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TECHNOLOGY AND THE TASK CONTENT OF JOBS ACROSS THE DEVELOPMENT SPECTRUM

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

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Abstract

Technology is the driver of labour allocation across sectors and occupations. Is the impact of technological change on developing countries similar to its impact on developed countries? Will developing countries follow the same development path that developed economies have taken? Our approach focuses on how technology shifts and reshapes the tasks workers perform on the job, and views occupations as the natural observable stand-in for these tasks. We first take stock of our knowledge on how technological change reallocates labour. We then construct a new measure of occupational task contents for each country and present new evidence on countries' task intensity. In the cross section, developed countries use non-routine analytical and interpersonal tasks more intensively than developing countries, but less intensively use routine-cognitive and routine-manual tasks. Both the occupational employment share and the occupational task contents of a country matter for these relationships. In the time dimension, non-routine analytical and interpersonal intensities rose and routine cognitive and routine manual intensities fell in most countries since 2006, regardless of their income levels. Our results show that occupational task contents ought to be measured for each country for proper analysis. More broadly, we should be careful about extrapolating what we know about the impact of technology on the labour market in developed countries to developing countries.

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1 Introduction

Most developed countries underwent a similar arc of structural change, or the reallocation of economic activity from agriculture to manufacturing and then to services. Economists agree that the differential rates of technological progress across these sectors have shaped their uneven growth. Until recently, the large literature on structural change has viewed labour as a homogeneous quantity to be freely allocated across sectors. A more recent literature, utilizing richer microeconomic data, has explored how technological change differentially affects workers across the demographic and socioeconomic spectrum. One important insight of this literature is that a worker's occupation is the relevant unit of analysis for identifying the pattern of technological change. Most works in this occupation-based literature focus on the US and other developed economies because of data availability.

An important question to be answered is whether developing countries will retrace the path of the developed countries, or is there a "natural" pattern of worker allocation across occupations and sectors along the process of economic development? There is evidence that the pattern of structural change has shifted for many developing countries, i.e. "premature deindustrialisation" (Rodrik, 2016). One possible explanation is that the availability and adoption of new technologies, automation in particular, may be eliminating low-skill manufacturing jobs that used to be gateways for workers leaving the agricultural sector (Hallward-Driemeier and Nayyar, 2017; Acemoglu and Restrepo, 2019). In other words, by redefining the nature of economic activity and the role of workers in a given occupation or sector, technological change can upend the once stable relationship between economic development and structural change. Answering the question, then, requires that we identify the pattern of technological change in developing countries.

Our approach focuses on how technology shifts and reshapes the tasks workers perform on the job, and views occupations as the natural observable stand-in for these tasks. This approach enables a richer analysis than what has been possible in the vast literature on skill-biased technological change, the dominant macroeconomic view on the impact of technological change on the labour market, or in the structural change literature, whose unit of analysis is sectors. There are three reasons. First, it focuses on workers' role in the labour market directly, instead of grouping them into broad categories (skilled vs. unskilled) based on their educational attainment. Second, it naturally brings into analysis occupational choices, which are subject to labour market frictions and the loss of job-specific human capital. Third, it opens the door to better measuring technological change by observing how workers' tasks evolve over time, instead of inferring them as a residual from sector-level growth accounting.

Our paper has two goals. The first is to take stock of our knowledge on the role of technological change in shaping the allocation of workers across occupations and sectors. The other is to motivate further research in this area using data from developing countries. For this purpose, we harmonise and analyse relevant data from countries across the economic development spectrum.

We start by reviewing the literature on worker reallocation across tasks. The literature has standardised methods designed for developed country data. We bring to attention the small literature that applies those methodologies to the data from developing countries. Next, we construct a new measure of the task content of occupations that varies across countries. We analyse how the task intensity of workers varies across occupations, demographic groups (by gender in particular), and countries. We also present new evidence on how the task intensity of countries has changed over time, together with the changes in worker allocation across occupations and sectors. Our analysis highlights the importance of measuring occupational task contents at the country level. It also shows that, when measuring structural change by labour reallocation, changes in the occupational composition of the labour force account for a larger part of that labour reallocation than do changes in the sector-level employment. Finally, we offer a theoretical framework to highlight channels inducing differences in the task content of an occupation across countries. We then use the implications of the theory to put forward open questions for future research on structural change along with the data challenges they entail. We conclude by summarizing the implications of current and future research for policy makers.

2 Technological Change and Employment across Occupations

How does technological change affect workers? The recent rise in automation and displacement of workers have heightened our interest in the effect of technology on wages and employment. The exposure of labour to technological change can be measured by the response of labour demand to technological change (Hicks, 1932; Robinson, 1934). Katz and Murphy (1992) were the first to highlight the increase in the relative demand for educated workers as the cause of the rise in skill premium and skill acquisition over the last century in the US. In the more recent task-based models of production, as reviewed in Acemoglu and Autor (2011), technological progress affects the demand for labour by increasing the productivity of workers and other factors of production at the level of tasks or by introducing new tasks altogether (Acemoglu and Restrepo, 2019). This reallocates workers across the task spectrum and ultimately changes the tasks a given type of worker performs.

One of the most salient labour market phenomena in developed countries over the last 40 years is job polarisation, or workers moving out of middle-skill occupations into low-skill and high-skill occupations. This polarisation is explained by technological change that enabled machines to replace middle-skill workers performing tasks that are routine in nature, i.e. the routinisation hypothesis. Autor et al. (2006) and Autor and Dorn (2013) provided evidence for the US, and Goos et al. (2014) for other developed economies. Beaudry et al. (2016) showed that the decline of middle-skill jobs was first mirrored by the rise of high-skill jobs but after 2000 increasingly by the rise of low-skill jobs. Autor et al. (2003), Aum (2017) and Aum et al. (2018) point to the role of computerisation and Caunedo et al. (2019) to the technological change embodied in a broader set of tools that workers use.

Recent works show that polarisation and structural change from manufacturing to services are interconnected. Barany and Siegel (2018) point to the tight connection between the loss of routine jobs and the decline of manufacturing, and Lee and Shin (2017) show that polarisation took place within services as well as within manufacturing, although the pace was faster in manufacturing.[1]

[1] Duernecker and Herrendorf (2016) is another paper showing that occupation-level technological change can

It seems productive then to take this approach to developing country data. The task contents of jobs and occupational employments in developing countries can help identify the direction of technological progress and account for past and future structural changes. Ultimately, this approach may lead to new implications for cross-country income differences.

A few papers have started to look at differences in the occupational composition of the labour force across countries. Vizcaino (2019) documents that developed countries have disproportionately more workers in high-skill intensive occupations. Gottlieb et al. (2020) report that workers in developing countries are employed in occupations that are less amenable to be executed from home than workers in developed countries. Less is known about the change in occupational employment for developing countries. Maloney and Molina (2016) show that the occupational employment changes in developing countries did not feature a hollowing out of middle-skill jobs. Das and Hilgenstock (2018) tested the routinisation hypothesis for a large set of countries, with the assumption that the task content (routineness in particular) of a given occupation is the same in all countries. They find that in developing countries the employment in routine-intensive occupations was small in 1990 but has grown over the years, which is the exact opposite of what happened in developed economies. Lewandowski et al. (2020) allow the task content of a given occupation to differ across countries in a systematic matter, and construct an imputed measure of the routineness of jobs in developing countries. They find that developing countries also experienced a shift away from routine to non-routine jobs (or "de-routinisation" of jobs), contradicting Das and Hilgenstock (2018), but its pace was slower than in developed countries. Lo Bello et al. (2019) also show that the assumption of equal task contents of an occupation across countries underestimates the job de-routinisation in developing countries.

What can explain these different patterns between developed and developing countries? There are several possible answers, although they have not been examined rigorously. First, the higher price of capital relative to consumption (Hsieh and Klenow, 2007) and the scarcity of skilled labour in developing countries (Caselli and Coleman, 2006) may deter the adoption of technology that causes de-routinisation. Second, as suggested by Lo Bello et al. (2019) and Das and Hilgenstock (2018), trade is a force offsetting de-routinisation in developing countries:

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result in structural change, because some occupations are manufacturing occupations and others are service occupations.

Routine jobs are being offshored from developed to (at least some) developing countries. These two suggest that developed and developing countries are *effectively* exposed to (or choose to adopt) a different set of technologies and paths of technological change. Third, labour markets may respond differently to the same technological change, depending on labour market frictions, training costs and demographics. There is indeed some evidence on a disparate effect of information and communications technology (ICT) across countries in different stages of development. Consistent with the effect of computerisation in the US, Akerman et al. (2015) found in Norway that broad-band internet had favourable effects on skilled workers but not on unskilled workers performing routine tasks. However, Hjort and Poulsen (2019) found that the introduction of broad-band internet in a group of sub-Saharan African countries had large positive effects on the employment of less educated workers, as well as highly educated workers. This does not necessarily mean that the same technological change always affects developed and developing countries differently. Lo Bello et al. (2019) find that the adoption of ICT in developing countries correlates with a decline in routine-cognitive jobs, consistent with the evidence from the computerisation in the US and Western Europe.[2]

We draw two lessons from the literature. First, technological change is central to the pattern of labour allocation across occupations and sectors. Second, technological change can redefine the task content of an occupation. In addition, while the literature on developed economies favours the mapping between detailed occupations and the one task they perform most intensively, when using more aggregated occupational classifications of developing countries, we find it useful to consider an occupation as a collection of tasks.

In the next two sections, we empirically address the question of technological change and its impact on labour allocation. A reasonable conjecture is that the task contents of occupations change systematically with the level of economic development. For example, a clerk at a bank in Mombasa, Kenya may perform tasks that are different from those performed by a clerk at a bank in the City of London. If developing countries operate older and more labour-intensive technologies, the link between technological change and tasks implies that this technology

[2]However, not all ICT replaces routine jobs and complement abstract jobs. Software in particular can have the effect of reducing the demand for workers performing abstract tasks, as shown for the US by Aum (2017) and for Chile by Almeida et al. (2017). In addition, artificial intelligence (AI) is also expected to replace some abstract, cognitive-intensive jobs (Aghion et al., 2018, 2020).

difference will show up as differences in task contents of occupations across countries. We first develop a country-specific measure of task intensity for occupations, based on surveys and employment data from countries covering a large swath of income levels. Relative to the literature, we are significantly expanding the set of countries in our analysis. We then document how task intensity varies across countries (Section 3) and over time (Section 4). Our empirical findings naturally raise new research questions, some of which are outlined using a simple theoretical framework in Section 5.

3 Occupational Task Contents across Countries

In this section, we document the task contents of production across the development spectrum, in the aggregate and by demographic groups. We separate the roles of the tasks performed by workers within an occupation and of the distribution of workers across occupations in shaping these cross-country patterns.

For this purpose, we combine information on the task content of occupations by leveraging 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 elicit adults' proficiency in key information-processing skills at work, such as literacy, numeracy and problem solving. It provides information on the tasks performed by 1-digit occupations in 41 countries at different levels of development, of which 35 countries have full information on occupational categories that can be merged with 1-digit occupational employment data from the International Labour Organization (ILO). The poorest country in this sample is Ecuador and the richest is Singapore. The survey collects data on how intensively and how often broad categories of tasks are performed in the workplace by occupation. These categories are: cognitive skills, interaction and social skills, physical skills, and learning skills.

STEP is designed to measure skills of the labour force in poor and middle-income countries. It covers 16 countries of which nine have full information on occupational task contents and employment shares. The poorest country in this sample is Ghana and the richest is Macedonia. STEP only surveys those in urban areas.

Questionnaires are similar between PIAAC and STEP, but they have different integer scales for the answers. These disparities in scale could generate systematic differences in answers through extreme responding behaviour, i.e. respondents tend to choose the extremes of the options, which makes the surveys not comparable, even after standardisation.

To overcome this hurdle, we exploit questions on computer usage, because they are posed in exactly the same manner in both surveys with the same response scales. From the answers to computer usage questions, we predict the responses that we would have observed in STEP for all available tasks if STEP had the same response scale as PIAAC. The main assumption for the validity of this imputation is that the relationship between task contents and computer usage in the middle- and high-income countries from PIAAC applies to the poorer economies in STEP. We find that the relationship between task content and GDP per capita follows the same trend for the PIAAC sample and the full sample with STEP imputation, except for the non-routine analytical (NRA) tasks.[3] In this section, we report the results using the STEP imputation. In the Data Appendix we report the same results using the raw STEP data.

3.1 Task Intensity

We start by documenting systematic cross-country differences in task intensity. For each task category i, a measure of task content is constructed for each occupation o and country c: τ_{ioc}. For any task i, we can rank occupations by this measure. ILO provides employment data by occupation at the 1-digit level, the highest degree of aggregation for ISCO-08.[4] We then use the share of workers in occupation o for country c from ILOSTATS, s_{oc}, to build a country-level measure of the intensity of task i:

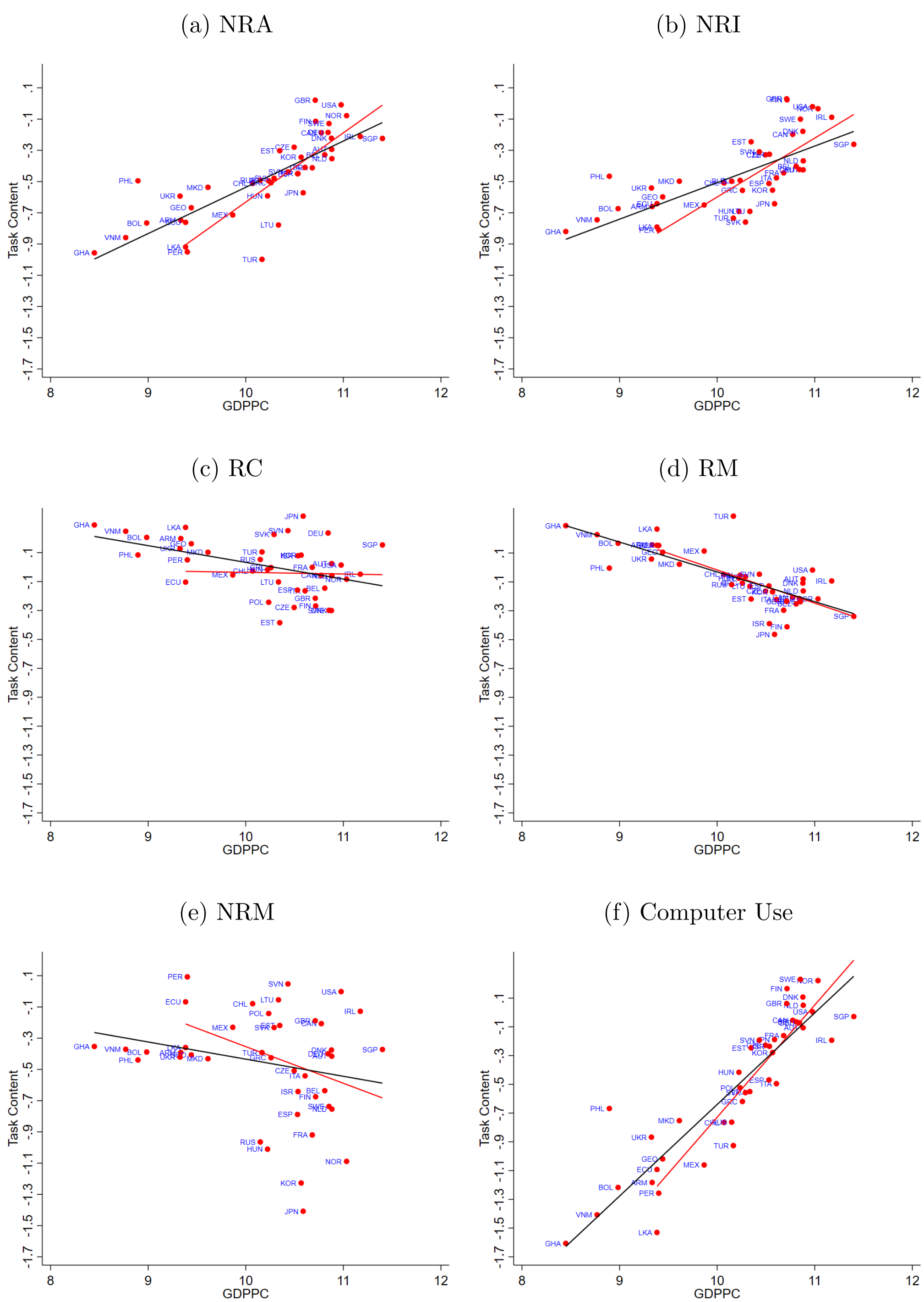
$$\tau_{ic} = \sum_{o} s_{oc} \tau_{ioc}. \tag{1}$$

The first five panels of Figure 1 display the intensity of a given task performed by a country's workers against GDP per capita in 2015 (PPP in log). For completeness, the last panel plots the

[3]The variation in task content and computer usage is much larger for STEP countries than PIAAC countries. We harmonise each survey question and aggregate them into task categories: non-routine analytical (NRA), non-routine interpersonal (NRI), non-routine manual (NRM), routine cognitive (RC), and routine manual (RM). To assure comparability across occupations and countries, we standardise the task content measures using the US mean and variance. This implies that the distribution of task contents in the US has the same mean 0 and variance 1 in both PIAAC and the US's O*NET. Additional details are in the Data Appendix.

[4]PIAAC and STEP occupation classification is at the 3-digit level.

Figure 1: Task Intensity and Development



(a) NRA (b) NRI (c) RC (d) RM (e) NRM (f) Computer Use

Note: The figure plots the task intensity in a country against its GDP per capita in 2015 (PPP in log) for each of the five task categories. The black line is the regression line for the full sample that includes the STEP imputation. The red is for the PIAAC sample only. Panel (f) plots computer usage.

Table 1: Task Content and GDP Per Capita

	NRA	NRI	RC	RM	NRM	CU
GDP Per Capita	0.296***	0.234***	-0.116***	-0.206***	-0.110	0.637***
	(0.0361)	(0.0381)	(0.0366)	(0.0278)	(0.0740)	(0.0484)
N	42	42	42	42	42	42
R^2	0.627	0.485	0.200	0.580	0.052	0.812

Note: This table shows the regression results for task intensity on log of GDP per capita in 2015 in each country (WDI).

intensity of computer usage. (The slope coefficients are reported in Table 1.) The intensity of non-routine tasks in the labour force is positively correlated with income per capita, consistent with the findings in Vizcaino (2019), although non-routine manual display a slight negative correlation.[5] At the same time, the intensity of routine manual and routine cognitive tasks is negatively correlated with income per capita. This finding differs from Lewandowski et al. (2019) who reported an inverted-U relationship between routine task intensity and income per capita.[6] A one log-point increase in income is associated with a 29% standard deviation increase in the intensity of NRA and a 23% standard deviation increase in the intensity of NRI. On the flip side, it is associated with a 12% standard deviation decrease in the RC intensity and a 20% standard deviation decrease in RM. Furthermore, it is associated with a 64% standard deviation increase in computer usage.

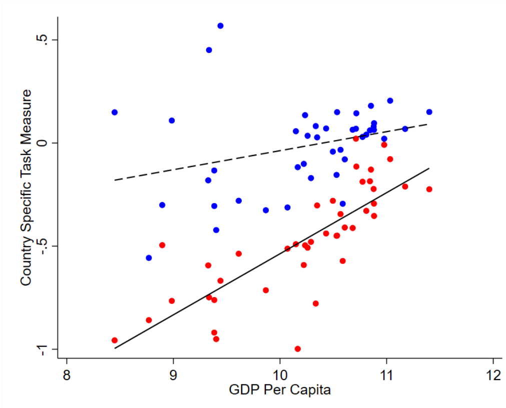
High-skill workers typically choose occupations that are intensive in non-routine tasks, and low-skill workers choose occupations that are intensive in manual tasks. Therefore, the pattern displayed in Figure 1 is consistent with disparities in the skill composition of the labour force across countries, with a larger share of educated workers in developed economies. However, the correlations between task intensity and income persist, even after controlling for the schooling level of the labour force (Table 2). This finding suggests that the correlations between task intensity and income per capita reflect disparities in the occupational composition of the labour force and/or in the occupational task intensity, rather than disparities in the skill composition of the labour force measured by educational attainment.

[5] Unlike in Vizcaino (2019), our data allows for within-occupation differences in task intensity across countries.

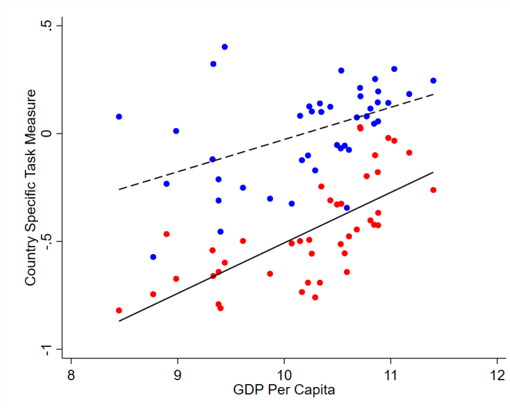
[6] Lewandowski et al. (2019) maximise STEP and PIAAC comparability to the O*NET assignment, whereas we maximise comparability between STEP and PIAAC. We use the O*NET measures in the US for comparison purposes only. Whereas STEP and PIAAC assessments of task contents are self-reported, those in O*NET stem from external assessments of the activities for each occupation. Further details of the assignment are in the Data Appendix.

Figure 2: Task Content Decomposition and Development

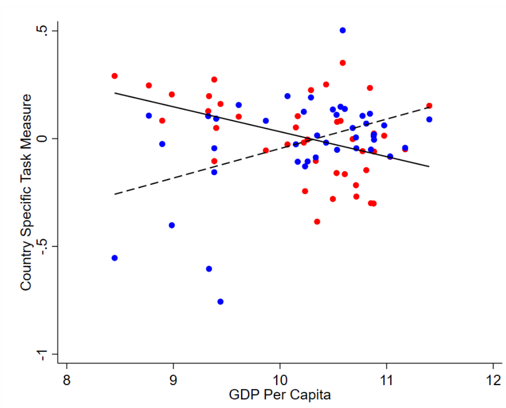
(a) NRA



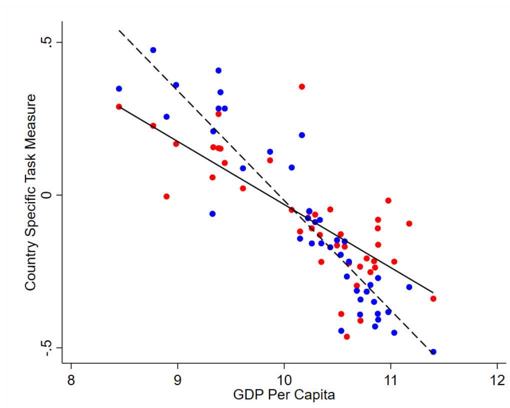
(b) NRI



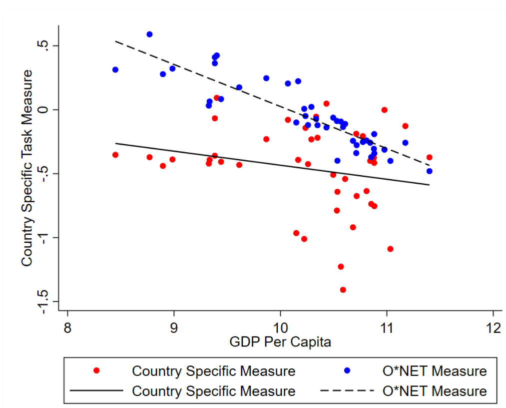
(c) RC



(d) RM



(e) NRM



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

Table 2: Task Content and GDP Per Capita

	NRA	NRI	RC	RM	NRM	CU
Panel A						
GDP Per Capita	0.367***	0.273***	-0.109*	-0.211***	-0.209*	0.722***
	(0.0568)	(0.0618)	(0.0582)	(0.0452)	(0.122)	(0.0667)
Post Secondary Education	0.000807	0.00236	0.00373	-0.00312	-0.00233	0.00258
	(0.00292)	(0.00318)	(0.00299)	(0.00232)	(0.00626)	(0.00343)
N	28	28	28	28	28	28
R^2	0.673	0.520	0.133	0.577	0.147	0.856
Panel B						
GDP Per Capita	0.373***	0.292***	-0.0803	-0.235***	-0.227**	0.742***
	(0.0510)	(0.0561)	(0.0538)	(0.0420)	(0.110)	(0.0605)
N	28	28	28	28	28	28
R^2	0.672	0.510	0.079	0.546	0.142	0.852

Note: Panel A shows the regression results of a country's task intensity on its log GDP per capita in 2015, controlling for the share of workers with post secondary education in 2015 (WDI). Education information is available for Armenia, Austria, Belgium, Bolivia, Chile, Czech Republic, Denmark, Ecuador, Finland, France, Germany, Greece, Hungary, Israel, Italy, Korea, Lithuania, Mexico, the Netherlands, Norway, Peru, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey, USA. Panel B shows the regression results without the education control for this subset of countries.

A commonly used measure of occupations' task content is the one available from O*NET for the US (Autor and Dorn, 2013).[7] If jobs are similar across countries, one could impute this task content information to the occupational composition of the labour force across countries and construct measures of task intensity as in equation (1). For European countries, Handel (2012) shows that country-specific measures of occupational task contents are similar to O*NET measures. However, when studying a broader set of countries this conjecture is rejected. Figure 2 compares the task intensity in each country constructed from our country-specific occupational task contents with the intensity using the common task contents from the US O*NET. By construction, the variation across countries in the latter are only due to differences in the occupational composition of the labour force.

The first differences that are noticeable are in the predicted task intensity for non-routine tasks. The ones based on O*NET task intensity are higher than the country-specific ones. The correlation between non-routine interpersonal intensity and income per capita is similar

[7]The Dictionary of Occupational Titles (DOT) is the precursor to the O*NET.

whichever measure of task intensity we use, suggesting that most of the positive correlation between the non-routine interpersonal intensity and income across countries is driven by the occupational composition of the labour force. For example, the share of managers and professionals (high NRI occupations) in the labour force is smaller in developing countries. For non-routine abstract, the positive slope of the dashed line shows that developing countries have fewer workers in the NRA-intensive occupations, and the steeper solid line implies that a given occupation in developing countries is less NRA-intensive than the same occupation in developed countries.

For routine manual and non-routine manual tasks, the correlations between task intensity and income are negative, implying that poorer countries are relatively more intensive in manual intensive occupations. The fact that the solid line is less steep than the dashed line shows that a given occupation is not as routine manual or non-routine manual intensive in developing countries as in developed countries.

For routine cognitive tasks, the correlations between task intensity and income are substantially different between the two measures. When we use the O*NET-based measures, there is a positive correlation between routine-cognitive intensity (RC) and income, but the country-specific measures indicate that this correlation is negative. One log point increase in income per capita is associated with a 14% standard deviation increase in the routine cognitive intensity when using O*NET (Table 6 in the Appendix), and a 11% decrease when using country-specific measures. Hence, developing countries have disproportionately less workers in routine-cognitive intensive occupations (this is why the dashed line slopes upward), but those occupations involve a lot more routine-cognitive tasks in developing countries than in developed economies, so much so that the solid line slopes downward.

The patterns uncovered for routine-manual and routine-cognitive tasks are particularly relevant for assessing the impact of technological change on labour allocation across the development spectrum. On the one hand, developing countries tend to have larger fractions of workers in routine-manual occupations, exactly those that could be automated easily (Autor and Dorn, 2013). However, those occupations are slightly less intensive in routine-manual tasks in developing countries than in developed economies, making them harder to automate. Routine-cognitive tasks are also more prone to automation. However, developing countries have relatively small fraction of their labour force engaged in these occupations, although the RC intensity of a given job is higher in developing countries. In sum, the exposure to technologies that can replace routine-intensive jobs (RC plus RM) does not seem to vary much with income, when the occupational task intensity is measured at the country level.

To further investigate the role of cross-country disparities in the occupational composition of the labour force and the task content of occupations, we decompose the differences in county-level task intensity as follows. Let the average task content (i) across countries of occupation o be $\bar{\tau}_{io}$ and the average employment share across countries of occupation o be $\bar{s}_o$. Differences across countries in the intensity of task i relative to the cross-country mean, $\sum_o(\tau_{ico}s_{co} - \bar{\tau}_{io}\bar{s}_o)$, can be decomposed into differences in task contents within an occupation (*task effect*), differences in the allocation of workers to a given occupation relative to the average (*employment effect*), and the correlation between the within occupation task contents and their employment allocation across countries (*cross effect*).

$$\sum_o(\tau_{ico}s_{co} - \bar{\tau}_{io}\bar{s}_o) = \underbrace{\sum_o(\tau_{ico} - \bar{\tau}_{io})\bar{s}_o}_{\text{task effect}} + \underbrace{\sum_o \bar{\tau}_{io}(s_{co} - \bar{s}_o)}_{\text{employment effect}} + \underbrace{\sum_o(\tau_{ico} - \bar{\tau}_{io})(s_{co} - \bar{s}_o)}_{\text{cross effect}} \qquad (2)$$

For each country in our sample, we compute the differential in task intensity from the mean and each of the three components. We correlate these components with countries' income per capita, and the results are reported in Table 3. The reported coefficients are broadly consistent with the regression lines shown in Figure 2. For non-routine analytical and non-routine interpersonal, developing countries have fewer workers in the occupations that use these tasks intensively (a positive employment share coefficient) than do developed countries, and a given occupation in developing countries uses these tasks less intensively than the same occupation in developed countries (a positive task content term). The relative contributions of the task content and employment effects to the variation in cross-country task intensity is between 23 and 31% for the former and 68% for the latter.

The correlations between these components and income are exactly the opposite for routine-manual, routine-cognitive and non-routine-manual intensity. For routine cognitive, the coefficient on the employment share seems opposite of what is suggested by Figure 2. One explanation for this inconsistency is that Figure 2 is a comparison between country-specific task intensities relative to the O*NET-based intensities of the US, while what is shown in the table comes from the variation in country-specific task intensities across countries. Such a divergence is possible if the O*NET intensities are an outlier in the intensity-income relationship. We also see that some of the cross terms are significant, but they are smaller in magnitude than the other two terms.

Table 3: Task Content Decomposition and Development

	Task Content	Employment Share	Cross Term
Non-Routine Analytic:			
log(GDP Per Capita)	0.130***	0.175***	-0.0225***
	(0.0309)	(0.0191)	(0.00776)
R^2	0.307	0.679	0.174
Non-Routine Interpersonal:			
log(GDP Per Capita)	0.110***	0.145***	-0.0177**
	(0.0321)	(0.0160)	(0.00810)
R^2	0.228	0.673	0.107
Routine Cognitive:			
log(GDP Per Capita)	-0.0482	-0.0693***	0.00534
	(0.0374)	(0.0122)	(0.00760)
R^2	0.040	0.445	0.012
Routine Manual:			
log(GDP Per Capita)	-0.101***	-0.204***	0.0608***
	(0.0252)	(0.0152)	(0.00894)
R^2	0.287	0.817	0.536
Non-Routine Manual:			
log(GDP Per Capita)	-0.0823	-0.0801***	0.0264**
	(0.0739)	(0.00752)	(0.00978)
R^2	0.030	0.739	0.154

The analysis in this section emphasises the need to measure occupation-level task contents for each country, which turn out to vary systematically across the development spectrum. One implication is that the question of why occupation-level task contents vary across countries should be addressed jointly with the question of why employment across occupations varies across countries.

3.2 Gender Disparities

The systematic cross-country differences in task intensity we document hide substantial heterogeneity across workers from different skill and demographic groups within each country. To illustrate this heterogeneity, we focus on one characteristics of the worker: gender. Our choice is motivated by the documented link between the labour market prospects for women and structural change, in relation to sectoral differences in task contents (Lee and Wolpin, 2006; Rendall, 2010; Goldin and Katz, 2012; Goldin, 2014; Ngai and Petrongolo, 2017). In this section, we document how the differences in the tasks performed by males and females vary across the development spectrum and investigate their main drivers.

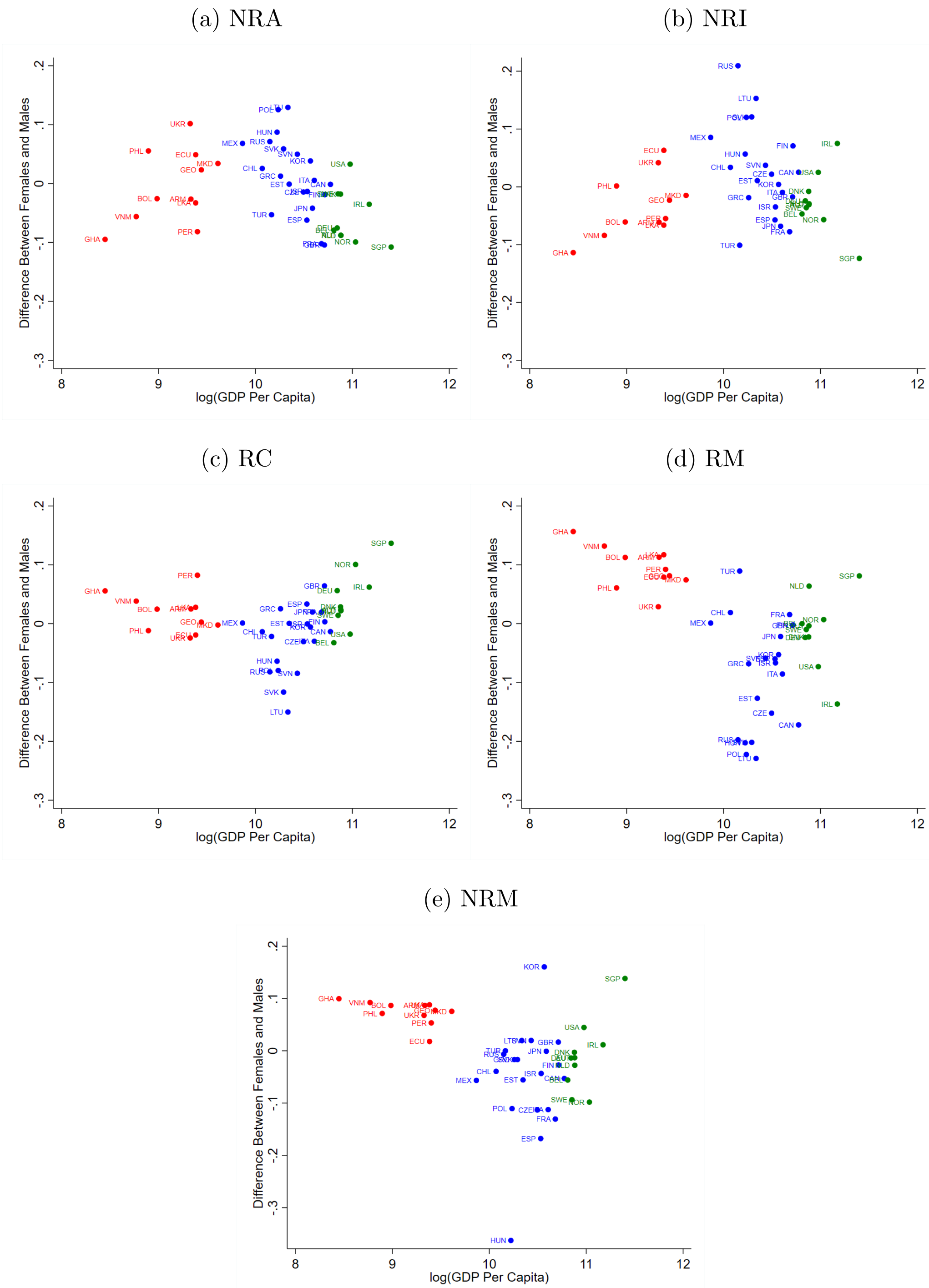
For each task i, we define the gender task differential as the sum across occupations of the country-specific task intensity of the occupation (common for men and women) multiplied by the difference between the female f and male m employment shares:

$$\sum_{o} \left(\tau_{ico} \Delta^g s_{co}\right), \quad \text{with } \Delta^g s_{co} \equiv s_{co}^f - s_{co}^m,$$

where $\Delta^g s_{co}$ is the gender difference in the employment share of occupation o in country c. Figure 3 plots the gender differentials in task intensity against GDP per capita (PPP in log) for each task. We divide countries into three groups based on their GDP per capita, with low-income countries in the lowest quartile, high-income countries in the highest quartile, and middle-income countries in the second and the third quartiles. For non-routine analytical and non-routine interpersonal tasks, the gender differential has an inverted-U shape against countries' income levels. There is a positive association between income per capita and the gender task differential among low-income countries but a negative one among middle- and high-income countries. On the other hand, the gender differential for routine cognitive, is U-shaped across countries. In low- and high-income countries, women tend to perform more routine cognitive tasks than men, while in middle-income countries the opposite is true. Finally, the gender differential for routine manual and non-routine manual tasks is mostly negatively correlated with income levels across countries.

These patterns in the gender task differentials across countries are driven by gender differences in occupational choices across countries. Men and women tend to choose different

Figure 3: Gender Task Differential and Development



Note: The figure plots the gender task intensity differential against GDP per capita (PPP in log) in 2015. Countries are divided into three groups based on their income level: low-income countries have 2015 PPP GDP per capita in the lowest income quartile (red), high-income countries in the highest quartile (green), and middle-income countries are in the second and the third quartiles (blue).

occupations in all countries, due to skill endowment differences (Galor and Weil, 1996; Rendall, 2010) or labour-market distortions that impact men and women differently (Fernández et al., 2004; Hsieh et al., 2019).[8] In addition, the gender task differential varies across countries even when gender differences in occupational choice were identical across countries, as long as the occupational task contents vary across countries, as shown in Section 3.1. We assess the role of each of these two effects with a decomposition exercise.

We take the average across the countries in our sample and decompose the difference in the gender differential in task i between country c and this average into three components:

$$\begin{aligned}\sum_o (\tau_{ico}\Delta^g s_{co} - \bar{\tau}_{io}\Delta^g \bar{s}_o) &= \sum_o \bar{\tau}_{io}(\Delta^g s_{co} - \Delta^g \bar{s}_o) + \sum_o \Delta^g \bar{s}_o(\tau_{ico} - \bar{\tau}_{io}) + \\ &\quad \sum_o (\Delta^g s_{co} - \Delta^g \bar{s}_o)(\tau_{ico} - \bar{\tau}_{io}),\end{aligned} \tag{3}$$

where $\bar{\tau}_{io}$ is the cross-country average of task i intensity in occupation o and $\Delta^g \bar{s}_o$ is the cross-country average of the gender difference in employment share in occupation o. The first term on the right-hand side is the role of gender differences in occupational choices that vary across countries, for a given structure of occupational task contents (*employment effect*). The second term is the role of occupational differences in task contents across countries, for a given gender difference in occupational choices between women and men (*task effect*). The last term is the *cross effect*.

Table 4: Decomposition of the Gender Task Differential (1)

	Employment effect	Task effect	Cross effect
Non-routine analytical	64.8%	23.4%	11.9%
Non-routine interpersonal	50.7%	30.6%	18.7%
Routine cognitive	37.6%	44.0%	18.4%
Routine manual	43.9%	49.8%	6.3%
Non-routine manual	19.8%	72.3%	7.9%

Note: The table shows what fraction of the cross-country variation in gender task intensity differential is accounted for by each of the three terms in the decomposition equation (3).

Table 4 summarises the results of the decomposition across countries, for the five task

[8] These two channels are important determinants of the gender gap in occupational choices in the US (Hsieh et al., 2019) and can, at the same time, partly account for the evolution of US occupational employment.

categories in our analysis. The employment effect is most important in explaining the cross-country differences in the gender task differential for non-routine analytical and non-routine interpersonal, explaining 65 and 51%, respectively. Instead, the task effect is most important in explaining the gender differential for non-routine manual, of which it explains 72%. Both effects are important in explaining the cross-country variation in the gender differential for routine cognitive and routine manual tasks. The cross term plays only a minor role for all five task categories.

Table 5: Decomposition of the Gender Task Differential (2)

	Total-L	Total-MH	Task-L	Task-MH	Empl.-L	Empl.-MH	Cross-L	Cross-MH
Non-routine analytical:								
log(GDP Per Capita)	0.0784	-0.128***	0.0423*	-0.0562***	0.0654	-0.0403	-0.0294	-0.0314***
	(0.0522)	(0.0271)	(0.0205)	(0.0141)	(0.0572)	(0.0258)	(0.0206)	(0.00679)
R^2	0.201	0.436	0.323	0.352	0.127	0.078	0.184	0.425
Non-routine interpersonal:								
log(GDP Per Capita)	0.0801*	-0.104***	0.0432**	-0.0336*	-0.0136	-0.0373	0.0505*	-0.0335***
	(0.0427)	(0.0350)	(0.0188)	(0.0173)	(0.0476)	(0.0237)	(0.0229)	(0.00869)
R^2	0.281	0.234	0.370	0.116	0.009	0.079	0.350	0.338
Routine cognitive:								
log(GDP Per Capita)	-0.0302	0.112***	-0.0147	0.0406**	-0.0567	0.0324**	0.0412	0.0386***
	(0.0293)	(0.0244)	(0.0130)	(0.0185)	(0.0343)	(0.0147)	(0.0231)	(0.00597)
R^2	0.106	0.418	0.125	0.142	0.233	0.143	0.260	0.590
Routine manual:								
log(GDP Per Capita)	-0.0578*	0.0902*	-0.0373*	0.0457**	-0.0628	0.0285	0.0423	0.0160
	(0.0274)	(0.0451)	(0.0180)	(0.0191)	(0.0573)	(0.0246)	(0.0307)	(0.0120)
R^2	0.331	0.121	0.323	0.165	0.118	0.044	0.173	0.058
Non-routine manual:								
log(GDP Per Capita)	-0.0307	0.0789	-0.0226	0.0291	-0.0291	0.0295**	0.0210	0.0203
	(0.0187)	(0.0466)	(0.0153)	(0.0348)	(0.0308)	(0.0141)	(0.0263)	(0.0130)
R^2	0.230	0.090	0.196	0.023	0.090	0.131	0.066	0.078

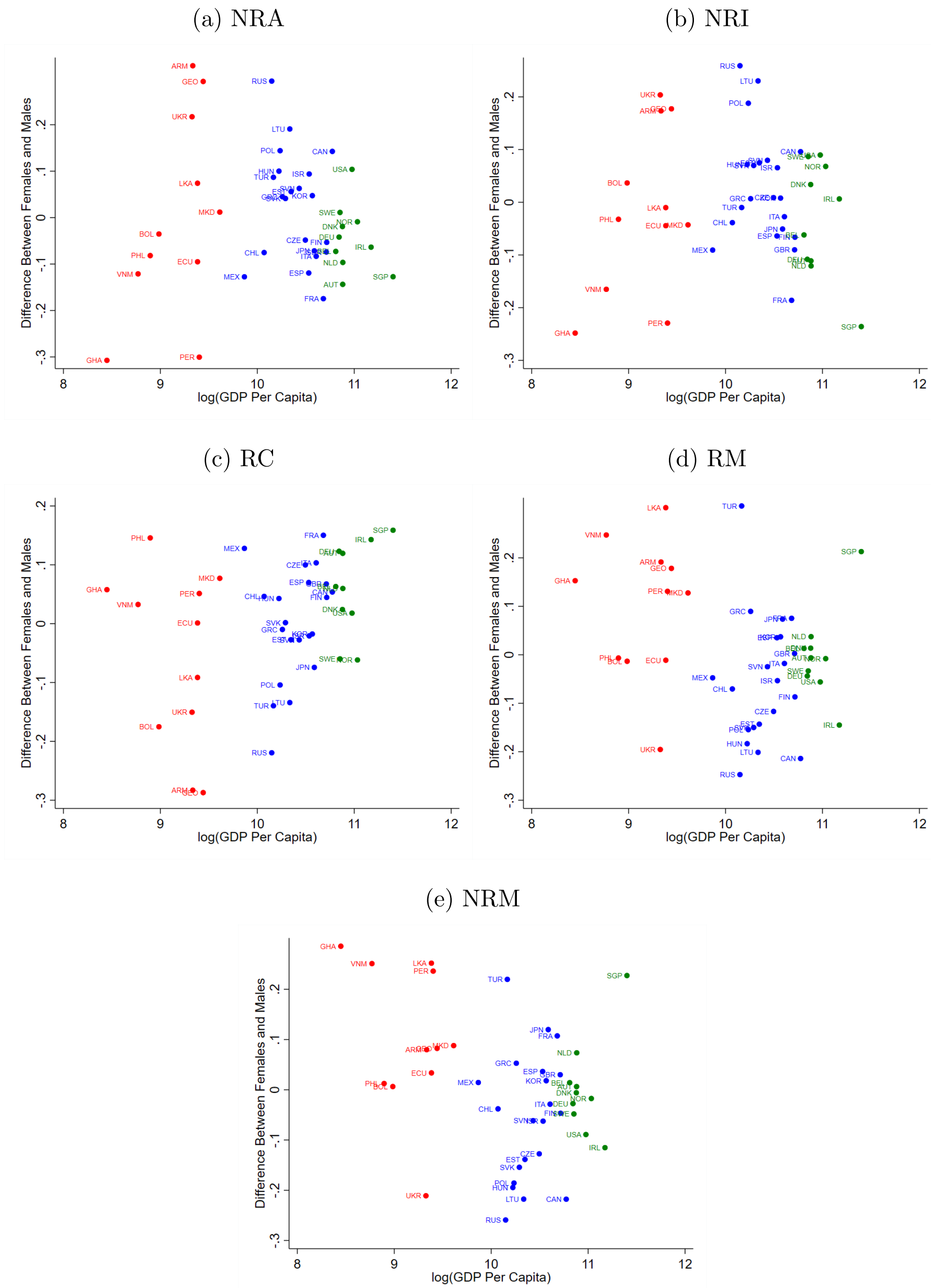
Note: This table shows the outcomes from regressing the variables on the columns on GDP per capita (PPP in log) in 2015 and an intercept. The column labels *Total*, *Task*, *Empl.* and *Cross* represent the gender task differential, the task effect, the employment effect, and the cross effect, respectively. We only report the coefficients on GDP per capita (standard errors are in parentheses) and the R^2. Countries are divided into two groups, with low-income countries (L) in the lowest income-per-capita quartile, and middle- and high-income countries (MH) in the other three quartiles.

Next, we study the contribution of each effect to the patterns of gender task differentials across the development spectrum. Table 5 reports the coefficients from regressing the gender task differential and its decomposition components on GDP per capita (PPP in log). We run the regressions separately for low-income countries and middle-to-high income countries to accommodate the non-monotonic relationship between the gender task differential and income in Figure 3.

Overall, focusing only on the statistically significant coefficients, we find that the task effect is more important than the other effects for generating the association between gender differential in task intensity and income for both groups of countries. In particular, among middle- and high-income countries, the task effect is the most important in explaining the covariation of non-routine analytical and routine manual task gender differential with income. For routine cognitive and non-routine interpersonal, all three effects have similar magnitudes, even though GDP per capita accounts for a higher fraction of the statistical variation in the cross effect. Turning to low-income countries, the smaller sample size implies fewer significant results. The task effect is important in explaining the covariation of non-routine interpersonal task gender differential together with the cross effect, and GDP per capita accounts for a significant fraction of the statistical variation in both effects.

The findings above document the quantitative relevance of the task effect, along with the employment effect. The task effect has been mostly ignored in previous studies, which assumed identical occupational task contents across countries, due to data limitations. How would our findings on the gender task differential change if, instead of measuring occupational task contents for each country, we assumed all countries have the same occupation-level task contents? Figure 4 plots countries' gender differentials in task contents under this alternative computation, fixing all occupational task contents at the US levels from O*NET. Comparing Figures 3 and 4, we see that the alternative computation results in more variation in the gender task differential among poor countries. As a consequence, we would have inferred no consistent variation across the development spectrum for all tasks but routine cognitive. In summary, the country-specific occupational content helps uncover the systematic relationship between gender task differential and a country's income level. It shows that when exploring the cross-country difference in the occupational employment of men and women, one also needs to consider the fact that occupation-level tasks vary across countries systematically across the development spectrum.

Figure 4: Gender Task Differential and Development Based on O*NET.



Note: The figure plots, for each task, the gender tasks differential computed using O*NET data for the US against GDP per capita (PPP in log) in 2015. Countries are divided into three groups based on their income: low-income countries in the lowest income quartile (red), high-income countries in the highest income quartile (green), and middle-income countries in the second and the third income quartiles (blue).

4 Changes in Task Intensity over Time

Technological change can replace workers with machines in certain tasks and reallocate workers to other tasks, including new ones. As defined in Section 2, the exposure of labour to technological change is the response of labour demand to technological change. From the data, in the absence of information about the supply side, we infer the shift in demand for labour from the change in overall task intensity of the labour market over time. Using the task content of occupations across countries constructed in Section 3, we examine the direction of technological change and its relationship with countries' income level and initial employment structure. We look into the allocation of labour across both occupations and sectors.

4.1 Role of Occupational Employment Changes

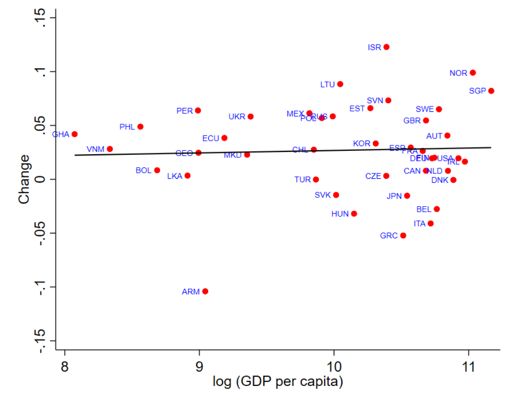
We have seen how the tasks that workers perform, as defined by equation (1), vary across the development spectrum at a point in time. Workers in developed countries perform more non-routine analytical and interpersonal tasks and less routine tasks than in developing countries. As reviewed in Section 2, since 1980, developed countries have experienced clear patterns of polarisation and de-routinisation, or the loss of middle-skill, routine-intensive jobs. The pattern for developing countries is less clear, and the small literature on this topic reached conflicting conclusions, depending on whether or not the task content of occupations was assumed to be the same across countries.

We now use our country-specific measures of task contents of occupations to quantify the changes in task intensity over time for each country in our sample. Note that the country-specific task contents of occupations are fixed over time, so any change in country-level task intensity comes from the shifts in the occupational composition of the labour force.

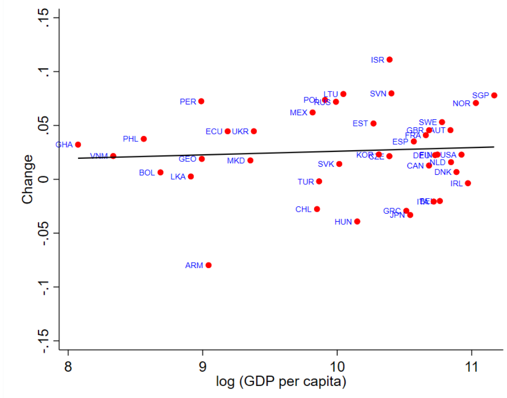
Figure 5 plots the change in overall task intensity of a country between 2006 and 2015 against its GDP per capita (PPP in log) in 2006. For all five task categories, there is no clear relationship between a country's income level and the changes in its task intensity between 2006 and 2015. Although not shown here, the task intensity changes are not correlated with the initial (2006) level of the respective task intensities either. However, we do observe that, on average, countries' non-routine analytical and non-interpersonal task intensities rose, while the routine

Figure 5: Task Intensity Change and GDP per Capita, Country-specific Task Measure

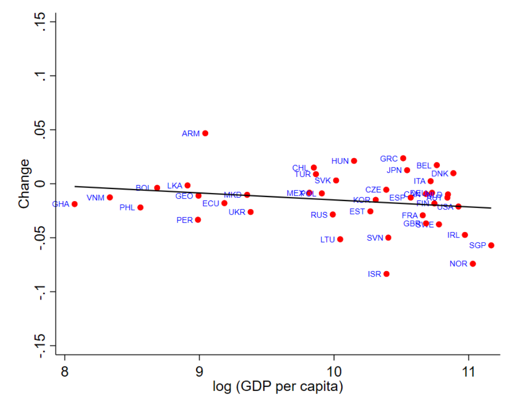
(a) NRA



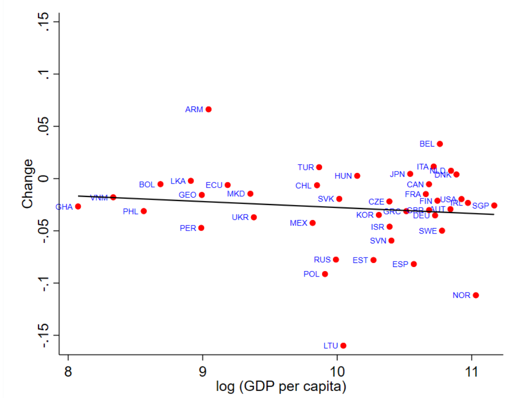
(b) NRI



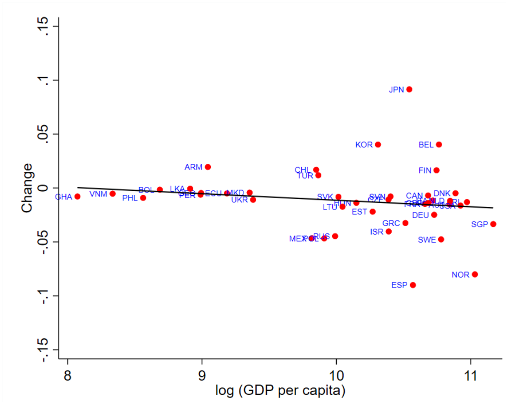
(c) RC



(d) RM



(e) NRM



Note: This figure shows the change in countries' task intensity between 2006 and 2015 against the log GDP per capita in 2006 for each country. The change in task intensity is solely accounted for by the occupational employment changes between 2006 and 2015, because occupational task contents are country-specific but fixed over time. GDP per capita is PPP and is from the World Development Indicators (WDI).

cognitive and routine manual intensities fell. These patterns suggest that the technological change between 2006 and 2015 was indeed in the direction of replacing routine-intensive jobs and complementing analytical jobs in the majority of countries, regardless of their income levels or initial task intensities.

We repeat the exercise but now use occupational task contents that are common across countries, based on the US O*NET classification. The results are shown in Figure 7 in the appendix. Applying US classification to all the countries, we again see that non-routine interpersonal intensities rose and routine-manual intensities fell on average across countries, but uncorrelated with the initial task intensities of income levels. However, the rise in non-routine analytical intensity becomes insignificant and the routine cognitive shows a statistically significant increase instead.

These differing results show that one has to be mindful of the difference in task intensities of a given occupation across countries in thinking about the direction of technological changes. They also help rationalise the inconsistent findings in the literature on employment polarisation, especially for developing countries.

4.2 Role of Employment Reallocation across Sectors

For each country, occupational task contents are measured at a point in time. As a result, the changes in task intensity over time are the result of the changing employment across occupations over time. Our view is that such changes in occupational employment are driven by technological change at the level of tasks and occupations. However, because most countries are undergoing structural change, it is possible that the occupational employment changes 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.[9]

We assess, albeit indirectly, the relative importance of occupation-specific and sector-specific technological change for occupational employment changes using the following decomposition.

[9]This compositional link between occupations and structural change accords with Lee and Shin (2017) but differs from that in Duernecker and Herrendorf (2016), who classify occupations based on the goods they are likely to produce.

First, the employment share of occupation o in period t is defined as

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

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. The employment share change of occupation o from year s to t can be written as

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

where $\Delta(x_t) \equiv (x_t - x_s)/(t-s)$ and $\overline{(x)} \equiv (x_t + x_s)/2$.[10] 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. This term captures by how much occupational employment changed *within* 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 at the sector level. 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.

Our data allows us to consistently use nine occupations in the 1-digit classification. For sectors, we consider three classifications. First, we use the 19 industries in the 1-digit industry classification. We then consider a simple manufacturing vs. service dichotomy, and finally divide services into high-skill and low-skill services to have three sectors.[11] We compute the within-industry component for each occupation in a given country and then average the within-component across the nine occupations using occupational employment shares as weights.

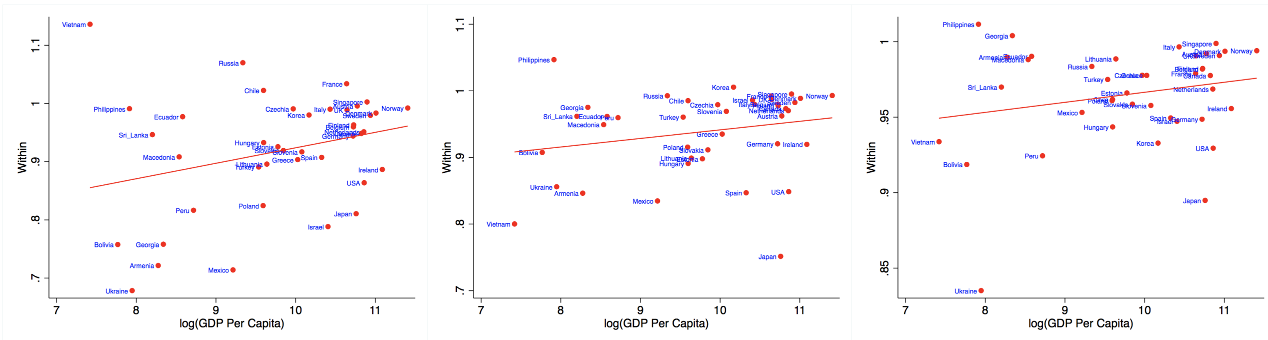
The results are shown in Figure 6. We first note that the within-sector component ex-

[10]This decomposition follows Aum et al. (2017).

[11]Because STEP is a survey of urban areas only, we drop agriculture in our analysis.

Figure 6: Decomposition of Occupational Employment Change: Within-industry Component

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



Note: This figure shows the within-industry component of the changes in occupational employment share between 2006 and 2015 for each country. 1 minus the within-industry component is the between-industry component, i.e. the change in occupational employment share due to the changes in industrial employment share. There are nine 1-digit occupations. In the left panel, we use 19 industries in the 1-digit industry classification. In the centre panel, we only have two sectors: manufacturing and services. In the right panel, we have three sectors: manufacturing, low-skill services and high-skill services.

plains over 90% of occupational employment changes in the vast majority of countries, in all sector classifications, but especially with the 3-sector classification in the right panel. In other words, occupational employment has changed significantly within any given sector, implying that technological change at the occupation level is the dominant driver of overall occupational employment and hence task intensity changes in most countries. Second, the within-sector component is more important in richer countries, as indicated by the positive slopes. One interpretation is that technological change at the sector level and hence structural change play a more important role in developing countries than in developed ones, although they are still much less important than technological change at the task and occupation levels. This is consistent with the hypothesis in the literature that agriculture-to-manufacturing structural change may be offsetting de-routinisation trends in developing countries (Das and Hilgenstock, 2018).

5 Where to from Here

To take stock, we re-visit the main question that motivates our paper. Are workers in developing countries and those in developed countries differentially exposed to technological change? The robust differences in task intensity across countries in Section 3 suggest so, although countries' income levels are not correlated with the changes in task intensities since 2006 (Section 4). Our analysis showed that the patterns differ depending on whether the occupational task measures are country-specific or US-based. This calls for caution when extrapolating what we know about the impact of technology on the labour market in developed countries to developing countries.

Whether this differential exposure implies disparities in the development path between developing countries and developed ones is still an open question, although the lack of evidence for convergence in Figure 5 suggests divergent paths. Another open question is whether the current occupational composition of the labour force influences a country's technology adoption decisions and the speed of labour reallocation in response to technological change.

In order to more precisely illustrate our ideas, we now sketch a model of technology choice that endogenises how task contents of an occupation vary across countries. The model can also be used for exploring how technological changes reallocate workers across jobs and affect the path of development.

5.1 A Simple Theoretical Framework and Open Questions

An occupation (indexed by o) is a technology that produces output y_o by combining tasks performed by workers. For expositional purposes, we here assume that occupational output is a CES aggregate of two tasks, analytical and manual, denoted by a and m:

$$y_o = [(\tau_{ao} n_{ao})^{\sigma_o} + (\tau_{mo} n_{mo})^{\sigma_o}]^{1/\sigma_o},$$

where $1/(1 - \sigma_o)$ is the elasticity of substitution between the two tasks. Each task input is the product of the task units per efficiency unit of labour, τ, and the efficiency units of labour assigned to the task, n. The efficiency units of labour are provided by the workers employed in the occupation, and a worker supplies both tasks. For example, the analytical task utilises workers' math proficiency or IQ, while the manual task utilises their physical strength or dexterity. In this example, the number of workers in an occupation (denoted by q_o) times their average math proficiency (denoted by $\bar{n}_{ao}$) is the total efficiency units assigned to the analytical task, $n_{ao} \equiv q_o \bar{n}_{ao}$. Similarly, the total efficiency units assigned to the manual task would be $n_{mo} \equiv q_o \bar{n}_{mo}$.

In the context of this occupation-level production technology, the task content or intensity measured by survey is $\tau_{ao}\bar{n}_{ao}$ and $\tau_{mo}\bar{n}_{mo}$. The average efficiency of workers, $\bar{n}_{ao}$ or $\bar{n}_{mo}$, is a part of the measured task content, because many survey questions in PIAAC and STEP ask the frequency of performing a given task, as shown in the Data Appendix.[12]

The observed disparities in task intensity across countries can be rationalised by endogenous choices of the task units per efficiency unit of labour, τ_{ao} and τ_{mo}. For simplicity, we for now assume an exogenously given allocation of workers across occupations.[13]

The choice set of the technologies for an occupation in a country is the production possibility frontier (PPF) in the task space,

$$(\tau_{ao})^{\omega_o} + \gamma_o(\tau_{mo})^{\omega_o} \leq B_o, \quad \text{for } \gamma_o > 0,\ \omega_o > 1,\ B_o > 0.$$

The parameter B_o is the "height" of the PPF. The parameters ω_o and γ_o determine its curvature and the tradeoff between tasks. This PPF is analogous to the one for skill-intensive technologies in Caselli and Coleman (2006).

The optimal choices of τ_{ao} and τ_{mo} satisfy, given the average efficiency of workers $\bar{n}_{ao}$ and $\bar{n}_{mo}$:

$$\frac{\tau_{ao}\bar{n}_{ao}}{\tau_{mo}\bar{n}_{mo}} = \gamma_o^{\frac{1}{\omega_o - \sigma_o}} \left(\frac{\bar{n}_{ao}}{\bar{n}_{mo}}\right)^{\frac{\omega_o}{\omega_o - \sigma_o}} \text{ with } \omega_o - \sigma_o > 0. \tag{5}$$

This condition highlights the determinants of a country's measured task contents ($\tau_{ao}\bar{n}_{ao}$ and $\tau_{mo}\bar{n}_{mo}$) of an occupation. The first is the relative average efficiency of workers between tasks in the occupation, $\bar{n}_{ao}/\bar{n}_{mo}$, in a country. Countries with a higher average analytical efficiency of workers in the occupation relative to manual efficiency choose technologies that use analytical tasks more intensively. Second, this effect is stronger when the tasks are more substitutable in producing occupational output (a higher σ_o), as long as $\omega_o > \sigma_o$. When the tasks are complements in production ($\sigma_o < 0$), then the ratio of τ_{ao} to τ_{mo} is inversely related to $\bar{n}_{ao}/\bar{n}_{mo}$. Still, the measured relative task intensity on the left-hand side of equation (5) is positively related to $\bar{n}_{ao}/\bar{n}_{mo}$.

The natural next question is: What determines the relative average efficiency of workers

[12] One could also compute task intensities by demographic groups, e.g. by gender and education attainment, which we view as a promising extension of our work.

[13] As we show below, this is a restrictive assumption: The average efficiency of workers $\bar{n}_{ao}$ and $\bar{n}_{mo}$ in an occupation determines the technology choice, and hence the selection of workers into occupations needs to be considered.

between tasks in an occupation? The average task efficiency of workers $\bar{n}_{ao}$ and $\bar{n}_{mo}$ will be a function of their characteristics, such as schooling, experience, and other demographic variables. For example, college graduates and high-school graduates may supply the same amount of manual dexterity, but college graduates will supply more math and analytical proficiency than high-school graduates.

However, this does not necessarily mean that workers in countries with higher schooling attainment or better school quality perform relatively more analytical tasks in the occupation. What matters is the selection of workers with different characteristics into occupations, since the choice of occupation-level production function depends on the average efficiency of workers in each occupation. As a result, there will be non-trivial feedback between workers' occupational choices and the choice of occupation-level production technologies.

Indeed, the empirical evidence in Section 3 suggests that these selection effects are important. In developing countries, a higher fraction of workers are in occupations that are less intensive in NRA, NRI tasks and more intensive in RC, RM, NRM tasks. At the same time, workers in a given occupation perform relatively more NRA, NRI and relatively less RC, RM, NRM tasks than developed country workers in the same occupation. Worker selection can explain this pattern. As large fractions of workers in developed countries are in the NRA and NRI intensive occupations, the average analytical efficiency of these workers may be lower than the average of the select few workers working in these occupations in a developing country, consistent with the occupation-level NRA and NRI task intensity measured by the survey across countries. More broadly, it would be useful to make more progress on how differences in skill endowments shape technology choices, not only between occupations along the lines of Autor and Handel (2013), but also within an occupation.

Because the selection of workers into occupations affects the occupation-level technology choices, an important implication is that forces that shape the former, such as trade, offshoring, income effects that drive structural change, and broader technological changes also shape the latter. This points to the important effects that globalisation, which may increase the demand for certain occupations relative to others even within a sector, can have on the technology choice and the development trajectory of developing countries.

Such changes in occupational employment are more pronounced among young cohorts of workers, who naturally move into occupations that expand, unbound by occupation-specific human capital. Hobijn et al. (2018) document disparities in sectoral allocations of workers across cohorts in the US, and Adao et al. (2020) in Germany. Porzio et al. (2020) report similar patterns across countries in different stages of development. These differences could be caused by broader processes of deindustrialisation, as emphasised by Rodrik (2016) and Huneeus and Rogerson (2020). We are unaware of such patterns across occupations, a dimension particularly informative about the direction of technological change, not only between occupations but also within occupations across tasks.

In addition, any distortions to the allocation of labour across occupations ultimately distort the choice of occupation-level production technology. For example, in Section 3.2 we documented systematic differences in the tasks performed by men and women across the development spectrum, which may be partly due to disparities in gender norms. Related, the problem of skill portability as workers move across occupations and sectors should be particularly relevant in understanding rural-urban migration incentives in the developing world. Investigations into the role of such market and non-market frictions affecting occupational choices should be a priority, which should be complemented by more work on the measurement of the mismatch between worker skill and task.

Such research that centres on worker heterogeneity will lead to another important open question that we are merely scratching the surface of: How the exposure to technological change is distributed across socioeconomic groups within a country?

One possibility we have not considered up to now is that countries may have different "menus" of occupation-level production functions to choose from. Such a difference may result from disparate adoptions of modern technology, such as robots and artificial intelligence, that can fundamentally change the organisation of production. For example, the occupation-level production function may be of the form:

$$y_o = \left[\left((A_{ao})^{\eta_{ao}} + (\tau_{ao} n_{ao})^{\eta_{ao}} \right)^{\frac{\sigma_o}{\eta_{ao}}} + \left((A_{mo})^{\eta_{mo}} + (\tau_{mo} n_{mo})^{\eta_{mo}} \right)^{\frac{\sigma_o}{\eta_{mo}}} \right]^{1/\sigma_o},$$

where the use of artificial intelligence can be captured by the term A_{ao} and the use of robots by A_{mo}, with η_{ao} and η_{mo} between 0 and 1. In addition, various other factors, such as infrastructure, management practices, or market frictions and distortions, may show up as country-specific values of γ_o and/or B_o, which can be one source of the cross-country difference in occupation-level technologies.

In the same context, perhaps the most important question is whether the occupation level technology choices can significantly amplify various frictions and distortions that generate mismatch between workers and tasks. Understanding the cross-country differences in occupational task contents and employment shares is the first step in answering this ultimate development question.

5.2 Data Challenges and Needs

To make progress in answering the questions highlighted in the previous section, we must overcome non-trivial data challenges. The first, and perhaps the biggest, challenge is the dearth of high-quality harmonised data that includes information on workers' demographic characteristics, occupations, and earnings. An important first step is the employment survey data collected by Donovan et al. (2020), available at `https://www.lfsdata.com/`. Their data collection efforts emphasise the availability of rotating panels for the study of labour flows and expand the data currently available at ILO. Yet, earnings data is only available in half of their sample (21 countries), even though it is essential for answering questions about inequality. Another important step is the harmonisation of household surveys, e.g. LSMS and labour force surveys from African countries, which includes ongoing work by Doss et al. (2020).

Similar limitations exist for consistent 3-digit occupational compositions of the labour force. IPUMS international data has detailed information on worker demographics and occupations (at the 1-digit level), but the time span is scattered across countries. For task-based approaches, further disaggregation (i.e. at the 3-digit level) of occupations would be desirable.

Earnings or wage data is important for assessing the productivity of tasks performed by workers in different occupations as illustrated in the model above. Recent work by Hjort et al. (2020) document variation in the relative earning of middle managers across countries. Similarly, Saltiel (2020) explores earnings data in STEP to characterise task premia, for a limited set of countries. It is an open question whether the disparities in task intensity and occupational employment shown in Section 3 are consistent with disparities in relative earnings across occupations and countries.

Second, there is a need for detailed descriptions of occupational task contents and worker characteristics for countries at different levels of development, in a harmonised way. The PIAAC survey provides this information for middle- and high-income economies. The STEP survey focuses on poorer economies but, as we point out in Section 3, the wording of questions and the answer scales are different from those in PIAAC, making their comparison difficult. Further harmonisation of these surveys would be a big improvement. Additional effort to gather information in countries in Africa, Southwest Asia and the Middle East would be welcome. This includes collecting data on the task content of jobs in low-income countries, possibly as supplements to LSMS-ISA and labour force surveys. In particular, comparing the tasks performed by different groups of workers in a given occupation will allow for separating the technology (τ in our model) from the worker skill ($\bar{n}$).

Finally, workers' tools, along with tasks, embody technological change. Unfortunately, information on the tools used by workers is not consistently available across countries. For the US, the O*NET lists tool requirements for each occupation. When merged with data on capital stock and prices, this can be used to measure workers' exposure to capital-embodied technological change (Caunedo et al., 2019). It is desirable to collect harmonised data across countries on tool requirements by occupation, as well as time series of capital stock and quality-adjusted prices of capital goods. The stock data includes ubiquitous equipments such as computers, but also broader equipment categories such as communication equipment, optical equipment, and robots. Currently available datasets on capital stock for a broad set of countries include PWT 9.1, which collects national accounts data in a harmonised way, and KLEMS data. The level of aggregation is too coarse to properly measure trends in capital-embodied technological change across occupations, e.g. structures, machinery, transport, and other. The data on tasks and tool requirements of occupations could be collected as a module in LSMS-ISA and labour force surveys. In terms of prices, the latest publicly available ICP benchmark data dates from 25 years ago (1996). Efforts to make these detailed price data available to researchers would greatly improve our ability to answer the promising research questions above. Methodological contributions to the inference of technological change from limited cross-country data would also be another venue for progress.

6 Policy Implications and Concluding Remarks

We believe that answering the questions posed throughout this paper would greatly advance our understanding of the role of policy interventions in boosting growth while cognisant of their distributional effects. Recently, technological change and rising inequality have been emphasised as two linked phenomena, particularly for developed economies. But throughout history this was not always the case. The post-World War period was one characterised by strong growth, technological advances, and improvements in income levels across the board that shrank income inequality.

Policymakers can start with removing barriers and distortions that deter the reallocation of workers driven by technological change, which will make the economy more efficient. It is also important to further study the link between frictions in the labour market and incentives to adopt new technology.

Equally important is the study of the policies that can foster human capital accumulation through schooling, job training, and re-training so that workers can fully utilise and benefit from the ongoing technological progress.

Not everyone will benefit from technological change and some will fall through the cracks. Practitioners and academics alike will need to renew our thinking on the optimal design of social safety nets. Addressing job informality, a pervasive problem in poorer economies, should be a priority.

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A Additional Tables and Figures

Regression of task intensity, O*NET versus our own measures:

$$NRA_{ck} = \beta_0 + \beta_1 log(GDPPC)_c + \beta_2 Type_k + \beta_3 log(GDPPC)_c \times Type_k + \epsilon_{ck}$$

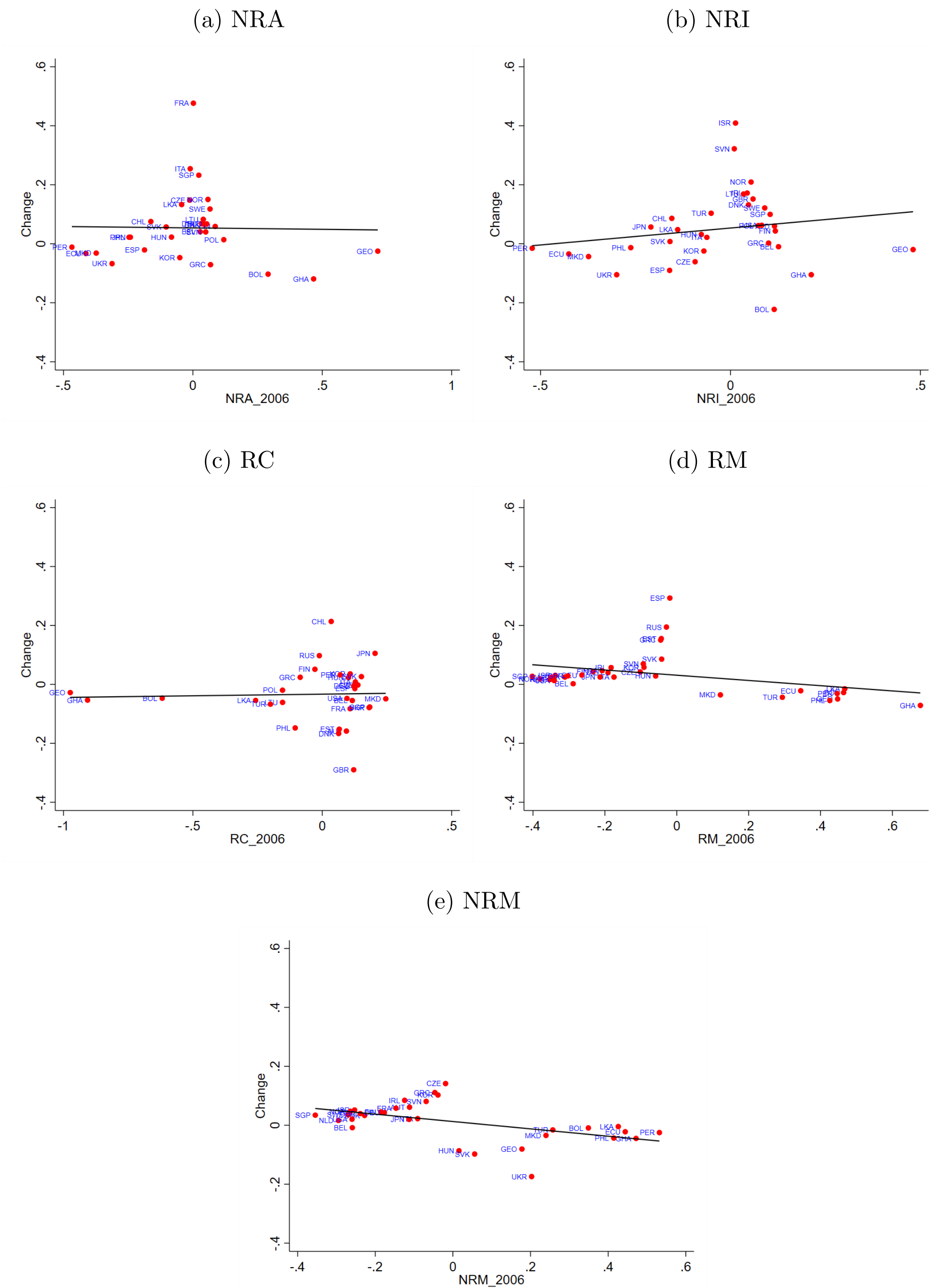
where $Type_k = 1$ denotes measures from country specific task content, while $Type_k = 0$ denotes measures from O*NET.

Table 6: Decomposition Using O*NET as Benchmark

	NRA	NRI	RC	RM	NRM
log(GDP Per Capita)	0.0922**	0.149***	0.137***	-0.359***	-0.329***
	(0.0412)	(0.0409)	(0.0403)	(0.0258)	(0.0555)
log(GDP Per Capita)×$Type_k$	0.204***	0.0848	-0.252***	0.153***	0.219***
	(0.0583)	(0.0578)	(0.0570)	(0.0364)	(0.0785)
$Type_k$	-2.539***	-1.327**	2.603***	-1.541***	-2.648***
	(0.597)	(0.592)	(0.584)	(0.373)	(0.805)
Intercept	-0.959**	-1.521***	-1.413***	3.575***	3.312***
	(0.422)	(0.419)	(0.413)	(0.264)	(0.569)
N	84	84	84	84	84
R^2	0.690	0.683	0.200	0.764	0.539

Note: This table shows regression results to test whether the task content measures from O*NET and those following our assignment have significantly different slopes against GDP per capita. $Type_k = 1$ denotes measures from country specific task content, while $Type_k = 0$ denotes measures from O*NET.

Figure 7: Task Intensity Change and Task Intensity in 2006, US-based Task Measure



Note: This figure shows the change in task intensity between 2006 and 2015 against the task intensity in 2006 for each country. The change in task intensity is solely accounted for by the occupational employment changes between 2006 and 2015, where occupational task content is based on the US O*NET and assumed the same for all countries.

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

DATA APPENDIX

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1 Data Sources and Descriptions

1.1 PIAAC: Survey of Adult Skills

PIAAC countries with task information: Austria, Belgium, Canada, Chile, Czechia, 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, UK, USA.

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.

Broad categories of generic work 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.

We classify answers to questions into different tasks following the classification and definition of tasks in O*NET. Details of these classification are discussed in Section 3.

1.2 STEP Skills Measurement Program (World Bank)

STEP countries used in our sample: Armenia, Bolivia, China (Yunnan province), Colombia, Georgia, Ghana, Kenya, Laos, Macedonia, Philippines, Sri Lanka, Ukraine, Vietnam.

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

1.3 Occupational and Sectorial Employment

The main data we use are employment (counts) by economic activity and occupation from Living Condition Survey available at the International Labour Organization (ILOSTAT). In the labour structure decomposition for the industry-level employment share across occupations, we use the table "Employment by economic activity and occupation (Annual)."[1]

Employment data is disaggregated at the 1-digit industry (ISIC-Rev.4) and 1-digit occupation level (ISCO-08).

The industry codes and occupation codes vary across countries and years.[2] In the labour structure decomposition for the gender specific employment share across occupations, we use the table "Employment by sex and occupation (Annual)."

The sector classification of services follows Eckert et al. (2019).

- 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 defence; compulsory social security

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

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

2 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 \$)." Measures of the labour force with post-secondary education are in the WDI under "Educational attainment, at least completed post-secondary, population 25+, total (%) (cumulative)."

3 Index of Task Intensity across countries

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 are 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, UK, USA, Vietnam.

Unfortunately, the questionnaires in the STEP and PIAAC surveys are not harmonized. Indeed, while questions are similar, they are not exactly the same, except for questions about computerisation. Disparities in computer usage across countries within occupations are interesting in their own right. Importantly for our exercise, we can use the comparability in this question to project differences across task content in a consistent way across surveys. In particular, we predict the task content of each occupation in the STEP sample by running an out-of-sample prediction using variation in computers as the explanatory variable.

Table 1: Data availability

Country	Source	Initial year	Final year	Note
Armenia	STEP	2008	2015	
Austria	PIAAC	2006	2015	
Belgium	PIAAC	2006	2015	
Bolivia	STEP	2006	2015	
Canada	PIAAC	2006	2014	
Chile	PIAAC	2006	2015	
Colombia	STEP	dropped		1-digit occupation available until 2009
Czechia	PIAAC	2006	2015	
Denmark	PIAAC	2006	2015	
Ecuador	PIAAC	2006	2015	
Estonia	PIAAC	2006	2015	
Finland	PIAAC	2006	2015	
France	PIAAC	2006	2015	
Georgia	STEP	2006	2015	
Germany	PIAAC	2006	2015	
Ghana	STEP	2006	2015	
Greece	PIAAC	2006	2015	
Hungary	PIAAC	2006	2015	
Ireland	PIAAC	2006	2015	
Israel	PIAAC	2006	2015	
Italy	PIAAC	2006	2015	
Japan	PIAAC	2006	2015	
Kenya	STEP	dropped		employment data only available in 1999
Korea	PIAAC	2006	2015	
Laos	STEP	dropped		employment data available in 2010 and 2017 only
Lithuania	PIAAC	2006	2015	
Macedonia	STEP	2006	2015	
Mexico	PIAAC	2004	20015	
Netherlands	PIAAC	2006	2015	
New Zealand	PIAAC	dropped		1-digit occupation available until 2008
Norway	PIAAC	2006	2015	
Peru	PIAAC	2006	2015	
Philippines	STEP	2006	2015	
Poland	PIAAC	2006	2015	
Russia	PIAAC	2006	2015	
Singapore	PIAAC	2006	2015	no employment in OCC6: agriculture
Slovakia	PIAAC	2006	2015	
Slovenia	PIAAC	2006	2015	
Spain	PIAAC	2006	2015	
Sri_Lanka	STEP	2006	2015	
Sweden	PIAAC	2006	2015	
Turkey	PIAAC	2006	2015	
Ukraine	STEP	2006	2015	
UK	PIAAC	2006	2015	
USA	PIAAC	2006	2015	
Vietnam	STEP	2007	2015	
Yunnan, China	STEP	dropped		

The dates reported in the table correspond to those with available occupational employment information in ILO. At this time, there is only one wave of PIAAC and STEP data available for analysis.

4 Construction of Task Measures

4.1 PIAAC and STEP

4.1.1 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)
    - 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 organisation? ($FQ04b$)
    - 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 organise 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 ($GQ04$)

- Construct the Measure
  - 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 summarise them into 8 measures: $READ$, $THINK$, $PERSON$, $GUIDE$, $STRUC$, $CONTRO$, $OPER$ and $COMP$.

    Take $READ$ as an example, $READ$ for each respondent i in country c from PIAAC equals

    $$READ_i = \frac{GQ01a_i + GQ01b_i + GQ01c_i + GQ01d_i + GQ01e_i + GQ01f_i + GQ01g_i + GQ01h_i}{8}$$

    This is the $PIAAC\text{-}SAMPLE$, with observations for each respondent.

4.1.2 STEP

- Detailed Questions
  - Non-Routine Analytic (NRA)
    - Read ($READ$)

        - Do you read anything at this work? (A-4)[3]
        - 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)
        - 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)
- Non-Routine Manual (NRM)
    * Operating/Hands/Manual ($OPER$)
        - Do you drive a car, truck or three-wheeler? (B-7)

[3] Different countries in STEP have different number for each question. We use the question number from the Armenian Household Survey here.

        · 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)

- Construct the Measure

  – Because answers to questions in STEP questionnaires are differently worded with different scaling than in PIAAC, we only extract Computer usage information from the questionnaire, and use this information to predict the 8 measures of tasks in the next step.

4.1.3 Combining PIAAC and STEP with Prediction

- **STEP 1**: Combine STEP and PIAAC. Predict the values of the 8 relevant measures of tasks using computer usage for the STEP sample. This is an out-of-sample prediction using the regression coefficients in the PIAAC sample. Take $READ$ as an example, run the following regression weighted by the sample weight

$$READ_i = \beta_0 + \beta_1 COMP_i + \epsilon_i$$

  With estimated $\hat{\beta}_0$ and $\hat{\beta}_1$, predict the $\hat{READ}_i$ in the STEP sample. Replace the 8 measures (e.g. $READ$, $THINK$, $PERSON$, $GUIDE$, $STRUC$, $CONTRO$, $OPER$, $COMP$) for STEP countries with their predicted values.

- **STEP 2**: Standardise the answers across all countries relative to the US. We use the sample weight to calculate the weighted mean and standard deviation of each of the 8 measures in the US. We standardise each measure of tasks by subtracting the weighted mean and dividing by the weighted standard deviation of the US. Take $READ$ as an example, the new value of $READ$ for each respondent i equals

$$READ_i = \frac{READ_i - MEAN}{SD}$$

  where $MEAN$ and SD are the weighted mean and standard deviation of $READ$ in the US. That is, we standardise these variables so that they are comparable to their O*NET counterpart.

- **STEP 3**: We further add up standardized $READ$ and $THINK$ to create NRA, $PERSON$ and $GUIDE$ to NRI. Besides, RC, RM, NRM and CU will take the value of $STRUC$,

$CONTRO$, $OPER$ and $COMP$ respectively. We standardise NRA, NRI and CU again. Take NRA as an example, the new value of NRA for each respondent i equals

$$NRA_i = \frac{NRA_i - MEAN}{SD}$$

where $MEAN$ and SD are weighted mean and standard deviation of NRA_i in the US.

- **STEP 4**: We calculate the weighted mean NRA, NRI, RC, RM, NRM and CU for each country c and 1-digit occupation level o with sample weights. Take NRA as an example, the new value of NRA for each country c and occupation o equals

$$NRA_{co} = \sum_i NRA_{ico} \times \text{weight}_{ico}$$

- **STEP 5**: We calculate the weighted mean NRA, NRI, RC, RM, NRM and CU at each country c with employment shares of occupation o in country c as weights. Take NRA as an example, the value of NRA for each country c equals

$$NRA_c = \sum_o NRA_{co} \times \text{EmpShare}_{co}$$

4.2 O*NET

- Detailed Questions
  - Non-Routine Analytic (NRA)
    - Read ($READ$)
      - Analysing 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 ($4.A.4.a.4$)
    - 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 (reverse) ($4.C.3.b.8$)
            - · Importance of repeating the same tasks ($4.C.3.b.7$)
    - Routine Manual (RM)
        - ∗ Controlling machines ($CONTRO$)
            - · Controlling machines and processes ($4.A.3.a.3$)
    - 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 ($1.A.2.a.2$)

- Construct the Measure
    - **STEP 1**: Occupation code concordance. The O*NET data is at the 8-digit ONET-SOC level. We change the original 8-digit ONETSOC code to 6-digit SOC code, and then crosswalk that to the one-digit ISCO code with weight directly constructed from the IPUMS-International US data.[4]
    - **STEP 2**: We take the average of answers to each question and summarise them into 8 measures: $READ$, $THINK$, $PERSON$, $GUIDE$, $STRUC$, $CONTRO$, $OPER$, and $COMP$. Take $GUIDE$ as an example,

$$GUIDE_i = 4.A.4.b.4_i + 4.A.4.b.5_i$$

    - **STEP 3**: Standardise the answers. We use the sample weight to calculate the weighted mean and standard deviation of each of the 8 measures in the US. We standardise each question by subtracting the US weighted mean and dividing by the US weighted standard deviation. Take $GUIDE$ as an example, the new value of $GUIDE$ for each ONETSOC i equals

$$GUIDE_i = \frac{GUIDE_i - MEAN}{SD}$$

[4]IPUMS-International US data have 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.

where $MEAN$ and SD are the weighted mean and standard deviation of $GUIDE$ in the US.

- **STEP 4**: We further add up standardized $READ$ and $THINK$ to NRA, $PERSON$ and $GUIDE$ to NRI. Besides, RC, RM, NRM and $COMP$ will take the values of $STRUC$, $CONTRO$, $OPER$ and $COMP$ respectively. We standardise NRA and NRI again with the weighted mean and standard deviation of each of them. Take NRA as an example, the new value of NRA for each ONETSOC i equals

$$NRA_i = \frac{NRA_i - MEAN}{SD}$$

where $MEAN$ and SD are the weighted mean and standard deviation of NRA_i in the US.

- **STEP 5**: We take the weighted mean NRA, NRI, RC, RM, NRM and $COMP$ at 1-digit occupation level (ISCO) o with constructed weight. Take NRA as an example, the value of NRA_o^{onet} for each occupation o equals

$$NRA_o^{onet} = \sum_i NRA_{io} \times \text{weight}_{io}$$

- **STEP 6**: We calculate the weighted mean NRA, NRI, RC, RM and NRM for each country c with employment share of occupation o in country c as weights. Take NRA as an example, the value of NRA for each country c equals

$$NRA_c = \sum_o NRA_o^{onet} \times \text{EmpShare}_{co}$$

where NRA_o^{onet} is the task intensity of an occupation o using the O*NET information for the US.

References

Eckert, Fabian, Sharat Ganapati, and Conor Walsh, "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 September 2019.