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

**Julieta Caunedo, Elisa Keller, and Yongseok Shin**

## 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 content and fewer workers in occupations with high non-routine content. More importantly, a given occupation has more routine content and less non-routine content in developing countries than in developed countries. Since 2006, occupations with high non-routine content gained employment relative to those with high routine content 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 content.

**JEL classification:** E24, J24, O14

**Keywords:** task, occupation, technological change, routinization

## 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).

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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 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 content and fewer workers in those with high non-routine content. In addition, a given occupation has more routine content and less non-routine content in developing countries than in developed countries. This is especially true for managers, professionals, and technicians, which are the occupations with the least routine content and the most non-routine content 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 content is the same across countries.

Next we find that, since 2006, occupations with high non-routine content gained employment relative to those with high routine content 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 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 content, drowning out the effect of offshoring that may reallocate such jobs from developed to developing countries.

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.

2 The occupational task content is held fixed over time, so the task-intensity changes only reflect the changing occupational composition over time.

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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. (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 content 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 United States in PIAAC closest to those constructed from the Occupation Information Network (O*NET) of the United States. 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 United States, we use all questions in PIAAC and focus on the comparability between PIAAC and STEP. Second, any rescaling 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 at 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 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 content as by their higher routine (both manual and cognitive) task content.

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)

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.

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

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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.

### 2.1. Data and Harmonization

Constructing the task-content measures of occupations involves combining the Survey of Adult Skills within the OECD's Programme 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 9 have full information on occupational task content 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 rescaling. Another serious challenge is that the non-response rates for some questions can be quite high in STEP, especially among the countries at 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

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 content, a phenomenon well established in many developed countries) for a large set of countries, with the assumption that the task content of a given occupation is the same in all countries. They found that, in developing countries, the employment share of the occupations with high routine content was small in 1990 but grew over the years, the opposite of what the literature had found in developed countries.

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 supplementary online appendix 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 supplementary online appendix provides more details on STEP.

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lower (less than 1 percent) in PIAAC countries. See table S2.2 of the supplementary 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 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 United States (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,

$$\mathrm{READ}_{oc} = \alpha_{\mathrm{READ}} + \beta_{\mathrm{READ}}\mathrm{COMP}_{oc} + \epsilon_{oc}, \tag{1}$$

where $o$ indexes one-digit occupations and $c$ countries. We then use the estimated $\hat{\alpha}_{\mathrm{READ}}$, $\hat{\beta}_{\mathrm{READ}}$, and the actual $\mathrm{COMP}_{oc}$ in STEP to predict the $\mathrm{READ}_{oc}$ 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 supplementary 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 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

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.

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 supplementary online appendix.

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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). 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 fig. S3.3 of the supplementary 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 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 content, and NRI the sum of personal and guide task content. 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 United States in PIAAC.

Constructing country-level task intensities from the occupation-level task content 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

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 S3.4 of the supplementary online appendix.

13 See section S3.6 of the supplementary 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.

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 supplementary online appendix.

15 PIAAC 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.

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**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 | −0.0003 | 0.0031 | 0.0091 | −0.0044 | −0.0057 | 0.0134** |
| | (0.0042) | (0.0061) | (0.0070) | (0.0046) | (0.0284) | (0.0051) |
| *N* | 28 | 28 | 28 | 28 | 28 | 28 |
| $R^2$ | 0.789 | 0.675 | 0.219 | 0.653 | 0.246 | 0.888 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*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, Netherlands, Norway, Peru, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey, United States. 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.

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 for Canada (from 2014). For each task category $i$, occupation $o$, and country $c$, we have a standardized task-content measure $\tau_{ioc}$. Denoting the share of workers in occupation $o$ in country $c$ by $s_{oc}$, the country-level task intensity $\tau_{ic}$ 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 $i$ content or because occupations in that country have higher task $i$ content than the same occupations in other countries.

The analysis that follows focuses on NRA and NRI tasks, as well as RC and 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

16 The ILO data do 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.

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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 fig. 1 with solid lines.

Typically, educated workers choose occupations with high NRA and NRI task content, while less educated workers choose occupations with high routine task content. 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 content, rather than the differences in the skill composition of the labor force as measured by educational attainment.

A widely used measure of occupational task content is the one available from O∗NET in the United States (Autor and Dorn 2013). If the task content of a given occupation is similar across countries, one can construct countries' task intensities as in equation (2) but with $\tau_{io}$ from O∗NET instead of $\tau_{ioc}$ on the right-hand side.[19] For many European countries, Handel (2012) showed that country-specific measures of occupational task content 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 content ($\tau_{ioc}$, solid lines) to the intensity based on O∗NET ($\tau_{io}$, 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 fig. 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 content (according to O∗NET) than developed countries, since for the dashed lines the task content of a given occupation is 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 content 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 2.5 times as steep. Overall, developing countries do have more workers in the occupations with high RC and RM content (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 content 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 content among the bottom quartile of countries and among the

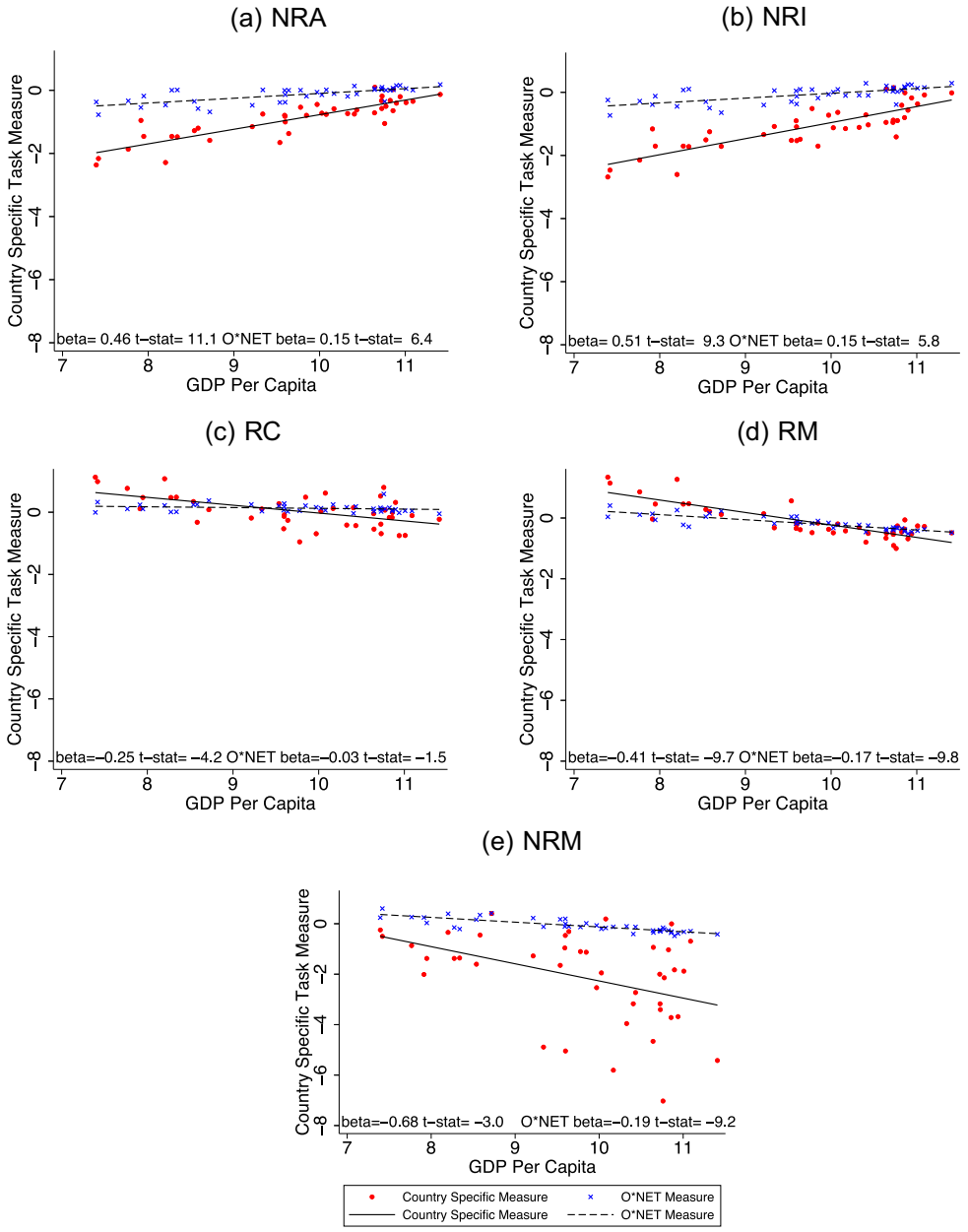
17 The unit is the standard deviation of occupational task content across occupations in the United States.

18 Panel B only considers the 28 countries for which educational attainment data are available (2 out of 9 STEP countries and 26 out of 33 PIAAC countries). The regression without the education variable for the 28 countries gives similar coefficients to those in panel B (lower half of panel A); if anything, the relationship between task intensity and income comes out marginally stronger.

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

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**Figure 1.** Task Intensity and Development.




*Source:* Authors' calculations using data from ILO: International Labour Organization, O*NET: Occupation Information Network, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.
*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 content 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.

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 content 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 content in all countries. On the other hand, occupations in the low-income countries have more RC and RM content than the

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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 content in all countries. The details of these comparisons are in section S3.7 of the supplementary 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 content 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 fig. 1. Developing countries have fewer workers in the occupations with high NRA and NRI content than developed countries (positive employment effect coefficient), and a given occupation in developing countries has less NRA and NRI content 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 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 fig. 1(d), developing countries have more workers in occupations with high RM content (negative employment effect coefficient), and a given occupation in developing countries has more RM content 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 fig. 1(c). The employment effect coefficient is significantly negative—that is, developing countries have significantly more workers in occupations with high RC content than developed countries, which contrasts with the nearly flat dashed line in fig. 1(c). At the same time, the task effect coefficient is insignificant, implying that there is no difference in RC content of occupations between developing and developed countries, which again contrasts with the slope of the solid line in fig. 1(c). These seemingly contradictory results can be reconciled, because fig. 1 is a comparison between country-specific occupational task content and the O*NET-based task content, while the decomposition here is about deviations from the cross-country mean.

20 One related question is whether the ranking of occupations in terms of a given task intensity within a country varies with the country's 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.

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**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 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAACC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.
*Note:* Column (1) reports the coefficients from regressing the countries' task intensity on log GDP per capita, with standard errors in parentheses. 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.

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 content 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 levels 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 has seen 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

21 As explained in the data and harmonization section, the irregularities in the ILO occupational employment data in earlier periods force us to start in 2006.

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**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 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

task content $\tau_{ioc}$ is 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 content gained employment relative to those occupations that have high RC and RM content. 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 supplementary 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 content. 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]

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 have 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

22 The unit is the standard deviation of occupational task content across occupations in the United States. 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 United States 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 United States 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).

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agriculture to manufacturing to services, the rise of manufacturing jobs with high RM content 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

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

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.

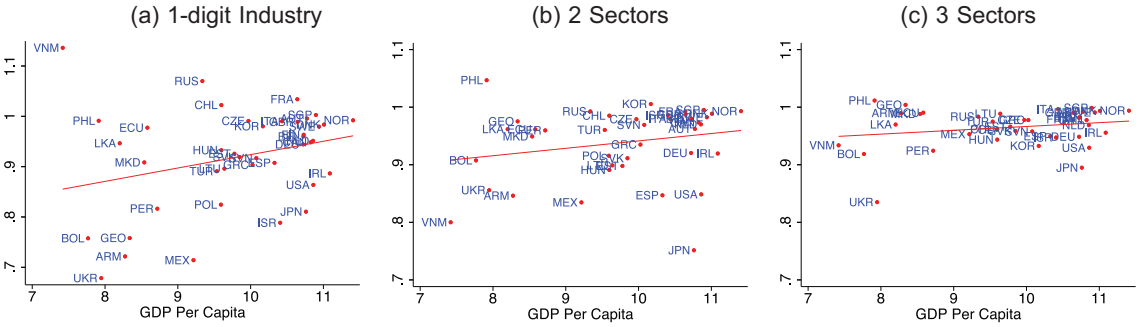
The data allow consistent use of nine occupations at the one-digit level, excluding agricultural occupations. Three different classifications of sectors are considered, again excluding agriculture: first, 19 industries in the one-digit industry classification; second, a simple manufacturing vs. service 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 fig. 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, plays a larger role in devel-

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.

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**Figure 2.** Decomposition of Occupational Employment Change: Within-Industry Component.




*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*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-hand 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-hand 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).

oping 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 United States 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 content country by country for uncovering these cross-country patterns.

One implication is that the question of why occupational task content varies 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 content encourages thinking of skills as a multidimensional 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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# Supplementary Online Appendix

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

**Julieta Caunedo, Elisa Keller, and Yongseok Shin**

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## S1. Data Sources and Descriptions

### S1.1. PIAAC: Survey of Adult Skills (OECD)

PIAAC countries with task information (34): Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Ecuador, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea, Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Russia, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey, United Kingdom, United States.

The survey is administered every 10 years and has had two cycles so far. In the first cycle, there were three rounds of data collection, between 2011 and 2018. In 2018, the second cycle began, with results to be published in 2023.

Most of the PIAAC countries above were surveyed in the first round (2011–12). The exceptions are Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia, and Turkey during the second round (2014–15), and Ecuador, Hungary, Mexico, Peru, and United States during the third round (2017).

Broad categories of generic worker skills are as follows:

- Cognitive skills encompass reading, writing, mathematics, and the use of information and communication technologies.
- Interaction and social skills cover collaboration and co-operation, planning work and use of time for oneself and others, communication and negotiation, and customer contact (e.g., selling products/services and advising).
- Physical skills involve the use of gross and fine motor skills.
- Learning skills cover activities such as instructing others, learning (formally or informally), and keeping up to date with developments in one's professional field. In addition, all respondents are asked about the frequency and intensity of their reading- and numeracy-related activities, as well as their use of ICTs at home and in the community.

### S1.2. STEP Skills Measurement Program (World Bank)

There are 13 STEP countries: Armenia, Bolivia, China (Yunnan province), Colombia, Georgia, Ghana, Kenya, Laos, Macedonia, Philippines, Sri Lanka, Ukraine, Vietnam. The surveys were conducted in 2012–13 in these countries, with the exception of the Philippines in 2015–16.

We classify answers to the household module into different tasks following the classification and definition of tasks in the O*NET. Whenever necessary, responses are rescaled to homogenize answers across questionnaires.

### S1.3. Occupational and Sectorial Employment

The main data we use are employment (counts) by economic activity and occupation from the Living Condition Survey available at the International Labour Organization (ILOSTAT). In the labor structure decomposition for the industry-level employment share across occupations ( the section on the role of sectoral changes in the main paper), we use the table "Employment by economic activity and occupation (Annual)."[25]

Employment data is disaggregated at the one-digit industry (ISIC-Rev.4) and one-digit occupation level (ISCO-08). The industry codes and occupation codes vary across countries and years.[26] The sector

25 Available at https://www.ilo.org/shinyapps/bulkexplorer44/?lang=en&segment=indicator&id=EMP_TEMP_ECO_OCU_NB_A.

26 Available at https://www.ilo.org/shinyapps/bulkexplorer4/?lang=en&segment=indicator&id=EMP_TEMP_SEX_OCU_NB_A.

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classification of services that we use in the section on the role of sectoral changes in the main paper follows Eckert, Ganapati and Walsh (2019):[27]

- High-skill service
  - Information and communication
  - Financial and insurance activities
  - Professional, scientific, and technical activities
  - Education
  - Human health and social work activities
- Low-skill service
  - Wholesale and retail trade; repair of motor vehicles and motorcycles
  - Transportation and storage
  - Accommodation and food service activities
  - Real estate activities
  - Administrative and support service activities
  - Public administration and defense; compulsory social security

#### S1.4. Output and Education

We use PPP measures of gross domestic product per capita reported by the World Development Indicators (WDI) under "GDP per capita, PPP (constant 2017 international dollar)." Measures of the labor force with post-secondary education are in the WDI under "Educational attainment, at least completed post-secondary, population 25+, total (%) (cumulative)."

## S2. Construction of Task Intensity across Countries

### S2.1. Questionnaires of PIAAC and STEP

*S2.1.1. PIAAC*

- Detailed questions
  - Non-routine analytical (NRA)
    - Read (READ)
      - How often do you read directions or instructions? (GQ01a)
      - How often do you read letters, memos, or e-mails? (GQ01b)
      - How often do you read articles in newspapers, magazines, or newsletters? (GQ01c)
      - How often do you read articles in professional journals or scholarly publications? (GQ01d)
      - How often do you read books? (GQ01e)
      - How often do you read manuals or reference materials? (GQ01f)
      - How often do you read bills, invoices, bank statements, or other financial statements? (GQ01g)
      - How often do you read diagrams, maps, or schematics? (GQ01h)
    - Think creatively (THINK)
      - How often do you take at least 30 minutes to find a good solution? (FQ05b)
  - Non-routine interpersonal (NRI)

27 Eckert, F., Ganapati, S., and Walsh, C. (2019). Skilled Tradable Services: The Transformation of U.S. High-Skill Labor Markets. Opportunity and Inclusive Growth Institute Working Papers 25, Federal Reserve Bank of Minneapolis.

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        * Personal relationship (PERSON)
            - How often do you share work-related information with co-workers? (FQ02a)
            - How often do you sell a product or a service? (FQ02d)
            - How often do you persuade or influence people? (FQ04a)
            - How often do you negotiate with people either inside or outside your firm or organization? (FQ04b)
        * Guiding/coaching (GUIDE)
            - How often do you instruct, train, or teach people, individually or in groups? (FQ02b)
            - How often do you advise people? (FQ02e)
            - How often do you plan the activities of others? (FQ03b)
    - Routine cognitive (RC)
        - Structured/repetition (STRUC)
            - How often do you plan your own activities? (Inverse) (FQ03a)
            - How often do you organize your own time? (Inverse) (FQ03c)
    - Routine manual (RM)
        * Controlling machines (CONTRO)
            - How often do you work physically for a long period? (FQ06b)
    - Non-routine manual (NRM)
        * Operating/hands/manual (OPER)
            - How often do you use skill or accuracy with your hands or fingers? (FQ06c)
    - Computer usage (CU)
        * Computer usage (COMP)
            - Did you use a computer (GQ04)

- Constructing content measures: Answers to questions in the PIAAC questionnaires have a fixed range from 1 to 5. We take the average of answers to each question and summarize them into eight measures: READ, THINK, PERSON, GUIDE, STRUC, CONTRO, OPER, and COMP. Take READ as an example: READ for each respondent $j$ in country $c$ from PIAAC equals

$$\mathrm{READ}_j = \frac{\begin{array}{c}\mathrm{GQ01a}_j+\mathrm{GQ01b}_j+\mathrm{GQ01c}_j+\mathrm{GQ01d}_j \\ +\mathrm{GQ01e}_j+\mathrm{GQ01f}_j+\mathrm{GQ01g}_j+\mathrm{GQ01h}_j\end{array}}{8}.$$

*S2.1.2. STEP*

- Detailed questions
    - Non-routine analytical (NRA)
        * Read (READ)
            - Do you read anything at this work? (A-4)[28]
            - Do you read forms? (A-5-1)
            - Do you read bills or financial statements? (A-5-2)
            - Do you read newspapers or magazines? (A-5-3)
            - Do you read instruction manuals/operating manuals? (A-5-4)

28 Different countries in STEP have different numbers for each question. We use the question numbers from the Armenian Household Survey.

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        - Do you read books (other than instruction/operating manuals)? (A-5-5)
        - Do you read reports? (A-5-6)
    * Think creatively (THINK)
        - How often do you have to undertake tasks that require at least 30 minutes of thinking? (B-10)
  – Non-routine interpersonal (NRI)
    * Personal relationship (PERSON)
        - Do you have any contact with people other than co-workers, for example with customers, clients, students, or the public? (B-5, B-6)
    * Guiding/coaching (GUIDE)
        - Do you direct and check the work of other workers (supervise)? (B-13)
  – Routine cognitive (RC)
    * Structured/repetition (STRUC)
        - How much freedom do you have to decide how to do your work in your own way? (Inverse) (B-14)
        - How often does this work involve carrying out short, repetitive tasks? (Inverse) (B-16)
        - How often does this work involve learning new things? (B-17)
  – Routine manual (RM)
    * Controlling machines (CONTRO)
        - What number would you use to rate how physically demanding your work is? (B-3)
        - Do you operate or work with any heavy machines or industrial equipment? (B-9)
  – Non-routine manual (NRM)
    * Operating/hands/manual (OPER)
        - Do you drive a car, truck, or three-wheeler? (B-7)
        - Do you repair/maintain electronic equipment? (B-8)
  – Computer usage (CU)
    * Computer usage (COMP)
        - As part of your work, do you use a computer? (B-18)

• Constructing content measures
  – Because the questions in STEP questionnaires are differently worded with different answer scales from those in PIAAC, we only extract the computer-usage information from the questionnaire, and use this information to predict the seven detailed task categories in the next step. Note that the computer-use question is identical in PIAAC and STEP, and also has the lowest non-response rates, as will be shown in table S2.2.

*S2.1.3. Harmonizing PIAAC and STEP*

S2.1.3.1. STEP 1*:* Predict the values of the seven relevant detailed task categories using computer usage for the STEP sample. This is an out-of-sample prediction using the regression coefficients in the PIAAC sample for each detailed task category. Because computer use is a binary for each individual respondent we generate a continuous variable for computer use in each occupation $COMP_o$ as the weighted average of the binary individual responses, with weights equal to the sample weights. Similarly, we construct mea-

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sures of each detailed task category by averaging individual responses using sample weights. Then we run the following regression in each country using the PIAAC sample. Take READ as an example:

$$\text{READ}_{oc} = \beta_0 + \beta_1 \text{COMP}_{oc} + \epsilon_{oc},$$

where $o$ indexes one-digit occupations and $c$ countries.

With the estimated $\hat{\beta}_0$ and $\hat{\beta}_1$, use the actual $\text{COMP}_{oc}$ measure in STEP to predict the $\widehat{\text{READ}}_{oc}$ in the STEP sample. We apply the same procedure to the remaining six detailed task categories, THINK, PERSON, GUIDE, STRUC, CONTRO, and OPER, for STEP countries.

S2.1.3.2. STEP 2*:* Standardize the answers across all countries relative to the United States. We use the sample weight for each occupation in a country to calculate the weighted mean and standard deviation of each of the eight measures in the United States. We standardize each content measure by subtracting the weighted mean and dividing by the weighted standard deviation of the United States. Take READ as an example: the new value of READ for each occupation $o$ and country $c$ equals

$$\text{READ}_{oc} = \frac{\text{READ}_{oc} - \text{MEAN}}{\text{SD}},$$

where MEAN and SD are the weighted mean and standard deviation of READ in the United States.

S2.1.3.3. STEP 3*:* We further add up standardized READ and THINK to create NRA, PERSON and GUIDE to NRI. In addition, RC, RM, and NRM will take the values of STRUC, CONTRO, and OPER, respectively. We standardize NRA and NRI again. Take NRA as an example: the new value of NRA for each occupation $o$ and country $c$ equals

$$\text{NRA}_{oc} = \frac{\text{NRA}_{oc} - \text{MEAN}}{\text{SD}},$$

where MEAN and SD are the weighted mean and standard deviation of $\text{NRA}_o$ in the United States.

S2.1.3.4. STEP 4*:* We calculate the weighted mean of NRA, NRI, RC, RM, and NRM for country $c$ with employment shares of occupation $o$ in country $c$ as weights. Take NRA as an example: the value of NRA for country $c$ equals

$$\text{NRA}_c = \sum_o \text{NRA}_{co} \times \text{EmpShare}_{co}.$$

**S2.2. O∗NET**

Note that the observation unit of the O∗NET is an occupation, not a respondent.

- Detailed questions
  - Non-routine analytical (NRA)
    - ∗ Read (READ)
      - Analyzing data/information (4.A.2.a.4)
    - ∗ Think creatively (THINK)
      - Thinking creatively (4.A.2.b.2)
  - Non-routine interpersonal (NRI)
    - ∗ Personal relationship (PERSON)
      - Establishing and maintaining personal relationships (4.A.4.a.4)

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        * Guiding/coaching (GUIDE)
            - Guiding, directing, and motivating subordinates (4.A.4.b.4)
            - Coaching/developing others (4.A.4.b.5)
    - Routine cognitive (RC)
        * Structured/repetition (STRUC)
            - Structured vs. unstructured work (inverse) (4.C.3.b.8)
            - Importance of repeating the same tasks (4.C.3.b.7)
    - Routine manual (RM)
        * Controlling machines (CONTRO)
            - Using either control mechanisms or direct physical activity to operate machines or processes (not including computers or vehicles) (4.A.3.a.3)
    - Non-routine manual (NRM)
        * Operating/hands/manual (OPER)
            - Operating vehicles, mechanized devices, or equipment (4.A.3.a.4)
            - Spend time using hands to handle, control, or feel objects, tools, or controls (4.C.2.d.1.g)
            - Manual dexterity (1.A.2.a.2)

- Constructing content measures
    - **STEP 1:** Occupation code concordance. The O*NET data is at the eight-digit ONETSOC level. We change the original eight-digit ONETSOC codes to six-digit SOC codes, and then crosswalk them to the one-digit ISCO codes with weights directly constructed from the IPUMS-International US data.[29]
    - **STEP 2:** We take the average of answers to each question and summarize them into eight measures: READ, THINK, PERSON, GUIDE, STRUC, CONTRO, OPER, and COMP. Take GUIDE as an example:

$$\text{GUIDE}_o = 4.\text{A}.4.\text{b}.4_o + 4.\text{A}.4.\text{b}.5_o,$$

      where $o$ indexes occupations.
    - **STEP 3:** Standardize the answers. We use the sample weight to calculate the weighted mean and standard deviation of each of the eight content measures in the United States. We standardize each question by subtracting the US mean and dividing by the US standard deviation. Take GUIDE as an example: the new value of GUIDE for occupation $o$ equals

$$\text{GUIDE}_o = \frac{\text{GUIDE}_o - \text{MEAN}}{\text{SD}},$$

      where MEAN and SD are the employment weighted mean and standard deviation of GUIDE in the United States.
    - **STEP 4:** We further add up standardized READ and THINK to NRA, PERSON and GUIDE to NRI. In addition, RC, RM, NRM, and COMP will take the values of STRUC, CONTRO, OPER, and COMP, respectively. We standardize NRA and NRI again with the respective weighted mean and standard deviation.
    - **STEP 5:** We take the weighted mean NRA, NRI, RC, RM, NRM, and COMP at one-digit occupation level (ISCO) $o$ with constructed weight. Take NRA as an example: the value of

29 IPUMS-International US has SOC and ISCO code for each respondent. As SOC to ISCO is an *m-m* correspondence, we take the sum of sample weights for each SOC and ISCO pair as the new concordance weight.

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$\text{NRA}_o^{onet}$ for one-digit occupation $o$ equals

$$\text{NRA}_o^{\text{onet}} = \sum_j \text{NRA}_{jo} \times \text{weight}_{jo},$$

where $j$ indexes six-digit occupations belonging to the one-digit occupation $o$.

### S2.3. Data Availability

PIAAC and STEP allow us to construct measures of task intensity for each occupation in each country in the sample. We drop information for the Yunnan province in China, Colombia, Laos, and Kenya because of missing occupations in the sample. Our final set of 42 countries is Armenia, Austria, Belgium, Bolivia, Canada, Chile, Czechia, Denmark, Ecuador, Estonia, Finland, France, Georgia, Germany, Ghana, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea, Lithuania, Macedonia, Mexico, Netherlands, Norway, Peru, Philippines, Poland, Russia, Singapore, Slovakia, Slovenia, Spain, Sri Lanka, Sweden, Turkey, Ukraine, United Kingdom, United States, Vietnam, of which 33 are from PIAAC and 9 from STEP. Table S2.1 has the details.

The surveys have a non-trivial amount of missing responses, as we report in table S2.2. Missing responses are disproportionately numerous in STEP countries, particularly for the READ questions.

## S3. Additional Results

### S3.1. Results with Occupation-by-Occupation Projection

We present results when the estimation from PIAAC and the prediction for STEP allow for regression coefficients that vary across occupations. While our baseline estimates exploit variations across country and occupation, these alternative estimates exploit cross-country variations within an occupation to identify the relationship between computer use and the detailed task categories. The estimates are not significantly different from the baseline estimates, and the estimated coefficients have much larger standard errors, in part due to the reduced sample sizes ($N = 264$ in the baseline vs. $N = 33$ PIAAC countries in the occupation-by-occupation regressions).

The estimated coefficients from the PIAAC countries are reported in table S3.1. Figure S3.1 shows the correlations between task intensities and GDP per capita when this alternative specification is used. It is nearly identical to the benchmark result (fig. 1 of the main text).

### S3.2. Changes in Task Intensity over Time

Figure S3.2 is a visual representation of the relationship (or the lack thereof) between countries' task-intensity changes between 2006 and 2015 and their log GDP per capita in 2006. Each dot is a country and the solid line is the regression line, whose slope coefficient is reported in table 3 of the main text.

### S3.3. Interaction between Income Level and Computer Use

We present the results for an alternative specification for the data harmonization between PIAAC and STEP. In the estimation of equation (1) of the main text for the PIAAC countries and the resulting prediction for the STEP countries, this alternative specification allows for the interaction between computer use and countries' income level. That is, we allow for the possibility that the relationship between computer use and a given detailed task category may vary with countries' income level. This contrasts with the benchmark specification that the relationship between computer use and detailed task categories is the same between the PIAAC countries and the STEP countries.

Three sets of estimations for the PIAAC countries are shown in tables S3.2–S3.4. Table S3.2 is the baseline result, regressing each detailed task category on computer use only.

Table S3.3 is the estimation for the PIAAC countries when the interaction between computer use and log GDP per capita is included in the regression. The coefficient on the interaction term is statistically

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**Table S2.1.** Data Availability

| Country | Data source | Initial year | Final year | World Bank regions |
|---|---|---|---|---|
| Lower-middle income ($1,286 to $4,255) | | | | |
| Kenya | STEP | dropped | | |
| Ghana | STEP | 2006 | 2015 | Sub-Saharan Africa |
| Lao PDR | STEP | dropped | | |
| Vietnam | STEP | 2006 | 2015 | South Asia |
| Philippines | STEP | 2006 | 2015 | South Asia |
| Bolivia | STEP | 2006 | 2015 | Latin America |
| Ukraine | STEP | 2006 | 2015 | Europe & Central Asia |
| Sri Lanka | STEP | 2006 | 2015 | South Asia |
| Upper-middle income ($4,256 to $13,205) | | | | |
| Armenia | STEP | 2008 | 2015 | Central Asia |
| Georgia | STEP | 2006 | 2015 | Europe & Central Asia |
| Ecuador | PIAAC | 2006 | 2015 | Latin America |
| Colombia | STEP | dropped | | |
| Peru | PIAAC | 2006 | 2015 | Latin America |
| Turkey | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Mexico | PIAAC | 2006 | 2015 | North America |
| Russia | PIAAC | 2006 | 2015 | Europe & Central Asia |
| High income ($13,206 or more) | | | | |
| Chile | PIAAC | 2006 | 2015 | Latin America |
| Poland | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Hungary | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Slovak Republic | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Lithuania | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Greece | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Czech Republic | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Estonia | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Slovenia | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Spain | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Korea | PIAAC | 2006 | 2015 | East Asia |
| Italy | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Japan | PIAAC | 2006 | 2015 | East Asia |
| France | PIAAC | 2006 | 2015 | Europe & Central Asia |
| New Zealand | PIAAC | dropped | | |
| United Kingdom | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Israel | PIAAC | 2006 | 2015 | Middle-East |
| Belgium | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Canada | PIAAC | 2006 | 2014 | North America |
| Germany | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Finland | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Austria | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Sweden | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Netherlands | PIAAC | 2004 | 2015 | Europe & Central Asia |
| Denmark | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Singapore | PIAAC | 2006 | 2015 | East Asia |
| United States | PIAAC | 2006 | 2015 | North America |
| Ireland | PIAAC | 2006 | 2015 | Europe & Central Asia |
| Yunnan, China | STEP | dropped | | |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* Income groups are defined as World Bank country groups using gross national income per capita in 2021. The initial and final years refer to the availability of occupational employment data in ILOSTAT. Countries were dropped when substantial amounts of data were missing. Kenya had employment data only in 2009; Lao PDR had employment data available only in 2010 and 2017; Colombia had one-digit occupational employment data only until 2009.

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**Table S2.2.** Data Availability (Survey Responses)

| Country | Source | Read | Think | Person | Guide | Structure | Control | Operations | Computer | Full sample | Non-missing sample |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Armenia | STEP | 369 | 11 | 12 | 10 | 29 | 11 | 10 | 10 | 1,128 | 744 |
| Austria | PIAAC | 2 | 2 | 5 | 3 | 6 | 2 | 2 | 1 | 3,647 | 3,637 |
| Belgium | PIAAC | 5 | 8 | 7 | 6 | 7 | 4 | 4 | 4 | 3,304 | 3,292 |
| Bolivia | STEP | 844 | 6 | 5 | 4 | 21 | 3 | 4 | 4 | 1,950 | 1,102 |
| Canada | PIAAC | 32 | 49 | 86 | 46 | 41 | 21 | 20 | 2 | 19,111 | 18,907 |
| Chile | PIAAC | 8 | 13 | 26 | 15 | 12 | 10 | 8 | 1 | 3,539 | 3,478 |
| Czech Republic | PIAAC | 5 | 4 | 18 | 11 | 16 | 3 | 5 | 1 | 3,610 | 3,566 |
| Denmark | PIAAC | 9 | 13 | 32 | 13 | 17 | 8 | 7 | 5 | 5,275 | 5,216 |
| Ecuador | PIAAC | 5 | 9 | 9 | 7 | 7 | 5 | 4 | 5 | 3,324 | 3,308 |
| Estonia | PIAAC | 17 | 24 | 23 | 23 | 20 | 20 | 20 | 12 | 5,313 | 5,251 |
| Finland | PIAAC | 14 | 21 | 27 | 12 | 17 | 12 | 16 | 3 | 3,846 | 3,784 |
| France | PIAAC | 8 | 47 | 46 | 12 | 30 | 8 | 13 | 1 | 4,438 | 4,310 |
| Georgia | STEP | 419 | 6 | 6 | 5 | 19 | 8 | 6 | 5 | 1,105 | 672 |
| Germany | PIAAC | 1 | 4 | 15 | 4 | 11 | 2 | 5 | 1 | 3,995 | 3,960 |
| Ghana | STEP | 1,489 | 4 | 4 | 4 | 47 | 3 | 4 | 4 | 2,350 | 857 |
| Greece | PIAAC |  | 2 | 4 | 2 | 1 |  |  |  | 2,361 | 2,353 |
| Hungary | PIAAC | 2 | 5 | 6 | 4 | 4 | 2 | 2 | 2 | 4,207 | 4,195 |
| Ireland | PIAAC | 5 | 2 | 8 | 5 | 5 | 3 | 1 | 1 | 3,626 | 3,608 |
| Israel | PIAAC | 9 | 20 | 30 | 10 | 26 | 6 | 6 | 4 | 3,458 | 3,384 |
| Italy | PIAAC | 2 |  | 9 | 2 | 2 | 1 |  |  | 2,810 | 2,797 |
| Japan | PIAAC | 7 | 8 | 10 | 11 | 7 | 4 | 2 | 1 | 3,832 | 3,801 |
| Korea | PIAAC | 2 | 3 | 5 | 3 | 2 | 1 | 1 | 1 | 4,342 | 4,334 |

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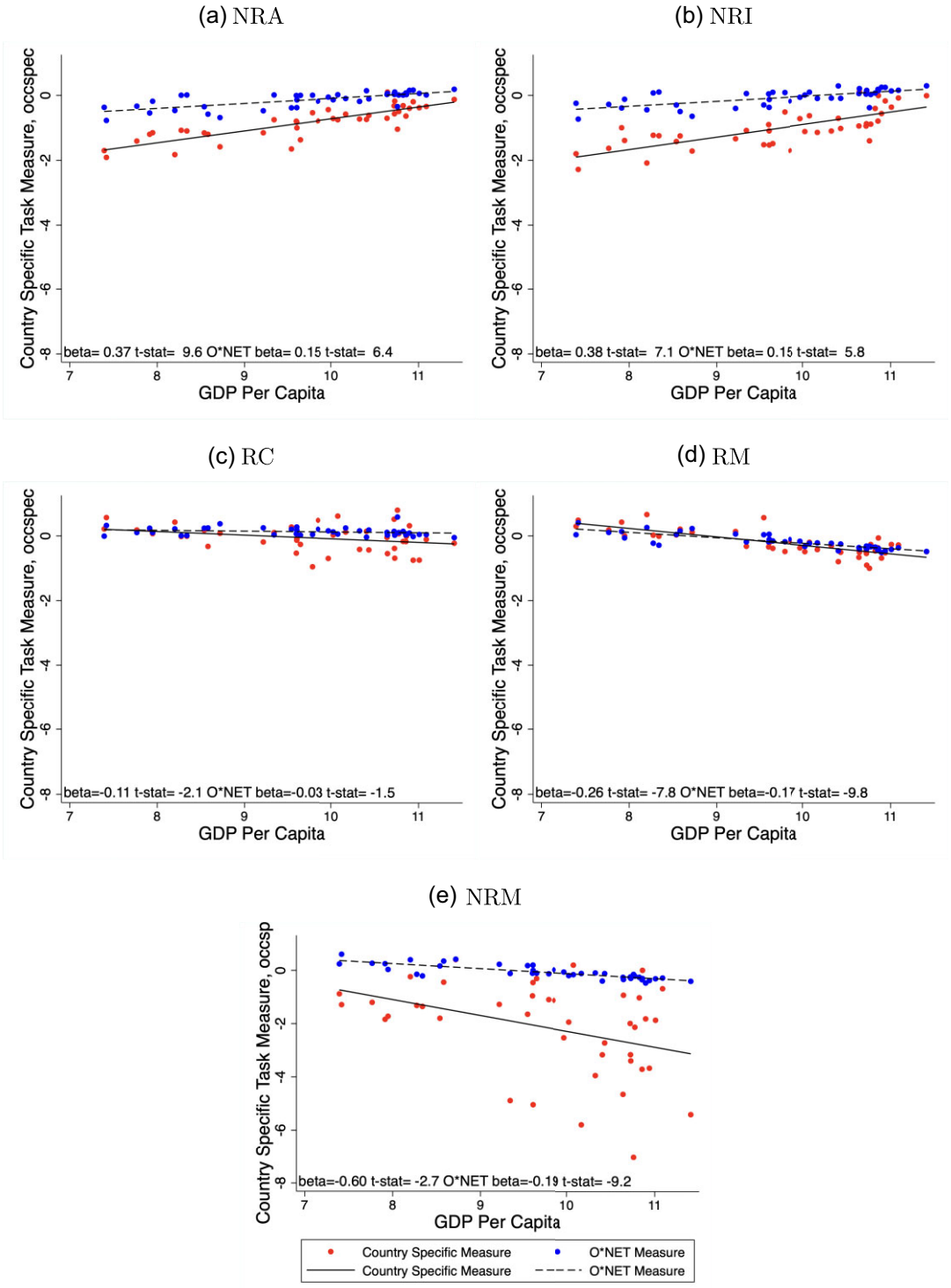
**Table S2.2.** Continued

| Country | Source | Read | Think | Person | Guide | Structure | Control | Operations | Computer | Full sample | Non-missing sample |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Lithuania | PIAAC | 2 | 7 | 3 | 2 | 1 | 1 | 2 | 1 | 3,175 | 3,165 |
| Macedonia | STEP | 618 | | | | 27 | | | | 1,958 | 1,332 |
| Mexico | PIAAC | 9 | 10 | 10 | 8 | 7 | 8 | 9 | 8 | 3,835 | 3,814 |
| Netherlands | PIAAC | 3 | 3 | 9 | 4 | 5 | 2 | 2 | | 3,890 | 3,867 |
| Norway | PIAAC | 9 | 9 | 20 | 6 | 7 | 6 | 7 | 3 | 3,491 | 3,454 |
| Peru | PIAAC | 7 | 18 | 9 | 6 | 7 | 4 | 4 | 4 | 5,199 | 5,173 |
| Philippines | STEP | 209 | 1 | 1 | 1 | 2 | 1 | 1 | 1 | 1,691 | 1,481 |
| Poland | PIAAC | 7 | 17 | 39 | 16 | 13 | 10 | 8 | 4 | 5,024 | 4,954 |
| Russia | PIAAC | 15 | 25 | 37 | 23 | 22 | 12 | 13 | 4 | 2,168 | 2,076 |
| Singapore | PIAAC | 4 | 1 | 2 | | 2 | 1 | | | 3,872 | 3,862 |
| Slovakia | PIAAC | 8 | 12 | 18 | 8 | 14 | 5 | 8 | | 3,276 | 3,216 |
| Slovenia | PIAAC | 1 | 9 | 19 | 3 | 13 | | | 1 | 2,953 | 2,913 |
| Spain | PIAAC | 6 | 9 | 12 | 5 | 7 | 3 | 3 | 2 | 3,312 | 3,285 |
| Sri Lanka | STEP | 957 | | | | 82 | | | | 1,703 | 736 |
| Sweden | PIAAC | 13 | 13 | 23 | 10 | 18 | 3 | 11 | 1 | 3,302 | 3,237 |
| Turkey | PIAAC | 5 | 2 | 2 | 5 | | 1 | 1 | | 2,154 | 2,142 |
| United Kingdom | STEP | 12 | 7 | 23 | 12 | 12 | 5 | 6 | 3 | 5,785 | 5,735 |
| USA | PIAAC | 4 | 5 | 17 | 6 | 5 | 6 | 3 | | 4,705 | 4,670 |
| Ukraine | PIAAC | 432 | 61 | 6 | 8 | 101 | 2 | 10 | 3 | 1,212 | 686 |
| Vietnam | STEP | 794 | 6 | 6 | 6 | 36 | 6 | 6 | 6 | 2,479 | 1,674 |
| Total | | 6,369 | 476 | 649 | 341 | 728 | 213 | 234 | 109 | 155,755 | 148,028 |

*Source:* Authors' calculations using data from PIAAC: International Assessment of Adult Competencies and STEP: World Bank's STEP Skills Measurement Program.
*Note:* Columns 3–10 show the number of missing responses. Column 11 reports the full sample sizes with some available information, and Column 12 the sample sizes excluding observations with missing entries in any task categories.

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**Figure S3.1.** Task Intensity and Development, Occupation-by-Occupation Projection.

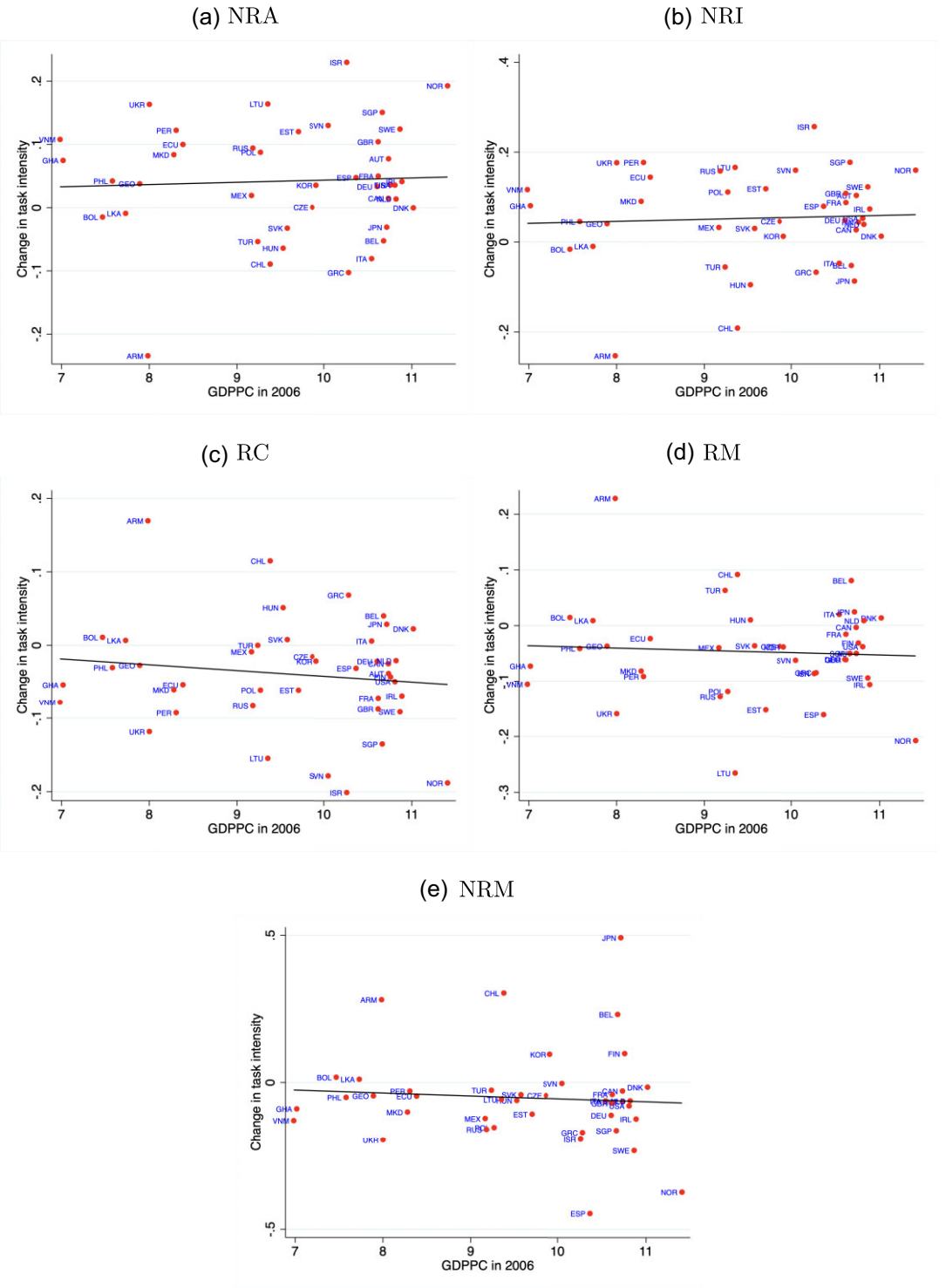



*Source:* Authors' calculations using data from ILO: International Labour Organization, O∗NET: Occupation Information Network, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* Countries' task intensity based on country-specific (red dots, solid lines) and O∗NET-based (blue dots, dashed lines) measures of occupational task content against GDP per capita (PPP in log). The estimation from PIAAC and the projection for STEP countries allow coefficients to vary across occupations.

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**Figure S3.2.** Changes in Task Intensity and Development.




*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* Countries' change in task intensity between 2006 and 2015 against its GDP per capita in 2006 (PPP in log). The solid line is the linear regression of the changes in task intensity on GDP per capita in 2006. Regression coefficients are presented in table 3 of the main text.

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**Table S3.1.** Estimation from PIAAC, Baseline and Occupation-by-Occupation Projection

| | READ | THINK | PERSON | GUIDE | STRUC | CONTRO | OPER |
|---|---|---|---|---|---|---|---|
| Baseline | 1.927*** | 1.418*** | 1.401*** | 1.774*** | −1.408*** | −2.787*** | −1.028*** |
| | (0.0498) | (0.0735) | (0.0743) | (0.0764) | (0.0823) | (0.102) | (0.122) |
| $N$ | 264 | 264 | 264 | 264 | 264 | 264 | 264 |
| $R^2$ | 0.851 | 0.587 | 0.576 | 0.673 | 0.528 | 0.741 | 0.212 |
| Managers | 1.566*** | 0.941* | 0.515 | 1.528*** | −0.485 | −3.899*** | −3.623** |
| | (0.402) | (0.499) | (0.453) | (0.424) | (0.391) | (0.609) | (1.351) |
| $R^2$ | 0.329 | 0.103 | 0.040 | 0.295 | 0.047 | 0.570 | 0.188 |
| Professionals | 1.289*** | 1.334** | 0.798* | 1.029 | −0.777 | −1.725* | −1.558 |
| | (0.448) | (0.601) | (0.467) | (0.650) | (0.471) | (1.017) | (1.471) |
| $R^2$ | 0.211 | 0.137 | 0.086 | 0.075 | 0.081 | 0.085 | 0.035 |
| Technicians | 1.665*** | 0.996** | 0.373 | 1.238** | −0.792 | −3.082*** | −1.480 |
| | (0.360) | (0.435) | (0.309) | (0.536) | (0.529) | (0.727) | (1.168) |
| $R^2$ | 0.408 | 0.145 | 0.045 | 0.147 | 0.067 | 0.367 | 0.049 |
| Clerical | 1.582*** | 0.452 | −0.151 | −0.0925 | −0.318 | −2.427*** | −1.219 |
| | (0.515) | (0.500) | (0.537) | (0.647) | (0.928) | (0.873) | (1.977) |
| $R^2$ | 0.233 | 0.026 | 0.003 | 0.001 | 0.004 | 0.199 | 0.012 |
| Sales | 1.175*** | −0.0337 | 0.216 | 1.336*** | 0.169 | 0.719** | 0.0715 |
| | (0.151) | (0.192) | (0.204) | (0.219) | (0.401) | (0.324) | (0.564) |
| $R^2$ | 0.661 | 0.001 | 0.035 | 0.546 | 0.006 | 0.137 | 0.001 |
| Craft and trade | 1.838*** | 0.459* | 0.750*** | 1.403*** | −0.254 | −0.0768 | −0.184 |
| | (0.191) | (0.260) | (0.229) | (0.249) | (0.387) | (0.333) | (0.369) |
| $R^2$ | 0.750 | 0.091 | 0.258 | 0.506 | 0.014 | 0.002 | 0.008 |
| Machine operators | 1.155*** | −0.324 | 0.402 | 1.119*** | −0.0391 | −0.151 | −0.678 |
| | (0.209) | (0.200) | (0.272) | (0.233) | (0.437) | (0.312) | (0.578) |
| $R^2$ | 0.497 | 0.079 | 0.066 | 0.426 | 0.000 | 0.008 | 0.042 |
| Elementary | 1.450*** | −0.111 | 1.215*** | 1.750*** | −0.244 | 0.244 | −0.859 |
| | (0.189) | (0.309) | (0.240) | (0.249) | (0.575) | (0.545) | (0.854) |
| $R^2$ | 0.654 | 0.004 | 0.453 | 0.614 | 0.006 | 0.006 | 0.032 |
| $N$ | 33 | 33 | 33 | 33 | 33 | 33 | 33 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, and PIAAC: International Assessment of Adult Competencies.
*Note:* Estimates from the regression of detailed task categories on computer use in PIAAC. The top panel is the baseline result, pooling across all occupations. The rest is the result for occupation-specific coefficients. Statistical significance at the 10, 5, and 1 percent levels is denoted with *, **, and ***, respectively.

**Table S3.2.** Task and Computer in PIAAC, Baseline

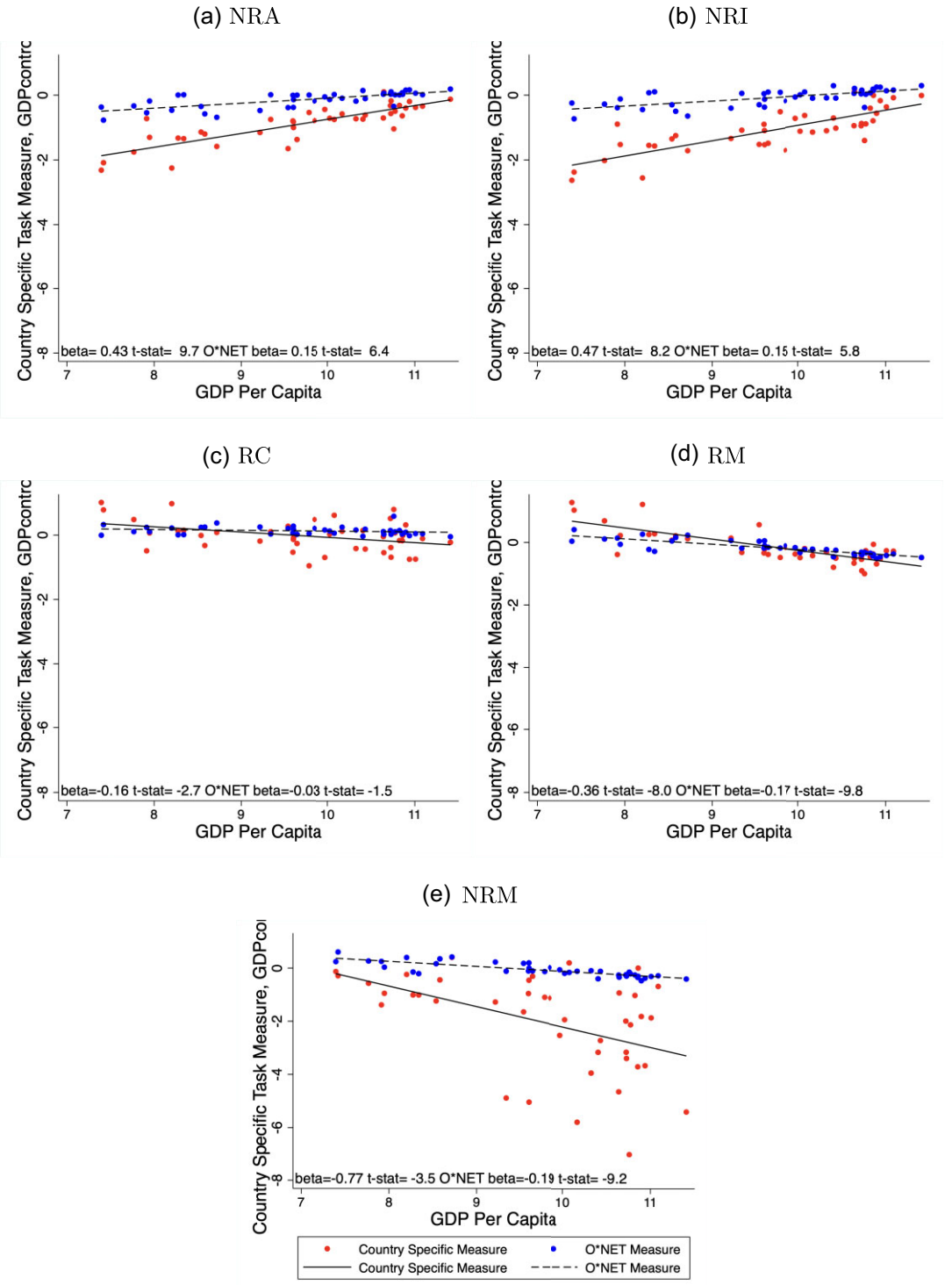
| | READ | THINK | PERSON | GUIDE | STRUC | CONTRO | OPER |
|---|---|---|---|---|---|---|---|
| Computers | 1.927*** | 1.418*** | 1.401*** | 1.774*** | −1.408*** | −2.787*** | −1.028*** |
| | (0.0498) | (0.0735) | (0.0743) | (0.0764) | (0.0823) | (0.102) | (0.122) |
| $N$ | 264 | 264 | 264 | 264 | 264 | 264 | 264 |
| $R^2$ | 0.851 | 0.587 | 0.576 | 0.673 | 0.528 | 0.741 | 0.212 |
| Adj. $R^2$ | 0.851 | 0.585 | 0.574 | 0.672 | 0.526 | 0.740 | 0.209 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, and PIAAC: International Assessment of Adult Competencies.
*Note:* Coefficients from the pooled regression of each detailed task category on computer use only. Statistical significance at the 10, 5, and 1 percent levels is denoted with *, **, and ***, respectively.

significant for five of the seven detailed task categories. However, the adjusted $R^2$ is little changed. Figure S3.3 is the main result, the relationship between countries' task intensities and GDP per capita, using this specification with the interaction term in the STEP prediction step. The results are nearly the same as the main result in fig. 1 of the main text, which is not surprising since the adjusted $R^2$ barely changed when the (statistically significant) interaction term was included.

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**Figure S3.3.** Projection with Interaction between Computer and GDP per Capita.




*Source:* Authors' calculations using data from ILO: International Labour Organization, O*NET: Occupation Information Network, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* Countries' task intensity based on country-specific (red dots, solid lines) and O*NET-based (blue dots, dashed lines) measures of occupational task content against GDP per capita (PPP in log). In the harmonization of the PIAAC and STEP data, the interaction term between computer use and GDP per capita is included, in addition to the computer-use term.

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**Table S3.3**. Task and Computer in PIAAC, Interaction with GDP per Capita

| | READ | THINK | PERSON | GUIDE | STRUC | CONTRO | OPER |
|---|---|---|---|---|---|---|---|
| Computers | 2.709*** | 2.558*** | 2.747*** | 2.360*** | −4.303*** | −5.265*** | 0.243 |
| | (0.348) | (0.514) | (0.517) | (0.538) | (0.552) | (0.701) | (0.860) |
| Computers∗GDP | −0.0745** | −0.109** | −0.128*** | −0.0559 | 0.276*** | 0.236*** | −0.121 |
| | (0.0328) | (0.0485) | (0.0488) | (0.0507) | (0.0521) | (0.0662) | (0.0811) |
| $N$ | 264 | 264 | 264 | 264 | 264 | 264 | 264 |
| $R^2$ | 0.854 | 0.594 | 0.587 | 0.675 | 0.574 | 0.753 | 0.219 |
| Adj. $R^2$ | 0.853 | 0.591 | 0.584 | 0.672 | 0.570 | 0.751 | 0.213 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, and World Development Indicators.

*Note:* Coefficients from the pooled regression of each detailed task category on computer use and its interaction with log GDP per capita. Statistical significance at the 10, 5, and 1 percent levels is denoted with *, **, and ***, respectively.

**Table S3.4**. Task and Computer, Interaction with GDP per Capita and Education

| | READ | THINK | PERSON | GUIDE | STRUC | CONTRO | OPER |
|---|---|---|---|---|---|---|---|
| Computers | 2.833*** | 1.986*** | 2.448*** | 2.426*** | −3.440*** | −5.082*** | 1.852* |
| | (0.426) | (0.607) | (0.621) | (0.639) | (0.673) | (0.864) | (0.970) |
| Computers∗GDP | −0.0726 | −0.0270 | −0.0849 | −0.0693 | 0.168** | 0.248*** | −0.324*** |
| | (0.0447) | (0.0637) | (0.0652) | (0.0671) | (0.0707) | (0.0906) | (0.102) |
| Computers∗Educ | −0.00441 | −0.00898** | −0.00556 | 0.00187 | 0.00854* | −0.00618 | 0.0128* |
| | (0.00297) | (0.00424) | (0.00434) | (0.00447) | (0.00470) | (0.00603) | (0.00678) |
| $N$ | 208 | 208 | 208 | 208 | 208 | 208 | 208 |
| $R^2$ | 0.853 | 0.607 | 0.586 | 0.681 | 0.567 | 0.734 | 0.299 |
| Adj. $R^2$ | 0.851 | 0.602 | 0.579 | 0.677 | 0.560 | 0.730 | 0.289 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, and World Development Indicators.

*Note:* Coefficients from the pooled regression of each detailed task category on computer use, its interaction with log GDP per capita, and its interaction with educational attainment (fraction of population with post-secondary education). Statistical significance at the 10, 5, and 1 percent levels is denoted with *, **, and ***, respectively.

Finally, in addition to the interaction between computer use and GDP per capita, we include the interaction between computer use and education (fraction of population with post-secondary education). The PIAAC estimation results are in table S3.4. The vast majority of the interaction terms are not statistically significant, and again the adjusted $R^2$ do not change much.

### S3.4. Results including Agricultural Workers

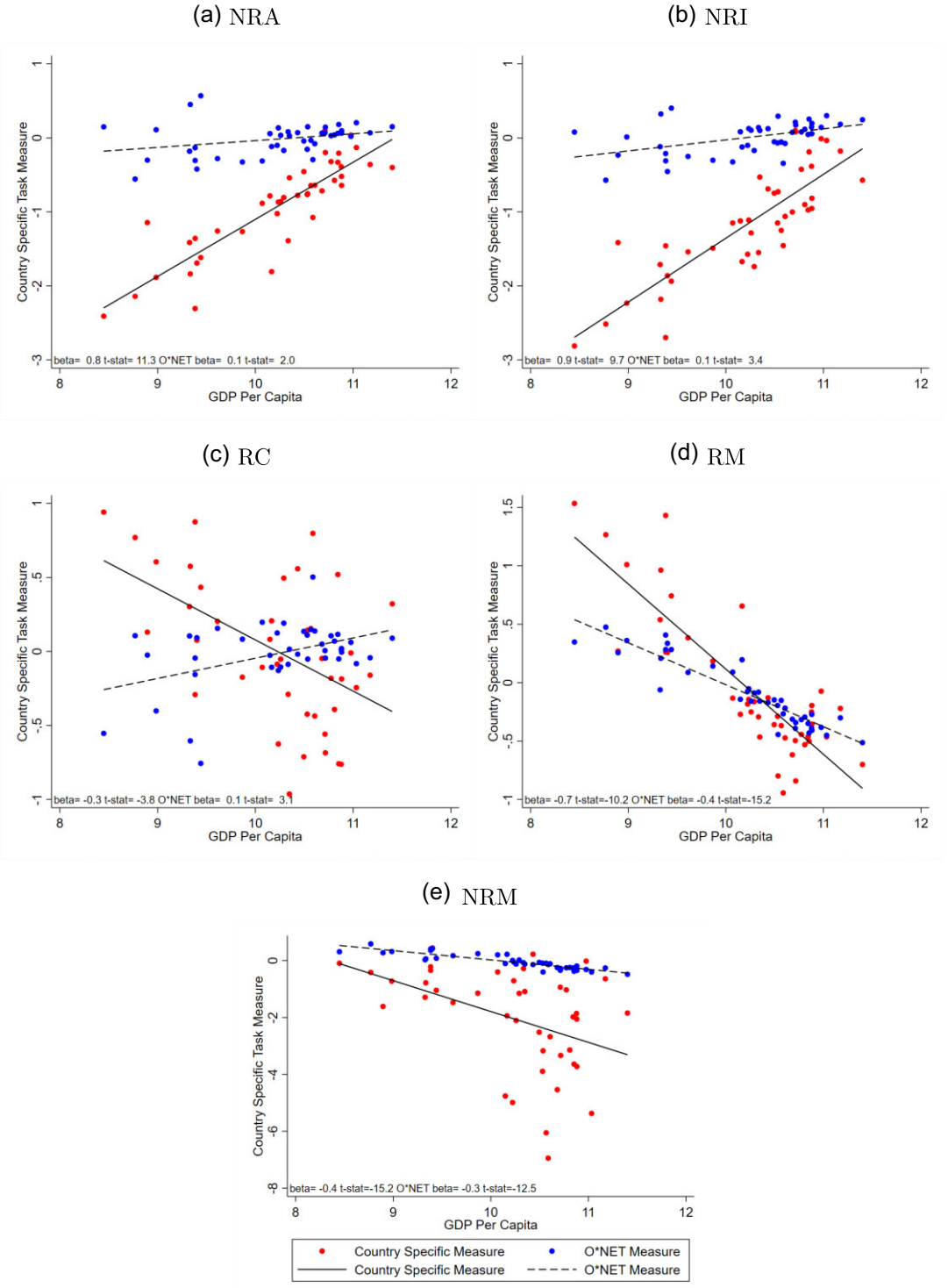
The analysis in the main text excludes all agricultural workers, for reasons given in the data and harmonization section. Here we report the results we obtain when we include agricultural workers in the analysis. Table S3.5 is the counterpart to table 2 of the main text, and fig. S3.4 is the counterpart to fig. 1 of the main text. The results are fairly similar whether or not agricultural workers are included. (Note that the figures may look different but that is only because they have different scales for the vertical axis.) One qualitative difference is that the RC intensity using the common O∗NET measures is positively correlated with GDP per capita (dashed line in panel 1(c)), whereas without agricultural workers, there was no significant relationship. In general, the difference between the patterns with country-specific task measures (solid lines) and those with the common O∗NET measures (dashed lines) is more visible when we include agricultural workers.

### S3.5. Analysis with Two-Digit Occupations

Figure S3.5 shows the correlation between task intensities and GDP per capita when the data harmonization between PIAAC and STEP is done at the two-digit occupation level. The two-digit occupation-level

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**Figure S3.4.** Task Intensity and Development, including Agricultural Workers.

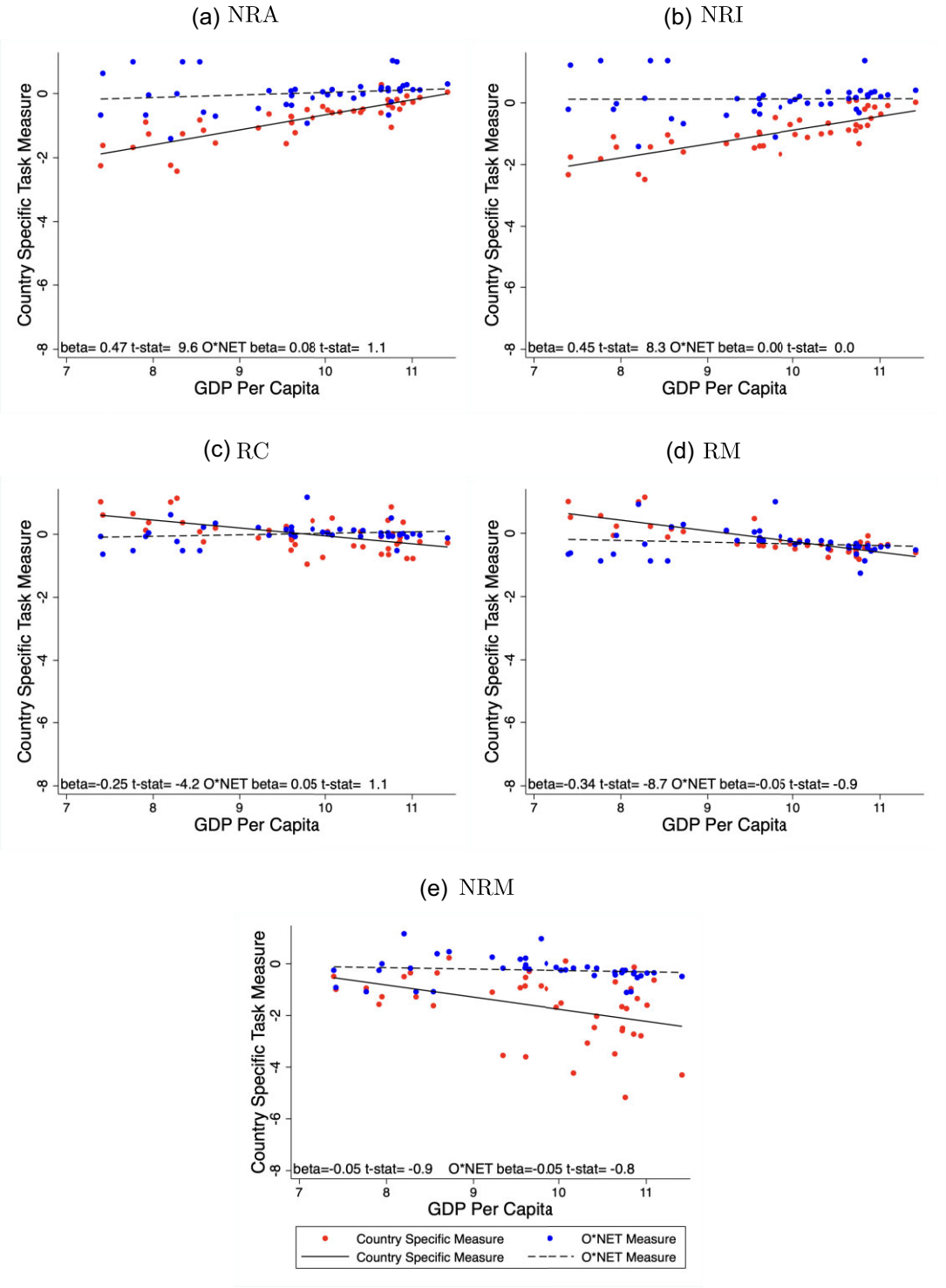



*Source:* Authors' calculations using data from ILO: International Labour Organization, O∗NET: Occupation Information Network, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* This figure plots a country's task intensity based on country-specific (red, solid line) and O∗NET-based (blue, dashed line) measures of occupational task content against GDP per capita (PPP in log). It replicates fig. 1 of the main text when agriculture workers are included in the analysis. The two figures may look different, but only because the vertical axes have different scales.

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**Figure S3.5.** Task Intensity and Development, with Two-Digit Occupations.




*Source:* Authors' calculations using data from ILO: International Labour Organization, O∗NET: Occupation Information Network, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* This figure plots a country's task intensity based on country-specific (red, solid line) and O∗NET-based (blue, dashed line) measures of occupational task content against GDP per capita (PPP in log). The task-content harmonization between PIAAC and STEP is done at the two-digit occupation level, unlike the one-digit occupation level of the benchmark.

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**Table S3.5.** Task-Intensity Decomposition and Development, with Agricultural Workers

| | Total | Task intensity | Employment share | Cross term |
|---|---|---|---|---|
| Non-routine analytic: | | | | |
| log(GDP per capita) | 0.490*** | 0.289*** | 0.212*** | −0.0117 |
| | (0.0417) | (0.0383) | (0.0212) | (0.00850) |
| $R^2$ | 0.775 | 0.587 | 0.714 | 0.045 |
| Non-routine interpersonal: | | | | |
| log(GDP per capita) | 0.552*** | 0.326*** | 0.234*** | −0.00775 |
| | (0.0538) | (0.0502) | (0.0218) | (0.00962) |
| $R^2$ | 0.725 | 0.512 | 0.743 | 0.016 |
| Routine cognitive: | | | | |
| log(GDP per capita) | −0.221*** | −0.102* | −0.111*** | −0.00827 |
| | (0.0573) | (0.0573) | (0.0176) | (0.0102) |
| $R^2$ | 0.271 | 0.073 | 0.498 | 0.016 |
| Routine manual: | | | | |
| log(GDP per capita) | −0.468*** | −0.247*** | −0.257*** | 0.0363*** |
| | (0.0422) | (0.0391) | (0.0177) | (0.0118) |
| $R^2$ | 0.754 | 0.500 | 0.841 | 0.190 |
| Non-routine manual: | | | | |
| log(GDP per capita) | −0.739*** | −0.471** | −0.264*** | −0.00483 |
| | (0.223) | (0.217) | (0.0243) | (0.0282) |
| $R^2$ | 0.216 | 0.105 | 0.746 | 0.001 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* This table presents the decomposition of cross-country variation in task intensities. It replicates table 2 of the main text when agriculture workers are included in the analysis. Column (1) reports the coefficients from regressing the countries' task intensity on log GDP per capita, with standard errors in parentheses. These coefficients are reported for the five task 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) in the main text. Robust standard errors in parentheses. *, **, and *** stand for significance at the 10-percent, 5-percent, 1-percent levels, respectively.

task content is aggregated to the one-digit occupation level using the survey weights. We use the ILO data to further aggregate it up to the country level. There is no substantial difference between fig. S3.5 and fig. 1 of the main paper. One exception is the weaker (negative) correlation between NRM and GDP per capita, with the slope changing from −0.17 to −0.05.

### S3.6. Raw STEP Data vs. the Predicted STEP Data

One way to validate our method of predicting task content for STEP countries from the computer use at work variable is to see whether the relationship between computer use and the "raw" task-content measures among STEP countries is similar to the one among PIAAC countries. The raw STEP data has significant measurement issues (due to non-responses), but it may still be useful to check for the stability of the relationship between task content and computer use between STEP and PIAAC.

The estimating equation is

$$\tau_{oc} = \beta_0 + \beta_1 \text{COMP}_{oc},$$

where $\tau_{oc}$ is the unadjusted task-content measure for occupation $o$ in country $c$ and $\text{COMP}_{oc}$ is the computer use. We run this regression for each of the seven task-content measures, and separately for PIAAC countries (table S3.6) and STEP countries (table S3.7).

Two comments are in order. First, the regression coefficients have the same sign between PIAAC and STEP except for OPER. The magnitudes are different, but that was expected because PIAAC and STEP have different response scales, which we did not adjust here. Second, OPER (which translates into NRM) is negatively correlated with computer use in PIAAC but has no significant relationship with computer

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**Table S3.6.** Task Content and Computer Use in PIAAC

| | READ | THINK | PERSON | GUIDE | STRUC | CONTRO | OPER |
|---|---|---|---|---|---|---|---|
| Computers | 1.904*** | 1.347*** | 1.397*** | 1.750*** | −1.212*** | −2.784*** | −0.970*** |
| | (0.0457) | (0.0663) | (0.0659) | (0.0699) | (0.0809) | (0.105) | (0.115) |
| *N* | 305 | 305 | 305 | 305 | 305 | 305 | 305 |
| $R^2$ | 0.852 | 0.577 | 0.598 | 0.674 | 0.425 | 0.699 | 0.190 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, and PIAAC: International Assessment of Adult Competencies.
*Note:* Coefficients from the pooled regression of each detailed task category on computer use among PIAAC countries. Statistical significance at the 10, 5, and 1 percent levels is denoted with *, **, and ***, respectively.

**Table S3.7.** Task Content and Computer Use in STEP

| | READ | THINK | PERSON | GUIDE | STRUC | CONTRO | OPER |
|---|---|---|---|---|---|---|---|
| Computers | 0.347*** | 1.320*** | 3.595*** | 0.490*** | −0.446*** | −3.367*** | 0.00189 |
| | (0.0243) | (0.172) | (0.416) | (0.0490) | (0.152) | (0.221) | (0.0352) |
| *N* | 115 | 115 | 115 | 115 | 115 | 115 | 115 |
| $R^2$ | 0.645 | 0.342 | 0.398 | 0.470 | 0.071 | 0.672 | 0.000 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, and STEP: World Bank's STEP Skills Measurement Program.
*Note:* Coefficients from the pooled regression of each detailed task category on computer use among STEP countries. Statistical significance at the 10, 5, and 1 percent levels is denoted with *, **, and ***, respectively.

use in STEP. The reason is that, as one can see in sections S2.1.1 and S2.1.2 of this supplementary online appendix, OPER questions are materially different between PIAAC and STEP. In this sense, the difference between the two OPER coefficients does not concern us, and in any case we do not focus on NRM in our analysis.

Given the measurement issues, it is not advisable to use the raw STEP data for a comparison with PIAAC data. However, for the sake of completeness, fig. S3.6 shows the counterpart to fig. S3.4 of this supplementary online appendix (i.e., including agricultural workers) that uses the raw STEP data without our harmonization. While the magnitudes are different, the qualitative features are similar, with the exception of NRM (OPER).

Finally, the task content in the raw STEP data and that predicted from the computer-use question are positively correlated, again with the exception of NRM. Table S3.8 shows the coefficients from regressing the predicted task content on their counterparts constructed from the raw STEP data. These positive correlations result in the similarity between fig. S3.6 (raw STEP data) and fig. 1 in the main text (predicted from computer use).

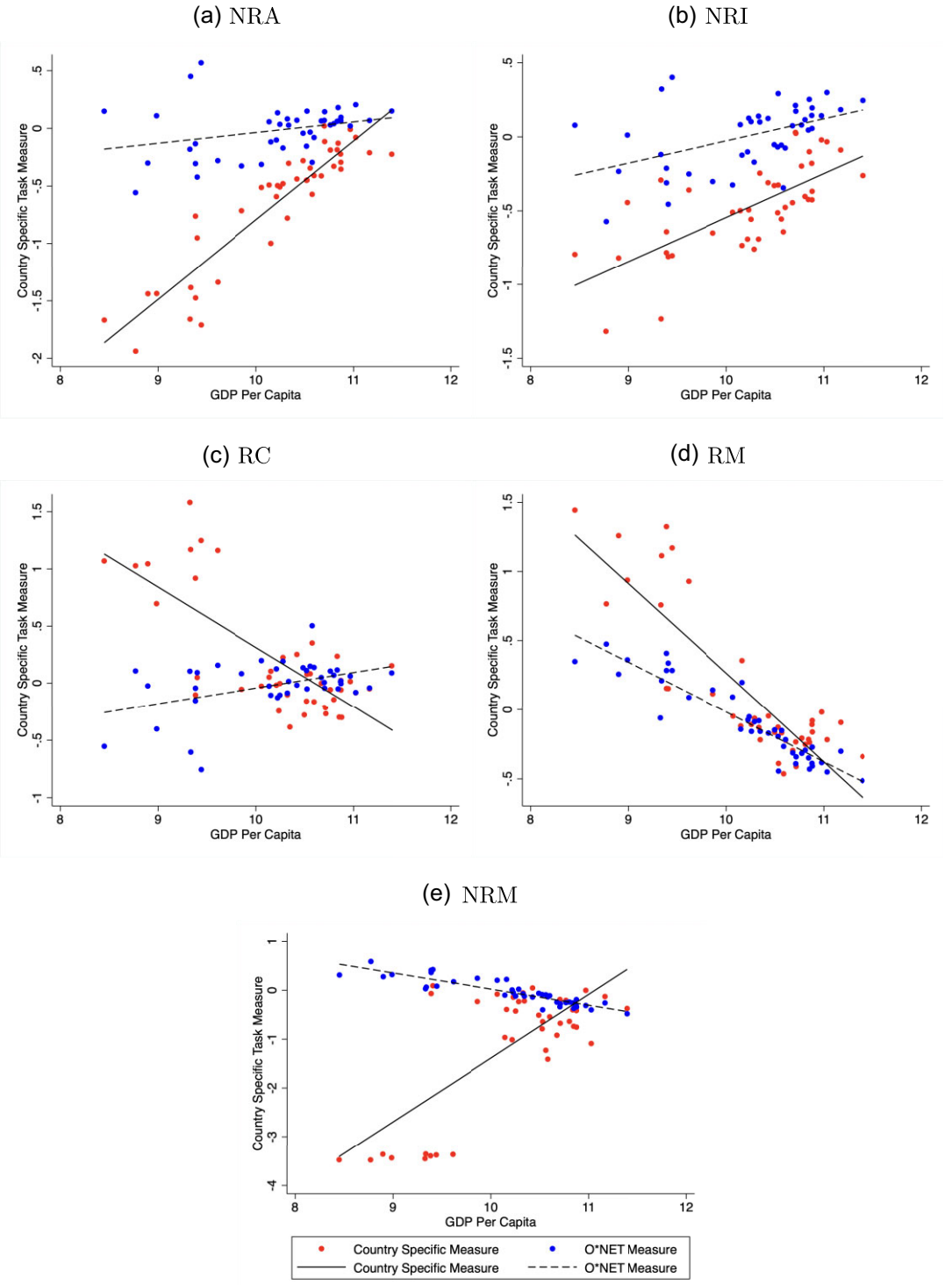
### S3.7. Occupational Task-Content Difference across Countries

Occupational task content is different across countries. We find that the occupations in developing countries have less NRA and NRI but more RC and RM content than the same occupations in developed countries. To further characterize this cross-country difference in occupational task content, we do the following. We first divide countries into quartiles by their income per capita. For each one-digit occupation and each task category, we compute the average occupational task content within each quartile of countries.

Figure S3.7 shows the occupational task-content difference between the richest quartile of countries (Austria, Belgium, Canada, Denmark, Germany, Ireland, Netherlands, Norway, Singapore, Sweden, and United States) and the poorest quartile of countries (Armenia, Bolivia, Ecuador, Georgia, Ghana, Peru, Philippines, Sri Lanka, Ukraine, and Vietnam). In each panel representing a task category, each dot is a one-digit occupation. The horizontal axis is the average task-content measure of a given occupation in the

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**Figure S3.6.** Task Intensity and Development, Raw STEP Data.

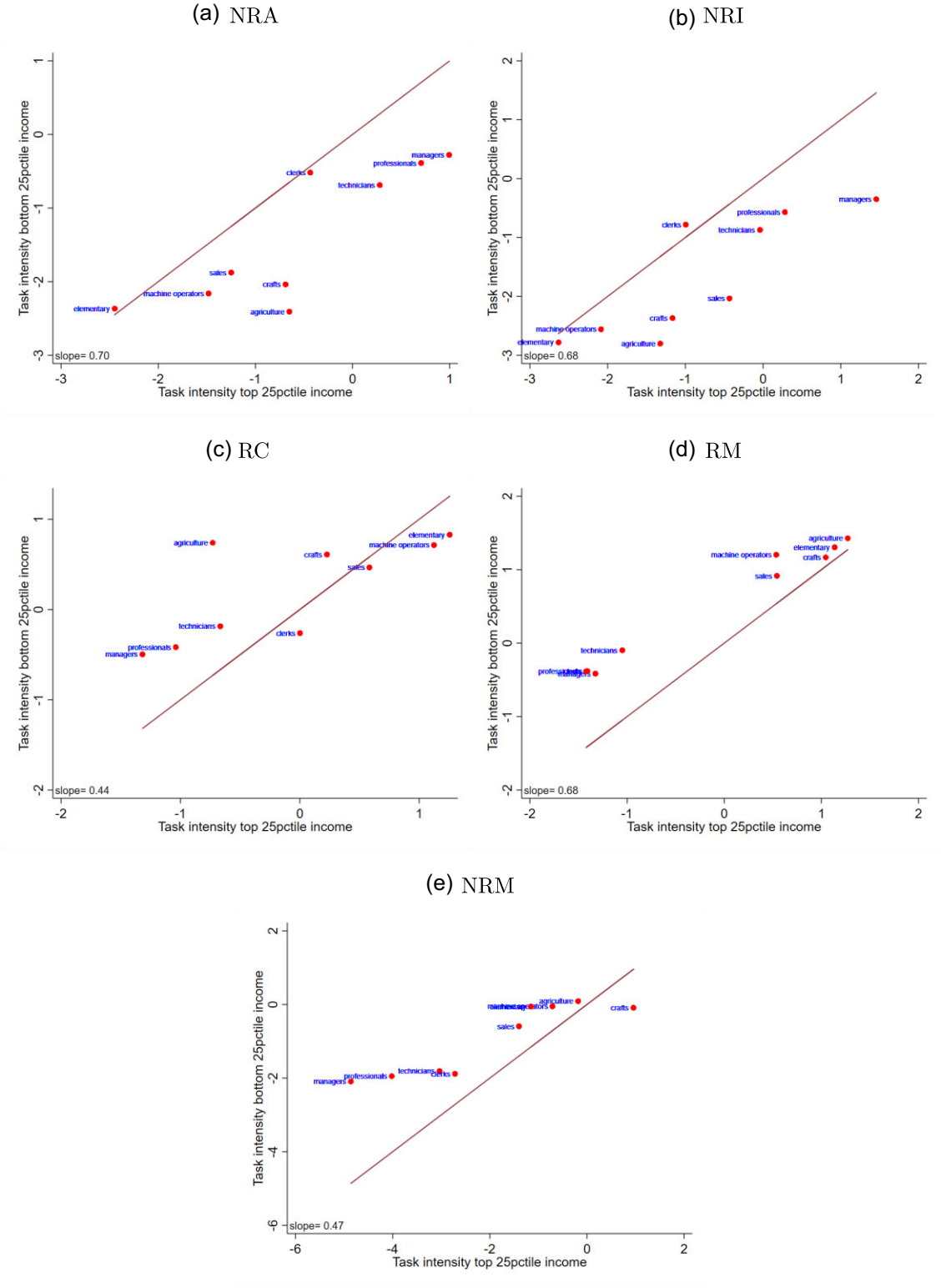



*Source:* Authors' calculations using data from ILO: International Labour Organization, O∗NET: Occupation Information Network, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* Countries' task intensity based on country-specific (red, solid line) and O∗NET-based (blue, dashed line) measures of occupational task content against GDP per capita (PPP in log). Unlike the benchmark, this alternative calculation constructs task-content measures from the raw STEP data.

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**Figure S3.7.** Occupational Task Content in Rich and Poor Countries.




*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, STEP: World Bank's STEP Skills Measurement Program, and World Development Indicators.

*Note:* This figure shows the task content of occupations in countries in the top income quartile (horizontal axis) against those in the bottom income quartile (vertical axis). Each dot corresponds to a one-digit occupation, and the solid line is the 45-degree line.

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**Table S3.8.** Regression of Predicted Task Intensity on Raw STEP Data

| | NRA | NRI | RC | RM | NRM |
|---|---|---|---|---|---|
| NRA_raw | 0.568*** | — | — | — | — |
| | (0.0847) | | | | |
| NRI_raw | — | 0.201*** | — | — | — |
| | | (0.0225) | | | |
| RC_raw | — | — | 0.159*** | — | — |
| | | | (0.0417) | | |
| RM_raw | — | — | — | 0.277*** | — |
| | | | | (0.0186) | |
| NRM_raw | — | — | — | — | 0.0208 |
| | | | | | (0.0678) |
| Constant | 0.292** | −0.470*** | −0.0418 | −0.164*** | −0.360 |
| | (0.132) | (0.0207) | (0.0474) | (0.0185) | (0.229) |
| *N* | 104 | 104 | 104 | 104 | 104 |
| $R^2$ | 0.306 | 0.440 | 0.125 | 0.685 | 0.001 |

*Source:* Authors' calculations using data from ILO: International Labour Organization, PIAAC: International Assessment of Adult Competencies, and STEP: World Bank's STEP Skills Measurement Program.

*Note:* Correlation between task content in the raw STEP data (rows) and those predicted from the computer-use question (columns), across occupations and countries. Statistical significance at the 10, 5, and 1 percent levels is denoted with *, **, and ***, respectively.

richest quartile of countries and the vertical axis is the average task-content measure of the occupation in the poorest quartile of countries. (The solid line is the 45-degree line.) A dot below the 45-degree line means that the occupation has more of the task content in high-income countries than the same occupation in low-income countries. The patterns are as discussed in the section on task intensity in the main text.

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