From Ghana to America: The Task Content of Jobs and Economic Development*

Salvatore Lo Bello[†] Maria Laura Sanchez Puerta[‡] Hernan Winkler[§]

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Abstract

This article provides new evidence on the task content of jobs in developing countries. It uses country-specific measures of the task content of occupations instead of US data. Measures based on US data do not provide a fair approximation of the levels, changes, and drivers of the manual task content of jobs in developing countries. In contrast to the US, skilled jobs in developing countries are not only more intensive in abstract tasks, but also in manual tasks when compared to unskilled jobs. The decline in routine jobs in developing countries is not linked to job polarization, because routine jobs are the bottom —not the middle— of the skill distribution. The article also uncovers several stylized facts on the drivers of the task content of jobs across countries. The routine task intensity of jobs declines with economic development, and it is positively linked to the demographic dividend and industrialization. In contrast, Information and Communications Technology (ICT) is associated with job de-routinization.

Keywords: Skills, Tasks, Economic Development, PDII, STEP
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*The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views either of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations or of the Executive Directors of the World Bank or the governments they represent.

[†]Bank of Italy. e-mail: salvatore.lobello@bancaditalia.it
[‡]The World Bank. e-mail: msanchezpuerta@worldbank.org
[§]Corresponding author. The World Bank. e-mail: hwinkler@worldbank.org

1 Introduction

Ever since the seminal study by Autor et al. (2003), a growing body of literature investigating trends in the task content of jobs in developed and developing countries has been emerging. To estimate the task content of jobs, most studies rely on measures tailored for the US economy, where occupations are ranked by the tasks they typically require. These occupation-level measures are then applied to other countries under the assumption that the task content of occupations is the same as in the United States.[1] This is a strong assumption, considering that jobs in different countries may require different task sets. For instance, manufacturing jobs in developed economies may be more intensive in routine tasks if the production technology is more capital intensive than in developing countries, where such jobs may be more intensive in manual tasks.

This article is not based on this strong assumption. We use skill surveys from developing countries (i.e. the *Skills Toward Employability and Productivity* (STEP) surveys) to create indicators of the task content of jobs comparable to those based on data for the US from the *Princeton Data Improvement Initiative* (PDII).[2] We find that both sets of measures lead to similar conclusions regarding the relative abstract and routine task content of jobs across countries and over time. However, occupations that are relatively more intensive in manual tasks are not necessarily the same, according to PDII and STEP. This is because skilled jobs—i.e., jobs associated with college degrees—that are intensive in abstract tasks are also intensive in manual tasks in developing countries when compared to the average job. In contrast, manual tasks are more prevalent among unskilled jobs—i.e., jobs associated with high school education or less—in the US. This implies that the estimated trends in the task

[1] There is a large body of literature examining trends in the task content of jobs using US-based data. Examples include Apella & Zunino (2017); Apella & Zunino (2018); Arias et al. (2014);Bussolo et al. (2018); Goos et al. (2009); Górka et al. (2017); Hardy, Keister & Lewandowski (2018); Maloney & Molina (2016); Mason & Shetty (2019); Nayar et al. (2012). In addition, some articles, such as Graetz & Michaels (2017) and Artuc et al. (2018), used US-based data on the task content of jobs and extrapolate them to other countries to construct variables that are key to their research designs.

[2] We also create indexes comparable to those of the *Occupational Information Network* (O*NET) classification, and the findings are very similar (Lo Bello et al. 2019)

content of jobs will depend on whether US or country-specific measures are used. We also find that the ranking of occupations by their task content is very similar within the sample of developing economies. This has important implications for measuring the task content of jobs in developing countries that have data limitations. The bias from using other developing countries' measures of the task content of occupations would be smaller than using those from a developed country such as the US.

When focusing on trends, we find that the changes in the task content of jobs in developing countries are similar to the changes observed in developed economies, where routine tasks decline while both abstract and manual tasks increase. However, the fact that manual tasks are linked to unskilled jobs in developed countries but are associated with skilled jobs in developing ones implies that de-routinization among the latter is not linked to job polarization—i.e., the simultaneous increase in the share of low and high skill jobs—as among the former. This is because routine jobs in developing countries are at the bottom—not the middle—of the skill distribution.

In addition to providing new evidence on the level and changes in the task content of jobs in developing countries, this article also contributes to the literature on their drivers by using a panel of 106 countries from the World Bank's International Income Distribution Dataset (I2D2). By applying the task-intensity measures to each occupation, we estimate cross-country regressions and find that the positive correlation between economic development and the intensity of jobs in abstract and manual tasks weakens once other factors are accounted for. An increase in the relative size of the industrial sector and the working-age population are accompanied by a rise in routine tasks. Routine tasks tend to decline with GDP per capita. While ICT adoption is linked to job de-routinization, exports are an offsetting force. The magnitudes of some of the estimated coefficients are economically significant: an increase in the share of the working-age population of about 10 percentage points is linked to an increase in routine tasks of about 1.16 standard deviations. These findings are robust to using several specifications.

The rest of this article is structured as follows. Section 2 provides a literature review, section 3 describes the data sources, section 4 presents the methodology, section 5 presents the results and section 6 concludes.

2 Literature review

While the canonical model assumes a one-to-one link between skills and tasks, there is a rising body of literature that emphasizes the distinction between these two concepts. In particular, while a task is a unit of work activity that produces output, skills are the workers' endowments of capabilities to perform several tasks (Acemoglu & Autor 2011). Since the seminal work of Autor et al. (2003), there has been a steady increase in the number of articles studying the task content of jobs. Autor & Dorn (2013) and Goos et al. (2009), for example, document the process of employment and wage polarization affecting labor markets in the US and Europe since the 1980s and 1990s. This process is characterized by job and wage growth that is higher at the tails of the skill and wage distribution than in the middle. They argue that new technologies, which allowed the automation of routine jobs (which tend to be in the middle of the wage distribution) and increased the demand for non-routine tasks (which tend to be at the top and bottom of the wage distribution), fostered this process.

There is also a growing and large body of research on the task content of jobs in developing countries. Even for developing countries, these studies use US-based task measures such as the *Occupational Information Network* (O*NET) or other broader occupational categories. Using a broad occupational classification, World Bank (2016) shows that labor market de-routinization is pervasive in the developing world. In comparison, studies that used more detailed data on tasks show a more nuanced picture. Hardy, Keister & Lewandowski (2018) find that in contrast to the US, jobs that are intensive in routine cognitive tasks—which tend to be middle-skill—increased in most Central and Eastern European countries. They also find that improvements in educational attainment and a decline in the share of agricultural jobs, rather than technology, were the main drivers of these changes. Accordingly, Apella & Zunino (2017) find that the evolution of the task content of jobs in Argentina and Uruguay was more similar to that of Central and Eastern European countries than to that of rich countries. Maloney & Molina (2016) use the same aggregate World Bank (2016) classification and find that only in two of twenty-one developing countries is there evidence of labor market de-routinization. The authors argue that developing countries are less likely than rich economies to experience job polarization for several reasons including that the share of workers in middle-skill tasks is small, that they are more likely to benefit from the jobs offshored from rich countries and that the rate of technology adoption is low. Aedo et al. (2013) estimate trends for 30 countries at different stages of development and find that the share of jobs intensive in non-routine, cognitive tasks is higher in richer countries.

To our knowledge, there are only four studies that use data on the task content of occupations from developing countries instead of relying on data from the US. Dicarlo et al. (2016) use data from STEP surveys to determine if the task content of jobs is different from that suggested by US-based skill surveys. Messina et al. (2014) analyze trends in the task content of jobs in four Latin American countries but do not investigate the drivers of such trends. Marcolin et al. (2016*b*) uses the *OECD Programme for the International Assessment of Adult Competencies* (PIAAC) surveys to estimate the routine intensity of jobs. Finally, Hardy, Lewandowski, Park & Yang (2018) investigate the task content of jobs using country-specific skills surveys for 46 economies, mostly in the developed world. They analyze whether the findings are different from those obtained when using US data from O*NET and investigate the drivers of the heterogeneity in the task content of jobs across countries but not over time. They find that ICT capital intensity, robot use and the position of the country in the global value chain (i.e. having a high share of foreign value added in the production of final goods and services) are negatively correlated with the share of routine jobs.

This article makes four important contributions to this body of literature. First, it relies on comparable measures on the task content of jobs in the US and developing countries. It does so by using data from the PDII and STEP surveys, which are both self-reported by individuals. Second, it provides new empirical evidence by showing that skilled jobs—i.e. jobs that tend to be held by college graduates—in developing countries are not only more intensive in abstract tasks—as in the US—but also more intensive in manual tasks—unlike the US. Fourth, it shows that when using country-specific measures of tasks, changes in the task composition of jobs in developing countries is similar to that observed in developed economies. However, the distributional implications are different, since jobs linked to routine tasks are at the bottom—not the middle—of the skill distribution in developing economies. Finally, by using a panel of 106 developing and developed economies, it provides new insights into the drivers of the task content of jobs while controlling for unobserved heterogeneity. The findings are robust to several alternative specifications.

3 Data

The empirical parameters are estimated using several data sets. First, it relies on the STEP and PDII surveys to measure the task content of jobs. In addition to socio-economic, demographic, employment, education and family background information, the surveys contain a series of harmonized questions on specific tasks that the respondent uses in his or her job. We use the STEP surveys for 12 developing countries (Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, FYR Macedonia, Philippines, Serbia, Sri Lanka, Ukraine and Vietnam), collected between 2012 and 2016.[3] These surveys are representative of the working-age population in urban areas. While they collect information on all individuals in the household, it randomly selects an individual between 15 and 64 years old to answer the complete questionnaire, which includes detailed employment and skills questions. The PDII survey was a random-digit dialing survey of individuals ages 18 and older, conducted in the US in 2008.

[3]The acronyms for these countries are, respectively, ARM, BOL, COL, GEO, GHA, KEN, MKD, PHL, SRB, LKA, UKR and VNM.

This research is also based on data from the World Bank's *International Income Distribution Data Set* (I2D2). The I2D2 is a data set of harmonized household surveys which are comparable across countries and time. It currently covers more than 150 countries and has more than 1,000 surveys. The time coverage goes from 1960 through 2016, but it varies by country. Table A9 shows the country and time coverage of the sample used in this article. This sample excludes the pre-1990 samples since the task content of jobs measured using the STEP data may not be a good approximation for that time period. Finally, we use several variables from the World Development Indicators (WDI), including GDP per capita in Purchasing Power Parity (PPP) terms, Information and Communication Technology (ICT) users (as a share of total population), population by age, exports and imports (both as a share of GDP).

4 Methodology

In order to estimate the task measures, we first need to conceptually link subtasks to tasks categories. We follow the same approach used by Autor et al. (2003), Acemoglu & Autor (2011), Handel (2008), SpitzOener (2006) and several other studies. Two main approaches can be distinguished in the literature. The first relies on occupation-level tasks indexes estimated by experts, who rank occupations on the basis of worker interviews. The O*NET dataset is the outcome of such analysis for the US economy, with 44 different scores being assigned to each detailed occupation. The second approach, on the other hand, relies on direct worker-level information on the specific tasks performed on the job. It was pioneered by Handel (2008), who developed and used the STAMP survey (which later became the PDII), for the US. This approach allows us to observe the tasks at a more disaggregated level, making within-occupation analyses possible. Our methodology falls into this second category, as we employ task information at the worker-level, exploiting the STEP surveys for 12 developing countries. As our objective is to compare our results with the counterfactual results that one would obtain using the US classifications, we construct similar task indexes in the STEP and PDII data.[4]

We follow closely the specifications of Autor & Handel (2013) and Messina et al. (2014) and define three task categories: Abstract, Routine and Manual. This classification is based on the framework developed by Autor et al. (2003), who rely on the following definitions:

- Abstract tasks: problem solving, creative, organizational and managerial tasks (both analytical and interpersonal tasks are in this bracket).
- Routine: codifiable cognitive and manual tasks that follow explicit procedures.
- Non-routine manual tasks: manual tasks that require physical adaptability.

The map between the STEP variables and task indexes is shown in Table 1. In general, given that both STEP and PDII derive from STAMP, the questions are in several cases very similar, and this guarantees a high degree of comparability.

In Autor and Handel (2013), the abstract task index is constructed using the following variables: 1) length of longest document typically read; 2) frequency of math tasks involving at least high school mathematics; 3) frequency of problem solving tasks requiring at least 30 minutes of thinking; 4) proportion of workday spent supervising other workers. We can recover almost exactly the same four items. As for (1) and (3), we have the same questions with the same scale. As for (2) and (4), the STEP survey includes them as a dummy variable. That is, we know whether an individual uses advanced math and/or supervises other workers, but we do not know how frequent that action is. In order to make the information comparable, we recode items (2) and (4) in the PDII into the same binary questions that we have in STEP.

The routine index is also based on four different items, as in Autor and Handel (2013): 1) proportion of workday spent performing short, repetitive tasks; 2) complete absence of inter-

[4]We also create variables similar to the O*NET variables and the findings are consistent. However, we prefer to compare our STEP-based measures against the PDII-based measures given that they are both self-reported by the workers instead of experts. The results for the O*NET-like indexes can be found in Lo Bello et al. (2019)

action with customers/clients; 3) complete absence of interaction with suppliers/contractors; 4) complete absence of interaction with students/trainees. All of these are categorical variables recorded over an intensity scale. In STEP, we have the same item as (1), with the same scale. For (2)-(4), however, we have a single dummy variable eliciting all the information: it asks whether the job involves interaction with people other than co-workers. We therefore use the item in the PDII on whether the job involves face-to-face contact with people other than co-workers or supervisors, and recode it to make it a dummy variable as in STEP.

A single variable elicits information for the manual index in Autor and Handel (2013): proportion of workday spent performing physical tasks, such as standing, operating machines or vehicles, or fixing things. In STEP, instead, we have information separately on the different tasks. That is, information is recorded on whether the job involves: 1) driving; 2) repairing objects or items; 3) operating machines. To make STEP and PDII comparable, we combine the three STEP variables (which are dummy variables) into a single dummy variable that takes the value of 1 if at least one of the three tasks is involved. At the same time, we also recode the PDII variable into a dummy variable.

To construct the indexes using STEP surveys, each variable is standardized over the entire population of the pooled STEP surveys for all countries, where all countries are equally weighted. We then sum up all standardized variables, constructing a task index that varies at the worker-level. For instance, in the PDII specification, we construct a Routine task index, which is the sum of the two standardized components (Contact with clients and Repetitiveness). These task indexes are standardized over the entire distribution, using the sampling weights. Finally, the indexes are collapsed at the occupational level (1-digit), again using the sampling weights. These occupation-specific indexes are calculated both for the pooled STEP sample and for each specific STEP country. The final task indexes that we apply to other survey years vary at the level of occupations, with a scale that depends on the underlying distribution. We multiplied the task indexes by 100. For the sake of concreteness, a 100-unit differential across occupations in a given task is interpreted as 1 standard deviation of the whole distribution of that task among the employed workforce of all STEP countries. When applying these indexes to other developing countries that do not have a STEP survey, we use those calculated for the pooled sample (i.e., not the country-specific ones) at the ISCO one-digit level.

Using the STEP surveys to measure tasks, rather than relying on PDII, has the obvious advantage of allowing us to investigate whether the task content of jobs differs across countries. Given that we can independently estimate occupation-specific task indexes, we do not need to assume that different countries use the same technology or have the same labor force. Nonetheless, a couple of caveats need to be made: first, mapping between tasks in the STEP variables and tasks is not trivial; second, we need to assume that workers do not differ in the way they report the tasks performed at work (which may be problematic in the case of subjective opinions); and third, by excluding rural areas, the sample under-represents the agricultural sector, which represents a significant fraction of employment in the developing world.

Our analysis is based on the ISCO-08 occupational classification at the 1-digit level. We do not use a higher level of disaggregation for two reasons. First, because for most of the countries covered in STEP surveys, the sample size is not large enough to make reliable inferences using more detailed occupations, as many of the cells would contain very few observations or be empty. Second, since the second goal of this article is to make comparisons across countries and across time, it is not feasible to harmonize the occupational classifications for all the household surveys (which are around 600 in this study). This is because in addition to changes in the ISCO over time, many countries use their own specific occupational categories that are difficult to map to ISCO at finer disaggregation levels.

5 Results

5.1 Measures of the Task Content of Jobs

Table 2 shows the unconditional average task scores by individual characteristics. As mentioned above, a value of 100 is equivalent to one standard deviation from the mean, which is equal to zero in the pooled sample. The patterns across individual characteristics for abstract and routine task intensity are, in general, similar according to the STEP and PDII indexes but different for manual ones. For example, while according to the STEP-based task data skilled workers have jobs more intensive in manual tasks, the opposite holds when using PDII task measures. Figure 1 shows the correlation between the average task content of jobs at the country level and GDP per capita. Income is positively correlated with abstract tasks according to both the STEP- and PDII-based indexes. Routine task intensity does not exhibit a strong correlation with income. While STEP-based manual tasks have a positive relationship with GDP per capita, those based on the PDII exhibit a negative correlation.

To facilitate the comparison of both sets of indexes, we estimate the following equation:

$$Task_{i,c} = \alpha + \Gamma X_{i,c} + \mu_c + \epsilon_{i,c} \tag{1}$$

Where $Task_{i,c}$ is the task content of invididual i's job in country c estimated using the pooled sample of countries, $X_{i,c}$ is a vector of individual characteristics, μ_c are country fixed effects and $\epsilon_{i,c}$ is the error term.

As seen in Table 3, educational attainment is linked to jobs more intensive in abstract tasks (columns 1 and 3), and to jobs less intensive in routine tasks (Columns 2 and 4). In contrast, while skilled workers report having jobs more intensive in manual tasks than their less skilled peers (column 3), the indexes estimated using the PDII for the US suggest the opposite pattern. This is explained by the fact that—in contrast to the US—jobs intensive in abstract tasks are also more intensive in manual tasks in developing countries. This is not driven by one particular component of the manual tasks index. As seen in Table A1 in the appendix, occupations that require driving, operating machinery or repair work have a higher abstract task content than the rest. This is also not driven by the procedure for imputing tasks measured using PDII to the STEP survey. In fact, Autor & Handel (2013)—using individual-level data from the PDII—find that higher educational attainment in the US is linked to a higher abstract task intensity and to a lower manual task intensity.[5] The positive link between abstract and manual tasks in developing countries could be driven by the fact that workers performing abstract tasks may be more likely than other workers to own assets, such as cars, that are required to carry out manual tasks. In contrast, asset ownership is more widespread in developed economies.

Table 3 also shows that, according to the STEP data, older workers have jobs with a higher abstract task intensity, and a lower routine task intensity. Manual tasks peak for the 25-34-year-old group and declines thereafter. Computer use is linked to abstract and manual tasks. Jobs in manufacturing have a higher abstract task content, while jobs in commerce and services have a lower routine and manual task content. Higher earnings are positively correlated with abstract tasks, but have no significant link with the routine and manual task content indexes. These patterns are, in general, very similar to estimating the same regressions for each country separately, using the task indexes based on their own data without pooling (see Tables A2, A3 and A4 in the appendix).

Tables A5, A6 and A7 in the appendix shows the correlation matrix of the average task measure at the 1-digit ISCO occupation, for each country in the STEP sample and the US. In general, the coefficients are positive, suggesting that both PDII and STEP measures lead to the same ranking of occupations in terms of the abstract, routine and manual task content. The correlations between PDII and STEP measures are considerably weaker for the manual task content of jobs, and in some cases negative. The Philippines also seems to be an outlier in terms of occupational rankings when compared to other countries. With

[5] See Table 1 in page S75 of Autor & Handel (2013)

a few exceptions, the occupational rankings are more similar among developing countries, than when comparing developing countries against the US. In other words, indexes of the task content of jobs estimated using the STEP survey are a better approximation for other developing countries' than US-based measures. This is confirmed in Figure 3, which plots the Spearman correlation coefficients of Tables A5, A6 and A7 against the bilateral differences in GDP per capita. The correlation in the abstract and manual task content of occupations is close to one for small differences in income, but it declines as the income gap widens. The correlations in terms of the routine task content, in contrast, do not change significantly with the income gap. These results suggest that applying occupation-level task measures from one country to another may be appropriate for abstract and manual tasks only when the income gap between both countries is narrow.

5.2 Imputing Average Occupation-level Scores to Other Household Surveys of STEP Countries

This section analyzes trends in the task content of jobs by applying the occupational-level task indexes (at the ISCO 1-digit level) to repeated cross-sections of household surveys for countries covered by the STEP data. Table A8 shows the list of survey-years included in this analysis. Figure 2 shows the coefficients of equation 1 associated with 1-digit ISCO occupations, where the category of managers is omitted. It also plots the average PDII indexes by occupation minus the average index for managers. The latter show that workers in crafts and elementary occupations have the highest and lowest levels of abstract and manual task intensity, respectively. In contrast, the STEP data shows that the only occupational category with a higher manual task content than managers is Plant and Machine Operators. The results are robust to controlling for country fixed effects and individual characteristics. In other words, the STEP-based measures of the task content of jobs across 1-digit ISCO occupations is not driven by other workers' characteristics.

Figure 4 shows the long-differences changes in the task content of jobs, where countries are grouped by the length of the time period covered by the data.[6] When looking at the total changes in the task content of jobs in all 11 countries, there are certain differences across countries and some key stylized facts emerge. In most countries, US- and STEP-based indexes show an increase in the abstract task content of jobs and a decline in the routine intensity. However, while the manual task content of jobs increased in six countries according to the STEP-based indexes, only two countries experienced such increase according to the US-based index. This is consistent with the evidence discussed above, where PDII and STEP-based indexes lead to different occupational rankings according to their manual task content, but to rather similar ones according to their abstract and routine task content.

When focusing on countries covered over a 25-year period—which would be a better proxy for long-term trends—changes in the task content of jobs according to the STEP-based indexes are more consistent with evidence for developed countries. They suggest a de-routinization of jobs, accompanied by a rise of both manual and abstract task intensity. However, in contrast to evidence for richer economies, this is not linked to labor market polarization. This is because in developing countries, jobs that are intensive in manual tasks are also intensive in abstract tasks, and they tend to be skilled.

To shed light on the drivers of the task content of jobs, we estimate the following equation using country-level data:

$$\Delta task_{c,t} = \gamma + \Omega \Delta W_{c,t} + \mu_t + \epsilon_{c,t} \tag{2}$$

where $\Delta task_{c,t}$ is the change in the content of a task in country c between year $t-1$ and t, and $\Delta W_{c,t}$ is a vector of control variables (in changes). The choice of explanatory variables $W_{c,t}$ is based on the literature about the drivers of changes in the task content of jobs.

First, we control for educational attainment, women's share of employment and the age structure of the population. We argue that changes in labor supply such as educational upgrading, increasing female labor force participation and the demographic transition could

[6] Kenya is excluded due to lack of data

affect the task content of jobs. The secular increase in educational attainment in developing countries could be one of the factors behind the rise of jobs intensive in abstract tasks, and the fall of routine jobs. The increasing participation of women in the labor force may also be an important factor if they are more likely to have jobs that are not intensive in physical work. Finally, the changing age structure may affect the task content of jobs through different channels, in three ways. First, aging societies may be more likely to incorporate labor-saving technologies (Acemoglu & Restrepo 2018), and may thereby be more likely to experience a decline in job routinization. Second, a higher share of the elderly in the population may also increase the demand for certain types of goods or services that may be more intensive in non-routine manual tasks, such as the care industry. Third, given that lifelong learning institutions are not widespread in most developing countries, skills tend to be acquired through formal education before young people enter the labor market. Larger cohorts of young workers would therefore contribute disproportionately to the stock of skills in the labor force.

We control for GDP per capita since the changing task content of jobs may also reflect the stage of economic development. As countries become richer, their bundle of consumption goods and services typically changes (Seale & Regmi 2006). When firms upgrade the quality of their products and production processes, this may increase the demand for abstract tasks (Bresnahan et al. 2002). The task content of jobs may also depend on the stage of the business cycle (Foote & Ryan 2015).

The structure of the economy—in terms of the share of agriculture, manufacturing and services in GDP—can shape the type of skills and tasks that are more in demand on the labor market. For example, the emergence of the high school movement was in part a response to the decline of the agricultural sector and the rise of manufacturing (Autor 2015). Bárány & Siegel (2018) argue that the process of job polarization is not a recent phenomenon, but it has been taking place since the 1950s and is connected to the transition from manufacturing to services. This is because manufacturing jobs tend to be in the middle of the distribution, and so an increase in that sectors productivity implies that workers reallocate to both low- and high-skilled services through changes in the supply and demand of labor.

Last, but not least, technology and trade are the two potential drivers that appear to have received most of the scrutiny in the empirical literature. New technologies may lead to a rapid decline in the demand for routine labor and an increase in the demand for non-routine labor (see, for instance, Acemoglu & Autor (2011)). Increasing exports may in contrast increase the demand for routine labor, since the tradeable sector is typically more intensive in this type of labor (Marcolin et al. 2016*a*). An increase in imports through offshoring may reduce the demand for routine labor. We therefore control for the share of internet users in the population, and the share of industry and services value added in total GDP.

Table 4 shows the estimates of equation 2. According to column (1), the relationship between abstract tasks and GDP per capita becomes negative when focusing on changes over time. However, according to columns (2), (4) and (6), the link between the task content of jobs and income is not significant in changes and when controlling for other factors. Growth in the services sector is linked to an increase in abstract tasks, and to a decline in routine tasks. Growth in the relative size of the working-age population is accompanied by a decline in abstract tasks and an increase in routine tasks. This is likely to be driven by growth in the size of the youngest cohort entering the labor market (aged 15 to 24), since they have the jobs most intensive in routine tasks (see Table 2). Internet use is linked to a decline in the routine content of jobs. Exports are linked to a decline in manual tasks, and the opposite holds for imports. The increase in the share of college graduates is also linked to a rise in manual tasks, which is consistent with the link between skills and manual tasks discussed above. The results using the PDII-based indexes in columns (8), (10) and (12) are, in general, similar to the STEP-based ones, except for manual tasks.

5.3 Extending the analysis to other countries

This section extends the cross-country analysis to other countries not covered by STEP surveys. It has the advantage of increasing the sample size dramatically, which allows for more precise estimates. Table A10 shows some descriptive statistics for these covariates, while Table A9 displays the country-year coverage of the sample. The main assumption behind this exercise is that STEP-based measures are a good proxy for the task content of jobs in other developing countries. Figure 5 shows the link between the task content of jobs and GDP per capita for this extended sample, which tends to be very similar to that of Figure 1 for the STEP sample. In this extended sample, the relationship between routine tasks and GDP per capita has an inverted U-shape, according to both the STEP- and PDII-based measures. Routinization increases with economic development up to a certain point, and then declines.

Table 6 sheds light on this link by estimating equation 2 for the extended sample. The results for abstract and routine tasks are, in general, consistent with those of the STEP sample (Table 4). The abstract task content of jobs is positively correlated with internet use and imports, but negatively correlated with exports, according to both STEP- and PDII-based indexes. Routine tasks are negatively linked to GDP per capita and internet use, but positively correlated to the share of industry value added, the relative size of the working-age population and exports. These results are also consistent with those using PDII-based indexes (columns 4 to 6). According to the STEP-based manual task index, the only covariate with a statistically significant—and positive—coefficient is imports to value added. In contrast, the manual task content estimated using the PDII is positively linked to exports and negatively correlated with internet use. As a robustness check, we estimate the same model including both developed and developing countries in the sample (see Table A11). The results are very similar to those of Table 6.

The magnitude of the coefficients is economically significant in some cases. An increase in the share of the working-age population of about 10 percentage points (roughly the gap between Ghana and Albania) is linked to an increase in routine tasks of about 116 percent of a standard deviation of the index in developing countries (see Table 2). An increase in the industry share of value added of about 10 percentage points (about the difference between Uganda and Vietnam) is linked to an increase in routine tasks of about 43 percent of the standard deviation. An increase of 40 percentage points in the share of internet users (about the increase experienced by low- and middle-income countries since the early 1990s)[7] is linked to an increase of half a standard deviation in the abstract content of jobs. Finally, an increase in the value of exports to GDP of about 10 percentage points was accompanied by an increase (decrease) in the abstract (routine) task content of jobs of about 16 percent (7 percent) of a standard deviation.

Tables A12 shows a robustness check by controlling for non-parametric trends across countries' income groups. We use the World Bank's classification into low-, lower-middle, upper-middle and high-income countries. In general, the main conclusions hold when compared to the baseline results in Table 6. A potential limitation of our findings is that we exclude agricultural jobs from the samples in Tables 6, A11 and A12. However, Table A13 shows the results when including agricultural jobs in the I2D2 sample. For this test, we compare the coefficients associated with the PDII since the STEP survey is not representative of the agricultural sector. The sign and magnitude of the coefficients is robust to including agricultural jobs.

6 Conclusions

This article contributes to a growing body of literature investigating the trends and drivers of the task content of jobs. While most articles impute US-based measures of the task content of occupations to other countries, we use harmonized data on the task content of jobs for 12 developing countries. We find that indexes based on the US and on developing countries

[7]WDI data (https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=XO), accessed on September 9th, 2019.

lead to similar conclusions regarding the stock, changes and drivers of the abstract and routine task content of jobs. However, the former does not provide a close approximation of the manual task content of jobs. This is explained by the fact that—in contrast to rich countries—skilled workers in developing economies are more likely to carry out both abstract and manual tasks than the average worker.

The correlation between the task content at the occupational level is higher among countries at a more similar level of economic development than among those with larger income gaps. These findings highlight the fact that to measure the stock and changes in the task content of jobs in a given country, imputing another country's task measures could lead to mistaken conclusions. The magnitude of the error seems to be positively correlated with the income gap between both countries.

Finally, the article shows that the sectoral structure of the economy, the age structure of the population, ICT use and international trade are more important correlates of the task content of jobs in developing countries than other factors such as educational attainment and the rise of the women's labor force participation.

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Tables

Table 1: Mapping of Tasks between STEP and PDII

STEP Task	PDII Task	Coding
Abstract		
Length of longest document typically read	Length of longest document typically read	Categorical (0-5)
Use of advanced math	Use of advanced math	Dummy*
Thinking for at least 30 min. to do tasks	Problem solving requiring at least 30 min. of thinking	Categorical (1-5)
Supervising others	Proportion of workday spent supervising	Dummy*
Routine		
Contact with clients	Absence of interaction with people other than coworkers	Dummy*
Repetitiveness	Proportion of workday spent performing short, repetitive tasks	Categorical (1-4)
Manual		
Driving, Repairing, Operating machines	Proportion of workday spent performing physical tasks	Dummy*

Note (*): the dummy variables are created adapting original variables which had a different scaling.

Table 2: STEP and PDII Task Measures by Demographic Group: Workers Ages 15 to 64

	(1)	(2)	(3)	(4)	(5)	(6)
	STEP			PDII (US)		
	Abstract	Routine	Manual	Abstract	Routine	Manual
15-24 years	-23.601	10.369	-11.687	-35.335	14.442	35.904
25-34 years	8.762	-3.677	5.306	-20.437	7.601	22.952
35-44 years	3.703	-3.414	1.494	-20.532	8.275	26.023
45-54 years	0.398	-0.262	1.204	-19.456	10.086	26.317
55-64 years	6.383	0.310	-0.022	-14.358	7.462	20.411
Computer use=0	-35.768	9.925	-10.811	-38.548	19.420	47.794
Computer use=1	30.978	-8.586	9.369	-7.876	0.796	7.656
Primary or less	-47.194	13.674	-6.029	-45.538	25.742	54.306
Secondary	-14.361	7.152	2.125	-33.530	15.984	37.911
Tertiary	45.991	-16.146	2.633	5.339	-7.679	-4.197
Men	9.514	-1.638	34.930	-20.032	13.847	29.811
Women	-8.410	1.448	-30.874	-23.910	5.532	23.154
Agriculture	-14.828	36.612	25.798	-37.312	30.312	42.376
Manufacturing and construction	-2.348	29.185	21.254	-12.536	24.521	45.266
Commerce	-23.460	-19.561	-13.312	-50.823	6.439	44.115
Services	17.213	-11.431	-2.630	-10.033	1.114	7.608

Note: the table shows the average task indexes for each demographic group. Sample includes the 12 countries in the STEP survey. The PDII indexes are imputed to each ISCO occupation at the 1 digit, while the STEP scores vary at the individual level. All the task scores have a mean equal to zero, and a standard deviation of 100.

Table 3: Regressions of Standardized STEP and PDII Task Variables on Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	STEP			PDII (US)		
	Abstract	Routine	Manual	Abstract	Routine	Manual
Secondary	27.26***	-8.030***	7.609***	7.180***	-4.805***	-9.103***
	(1.881)	(2.099)	(2.087)	(0.972)	(0.645)	(0.801)
Tertiary	76.52***	-30.65***	7.522***	40.62***	-26.20***	-41.53***
	(2.140)	(2.388)	(2.375)	(1.106)	(0.734)	(0.911)
Female	-16.90***	8.511***	-63.47***	-1.595**	-5.734***	-4.957***
	(1.316)	(1.468)	(1.460)	(0.680)	(0.451)	(0.560)
Age 25-34	17.97***	-10.73***	11.58***	3.559***	-0.838	-2.519***
	(2.099)	(2.343)	(2.330)	(1.085)	(0.720)	(0.894)
Age 25-44	21.95***	-12.82***	10.85***	6.721***	-2.541***	-2.962***
	(2.172)	(2.423)	(2.411)	(1.123)	(0.745)	(0.925)
Age 55-54	24.01***	-15.38***	8.767***	9.074***	-3.183***	-4.785***
	(2.254)	(2.515)	(2.501)	(1.165)	(0.773)	(0.960)
Age 55-64	30.22***	-19.41***	1.156	12.65***	-5.416***	-9.564***
	(2.574)	(2.871)	(2.856)	(1.330)	(0.883)	(1.096)
Computer use	53.11***	-15.56***	13.46***	18.07***	-10.78***	-23.28***
	(1.628)	(1.817)	(1.807)	(0.841)	(0.559)	(0.693)
Manufacturing and Construction	13.35***	-3.738	2.437	24.98***	-3.817***	3.408**
	(3.579)	(3.993)	(3.971)	(1.848)	(1.226)	(1.522)
Commerce	-1.872	-54.74***	-12.55***	-11.45***	-19.65***	1.430
	(3.660)	(4.084)	(4.062)	(1.890)	(1.254)	(1.557)
Services	16.13***	-40.68***	-14.77***	15.09***	-18.29***	-20.12***
	(3.465)	(3.866)	(3.845)	(1.789)	(1.187)	(1.473)
Log hourly earnings	1.094***	-0.454	-0.101	0.781***	-0.401***	-0.616***
	(0.254)	(0.283)	(0.281)	(0.131)	(0.0870)	(0.108)
Country fixed effects	YES	YES	YES	YES	YES	YES
Observations	17,563	17,551	17,563	17,570	17,570	17,570
R-squared	0.244	0.105	0.148	0.288	0.278	0.414

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The PDII measures are imputed to the 1-digit ISCO occupation in the STEP datasets. All the task scores have a mean equal to zero, and a standard deviation of 100.

Table 4: Cross-country Regressions of Standardized STEP and PDII Task Variables on Country Characteristics: Countries With a STEP survey

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	STEP						PDII (US)					
	$\Delta Abstract$		$\Delta Routine$		$\Delta Manual$		$\Delta Abstract$		$\Delta Routine$		$\Delta Manual$	
GDP per capita (log), change	-0.0480**	0.0142	-0.00802	-0.0890	0.00228	0.0368	-0.0410*	-0.0403	0.00672	-0.0411	0.0537***	-0.00363
	(0.0215)	(0.0790)	(0.0320)	(0.0933)	(0.0175)	(0.0601)	(0.0231)	(0.0766)	(0.0226)	(0.0655)	(0.0177)	(0.0677)
Industry value added (% GDP), change		-0.0520		0.157		0.0732		-0.179		0.148		-0.135
		(0.225)		(0.265)		(0.171)		(0.218)		(0.186)		(0.192)
Services value added (%GDP), change		0.256*		-0.336**		-0.0992		0.266*		-0.332***		-0.132
		(0.139)		(0.164)		(0.106)		(0.135)		(0.115)		(0.119)
College graduates (% pop.), change		0.0421		0.0143		0.0864*		-0.00619		0.0466		-0.0474
		(0.0607)		(0.0716)		(0.0462)		(0.0588)		(0.0503)		(0.0520)
Female workers (% pop.), change		-1.072*		1.040		-0.179		-1.030*		0.882*		0.505
		(0.541)		(0.638)		(0.412)		(0.524)		(0.448)		(0.463)
Population 15-64 (% pop.), change		-1.830***		3.563***		-0.236		-1.042		2.444***		0.307
		(0.658)		(0.777)		(0.501)		(0.638)		(0.546)		(0.564)
Population aged 65+ (% pop.), change		-2.094		6.451**		1.254		2.017		3.430*		0.787
		(2.132)		(2.516)		(1.623)		(2.066)		(1.767)		(1.826)
Internet users (% pop.), change		0.140		-0.220*		-0.0174		0.104		-0.169**		-0.0456
		(0.100)		(0.118)		(0.0762)		(0.0970)		(0.0830)		(0.0857)
Imports (%GDP), change		0.128		0.0864		0.193***		0.308***		0.0421		0.00218
		(0.0796)		(0.0939)		(0.0606)		(0.0771)		(0.0659)		(0.0681)
Exports (%GDP), change		-0.0584		-0.00540		-0.167**		-0.107		-0.0439		-0.0365
		(0.0932)		(0.110)		(0.0710)		(0.0903)		(0.0773)		(0.0798)
Year fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	73	67	73	67	73	67	73	67	73	67	73	67
R-squared	0.074	0.281	0.032	0.538	0.039	0.329	0.052	0.357	0.046	0.535	0.148	0.115

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample of survey-years is in Table A8. All the task scores have a mean equal to zero, and a standard deviation of 100.

Table 5: Task Content of Jobs Measures across Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	STEP			PDII (US)		
	Absract	Routine	Manual	Absract	Routine	Manual
	(a) Means					
Developing countries	-2.7	5.3	6.9	-24.2	16.3	32.0
Developed countries	16.4	-4.1	6.1	-13.0	8.7	13.9
	(b) Standard deviation					
Developing countries	10.7	6.6	6.2	9.8	6.4	9.5
Developed countries	7.1	4.2	2.4	6.1	5.0	7.2

Note: Averages and standard deviation of country-level task measures. The sample of survey-years is in Table A9. Developing countries include low and middle-income countries as well as the former socialist European economies.

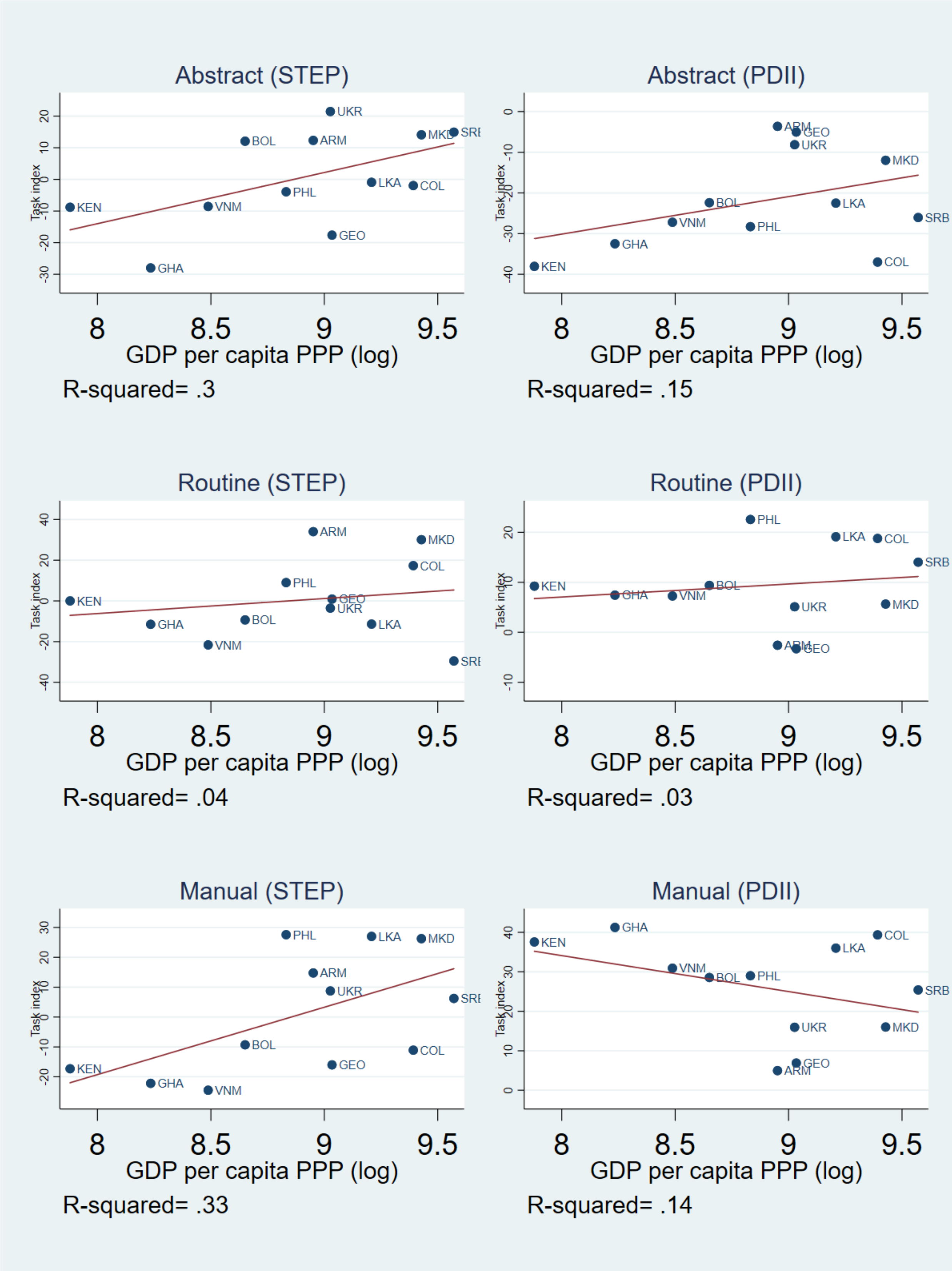
Table 6: Cross-country Regressions of Standarized STEP and PDII Task Variables on Country Characteristics: Developing countries sample

	(1)	(2)	(3)	(4)	(5)	(6)
	STEP			PDII (US)		
	$\Delta Abstract$	$\Delta Routine$	$\Delta Manual$	$\Delta Abstract$	$\Delta Routine$	$\Delta Manual$
GDP per capita (log), change	-0.0345	-0.0931***	0.0150	-0.0679	-0.0436*	0.0577
	(0.0477)	(0.0309)	(0.0355)	(0.0529)	(0.0255)	(0.0384)
Industry value added (% GDP), change	-0.225	0.284***	-0.00406	-0.00141	0.147*	0.164
	(0.154)	(0.0994)	(0.114)	(0.170)	(0.0821)	(0.124)
Services value added (%GDP), change	0.0710	-0.0665	0.0117	0.102	-0.0794	-0.0519
	(0.130)	(0.0843)	(0.0969)	(0.144)	(0.0697)	(0.105)
College graduates (% pop.), change	-0.0624	-0.00855	-0.0239	-0.104	0.00371	0.0195
	(0.0580)	(0.0376)	(0.0432)	(0.0644)	(0.0310)	(0.0468)
Female workers (% pop.), change	-0.140	0.112	-0.0705	-0.0858	0.0714	0.149
	(0.116)	(0.0752)	(0.0865)	(0.129)	(0.0622)	(0.0936)
Population 15-64 (% pop.), change	-0.0258	0.771***	-0.255	0.191	0.347	-0.422
	(0.418)	(0.271)	(0.311)	(0.464)	(0.224)	(0.337)
Population aged 65+ (% pop.), change	0.892	-0.324	0.0214	0.532	-0.373	-1.052
	(1.318)	(0.853)	(0.981)	(1.462)	(0.705)	(1.062)
Internet users (% pop.), change	0.130**	-0.0929**	0.0396	0.131*	-0.0958***	-0.111**
	(0.0634)	(0.0410)	(0.0471)	(0.0703)	(0.0339)	(0.0510)
Imports (%GDP), change	0.156**	-0.0192	0.0997**	0.252***	-0.0596*	-0.0675
	(0.0648)	(0.0420)	(0.0482)	(0.0719)	(0.0347)	(0.0522)
Exports (%GDP), change	-0.173**	0.0782*	-0.0240	-0.232***	0.115***	0.113*
	(0.0721)	(0.0467)	(0.0537)	(0.0800)	(0.0386)	(0.0581)
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	418	418	418	418	418	418
R-squared	0.102	0.185	0.050	0.088	0.182	0.107

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample of developing countries is in Table A9

Figures

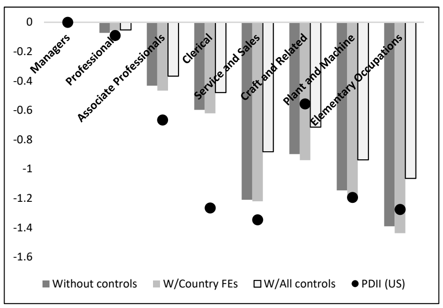
Figure 1: Standardized STEP and PDII Task Variables by country



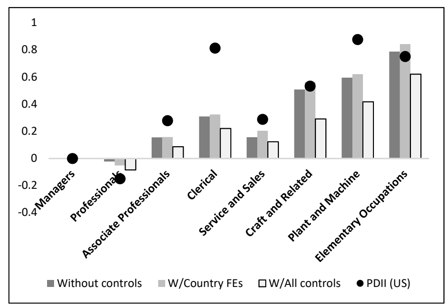
Note: Each dot shows the average task content of job by country.

Figure 2: Standardized STEP and PDII Task Variables by Occupation

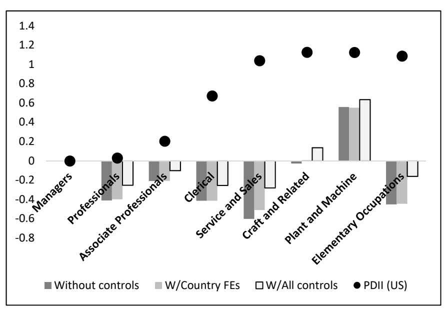
(a) Abstract tasks



(b) Routine tasks

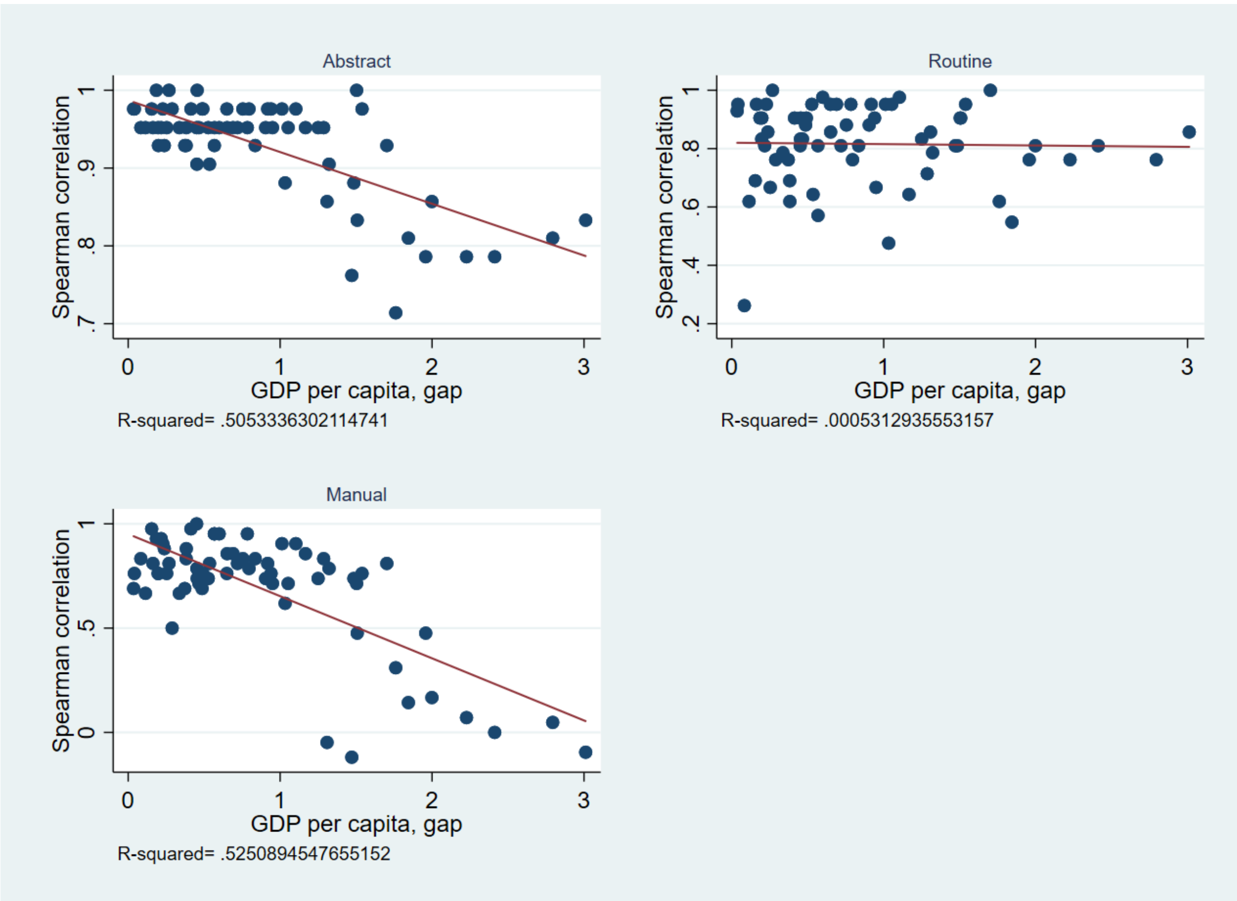


(c) Manual tasks



Note: each dark gray bar shows the difference between the average task index for the corresponding occupation and that of Managers. The lighter gray bars control for country fixed effects, and the white bars control for country fixed effects and individual characteristics (see Table 3). The dots shows the difference between the average PDII index for each occupation and that of managers.

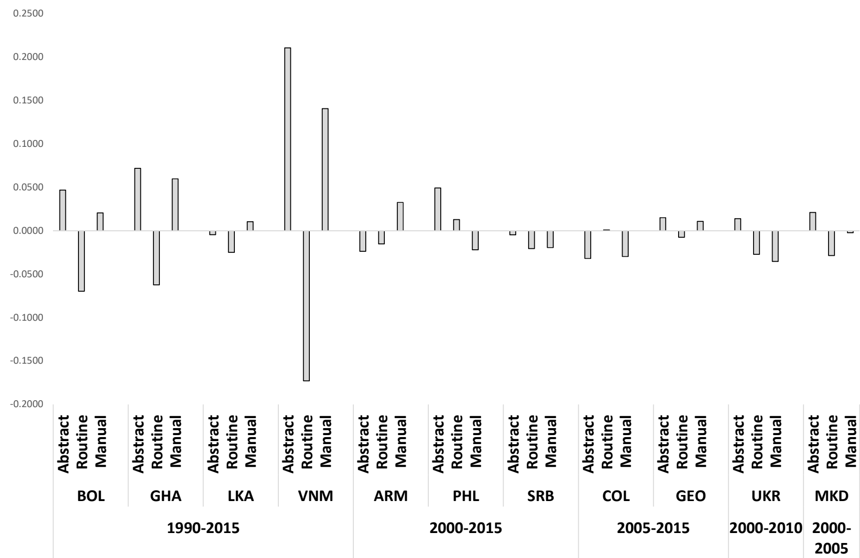
Figure 3: Correlation in the Task Content of Occupations vs. Income Gap



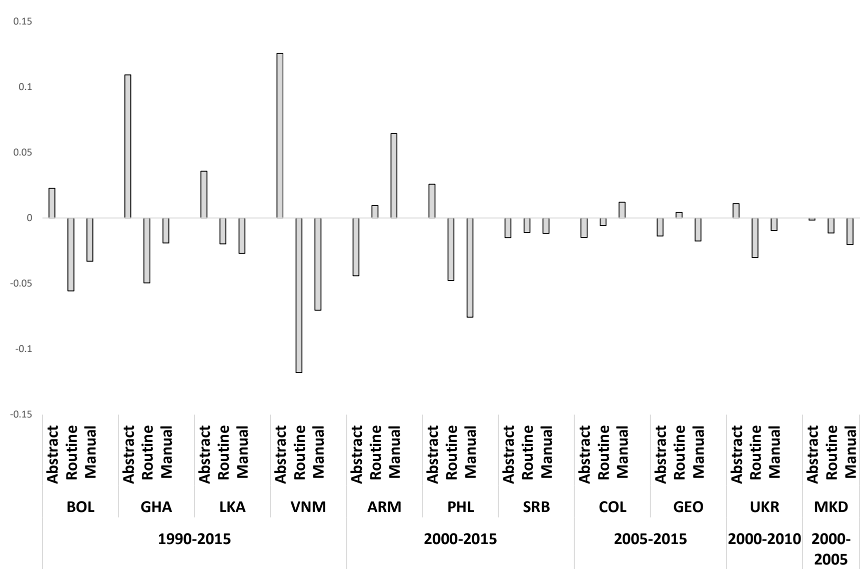
Note: The vertical axis measures the Spearman rank correlation between the average task content by occupation in country X and the average task content by occupation in country Y. The horizontal axis measures the difference in the logarithm of gdp per capita in PPP, in absolute value. It excludes the Philippines as an outlier.

Figure 4: Standardized STEP and PDII Task Variables, changes over time

(a) STEP-based measures



(b) PDII-based measures



Note: each var shows the change in the average task content measure between the earliest and latest survey year. The scores are imputed at the occupational level, thereby the changes over time are driven by changes in the occupational structure.

Figure 5: Standardized STEP and PDII Task Variables, Averages by Country

(a) STEP-based measures

(b) PDII-based measures

Note: each point shows the average task content measure for each country included in the I2D2 dataset. The scores are imputed to the microdata at the occupational level, thereby cross-country differences are driven by differences in the occupational structure.

Appendix A. Additional tables

Table A1: Average STEP task indexes by jobs' characteristics

	(1)	(2)	(3)
	Abstract	Routine	Manual
Drives a vehicle at work			
No	-0.057	0.046	-0.253
Yes	0.306	-0.245	1.366
Operate machinery at work			
No	-0.012	-0.033	-0.168
Yes	0.119	0.335	1.636
Repair things at work			
No	-0.052	0.011	-0.188
Yes	0.455	-0.091	1.606

Table A2: Regressions of Standardized STEP Abstract Task Variables on Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ARM	BOL	COL	GEO	GHA	KEN	LKA	MKD	PHL	SRB	UKR	VNM
Secondary	41.33***	10.62*	9.592	36.58*	12.06***	15.64***	44.80***	34.75***	39.20***	35.25**	45.49	25.31***
	(13.32)	(6.388)	(5.941)	(20.50)	(3.750)	(3.764)	(5.355)	(7.909)	(5.072)	(17.05)	(28.31)	(3.907)
Tertiary	100.4***	66.15***	35.61***	55.84***	67.56***	40.86***	76.14***	106.6***	66.65***	103.8***	102.2***	97.86***
	(13.78)	(6.722)	(7.053)	(20.37)	(5.536)	(4.961)	(8.038)	(9.037)	(3.643)	(18.90)	(27.43)	(5.217)
Female	-18.36***	-27.65***	-19.13***	4.482	-23.99***	-11.65***	-19.22***	-25.51***	4.858	-15.91**	-0.335	-18.14***
	(5.658)	(4.282)	(4.053)	(5.733)	(3.428)	(3.107)	(4.802)	(4.296)	(3.081)	(7.863)	(8.650)	(3.155)
Age 25-34	5.023	33.42***	12.78**	5.685	25.51***	15.54***	15.69**	40.97***	1.512	12.00	40.55***	15.32***
	(9.191)	(5.783)	(5.516)	(10.06)	(4.537)	(3.903)	(7.576)	(10.61)	(5.316)	(16.08)	(13.73)	(5.675)
Age 25-44	13.20	39.53***	16.40***	-9.884	30.99***	17.21***	22.13***	58.42***	8.512	17.33	45.43***	17.36***
	(9.696)	(6.268)	(6.179)	(10.10)	(4.822)	(4.496)	(7.638)	(10.55)	(5.255)	(15.49)	(14.39)	(5.677)
Age 55-54	27.13***	23.69***	9.813	5.220	35.20***	15.77***	18.59**	72.05***	6.842	33.82**	42.17***	22.66***
	(9.374)	(6.942)	(6.180)	(10.56)	(5.584)	(5.550)	(8.051)	(10.73)	(5.280)	(15.65)	(14.66)	(5.765)
Age 55-64	27.77***	16.72*	15.96**	4.991	31.00***	1.695	2.288	86.61***	13.82**	56.26***	71.42***	24.57***
	(10.09)	(8.612)	(7.710)	(11.31)	(6.553)	(7.929)	(9.247)	(11.15)	(5.963)	(17.41)	(16.03)	(6.702)
Computer use	47.09***	51.04***	41.27***	42.60***	48.60***	55.36***	62.11***	68.82***	19.02***	61.27***	66.97***	53.41***
	(6.872)	(5.039)	(4.725)	(6.865)	(4.627)	(4.463)	(6.821)	(6.006)	(3.459)	(11.04)	(9.114)	(4.138)
Manufacturing and Construction	8.985	-11.11	2.719	-85.01***	40.09***	12.45	24.99***	18.68	-3.876	27.60	2.403	-1.882
	(12.13)	(23.25)	(33.39)	(23.75)	(9.245)	(19.72)	(7.388)	(12.32)	(7.914)	(29.07)	(15.49)	(11.34)
Commerce	-10.81	-21.36	-22.64	-73.13***	-2.893	-12.16	25.69***	0.145	0.517	10.07	16.03	-18.58
	(12.78)	(23.27)	(33.41)	(23.85)	(9.005)	(19.49)	(8.436)	(12.79)	(8.543)	(29.91)	(17.63)	(11.36)
Services	5.933	0.822	-16.39	-77.68***	29.57***	5.396	50.71***	7.476	7.942	35.45	9.179	-5.022
	(10.34)	(23.10)	(33.32)	(22.93)	(8.896)	(19.35)	(7.788)	(12.22)	(7.455)	(28.52)	(14.94)	(11.19)
Log hourly earnings	2.796*	1.494*	15.62***	29.15***	-0.156	14.29***	4.233*	0.147	11.20***	-1.185	40.55***	0.230
	(1.486)	(0.903)	(2.181)	(3.354)	(0.318)	(1.615)	(2.397)	(0.497)	(1.626)	(0.992)	(7.039)	(0.495)
Constant	-95.77***	-51.13**	-146.9***	-43.62	-77.50***	-109.6***	-91.98***	-143.3***	-98.30***	-134.4***	-254.3***	-60.21***
	(17.80)	(23.70)	(37.80)	(29.48)	(9.698)	(20.57)	(13.82)	(16.40)	(9.716)	(34.24)	(37.08)	(12.23)
Observations	933	1,581	1,635	853	1,679	2,200	1,258	1,597	1,616	1,147	951	2,113
R-squared	0.246	0.327	0.205	0.218	0.407	0.355	0.318	0.292	0.318	0.131	0.195	0.411

Note: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Individual-level regressions using the STEP surveys for each country. Sample includes workers aged 15 to 64 years.

Table A3: Regressions of Standardized STEP Routine Task Variables on Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ARM	BOL	COL	GEO	GHA	KEN	LKA	MKD	PHL	SRB	UKR	VNM
Secondary	-13.89	4.302	-24.76***	10.35	-8.710*	-9.479**	-3.125	-37.41***	-8.743	-58.69***	-59.58*	-7.252
	(12.88)	(6.837)	(6.152)	(26.63)	(4.799)	(4.453)	(6.629)	(7.086)	(7.846)	(12.35)	(34.26)	(5.406)
Tertiary	-27.59**	-35.83***	-48.44***	-15.65	-15.25**	-13.83**	-20.37**	-71.71***	-20.72***	-103.7***	-93.88***	-28.76***
	(13.32)	(7.196)	(7.304)	(26.46)	(7.085)	(5.872)	(9.951)	(8.096)	(5.635)	(13.69)	(33.19)	(7.220)
Female	-1.774	5.351	7.968*	12.57*	-3.459	-0.632	23.92***	13.67***	6.015	32.96***	8.434	17.69***
	(5.470)	(4.584)	(4.197)	(7.452)	(4.387)	(3.677)	(5.944)	(3.849)	(4.766)	(5.695)	(10.47)	(4.366)
Age 25-34	-20.78**	0.529	-5.027	23.53*	-16.23***	-8.658*	-12.72	-18.53*	-15.81*	-27.11**	-12.36	-18.77**
	(8.885)	(6.191)	(5.712)	(13.06)	(5.807)	(4.619)	(9.378)	(9.510)	(8.223)	(11.65)	(16.62)	(7.854)
Age 25-44	-9.851	-3.750	-10.21	13.68	-8.733	-7.726	-11.90	-19.23**	-24.92***	-33.91***	-2.358	-24.59***
	(9.374)	(6.709)	(6.399)	(13.12)	(6.171)	(5.312)	(9.455)	(9.456)	(8.129)	(11.22)	(17.42)	(7.857)
Age 55-54	-5.149	-16.66**	-29.47***	10.66	-18.16**	-8.774	-8.977	-27.04***	-26.66***	-12.51	-3.617	-37.42***
	(9.062)	(7.431)	(6.400)	(13.71)	(7.146)	(6.563)	(9.967)	(9.617)	(8.167)	(11.34)	(17.74)	(7.978)
Age 55-64	-5.855	0.492	-15.79**	-3.307	-9.251	-23.43**	-35.89***	-29.96***	-33.39***	-19.20	-17.84	-30.67***
	(9.758)	(9.218)	(7.984)	(14.68)	(8.386)	(9.365)	(11.45)	(9.987)	(9.225)	(12.61)	(19.40)	(9.274)
Computer use	-6.554	-0.448	-1.803	-14.31	0.238	-11.09**	2.412	-30.75***	-18.52***	-13.68*	-16.63	-33.85***
	(6.643)	(5.394)	(4.893)	(8.913)	(5.922)	(5.278)	(8.445)	(5.381)	(5.350)	(7.993)	(11.03)	(5.726)
Manufacturing and Construction	5.220	-86.80***	27.20	15.41	-72.77***	24.49	19.60**	-22.03**	-8.789	-15.00	-26.18	47.11***
	(11.73)	(24.89)	(34.58)	(30.83)	(11.83)	(23.71)	(9.146)	(11.04)	(12.24)	(21.06)	(18.75)	(15.69)
Commerce	-56.80***	-133.9***	-18.26	-52.82*	-79.08***	-7.808	-27.07***	-89.39***	13.72	-103.8***	-86.36***	-39.27**
	(12.36)	(24.91)	(34.59)	(30.97)	(11.52)	(23.44)	(10.44)	(11.46)	(13.21)	(21.66)	(21.33)	(15.72)
Services	-41.46***	-121.5***	-10.31	-11.40	-71.42***	8.360	-22.80**	-72.28***	5.762	-94.11***	-92.77***	-6.897
	(9.997)	(24.73)	(34.51)	(29.78)	(11.38)	(23.27)	(9.642)	(10.95)	(11.53)	(20.66)	(18.08)	(15.49)
Log hourly earnings	-0.241	-1.414	-9.335***	-4.904	0.507	-9.687***	0.809	0.465	0.971	-0.457	-9.713	-0.692
	(1.436)	(0.967)	(2.258)	(4.350)	(0.407)	(1.913)	(2.967)	(0.445)	(2.515)	(0.718)	(8.518)	(0.685)
Constant	103.6***	122.6***	127.9***	17.18	83.29***	53.91**	0.885	173.8***	29.63**	127.3***	183.2***	15.73
	(17.21)	(25.37)	(39.14)	(38.29)	(12.41)	(24.74)	(17.11)	(14.69)	(15.03)	(24.80)	(44.87)	(16.93)
Observations	933	1,581	1,635	853	1,679	2,188	1,258	1,597	1,616	1,147	951	2,113
R-squared	0.095	0.110	0.109	0.055	0.040	0.057	0.070	0.260	0.041	0.226	0.084	0.154

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Individual-level regressions using the STEP surveys for each country. Sample includes workers aged 15 to 64 years.

Table A4: Regressions of Standardized STEP Manual Task Variables on Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	ARM	BOL	COL	GEO	GHA	KEN	LKA	MKD	PHL	SRB	UKR	VNM
Secondary	-15.51	8.356	8.420	-6.920	2.171	12.09***	12.12*	6.910	-30.13***	14.28	55.08	6.172
	(15.52)	(6.104)	(6.021)	(20.97)	(4.689)	(4.063)	(7.178)	(8.257)	(8.626)	(11.05)	(36.56)	(4.088)
Tertiary	0.567	19.23***	-0.980	-3.901	14.19**	6.054	17.81*	26.26***	-31.93***	5.782	39.23	6.124
	(16.06)	(6.424)	(7.149)	(20.84)	(6.921)	(5.356)	(10.77)	(9.433)	(6.195)	(12.25)	(35.43)	(5.459)
Female	-79.30***	-68.42***	-57.46***	-83.32***	-68.84***	-28.13***	-56.30***	-89.19***	-16.74***	-72.31***	-85.23***	-51.20***
	(6.593)	(4.092)	(4.108)	(5.866)	(4.286)	(3.354)	(6.436)	(4.484)	(5.240)	(5.095)	(11.17)	(3.302)
Age 25-34	2.224	23.51***	20.57***	11.52	5.736	7.590*	5.535	9.628	-19.57**	10.86	10.55	29.55***
	(10.71)	(5.527)	(5.591)	(10.29)	(5.673)	(4.214)	(10.15)	(11.08)	(9.040)	(10.42)	(17.74)	(5.938)
Age 25-44	20.26*	20.03***	26.32***	22.29**	0.201	6.035	-16.38	26.68**	-13.62	21.49**	7.291	15.85***
	(11.30)	(5.989)	(6.263)	(10.32)	(6.028)	(4.854)	(10.24)	(11.02)	(8.937)	(10.04)	(18.59)	(5.941)
Age 55-54	14.72	11.48*	17.24***	16.49	4.003	3.489	-26.61**	19.74*	-29.99***	37.41***	23.21	12.10**
	(10.92)	(6.634)	(6.264)	(10.80)	(6.981)	(5.992)	(10.79)	(11.20)	(8.979)	(10.14)	(18.94)	(6.033)
Age 55-64	1.414	2.270	16.88**	9.484	3.948	-3.507	-36.86***	14.00	-25.99**	17.39	4.432	-6.627
	(11.76)	(8.229)	(7.815)	(11.56)	(8.193)	(8.560)	(12.40)	(11.64)	(10.14)	(11.28)	(20.71)	(7.013)
Computer use	-1.016	-2.300	0.679	-9.361	-0.200	30.39***	23.79***	19.17***	48.05***	12.91*	8.013	12.73***
	(8.007)	(4.815)	(4.789)	(7.029)	(5.785)	(4.817)	(9.144)	(6.270)	(5.882)	(7.151)	(11.77)	(4.330)
Manufacturing and Construction	8.064	1.767	41.39	-14.02	-7.398	-5.510	30.74***	-16.78	-36.48***	-9.535	-16.10	17.61
	(14.14)	(22.22)	(33.84)	(24.28)	(11.56)	(21.29)	(9.903)	(12.86)	(13.46)	(18.84)	(20.01)	(11.87)
Commerce	-32.04**	-20.25	22.41	-28.03	-10.49	-59.93***	49.54***	-6.752	-43.13***	-1.738	-29.45	-4.223
	(14.89)	(22.24)	(33.86)	(24.40)	(11.26)	(21.04)	(11.31)	(13.35)	(14.53)	(19.38)	(22.77)	(11.89)
Services	-21.43*	-18.05	22.70	-32.60	-4.401	-51.38**	31.63***	-29.73**	-46.01***	-25.61	-23.94	1.813
	(12.05)	(22.08)	(33.77)	(23.44)	(11.12)	(20.89)	(10.44)	(12.75)	(12.68)	(18.49)	(19.29)	(11.71)
Log hourly earnings	-0.733	-0.740	3.947*	2.195	-0.152	9.142***	6.306**	-1.016*	1.989	-0.437	12.53	-0.0619
	(1.731)	(0.863)	(2.210)	(3.426)	(0.397)	(1.743)	(3.213)	(0.519)	(2.765)	(0.643)	(9.091)	(0.518)
Constant	82.50***	18.53	-60.22	64.04**	19.44	-18.16	-9.453	48.79***	71.88***	18.27	-3.962	-20.37
	(20.74)	(22.65)	(38.31)	(30.15)	(12.12)	(22.21)	(18.53)	(17.12)	(16.52)	(22.19)	(47.89)	(12.80)
Observations	933	1,581	1,635	853	1,679	2,200	1,258	1,597	1,616	1,147	951	2,113
R-squared	0.171	0.195	0.152	0.250	0.193	0.176	0.134	0.218	0.079	0.193	0.096	0.146

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Individual-level regressions using the STEP surveys for each country. Sample includes workers aged 15 to 64 years.

Table A5: Correlations among STEP and PDII Abstract Task Variables

	(1) ARM	(2) GEO	(3) MKD	(4) BOL	(5) COL	(6) GHA	(7) KEN	(8) UKR	(9) LKA	(10) VNM	(11) PHL	(12) SRB	(13) ALL STEP	(14) US
ARM	1													
GEO	0.976	1												
MKD	0.952	0.976	1											
BOL	0.976	1	0.976	1										
COL	0.976	0.952	0.976	0.952	1									
GHA	0.976	0.929	0.905	0.929	0.952	1								
KEN	0.976	0.952	0.976	0.952	1	0.952	1							
UKR	0.976	0.952	0.929	0.952	0.952	0.952	0.952	1						
LKA	0.929	0.952	0.976	0.952	0.952	0.881	0.952	0.952	1					
VNM	0.976	1	0.976	1	0.952	0.929	0.952	0.952	0.952	1				
PHL	0.952	0.976	1	0.976	0.976	0.905	0.976	0.929	0.976	0.976	1			
SRB	0.952	0.976	0.952	0.976	0.929	0.881	0.929	0.905	0.905	0.976	0.952	1		
ALL STEP	1	0.976	0.952	0.976	0.976	0.976	0.976	0.976	0.929	0.976	0.952	0.952	1	
US	0.857	0.786	0.762	0.786	0.833	0.81	0.833	0.81	0.714	0.786	0.762	0.857	0.857	1

Note: the table shows the Spearman rank correlation between the average task content at the 1-digit ISCO occupation.

Table A6: Correlations among STEP and PDII Routine Task Variables

	(1) ARM	(2) GEO	(3) MKD	(4) BOL	(5) COL	(6) GHA	(7) KEN	(8) UKR	(9) LKA	(10) VNM	(11) PHL	(12) SRB	(13) ALL STEP	(14) US
ARM	1													
GEO	0.952	1												
MKD	0.952	0.881	1											
BOL	0.952	1	0.881	1										
COL	0.905	0.81	0.929	0.81	1									
GHA	0.762	0.81	0.786	0.81	0.714	1								
KEN	0.952	0.952	0.952	0.952	0.905	0.81	1							
UKR	0.69	0.619	0.762	0.619	0.786	0.667	0.643	1						
LKA	0.857	0.833	0.762	0.833	0.667	0.476	0.833	0.262	1					
VNM	0.905	0.905	0.905	0.905	0.881	0.69	0.976	0.571	0.857	1				
PHL	0.429	0.31	0.429	0.31	0.214	0.357	0.333	-0.024	0.524	0.238	1			
SRB	0.952	0.952	0.952	0.952	0.905	0.81	1	0.643	0.833	0.976	0.333	1		
ALL STEP	0.952	0.952	0.929	0.952	0.905	0.905	0.952	0.762	0.714	0.881	0.31	0.952	1	
US	0.81	0.762	0.81	0.762	0.905	0.762	0.857	0.548	0.619	0.81	0.286	0.857	0.857	1

Note: the table shows the Spearman rank correlation between the average task content at the 1-digit ISCO occupation.

Table A7: Correlations among STEP and PDII Manual Task Variables

	(1) ARM	(2) GEO	(3) MKD	(4) BOL	(5) COL	(6) GHA	(7) KEN	(8) UKR	(9) LKA	(10) VNM	(11) PHL	(12) SRB	(13) ALL STEP	(14) US
ARM	1													
GEO	0.762	1												
MKD	0.738	0.69	1											
BOL	0.905	0.81	0.833	1										
COL	0.762	1	0.69	0.81	1									
GHA	0.786	0.833	0.786	0.952	0.833	1								
KEN	0.905	0.714	0.762	0.952	0.714	0.929	1							
UKR	0.976	0.667	0.69	0.881	0.667	0.714	0.857	1						
LKA	0.881	0.762	0.5	0.714	0.762	0.619	0.738	0.833	1					
VNM	0.976	0.738	0.762	0.929	0.738	0.833	0.952	0.952	0.857	1				
PHL	-0.333	0.119	-0.571	-0.286	0.119	-0.167	-0.381	-0.357	-0.119	-0.405	1			
SRB	0.857	0.762	0.81	0.81	0.762	0.738	0.81	0.81	0.786	0.905	-0.429	1		
ALL STEP	0.952	0.81	0.69	0.905	0.81	0.833	0.905	0.905	0.905	0.929	-0.214	0.762	1	
US	0.167	0.476	-0.119	0.071	0.476	0.048	-0.095	0.143	0.31	0	0.738	-0.048	0.238	1

Note: the table shows the Spearman rank correlation between the average task content at the 1-digit ISCO occupation.

Table A8: Repeated cross-sections of household surveys for countries included in STEP survey

ARM	BOL	COL	GEO	GHA	LKA	MKD	PHL	SRB	UKR	VNM
1998	1992	2008	2008	1991	1993	2002	2001	2003	2001	1992
2013	1997	2009	2010	1998	1994	2003	2002	2004	2007	1997
	1999	2010	2011	2005	1995	2004	2003	2005	2009	2002
	2000	2011	2012	2012	1996	2005	2004	2006		2004
	2001	2012	2013		1998	2006	2005	2007		2006
	2002	2013			1999		2006	2008		2007
	2003	2014			2000		2007	2009		2008
	2005				2001		2008	2010		2009
	2006				2002		2009	2013		2010
	2007				2003		2010			
	2008				2004		2011			
	2009				2006		2012			
	2011				2008		2013			
	2012				2009		2014			
	2014				2011					
					2012					
					2013					

Table A9: List of surveys from the I2D2 data set included in the cross-country regression

Country	First year	Final Year	Number of survey-years	Country	First year	Final Year	Number of survey-years
Developing countries							
Albania	2002	2008	3	Latvia	2005	2011	7
Argentina	2003	2014	12	Lebanon	2004	2011	2
Bangladesh	2000	2015	5	Lithuania	1998	2011	14
Belize	1996	1999	4	Mauritius	1999	2012	13
Bhutan	2003	2012	3	Mexico	1992	2006	9
Bolivia	**1997**	**2014**	**14**	Moldova	2006	2012	7
Bosnia and Herzegovina	2001	2007	2	Mongolia	2007	2011	4
Brazil	2002	2014	11	Montenegro	2005	2011	4
Bulgaria	2003	2010	5	Morocco	2005	2009	5
Burkina Faso	1998	2014	3	Nepal	1998	2010	4
Cabo Verde	2000	2007	2	Nicaragua	1998	2009	4
Cambodia	1997	2012	7	Pakistan	1999	2014	14
Cameroon	2001	2014	4	Panama	2001	2010	10
Chile	1992	2013	10	Paraguay	2001	2012	4
China	2007	2013	2	Peru	1997	2014	18
Colombia	**2008**	**2014**	**7**	**Philippines**	**2001**	**2014**	**14**
Costa Rica	2001	2012	11	Poland	1998	2011	14
Cote d'Ivoire	2008	2015	2	Russian Federation	1994	2009	12
Czech Republic	2005	2011	7	**Serbia**	**2004**	**2013**	**8**
Dominican Republic	2001	2013	5	Slovak Republic	2005	2011	7
Ecuador	2000	2014	6	Slovenia	2005	2011	7
Egypt, Arab Rep.	1998	2005	3	South Africa	1995	2008	10
El Salvador	1998	2014	13	**Sri Lanka**	**1994**	**2013**	**16**
Estonia	2000	2011	12	Tanzania	2000	2014	6
Ethiopia	2012	2014	2	Thailand	1994	2011	8
Gambia, The	1998	2015	4	Tunisia	1997	2011	4
Georgia	2008	2013	5	Turkey	2001	2012	11
Ghana	**1998**	**2012**	**3**	Uganda	2005	2012	3
Guatemala	2000	2006	5	Uruguay	2000	2011	12
Hungary	2004	2011	8	Uzbekistan	2000	2003	3
India	1993	2011	5	Venezuela, RB	1992	2006	5
Indonesia	2001	2007	7	Vietnam	1997	2010	8
Iraq	2006	2012	2	Yemen, Rep.	1998	2005	2
Jamaica	1996	2002	4	Zambia	1998	2015	5
Jordan	2000	2016	15				
Developed countries							
Austria	2002	2008	3	Luxembourg	1997	2012	7
Belgium	2003	2014	12	Netherlands	2001	2014	4
Cyprus	2000	2015	5	Norway	1992	2013	10
Denmark	1996	1999	4	Portugal	2007	2013	2
Finland	2003	2012	3	Puerto Rico	2008	2014	7
France	1997	2014	14	Seychelles	2001	2012	11
Germany	2001	2007	2	Spain	2008	2015	2
Greece	2002	2014	11	Sweden	2005	2011	7
Iceland	2003	2010	5	United Kingdom	2001	2013	5
Ireland	1998	2014	3	United States	2000	2014	6
Italy	2000	2007	2				

Note: Developing countries include low and middle-income countries as well as the former socialist European economies. Countries with a STEP survey in bold letters.

Table A10: Average changes in explanatory variables, I2D2 sample

Country group	Number of countries	GDP (log points), change	Industry VA (% of GDP), change	Services VA (% of GDP), change	Skilled (% of working-age population), change	Females (% of employment), change
Developing countries	84	3.2	0.0	0.1	0.5	0.0
Developed countries	22	0.9	-0.2	0.4	0.5	0.0
Country group		working-age population (% of population), change	Older than 65 years (% of population), change	Internet users (% of population), change	Imports (% of GDP), change	Exports (% of GDP), change
Developing countries	84	0.3	0.1	2.0	0.5	0.5
Developed countries	22	0.0	0.1	3.1	0.8	1.0

Table A11: Regressions of Standardized STEP and PDII Task Measures on Country Characteristics: Sample of Developed and Developing Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	STEP			PDII (US)		
	$\Delta Abstract$	$\Delta Routine$	$\Delta Manual$	$\Delta Abstract$	$\Delta Routine$	$\Delta Manual$
GDP per capita (log), change	-0.0265	-0.0937***	0.00819	-0.0654	-0.0388*	0.0591*
	(0.0399)	(0.0257)	(0.0294)	(0.0441)	(0.0218)	(0.0324)
Industry value added (% GDP), change	-0.206	0.276***	0.00693	0.00926	0.144**	0.147
	(0.132)	(0.0850)	(0.0971)	(0.146)	(0.0721)	(0.107)
Services value added (%GDP), change	0.0474	-0.0639	0.0105	0.0922	-0.0904	-0.0464
	(0.113)	(0.0728)	(0.0832)	(0.125)	(0.0618)	(0.0919)
College graduates (% pop.), change	-0.0537	-0.0126	-0.0295	-0.0935*	-0.00302	0.0127
	(0.0477)	(0.0307)	(0.0351)	(0.0527)	(0.0261)	(0.0388)
Female workers (% pop.), change	-0.133	0.100	-0.0804	-0.0834	0.0588	0.143*
	(0.103)	(0.0665)	(0.0759)	(0.114)	(0.0564)	(0.0839)
Population 15-64 (% pop.), change	-0.0332	0.779***	-0.189	0.169	0.383*	-0.394
	(0.358)	(0.231)	(0.264)	(0.396)	(0.196)	(0.291)
Population aged 65+ (% pop.), change	0.987	0.0504	0.153	0.971	-0.0865	-0.907
	(1.027)	(0.662)	(0.757)	(1.136)	(0.562)	(0.835)
Internet users (% pop.), change	0.112**	-0.0919***	0.0241	0.115**	-0.101***	-0.103**
	(0.0497)	(0.0320)	(0.0366)	(0.0549)	(0.0272)	(0.0404)
Imports (%GDP), change	0.141**	-0.0146	0.0979**	0.232***	-0.0551*	-0.0662
	(0.0551)	(0.0355)	(0.0406)	(0.0610)	(0.0302)	(0.0448)
Exports (%GDP), change	-0.161***	0.0648*	-0.0310	-0.215***	0.0952***	0.101**
	(0.0592)	(0.0382)	(0.0436)	(0.0655)	(0.0324)	(0.0482)
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	540	540	540	540	540	540
R-squared	0.091	0.169	0.042	0.081	0.158	0.096

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample of developing and developed countries is in Table A9

Table A12: Regressions of Standardized STEP and PDII Task Measures on Country Characteristics with Additional Controls : Sample of Developing Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	STEP			PDII (US)		
	$\Delta Abstract$	$\Delta Routine$	$\Delta Manual$	$\Delta Abstract$	$\Delta Routine$	$\Delta Manual$
GDP per capita (log), change	0.00571	-0.0583*	0.0605	0.00581	-0.0277	0.0177
	(0.0531)	(0.0336)	(0.0413)	(0.0609)	(0.0285)	(0.0426)
Industry value added (% GDP), change	-0.230	0.250**	-0.0564	-0.0231	0.115	0.160
	(0.155)	(0.0980)	(0.120)	(0.178)	(0.0833)	(0.125)
Services value added (%GDP), change	-0.0244	-0.108	-0.0392	-0.0235	-0.0793	0.0549
	(0.130)	(0.0825)	(0.101)	(0.150)	(0.0701)	(0.105)
College graduates (% pop.), change	-0.0714	-0.0128	-0.0321	-0.126*	0.00408	0.0200
	(0.0582)	(0.0368)	(0.0452)	(0.0668)	(0.0313)	(0.0467)
Female workers (% pop.), change	-0.148	0.155**	-0.0811	-0.0834	0.0897	0.128
	(0.115)	(0.0725)	(0.0892)	(0.132)	(0.0616)	(0.0922)
Population 15-64 (% pop.), change	-0.369	0.944***	-0.520	-0.232	0.466*	-0.258
	(0.458)	(0.289)	(0.356)	(0.526)	(0.246)	(0.368)
Population aged 65+ (% pop.), change	0.942	-1.393	-0.789	0.0504	-1.169	-0.977
	(1.397)	(0.883)	(1.085)	(1.603)	(0.750)	(1.122)
Internet users (% pop.), change	0.134**	-0.104**	0.0629	0.137*	-0.0957***	-0.0993*
	(0.0661)	(0.0418)	(0.0514)	(0.0759)	(0.0355)	(0.0531)
Imports (%GDP), change	0.175***	-0.0239	0.112**	0.281***	-0.0691**	-0.0775
	(0.0643)	(0.0406)	(0.0500)	(0.0738)	(0.0345)	(0.0516)
Exports (%GDP), change	-0.189**	0.0663	-0.0172	-0.260***	0.123***	0.137**
	(0.0735)	(0.0464)	(0.0571)	(0.0843)	(0.0395)	(0.0590)
Income group x Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	418	418	418	418	418	418
R-squared	0.294	0.390	0.187	0.234	0.352	0.303

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample of developing countries is in Table A9

Table A13: Regressions of Standardized PDII Task Measures on Country Characteristics with and without Agricultural Jobs : Sample of Developing Countries

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta Abstract$		$\Delta Routine$		$\Delta Manual$	
	w/o Agr.	w/ Agr	w/o Agr.	w/ Agr	w/o Agr.	w/ Agr
GDP per capita (log), change	-0.0679	-0.0994*	-0.0436*	-0.0235	0.0577	0.0677*
	(0.0529)	(0.0513)	(0.0255)	(0.0301)	(0.0384)	(0.0398)
Industry value added (% GDP), change	-0.00141	0.0191	0.147*	0.165*	0.164	0.0521
	(0.170)	(0.165)	(0.0821)	(0.0969)	(0.124)	(0.128)
Services value added (%GDP), change	0.102	0.246*	-0.0794	-0.0776	-0.0519	-0.118
	(0.144)	(0.140)	(0.0697)	(0.0822)	(0.105)	(0.109)
College graduates (% pop.), change	-0.104	-0.0616	0.00371	-0.0294	0.0195	-0.0206
	(0.0644)	(0.0625)	(0.0310)	(0.0366)	(0.0468)	(0.0485)
Female workers (% pop.), change	-0.0858	-0.0605	0.0714	0.0581	0.149	0.180*
	(0.129)	(0.125)	(0.0622)	(0.0733)	(0.0936)	(0.0970)
Population 15-64 (% pop.), change	0.191	0.316	0.347	0.128	-0.422	-0.472
	(0.464)	(0.451)	(0.224)	(0.264)	(0.337)	(0.349)
Population aged 65+ (% pop.), change	0.532	1.484	-0.373	-0.820	-1.052	-0.985
	(1.462)	(1.420)	(0.705)	(0.831)	(1.062)	(1.101)
Internet users (% pop.), change	0.131*	0.109	-0.0958***	-0.113***	-0.111**	-0.127**
	(0.0703)	(0.0682)	(0.0339)	(0.0400)	(0.0510)	(0.0529)
Imports (%GDP), change	0.252***	0.218***	-0.0596*	-0.0191	-0.0675	-0.0747
	(0.0719)	(0.0698)	(0.0347)	(0.0409)	(0.0522)	(0.0541)
Exports (%GDP), change	-0.232***	-0.163**	0.115***	0.0798*	0.113*	0.139**
	(0.0800)	(0.0777)	(0.0386)	(0.0455)	(0.0581)	(0.0602)
Year fixed effects	YES	YES	YES	YES	YES	YES
Observations	418	418	418	418	418	418
R-squared	0.088	0.089	0.182	0.147	0.107	0.111

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The sample of developing countries is in Table A9