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From Occupations to Embedded Skills

A Cross-Country Comparison

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Abstract

This paper derives the skill content of 30 countries, ranging from low-income to high-income ones, from the occupational structure of their economies. Five different skills are defined.. Cross-country measures of skill content show that the intensity of national production of manual skills declines with per capita income in a monotonic way, while it increases for non-routine cognitive and interpersonal skills. For some countries, the analysis is able to trace the development of skill intensities of aggregate production over time. The paper finds that although the increasing intensity of non-routine skills is uniform across countries, patterns of skill intensities with respect to different forms of routine skills differ markedly.

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From Occupations to Embedded Skills:

*A Cross-Country Comparison**

by

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1. Introduction

A central feature of development is the changing nature of the production process of goods and services. Typically, as countries become richer, production and trade patterns change with a higher share of domestic value added being generated through more sophisticated processes – both within agriculture, services and industries as well as due to a shift away from agriculture, accompanied by increasing production taking place in cities. The technology revolution, witnessed over the past two to three decades, has only accelerated this process and impacted on the technology content of modern service and industrial production significantly. Production in industrial countries itself has undergone unprecedented changes within mature industries while some developing economies have been able to make inroads into high-technology intensive service sectors – with the Indian success in developing its indigenous information technology industry one, often cited, example.

The mirror image of such shifting economic production is a change in occupations and, embedded, a transformation of the types of human skills used in an economy. Occupations which require intensively manual skills, associated with many jobs in low-machine intensity farming but also with specific trades as well as mass-manufacturing, give way to occupations requiring more cognitive skills. Such cognitive skills include verbal ability, working memory, numeracy, and problem solving abilities – teachers will need these intensively as well as computer operators. The more modern the economy and the more sophisticated the division of labor in production processes, the more important are also interpersonal skills which underlie behaviors such as teamwork, reliability, discipline, and work effort.

This paper derives the embedded human skill content of aggregate economic production for thirty countries, ranging from low-income to high income ones. We follow the methodology proposed by Autor, Levy and Murnane (2003) and updated by Acemoglu and Autor (2010). The approach conceptualizes and measures skills by assessing the specific tasks associated with different occupations rather than measuring the educational credentials of workers (e.g., years of education, diploma) performing those tasks. Five different skills are assessed: routine manual, non-routine manual physical, routine cognitive, non-routine cognitive analytical, and non-routine cognitive interpersonal skills. We then apply the occupation-skill grid to household labor force surveys contained in the World Bank's International Database on Income Distribution (I2D2) which contain standard employment modules, allowing for the application of the methodology. For a number of countries, namely for Brazil, Chile, Costa Rica, India, Poland, Sri Lanka, Turkey and the United States, we can extend the cross-country analysis to track the changing skill intensities of aggregate economic production over time.

The cross-country analysis yields that the intensity of routine skills, both manual and cognitive in nature, is negatively associated with GDP per capita. Conversely, the intensity of use of more sophisticated skills – both analytical as well as interpersonal in nature – rises. In the countries that allow us to track the change in the skill content of national production, we observe that the intensity of non-routine skills indeed increases across countries and time in a rather monotonic manner (as suggested by the cross-country results) but that the shift with respect to routine skills, both manual and cognitive, is not uniform. Exploring what lies behind these diverging patterns will require further research.

We should note that the skill assessment derived from the occupational structure of economies is only one possible measurement of the stock of skills. Direct measurement, rather than the indirect means employed here, is often conducted through large scale international or national assessment tests, such as through the Programme for International School Assessment (PISA), the Trends in International Mathematics and Science Study (TIMSS), or the Progress in International Reading Literacy Study (PIRLS).[1] Notwithstanding such alternatives, the methodology applied here is uniquely capable of quantifying the skill content actually employed in an economy and is as such complementary to the measurement of skill capabilities derived from assessment methods. Naturally, it does not allow for gradients as to *how good* the measured skills are – e.g., whether the analytical skills of medical doctor's in a given country is high or

[1] Although the skills measured on these tests appear to be purely academic or cognitive in nature, test scores reflect more than individuals' cognitive skills. A good part of the variation in achievement tests can be attributed to personality traits, or as well as to incentive systems (Heckman, Stixrud & Urzua, 2006). Recent studies have particularly emphasized the importance of social skills, often also labeled as non-cognitive skills, and their importance for labor market outcomes. Definitions and measurements have varied and ranged from self-esteem and locus of control (Heckman, Stixrud, & Urzua, 2006), to the Big Five personality traits (Borghans, Duckworth, Heckman, & ter Weel, 2008), to youth behavior (Cunha & Heckman 2007, 2008; Segal, 2008). World Bank (2011), for Peru, finds that specific personality traits are as highly remunerated as cognitive skills in the labor market.

low. For the latter, new forms of skill measurement are currently being pioneered, including with the PIAC study of the OECD and the STEP skill measurement study at the World Bank.[2]

This paper is structured as follows. The next section recaps the main features of the methodology, including a description of the mechanism employed to map the occupational structure of economies into measures of skill intensity. The third section provides information on the household surveys being used in our analyses while the fourth section presents results, both for the cross-country comparison of different 'stocks' of skills as well for several countries for which we are able to track skill developments over time. The final section concludes.

2. Methodology

We build here on the pioneering work of Autor et al (2003) followed by Acemoglu and Autor (2010), which provides an objective measure of the evolution of the skill content embedded in the employed US labor force. Measuring the human capital stock of nations through such assessment is a significant innovation compared to cruder measures such as the average years of schooling of a population.[3] The analysis relies on information on the skill content per occupation which is generated based on the Occupational Information Network (O*NET), a database constructed with support from the US Department of Labor/Employment and Training Administration. The O*NET characterizes different occupations in the US economy in terms of two types of factors. The first is *worker-oriented* factors, which include worker characteristics, worker requirements, and experience requirements. The second is *job-oriented* factors, which are comprised of occupational requirements, workforce characteristics and occupation-specific information. O*NET hence records various requirements for each individual occupation, derived from evaluations by peers and measured on a scale of 1 to 5.[4]

[2] The Skills Toward Employment and Productivity (STEP) Skills Measurement Study is an initiative of the World Bank to help countries measure levels and distributions of cognitive, technical and non-cognitive skills among adults; quantify the mismatch between the skills of the adult population and employers' needs; and assess how skills of individuals affect labor market outcomes. STEP skill measurement instruments collect information from participant countries through harmonized individual and employer surveys and by using comparable implementation protocols and technical standards.
[3] In addition to Autor, Levy and Murnane (2003) and Acemoglu and Autor (2010), see Handel (2007) for an application and discussion of the embedded-skill measurement method..
[4] Occupations in this scheme are then collapsed into the Standard Occupational Classification (SOC) used by the Census Bureau resulting in information for 974 different SOC occupations.

From the O*NET's detailed description of task requirements, Acemoglu and Autor (2010) – following Autor et al (2003) – construct five aggregate skill measures. They select and extract a subset of sixteen task requirements and classify these as routine-manual, non-routine manual physical, routine cognitive, non-routine cognitive/interpersonal and non-routine cognitive analytical skills. Importantly, each occupation is assigned a skill intensity value for each of the five skills – they are hence not exclusive. Each occupation $\boldsymbol{i}$, is then defined by a vector of skills, $\boldsymbol{X_i}$**,** which is composed of five skill aggregates:

$$X_i = \begin{bmatrix} X_i^{NON-ROUTINE\ COGNITIVE/ANALYTICAL} \\ X_i^{NON-ROUTINE\ COGNITIVE/INTERPERSONAL} \\ X_i^{ROUTINE\ COGNITIVE} \\ X_i^{ROUTINE\ MANUAL} \\ X_i^{NON-ROUTINE\ MANUAL\ PHYSICAL} \end{bmatrix}$$

The skills aggregates are defined in the following way. First, *routine-manual skills* characterize repetitive movements requiring physical abilities such as used in labor-intensive agricultural production (manual harvesting), specific trades (brick-layers), construction workers, for specific machine operators (e.g., textile workers), or for assembly lines (e.g., electronic equipment). The underlying O*NET skills/tasks included in this category are: ability to adapt to a pace determined by the speed of equipment (SPEED), to control machines and processes (CONTROL), spend time making repetitive motions (REPETITIVE).

$$X_i^{ROUTINE\ MANUAL} = f\left(x_i^{SPEED}, x_i^{CONTROL}, x_i^{REPETITIVE}\right)$$

Second, *non-routine manual physical* characterize the ability to vary and react to changing circumstances on a continuous basis – operators of heavy equipment in agriculture, industry or construction come to mind as well as trades such as electricians. The underlying O*NET skills/tasks included in this category are the ability to operate vehicles, mechanized devices, or equipment (OPERATE), to spend time using hands to handle, control or feel objects, tools or controls (HANDLE), manual dexterity (MANUAL), and spatial orientation (SPATIAL).

$$X_i^{NON-ROUTINE\ MANUAL\ PHYSICAL} = f\left(x_i^{OPERATE}, x_i^{HANDLE}, x_i^{MANUAL}, x_i^{SPATIAL}\right)$$

Third, *routine cognitive skills* characterize the ability to carry-out repetitive, non-physical tasks – call center operators or bookkeepers would use these intensively. The underlying O*NET skills/tasks included in this category are the ability to repeat the same task (REPEAT), to be exact or accurate (ACCURATE), and to handle structured vs. unstructured work (STRUCTURED).

$$X_i^{ROUTINE\ COGNITIVE} = f\left(x_i^{REPEAT}, x_i^{ACCURATE}, x_i^{STRUCTURED}\right)$$

Fourth, *non-routine cognitive/analytical* consisting of thought processes requiring the absorption, processing and decision-making of abstract information. Computer programmers, teachers, lawyers, doctors and nurses, and many other professional occupations will need such abilities intensively. The underlying O*NET skills/tasks included in this category are the ability to analyze data/information (ANALYZE), to think creatively (THINK), to interpret information form others (INTERPRET).

$$X_i^{NON-ROUTINE\ COGNITIVE/ANALYTICAL} = f\left(x_i^{ANALYZE}, x_i^{THINK}, x_i^{INTERPRET}\right)$$

Lastly, *non-routine cognitive/interpersonal*[5] characterize personality traits that underlie behaviors such as teamwork, reliability, discipline, and work effort. These are important for professional occupations as well as for all team-based work environments as well as services which establish direct client contact. The underlying O*NET skills/tasks included in this category are the capacity to establish and maintain personal relationships (RELATIONSHIPS), to guide, direct and motivate subordinates (GUIDE), and to coach/develop others (COACH).

$$X_i^{NON-ROUTINE\ COGNITIVE/INTERPERSONAL} = f\left(x_i^{RELATIONSHIPS}, x_i^{GUIDE}, x_i^{COACH}\right)$$

Figure 1 summarizes the different characteristics of the five skill measures and provides occupational examples.

A vector X with skill information for all the 974 occupations that have information on the O*NET database is constructed:

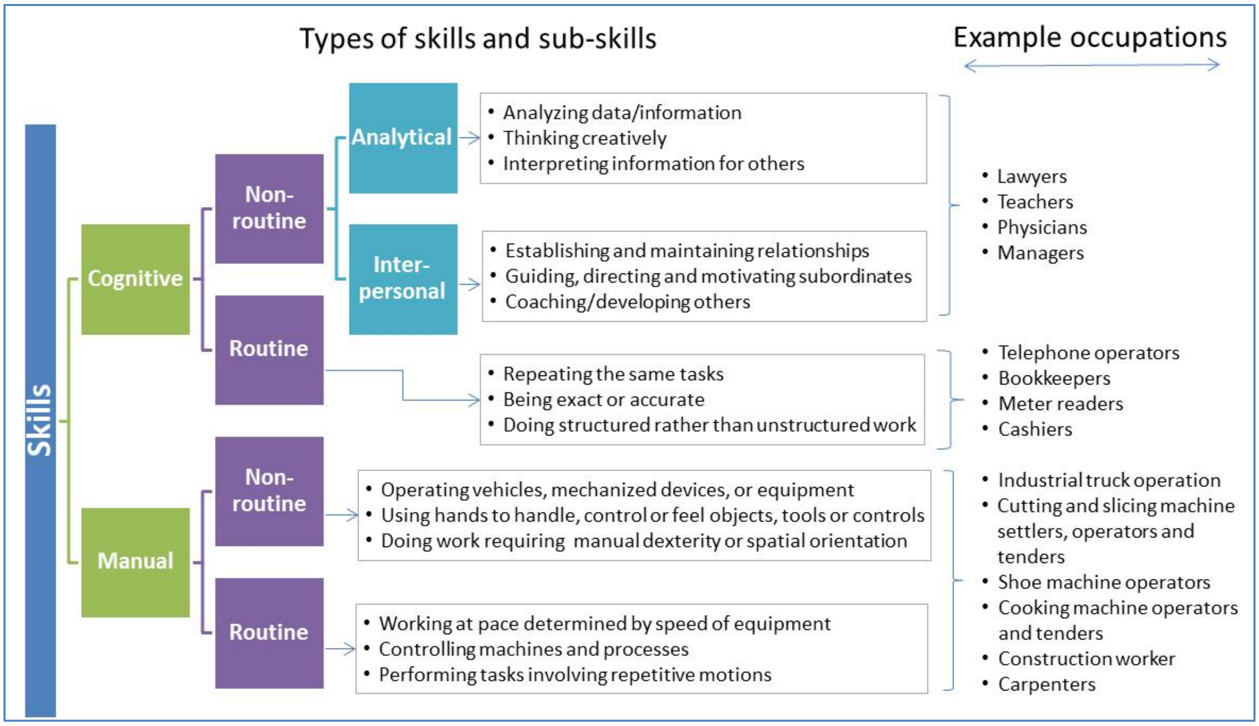
$$\mathrm{X} = \begin{bmatrix} X_1{}' \\ \vdots \\ X_{I=974}{}' \end{bmatrix}$$

After the vector X is constructed, it needs to be linked to the occupational structure so that weighted skills measures for economies can be computed. Employing Census data for

[5] These skills have obtained much attention in the more recent literature E.g., Blom and Saeki (2011), World Bank (2011, 2012), Heckman, J. J., Stixrud, J., & Urzua, J. (2005), Cunha, F., & Heckman, J. J. (2008), Borghans, L, Duckworth, A. L., Heckman, J. J., & ter Weel, B. (2008).

different years, complemented with data from the Current Population Survey (CPS) data, Acemoglu et al (2010) calculate the share in the labor force for each occupation i, θ_i for the United States as:

Figure 1



Source: Based on descriptions in O*Net, Autor, Levy and Murnane (2003) and Acemoglu and Autor (2010).[6]

$$\theta_{i,USA} = \frac{ACTIVE\ WORKERS\ ON\ OCCUPATION\ i\ IN\ USA}{TOTAL\ ACTIVE\ LABOR\ FORCE\ IN\ USA}$$

$$\sum_i \theta_{i,USA} = 1$$

The vector of all the shares of all occupations, define the overall structure of the labor force Θ_{USA} for the USA:

[6] Special thanks to Jee-Peng Tan for this illustration.

$$\Theta_{USA} = [\theta_{1,USA} \quad \cdots \quad \theta_{I,USA}]$$

Finally, to construct the skill structure of the USA, the information on the skill content by occupation as defined in **X** and the labor force structure Θ_{USA} is combined (Acemoglu and Autor 2010). The skill structure will be a vector with five elements, one per skill aggregate:

$$SKILL\_STRUCTURE_{USA} = \Theta_{USA}\mathrm{X} = \begin{bmatrix} \sum_i \theta_{i,USA} X_i^{NON-ROUTINE\ COGNITIVE/ANALYTICAL} \\ \sum_i \theta_{i,USA} X_i^{NON-ROUTINE\ COGNITIVE/INTERPERSONAL} \\ \sum_i \theta_{i,USA} X_i^{ROUTINE\ COGNITIVE} \\ \sum_i \theta_{i,USA} X_i^{ROUTINE\ MANUAL} \\ \sum_i \theta_{i,USA} X_i^{NON-ROUTINE\ MANUAL\ PHYSICAL} \end{bmatrix},$$

We apply the above methodology to data from thirty countries, ranging from low-income countries to higher middle-income ones, for which nationally representative household surveys were available in the required form. Based on the household data, we characterize the occupation structure by estimating the shares of all occupations ***i*** in country ***j*** included $\boldsymbol{\theta_{i,j}}$**:**

$$\theta_{i,j} = \frac{ACTIVE\ WORKERS\ ON\ OCCUPATION\ i\ IN\ COUNTRY\ j}{TOTAL\ ACTIVE\ LABOR\ FORCE\ IN\ COUNTRY\ j}$$

$$\sum_i \theta_{i,j} = 1$$

Therefore, the labor market structure for country j will be defined by:

$$\Theta_j = [\theta_{1,j} \quad \cdots \quad \theta_{I,j}]$$

To assess the skill structure for country **j**, we employ the skill intensities for each occupation as presented in the O*NET for the United States. This is an important assumption.[7] No country-specific applications of the O*NET equivalence table exist so that we are applying the Unites States skill equivalence to all countries in our sample. By applying the O*NET to

[7] Some of the limitations of O*NET were documented by Haendel (2007).

countries around the world, we hence assume that the skill content of a given occupation is comparable internationally.

This assumption might hold for some occupations but not for others – hence it is important to understand the potential bias in the computations which we are introducing. Countries differ in technology and regulatory contexts which may imply different skill profiles for specific occupations. For example, teachers in low-income settings are more likely to lack the tools (especially ICT tools) that support innovative teaching than teachers in developed countries. Similarly, doctors or nurses might have access to equipment as well as medical knowledge which impacts on the skill content and mix they can bring to bear in different settings. Generally, we can postulate that especially those occupations which use less routine type of skills are likely to be more skill intensive in more advanced economic settings than in lower-income ones. This would, hence, signal a possible upward bias in the measured skill intensity of non-routine cognitive analytical and interpersonal skills in our sample, especially so for the lower-income countries included.

The matching and adjustment process allows for the computation of average intensity scores for all the five skills considered. As each occupation is matched with a specific value for all skills, the average across all occupations for each skill represents a measure of the, composite and normalized, intensity of skills.[8] We then use the skill intensity computations for the United States as a benchmark value when presenting the results.[9]

To assess the shift in skill structure through time we follow Autor et al (2003) and use the complete distribution per type of skill and focus on the behavior of the median of the base distribution. Skills per occupation are held constant so that changes in skill structure will reflect changes in the occupation structure.[10]

Autor et al (2003) find that, over four decades, a remarkable shift in the skill intensity of the US labor force took place with a significant increase in analytical and interpersonal skills and a sharp decline in the use of routine cognitive skills. Over this time period, the United States

[8] The ONET equivalency scale includes values for all five skills, ranging from 1 to 5, for each occupation.
[9] We followed Acemoglu and Autor (2010) in building the composite scores with the exception of the skill category 'offshore ability' which we did not include in our analysis.
[10] The procedure can be summarized in three steps. First, the distribution of a given skill on the labor force in a base year is constructed and its median is recorded. Second, the distribution of the comparator year for the same skill is obtained and its median calculated. Third, the median of the comparator year is projected into the base year distribution. The difference between the median of the base distribution and the projected median from the comparator year corresponds to the percentile change. This allows for comparisons across an arbitrary scale.

experienced a dramatic structural change, witnessing a significant decline of its manufacturing output which has shifted to other parts of the world, especially East Asia. The occupational structure has shifted, in parallel, to white color jobs which more intensively use interpersonal and analytical skills.

3. Data

We use labor force surveys and households income and expenditure datasets with national representation. A large part the surveys come from the International Income Distribution Database (I2D2), developed by the Development Economics Groups at the World Bank. The I2D2 is a harmonized database that represents 158 economies from developed and developing countries and it covers a long period in time (1970-2012). It includes a set of standardized variables on employment, education and income. An additional set of surveys used in this study corresponds to the new member states in the European Union and comes from the Labor Force Surveys harmonized by EuroStat.

All surveys include an employment module which classifies occupations according to the International Standard Classification of Occupations version 1988 (ISCO88) developed by the International Labor Office. We also included the United States, using the American Community Survey, to obtain benchmark values.[11] For the thirty countries, we match all occupations contained in the household surveys with their respective skill content from the O*NET database. To achieve this, we apply an equivalency between the ISCO88 and the United States Bureau of Labor Standard Occupational Classification System in its 2000 version (SOC 2000) on which ONET is based. Whenever possible, we matched the occupations and their content at the three-digit level but for most countries, a two-digit match was used.[12] In the countries that had national variations of the ISCO88, we identified those changes manually, and established proper equivalencies.[13] In most of the countries, we were able to obtain the skill structure for approximately 90 percent of the employed labor force.

[11] Annex 1 includes the list of countries and surveys used.
[12] A four-digit match was possible for some countries but it was not considered because some occupations lacked scores in the ONET dataset.
[13] In case a country did not use the ISCO88 scheme we analyzed whether a national adaptation of ISCO88 or even an older version scheme as ISCO68 was available to construct a crosswalk table. If no mapping codebook was available, we explored the distribution of the occupational groups at two and three digits to identify if it was possible

We made two adjustments to the available data to reflect the different meaning and job contents of labor markets in developing countries compared to the United States: First, for the category of '*general manager'*, O*NET assigns high values for both analytical and interpersonal skills. However, in many developing countries in our sample, this category of occupation includes self-employment in small and informal businesses in the industrial and manufacturing economic sectors. We therefore replaced the skill content of the work of those individuals with less than 12 years of education (in the industrial sector) with the average skill score of all other individuals with a similar level of education and occupied in the same economic sector. After this adjustment, composite scores in higher income countries were barely affected; scores in lower income countries which had a significant share of 'general manager' classifications (e.g. Pakistan) showed a downward adjustment in their average scores for interpersonal and analytical skills.

The second adjustment concerns the classification of the work force in the agricultural sector. In various countries in our sample, low-education agricultural workers were reported as one single group without further distinction between those working in subsistence agriculture or modern agriculture and whether they work as farmers, farm managers or farm laborers. We reclassified all agricultural workers based on the type of employment reported. If a worker is classified in an agriculture-related occupation and is self-employed or is a non-remunerated family worker, we assumed that he/she worked as a traditional agriculture sector subsistence worker. This adjustment lowered the average cognitive skills scores in economies dominated mostly by the agriculture sector.

For the cross-section analysis, we arrived at a sample of thirty countries with all world regions being represented. For the time trend analysis, we were able to assemble comparable data sources for Brazil, Chile, Costa Rica, India, Poland, Sri Lanka, Turkey and the USA.

to produce a manual mapping table. Due to this methodology, we excluded from the analysis countries where occupations were coded at the most aggregated level (1 digit occupational code).

4. Results

Cross-Country Analysis

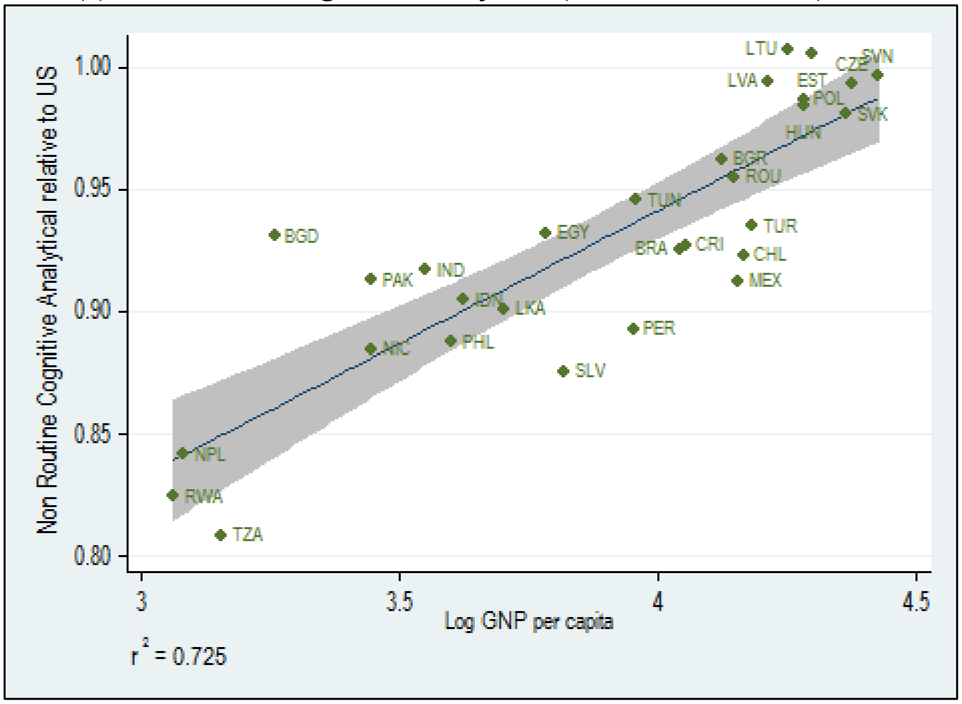
The occupation-based skill-measurement returns five skill scores for thirty countries (see Annex Table 1 for the list of countries and the data sources used). In Figure 2, these intensity scores are plotted against real GDP per capita for each of the five different skills we are considering in this analysis. The skill scores are normalized by the value of the United States (see Annex Table 2 for the raw data per skill type). A measure of 1, hence, implies that the intensity of use of a particular skill in national production of a given country is equivalent to that obtained for the United States. The plotted line shows the correlation between the variables; the grey area visualizes the two standard deviation confidence interval around the line.

We observe that countries with higher incomes tend to use more non-routine cognitive (analytical and interpersonal) as well as more routine cognitive skills in their overall economic production as shown in Figure 2 (panels A, B and C). While these are cross-section plots only and hence the interpretation of the relationship between skills and economic activities needs to be made with care (as technologies and production possibilities differ across countries and time), it appears that the correlation with economic development is particularly strong for non-routine skills (+ 0.85 for non-routine cognitive analytical, +0.79 for non-routine cognitive interpersonal) as well as routine cognitive skills (+0.85). Interestingly, we find that both Estonia and Lithuania use non-routing cognitive skills more intensively that the USA, our benchmark country. The USA leads with respect to its intensity of non-routine cognitive interpersonal and routine cognitive skills embedded in its occupational structure. The Baltic States and also Slovenia and Costa Rica (for routine cognitive skills) show high skill intensity values for these advanced skills as well.

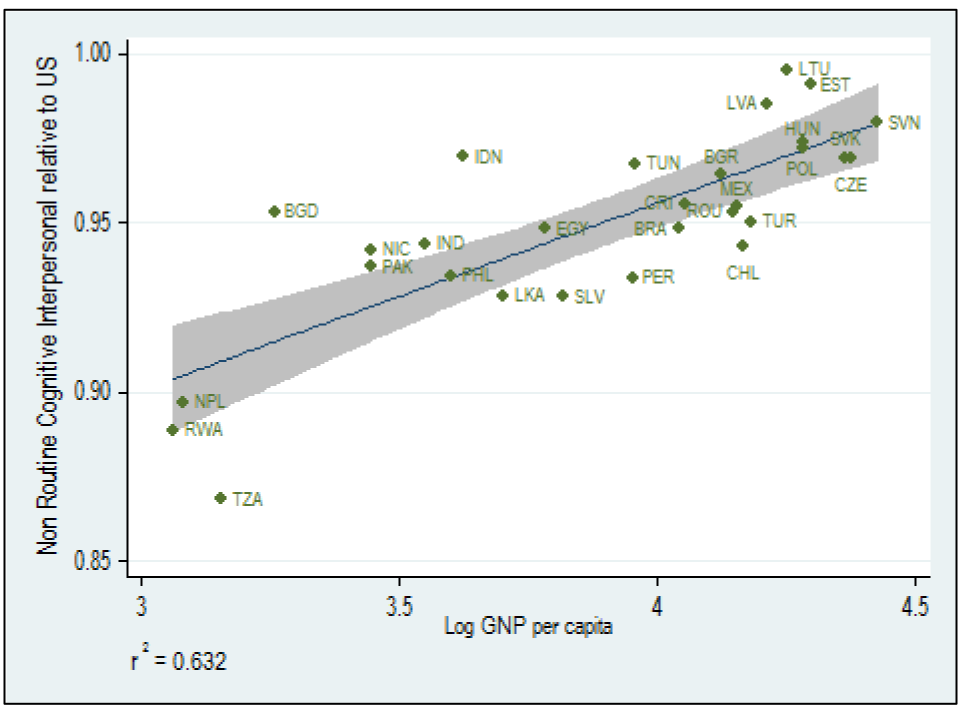
Some countries have an occupational structure that favors jobs requiring more intensive use of non-routine analytical and interpersonal than predicted by their income levels. Identifying country plots distant from the confidence interval plotted in Figure 2 (two standard deviations), we find that Bangladesh, Estonia, India, Latvia, Lithuania and Pakistan present a higher than expected intensity of non-routine cognitive analytical skills; while Chile, Mexico, Peru, Slovenia, Tanzania and Turkey present a lower than predicted intensity.

Figure 2: Relation between skill usage and income by type of skill

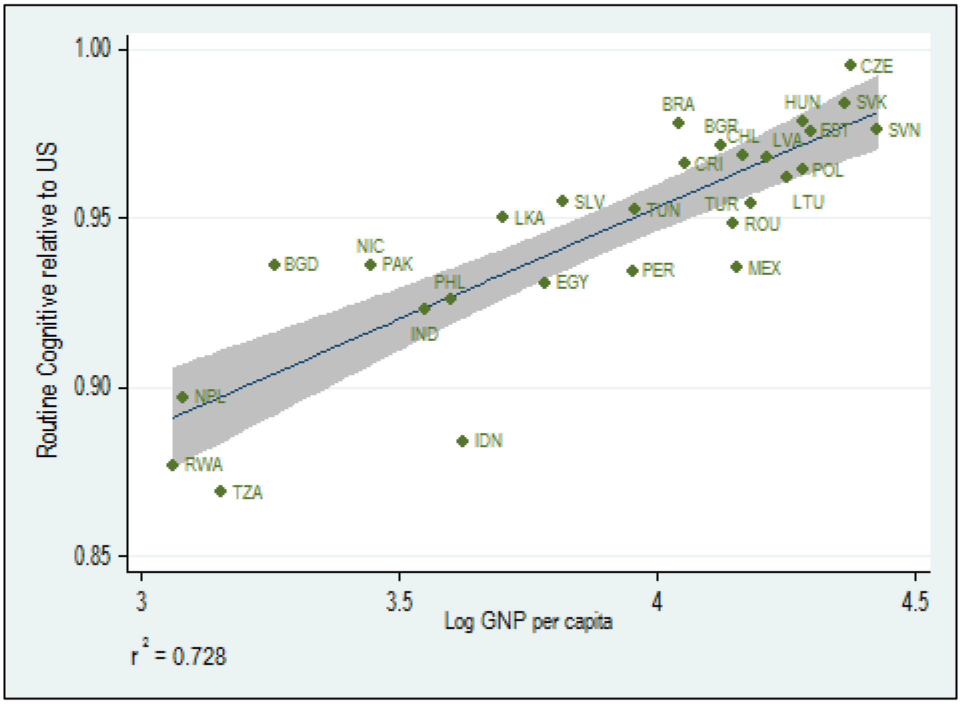
Panel (a) Non-routine Cognitive Analytical (relative to the USA)*



Panel (b) Non-routine Cognitive Interpersonal (relative to the USA)*



Panel (c) Routine Cognitive (relative to the USA)*



Panel (d) Routine Manual (relative to the USA)*

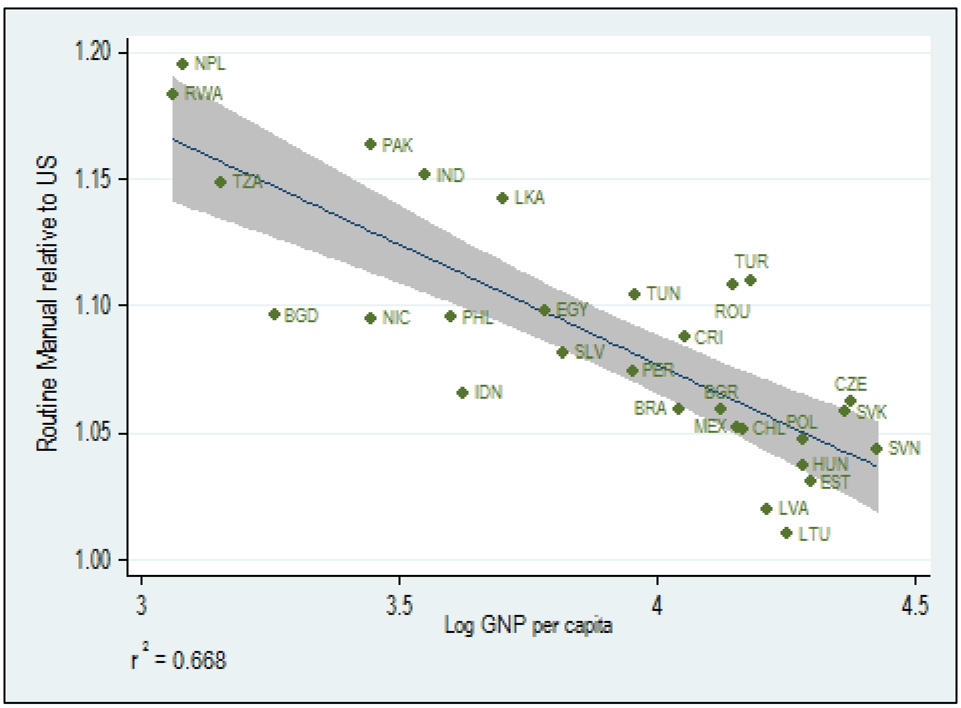
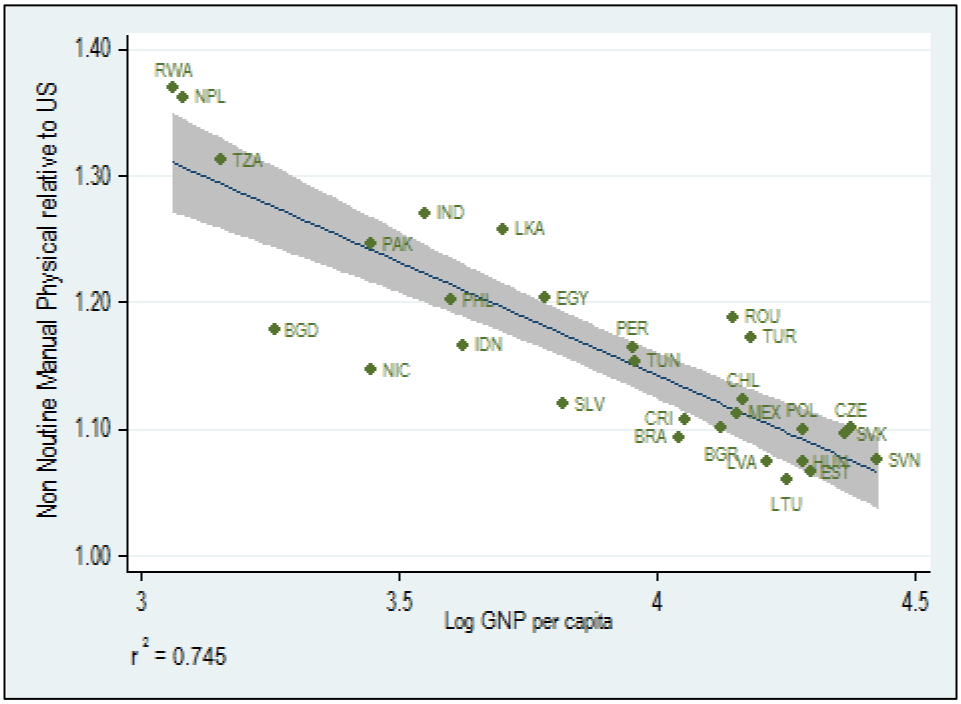


Fig. 2: Panel (e) Non-routine Manual Physical (relative to the USA)*



***** BGD: Bangladesh, BRA: Brazil, BGR: Bulgaria, CHL: Chile, CRI: Costa Rica, CZE: Czech Republic, EGY: Egypt, SLV: El Salvador, EST: Estonia, HUN: Hungary, IND: India, IDN: Indonesia, LVA: Latvia, LTU: Lithuania, MEX: Mexico, NPL: Nepal, NIC: Nicaragua, PAK: Pakistan, PER: Peru, PHL: Philippines, POL: Poland, ROU: Romania, RWA: Rwanda, SVK: Slovak Republic, SVN: Slovenia, LKA: Sri Lanka, TZA: Tanzania, TUN: Tunisia, TUR: Turkey.

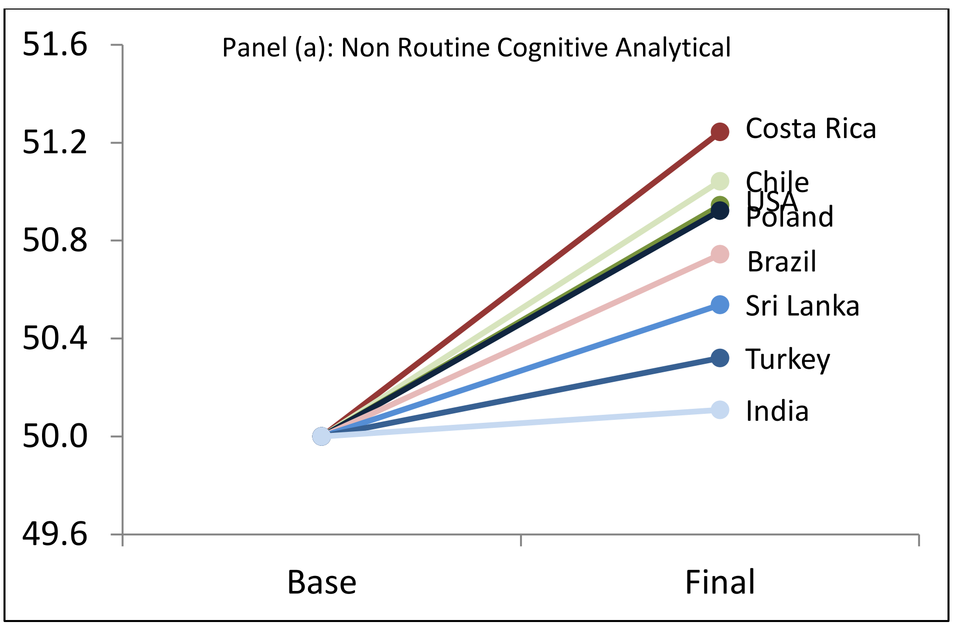
In parallel, we find that the intensity of manual skills, both routine and non-routine, decreases with the level of economic development as shown in Figure 2 (panels D and E). As agriculture and low-skilled manufacturing tends to contribute less to economic activity with incomes rising, so do the skills used intensively in their production processes. The negative cross-country correlation between economic activity and the intensity of manual skill use is strong (-0.82 for routine manual and -0.86 for non-routine manual physical). While all countries in our sample show manual skill intensity measures higher than the United States (=1.0), several of them are approaching that value, namely Lithuania, Latvia, Estonia and Hungary in terms of both routine and non-routine manual skills . Again, using the cross-country relationship as a baseline, some countries present relatively less routine manual skill intensity than would be predicted. This is the case of Bangladesh, Indonesia, Latvia, Lithuania and Nicaragua while

India, Nepal, Pakistan, Romania, Sri Lanka, Tunisia and Turkey return higher than predicted routine manual skill intensity values.

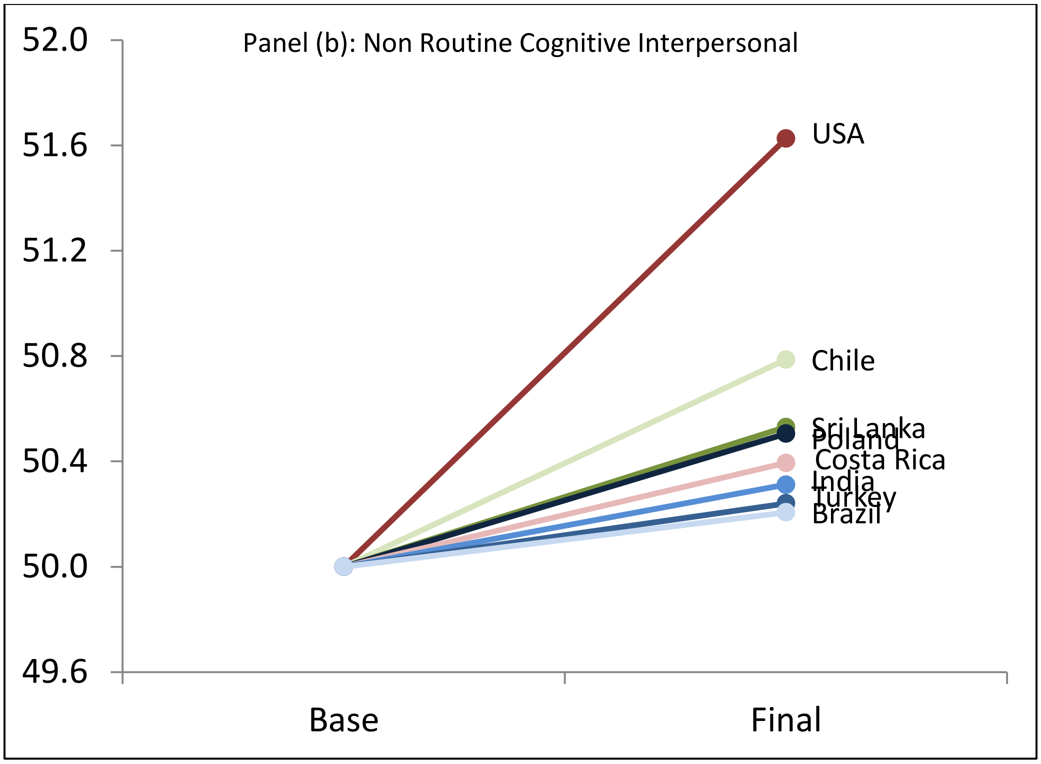
Timeline Analysis

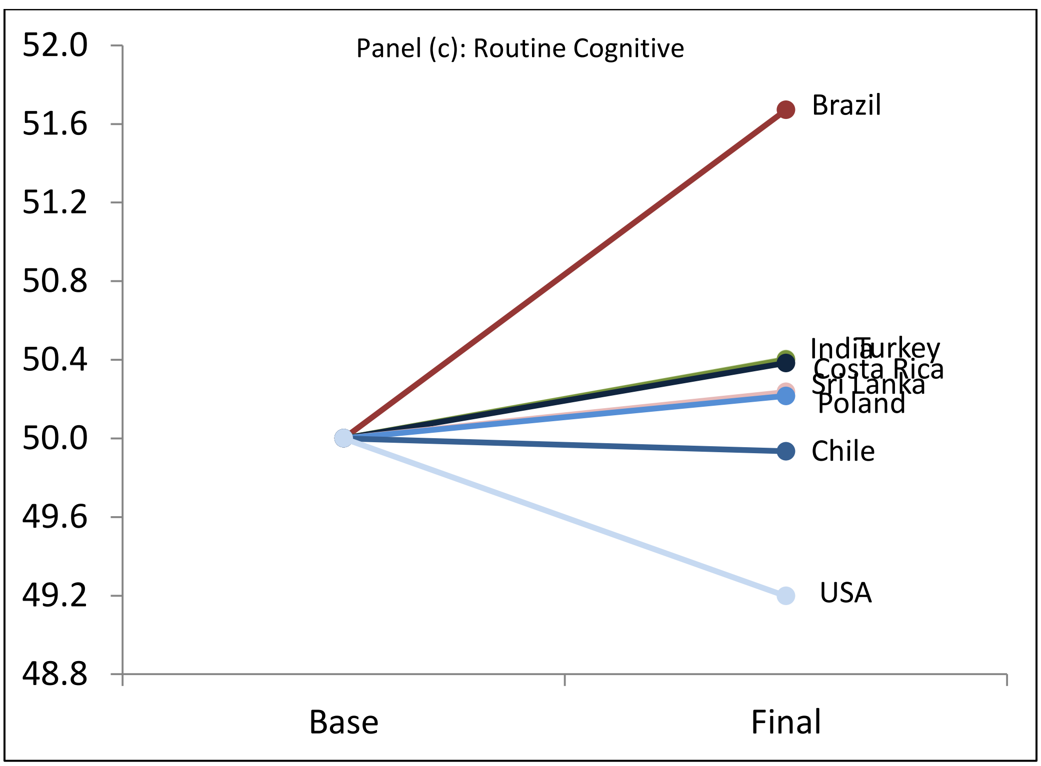
The cross-section analysis above presents the current structure of the skill content in the selected countries at one point in time but it does not allow for tracking dynamic developments. To assess such evolution, we conduct a time comparison of skill intensities for all those countries for which we were able to access appropriate household surveys at different times.[14] We derive skill score time trends for Brazil, Chile, Costa Rica, India, Poland, Sri Lanka, Turkey, and USA. The metric employed for the comparisons are the changes in the relative position of the median score in each of the five skill category between the base and the final year.[15] The numeric results for these eight countries are presented in Annex Table 3.

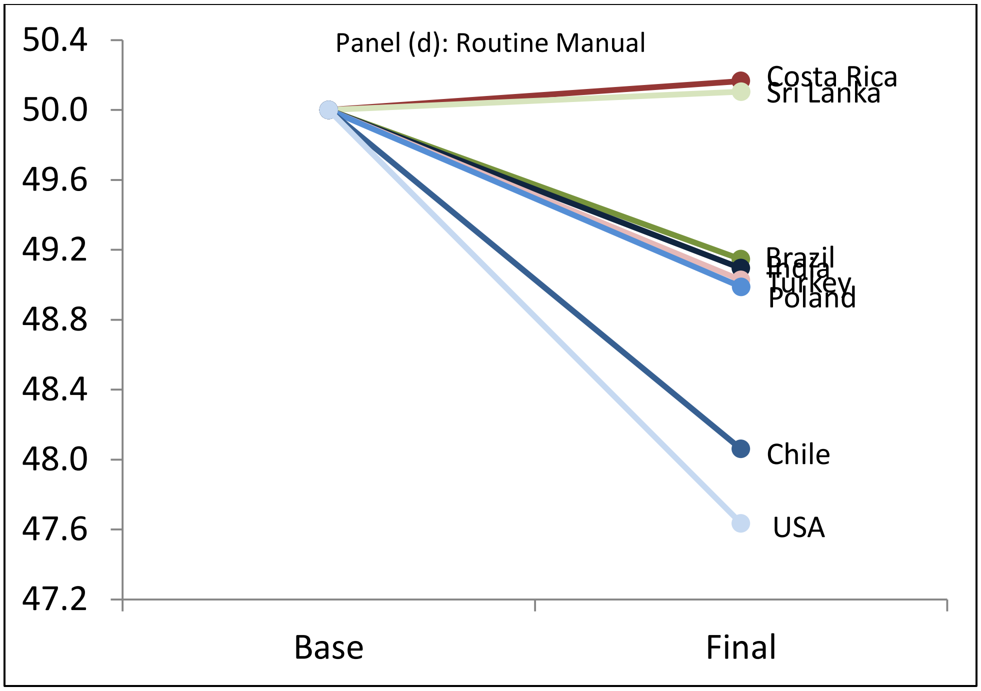
Figure 3: Time trends in skills utilization

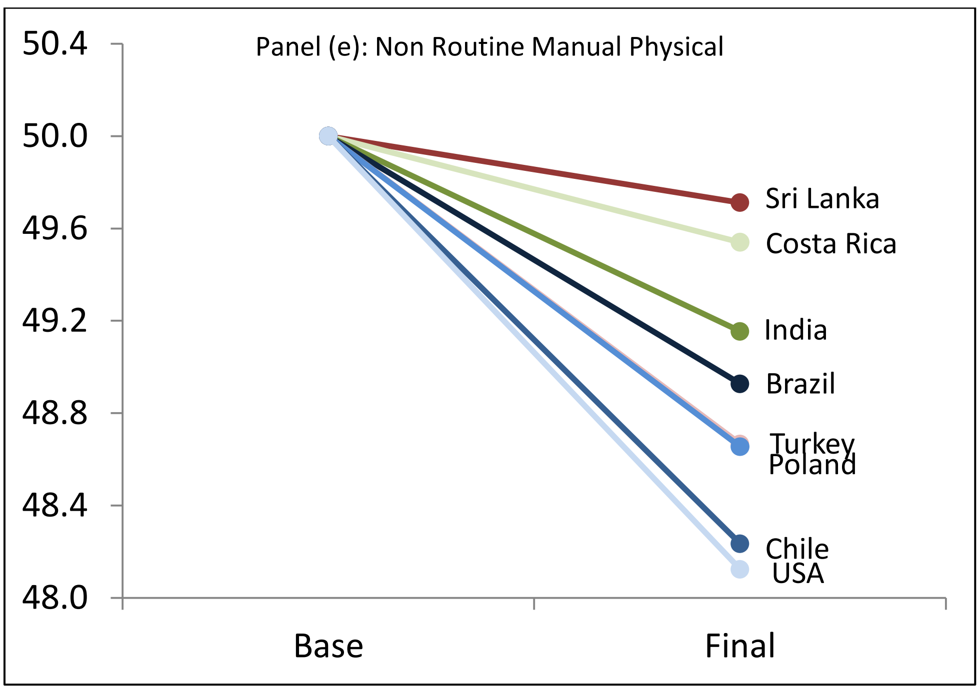


[14] Many countries changed the way they classify occupations which limits the number of countries in our timeline analysis.
[15] The methodology identifies the skill content of the median individual in the final years, and identifies in the base year the individual with that skill distribution. Note that there is a median individual per each skill.


Panel (b): Non Routine Cognitive Interpersonal
52.0
51.6
51.2
50.8
50.4
50.0
49.6
USA
Chile
Sri Lanka
Poland
Costa Rica
India
Turkey
Brazil
Base
Final


Panel (c): Routine Cognitive
52.0
51.6
51.2
50.8
50.4
50.0
49.6
49.2
48.8
Brazil
India
Turkey
Costa Rica
Sri Lanka
Poland
Chile
USA
Base
Final





Note: See Annex 3 to see base and final years for the countries in Figure 3.

The country-specific dynamic analysis reveals more divergence in skill development patterns than the cross-section analysis above might have suggested. First, we observe a rather uniform pattern with regards to a more intensive use of non-routine cognitive as well, to a somewhat lesser extent, non-routine interpersonal skills. The Costa Rica, Chile, the USA, Poland and Brazil (in that order) present a strong increase in non-routine cognitive analytical skills over time while the increase is somewhat more moderate in Sri Lanka, Turkey and India. For non-routine cognitive interpersonal skills, the increase is strongest in the USA, somewhat slower in Chile, and moderate in all the other countries.

Second, we similarly observe a uniform decline in the use of non-routine manual skills; strongest in the United States and Chile, less so in Sri Lanka and Costa Rica. As illustrated in Annex Table 4, between 1992 and 2008, Chile underwent a significant structural change which reduced the share of its working population engaged in elementary occupations as well as craft and related trade workers. Such fall is not so pronounced in either Costa Rica or Sri Lanka.

Third, patterns start diverging when we look at the use of routine manual skills (panel d): overall, the intensity of use is decreasing in many of the sampled countries, most pronounced so in the United States and Chile – but they increase (even if marginally) for Sri Lanka and Costa Rica. In Sri Lanka, this is due to an increasing share the labor force working as plant and machine operators and assemblers between 2000 and 2008 while there was a rise in Costa Ricans employed as clerks between 2001 and 2009.

Lastly, we observe a higher divergence for the change in the intensity of routine cognitive skills. Here, Brazil shows a significant increase. A second group of countries shows more moderate increases (India, Turkey, Costa Rica, Sri Lanka and Poland) while Chile records a mild decline (1992 to 2009) and the USA shows a strong and significant decline (1980 to 2008). Brazil, between 1981 and 2009, shows a significant increase in the share of workers in occupations with a higher use of routine cognitive skills such as technicians and associate professionals, plant machine operators and service workers, and shop and market sales workers (Annex 4), explaining the rather remarkable increase in the use of routine cognitive skills at a time when income levels of the country increased threefold.

While a number of caveats exist, not least due to varying time periods we were able to look at, we do find that there is some merit to establish a *classical* skill transition pattern which matches the correlations we had established when examining the cross-country relationships above: this would be one in which, alongside economic development, the intensity of non-routing cognitive skills (analytical and inter-personal) increase alongside with routine cognitive skills while manual skills (routine and non-routine) become less important. Brazil, India, Poland and Turkey would serve as this 'benchmark' here. But we do find quite some variations given the analyses we conducted: one in which routine cognitive skills are also used less intensively (Chile and the USA); as well as one in which the intensity of routine manual and routine cognitive skills keeps increasing (Costa Rica and Sri Lanka) alongside the non-routine skills. Understanding such different patterns of occupational developments – and with it the measured skill intensities – would be an important task for further research.

Concluding Remarks

In this paper, we employed labor force and household surveys to compute skill intensities for 30 countries in the developing world at one point in time and for eight countries over time. Using the occupational structure derived from such surveys and matching them with a detailed skill mapping which had been developed for the United States, we derived such intensity measures for five different skills. Our cross section results indicate strong positive correlations between economic development and the skill intensity of non-routine cognitive analytical and interpersonal skills as well as routine cognitive skills while strong negative correlations with both routine and non-routine manual skills resulted. The dynamic analysis confirms this general pattern but showed significant variation, especially for the changing intensity of routine cognitive skills.

We pointed out a number of caveats related to this analysis which need to be taken into account when interpreting the results. First, and most important, is the application of the US-specific skill intensity per occupation to the entire sample of countries studied in this paper. While we were able to make some adjustments for individual categories to reflect labor market realities in developing and emerging economies, the use of the US skill intensities will most likely have led to an upward bias in the measured skill intensities for advanced skills – both non-routine analytical as well as interpersonal skills. Second, while the skill intensity measures are an important data point, they cannot substitute for a proper measure of the quality of such available skills. For that, direct measurement techniques – as they are currently being developed – are necessary.

The observed skill intensity patterns are the result of the interaction between skill supply (i.e., the output of the education and skill building system, both in schools and workplaces alike) and demand (i.e., derived from public and private investment decisions as well as the business opportunities for self-employment in agriculture and urban areas). As such, they represent the equilibrium outcome of the dynamic development of comparative advantage (with all its determinants) and the cumulative impact of public policies in various spheres of the economy. Understanding the origins of varying skill patterns and, especially, their diverging developments through time, would be an area of fruitful future research. One core, but most likely also difficult, question to answer is to what degree skill supply has (endogenously) shaped innovation and economic growth opportunities and has thereby contributed to the observed changes in skill intensities of economies.

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Annex

Annex Table 1: Countries and surveys included in the analysis.

Country	Year	Survey Name
Bangladesh	2005	Household Income and Expenditure Survey
Brazil	2009	A Pesquisa Nacional por Amostra de Domicílios (PNAD)
Bulgaria	2010	EU Labour Force Survey
Chile	2009	Encuesta de Caracterización Socioeconómica Nacional (CASEN)
Costa Rica	2008	Encuesta de Hogares de Propositos Multiples (EHPM)
Czech Republic	2010	EU Labour Force Survey
Egypt	2006	Egypt Labor Market Survey (ELMS)
El Salvador	2008	Encuesta de Hogares de Propositos Multiples (EHPM)
Estonia	2010	EU Labour Force Survey
Hungary	2010	EU Labour Force Survey
India	2010	National Sample Survey Organisation (NSSO)
Indonesia	2008	Survey Sosial Ekonomi Nasional
Latvia	2010	EU Labour Force Survey
Lituania	2010	EU Labour Force Survey
Mexico	2009	Encuesta Nacional de Ingresos y Gastos de los Hogares (ENNIG)
Nepal	2008	Labour Force Survey
Nicaragua	2009	Encuesta Nacional de Hogares sobre Medición de Nivel de Vida (EMNV)
Pakistan	2008	Labour Force Survey
Peru	2010	Encuesta Nacional de Hogares (ENAHO)
Phillipines	2010	Labour Force Survey
Poland	2010	EU Labour Force Survey
Romania	2010	EU Labour Force Survey
Rwanda	2005	Enquete Integrale sur les Conditions de Vie des Menages
Slovak Republic	2010	EU Labour Force Survey
Slovenia	2010	EU Labour Force Survey
Sri Lanka	2008	Sri Lanka Labour Force Survey
Tanzania	2006	Integrated Labour Force Survey
Tunicia	2010	Labour Force Survey
Turkey	2010	Household Labour Force Survey
USA	2006-2008	American Community Survey (ACS)

Annex Table 2: Raw Skills Scores for Selected Countries.

	YEAR	Non Routine cognitive: Analytical	Non Routine cognitive: Interpersonal	Routine cognitive	Routine manual	Non routine manual physical
Brazil	2009	2.798	2.921	3.06	2.646	2.554
Bangladesh	2005	2.813	2.936	2.929	2.737	2.751
Bulgaria	2010	2.909	2.969	3.04	2.644	2.571
Chile	2009	2.79	2.904	3.031	2.626	2.624
Costa Rica	2008	*2.803*	*2.943*	*3.023*	*2.716*	*2.587*
Czech Republic	2010	3.002	2.985	3.114	2.652	2.57
Egypt	2006	2.817	2.92	2.913	2.742	2.811
El Salvador		*2.647*	*2.859*	*2.988*	*2.701*	*2.614*
Estonia	2010	3.039	3.052	3.053	2.574	2.49
Hungary	2010	2.975	2.995	3.062	2.59	2.509
India	2010	2.772	2.907	2.889	2.875	2.966
Indonesia	2008	2.735	2.986	2.766	2.662	2.724
Latvia	2010	3.005	3.035	3.029	2.548	2.508
Lituania	2010	3.045	3.066	3.01	2.523	2.477
Mexico		*2.759*	*2.941*	*2.926*	*2.628*	*2.598*
Nepal	2008	2.544	2.763	2.807	2.985	3.18
Nicaragua	2009	*2.674*	*2.901*	*2.93*	*2.734*	*2.677*
Pakistan	2008	2.759	2.886	2.93	2.904	2.909
Peru	2010	2.699	2.876	2.924	2.683	2.718
Phillipines	2010	2.683	2.878	2.897	2.735	2.807
Poland	2010	2.983	2.999	3.018	2.615	2.568
Romania	2010	2.887	2.936	2.968	2.766	2.776
Rwanda	2005	2.493	2.738	2.744	2.955	3.196
Slovak Republic	2010	2.964	2.985	3.08	2.643	2.56
Slovenia	2010	3.012	3.018	3.055	2.606	2.512
Sri Lanka	2008	2.723	2.86	2.973	2.852	2.936
Tanzania	2006	2.444	2.675	2.72	2.868	3.064
Tunicia	2010	2.859	2.98	2.98	2.757	2.694
Turkey	2010	2.827	2.927	2.986	2.771	2.738
USA	2008	3.023	3.08	3.13	2.497	2.335

Annex Table 3: Skills Trends Summary (expressed as percentiles)

Country		Non Routine cognitive: Analytical	Non Routine cognitive: Interpersonal	Routine cognitive	Routine manual	Non routine manual physical		Non Routine cognitive: Analytical	Non Routine cognitive: Interpersonal	Routine cognitive	Routine manual	Non routine manual physical
USA	1980	2.967	2.983	3.181	2.621	2.426	2008	3.023	3.080	3.130	2.497	2.335
Chile	1992	2.733	2.859	3.035	2.732	2.720	2009	2.790	2.904	3.031	2.626	2.624
Costa Rica	2001	2.735	2.920	3.000	2.707	2.611	2008	*2.803*	*2.943*	*3.023*	*2.716*	*2.587*
Brazil	1981	2.757	2.909	2.961	2.692	2.610	2009	2.798	2.921	3.060	2.646	2.554
Poland	2002	2.929	2.969	3.005	2.669	2.639	2010	2.983	2.999	3.018	2.615	2.568
Turkey	2004	2.809	2.913	2.962	2.826	2.813	2008	2.827	2.927	2.986	2.771	2.738
Sri Lanka	2000	2.694	2.830	2.959	2.846	2.953	2008	2.723	2.860	2.973	2.852	2.936
India	1994	2.766	2.889	2.866	2.928	3.017	2010	2.772	2.907	2.889	2.875	2.966

a. Source: Own calculations.

Annex Table 4: Share of Occupations (ISCO-88, 1 digit)

	Turkey 15-64 years old		Chile 15-64 years old		Sri Lanka 15-64 years old		Poland 15-64 years old		Costa Rica 15-64 years old		Brazil 15-64 years old		India 15-64 years old	
	2004	2008	1992	2009	2000	2008	2002	2010	2001	2009	1981	2009	1994	2010
1 Legislators, senior officials and managers	8.6	8.8	5.3	2.6	1.2	8.2	6.4	7.3	2.5	3.5	5.1	6.1	2.1	5.7
2 Professionals	6.2	6.4	7.4	11.0	5.6	6.0	10.5	16.1	9.7	10.9	6.8	10.7	2.0	3.9
3 Technicians and associate professionals	5.0	7.3	5.7	10.0	5.0	5.7	12.7	11.7	12.0	13.8	5.1	7.8	4.2	3.1
4 Clerks	5.3	6.8	7.9	8.0	4.3	4.2	8.0	7.3	7.5	9.1	9.7	9.8	1.9	2.0
5 Service workers and shop and market sales workers	10.4	12.3	13.8	17.7	12.0	7.8	11.4	12.2	15.4	15.9	13.8	16.8	8.0	7.4
6 Skilled agricultural and fishery workers	27.9	17.9	5.8	3.7	25.5	21.5	18.7	12.0	4.5	3.4	20.4	5.1	39.1	31.0
7 Craft and related trade workers	14.2	14.6	18.6	14.0	16.8	16.9	16.1	15.8	11.8	10.1	17.8	14.2	10.0	12.0
8 Plant and machine operators and assemblers	10.0	11.0	8.1	9.3	5.7	7.5	8.9	10.1	9.9	8.9	4.6	9.2	5.0	3.9
9 Elementary occupations	12.5	14.9	27.4	23.8	24.0	22.2	7.4	7.6	26.8	24.5	16.7	20.4	27.8	31.0