has a correlation coefficient exceeding 0.95. The ranking difference in terms of RM and NRM tasks comes from middle skill occupations (clerks and crafts). The ranking difference in terms of NRA, NRI and RC tasks is due to elementary and sales occupations.

the cross-country variation in the NRA and NRI task intensities. For NRA, the task effect coefficient is 0.27 and the employment effect is 0.19. For NRI, the task effect coefficient is 0.32 and the employment effect coefficient is 0.19.

For the RM task, 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 -0.20 and -0.26, respectively, and the task effect is somewhat more important for the cross-country variation in the RM task intensity.

However, the coefficients for the RC task 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 and their magnitudes are much smaller than the other coefficients.

3 Changes in Task Intensity over Time

Technological change can replace workers by automation 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 the finding that the RC and the RM intensities nowadays are lower in developed countries than in developing countries may be the result of this trend. One natural question is then whether the higher RC and RM intensities of developing countries mean they had been subjected to a different trend. This section examines the changes in task intensities and their relationship with countries' income level and initial employment structure. The allocation of labor across both occupations and sectors is considered.

3.1 Role of Occupational Employment Changes

So far, one 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.[21] 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}).

In the first row of Table 3 appears 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.[22] 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. In the lower panel are 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. More information is given in Section S3.2 of the online appendix. Although not shown here, the task intensity changes are not correlated with the initial level of the respective task intensity in 2006 either.

The finding that the RC and RM intensities fell by similar magnitudes across countries contrasts with earlier papers that reported smaller decreases of the routine task intensity (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, Sanchez Puerta, and Winkler (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.[23]

[21] As explained in Section 2.1, the irregularities in the ILO occupational employment data in earlier periods force us to start in 2006.

[22] 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.

[23] This is consistent with the evidence in Lo Bello, Sanchez Puerta, and Winkler (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

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 would have shown a rise or at least a slower decline of the RM intensity. The common trend in the task intensities we find complements 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.[24]

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, Lee, and Shin (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

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

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, Fernandes, and Viollaz (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, Jaume, and Keller (2019).

[24] 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.

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.

The data allows a consistent use of nine occupations at the one-digit level, excluding agricultural occupations. Three different classifications of sectors are considered, again excluding agriculture. First, 19 industries in the one-digit industry classification. Second, a simple manufacturing vs. service dichotomy, and finally a division of 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 nine occupations using occupational employment shares as weights.

The results are shown in Figure 2. First, the within-sector component explains over 90 percent of the occupational employment changes in the vast majority of countries, in all three sector classifications, but especially with the three-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. This 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. This paper shows the importance of measuring within-occupation 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. The variation in occupational employment structure is likely linked to the availability of skills in the workforce, and a study of endogenous skill acquisition and shifts in occupational demand is a promising avenue for understanding the mechanisms behind the empirical facts that this paper uncovered. Our framework of multiple task contents encourages thinking of skills as a multi-dimensional object rather than a simple measure like schooling. Another open question is whether these 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. The task measures we constructed may aid future research on these compelling questions.

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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 (dots, solid lines) and O*NET-based (crosses, dashed lines) measures of occupational task contents against GDP per capita (PPP in log). The text in each plot reports the coefficient for a regression of task-intensity on log GDP per capita and the t-statistic with robust standard errors.

Source: Authors' calculations using data from ILO, O*NET, PIAAC, STEP and World Development Indicators

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 one-digit occupations. In the left panel, we use 19 industries in the one-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).

Source: Authors' calculations using data from ILO, PIAAC, STEP and World Development Indicators

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	0.476***	0.514***	-0.189**	-0.364***	-0.947***	0.827***
	(0.0483)	(0.0705)	(0.0829)	(0.0534)	(0.326)	(0.0661)
N	28	28	28	28	28	28
R^2	0.789	0.671	0.166	0.641	0.245	0.857
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: The upper half of panel A shows the regression results of a country's task intensity on its log GDP per capita in 2015 across 42 countries, and its corresponding standard errors. 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. The lower half of panel A is the regression of task intensities on GDP per capita for these 28 countries. Robust standard errors in parentheses. *, **, and *** stand for significance at the 10-percent, 5-percent, 1-percent levels, respectively.

Source: Authors' calculations using data from ILO, PIAAC, STEP and World Development Indicators

Table 2: Task Intensity Decomposition and Development

	Total (1)	Task Effect (2)	Employment Effect (3)	Cross Effect (4)
Non-Routine Analytic:				
log(GDP Per Capita)	0.462***	0.279***	0.188***	-0.00468
	(0.0418)	(0.0410)	(0.0264)	(0.00920)
R^2	0.754	0.537	0.559	0.006
Non-Routine Interpersonal:				
log(GDP Per Capita)	0.509***	0.316***	0.184***	0.00912
	(0.0545)	(0.0515)	(0.0278)	(0.0102)
R^2	0.685	0.485	0.522	0.019
Routine Cognitive:				
log(GDP Per Capita)	-0.252***	-0.120*	-0.133***	0.000581
	(0.0595)	(0.0610)	(0.0194)	(0.00823)
R^2	0.310	0.088	0.542	0.000
Routine Manual:				
log(GDP Per Capita)	-0.410***	-0.235***	-0.197***	0.0217*
	(0.0422)	(0.0402)	(0.0209)	(0.0120)
R^2	0.702	0.460	0.690	0.076
Non-Routine Manual:				
log(GDP Per Capita)	-0.680***	-0.458**	-0.205***	-0.0164
	(0.223)	(0.218)	(0.0255)	(0.0236)
R^2	0.188	0.100	0.618	0.012

Note: Column (1) reports the coefficients from regressing the countries' task intensity on log GDP per capita, with standard errors in parenthesis. These coefficients are reported for the five tasks categories. Columns (2)–(4) report the coefficient from regressing a given component of task intensity in each country on log GDP per capita. The three components are defined in equation (3). Robust standard errors in parentheses. *, **, and *** stand for significance at the 10-percent, 5-percent, 1-percent levels, respectively.

Source: Authors' calculations using data from ILO, PIAAC, STEP and World Development Indicators

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)	0.003	0.004	-0.008	-0.004	-0.010	0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
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 their standard errors in parentheses. GDP per capita is in PPP from the World Development Indicators (WDI). Robust standard errors in parentheses.

Source: Authors' calculations using data from ILO, PIAAC, STEP and World Development Indicators