The skill content of occupations across low and middle income countries: evidence from harmonized data

Emanuele Dicarlo, Salvatore Lo Bello, Sebastian Monroy, Ana Maria Oviedo, Maria Laura Sanchez Puerta and Indhira Santos

Abstract

Introduction and motivation

Does an office clerk in Bolivia perform the same tasks as a clerk in Macedonia, or in the United Sates? The question on how intensive the use of skills is for the same occupations in different countries is still unanswered. The fact that capital and labor are complementary necessarily implies that the type of tasks that workers perform in their jobs depends closely on the type of capital that is at their disposal. In other words, as long as there is heterogeneity of capital within occupations (across firms or across countries), it is likely that there is also heterogeneity in the type of tasks performed. Furthermore, the recent pace of technological change in many low and middle income countries has brought more attention to the questions of the skills that can best complement labor with capital.

This paper build upon the seminal works of Autor, Levy and Murnane (2003) –ALM henceforth—who were among the first to analyze the skill content of tasks within occupations in the United States. They sort occupations by the intensity of the skills used, and classify them as "routine" and "non-routine" on the one hand, and "cognitive" and "manual" on the other, first using the Dictionary of Tasks (DOT) and then O*NET. The idea is to sort occupations according to their degree of complexity (analytical/interpersonal vs. manual), and whether they require constant decision making ability (routine vs. non-routine). As ALM show, the widespread use of computers in the economy has transformed the US labor market, by increasing the share of non-routine occupations that require analytical and interpersonal skills, and decreasing the share of routine occupations that require manual skills (those that can be more easily replaced by technology). This is the polarization of the labor market (Autor, 2014). The US is a particular case to illustrate this evolution as it has the data sources to map specific tasks (thus skills) to occupations, which can then be tracked over time.

Subsequent works, in particular Aedo et al. (2014) have applied the ALM classifications of occupations to other countries, and looked at their composition and how it has changed over time. Though this approach is very useful to understand the evolution of the distribution of employment across occupations, a major problem with it is that it assumes that the skill content of the tasks performed in each occupation in each country is exactly the same as in the US (e.g., an office clerk does the exact same tasks everywhere). This in a way assumes that the productivity of each job is roughly similar across countries, which is clearly not the case.

A second (though different) problem with the methodology of ALM is that it is based on a dataset (O*NET) that contains only one observation per occupation, which corresponds to an aggregation of responses to surveys applied to a sample of worker population and occupation experts. But in essence it provides no sense of the heterogeneity of tasks within an occupation.

This paper contributes to the literature by providing relevant information on the nature of skill requirements across a group of low- and middle-income countries. This is mainly through the production of a measure of skill content of tasks, which comes directly from workers in the developing world. This paper uses a unique set of comparable individual level data, taken across 10 countries, that documents the nature of the tasks that workers carry out in their jobs and in their daily lives.[1] The type of survey is similar to the US STAMP survey, and it allows for the measurement of tasks at the worker level, thus capturing heterogeneity not only across occupation but also within occupations.

Following the methodology of Acemoglu and Autor (2011) and Autor and Handel (2013) the paper constructs four indices of skill intensity for each 3-digit level occupation, thus obtaining a classification of the skill content of tasks for each occupation.

The paper finds that the US classification of skill composition of occupations does not match well with the actual intensity observed at the worker level. On the other hand, the paper finds that middle income and low income countries have similarities in the skill intensity of occupations, which the paper explores and discusses, linking it with the different pace of technological change across countries. The paper finally argues that studies that take the US skill composition to study skill use in other countries might be over estimating the extent of technological change and the intensity of analytical skill use.

Data

The World Bank's Skills Toward Employment and productivity (STEP) household (and employer) surveys represent a unique resource for understanding (i) job skill requirements, (ii) backward linkages between skill acquisition and educational achievement, personality, and social background, and (iii) forward linkages between skill acquisition and living standards, reductions in inequality and poverty, social inclusion, and economic growth. STEP includes both a household-based survey and an employer survey. The household survey includes three unique modules: (i) a direct assessment of reading proficiency and related competencies scored on the same scale as the OECD's PIAAC assessment; (ii) a battery of self-reported information on personality, behavior, and preferences (e.g., Big Five, GRIT, decision-making, and hostility bias); and (iii) a series of questions on task-specific skills that the respondent possesses or uses in his or her job. The employer survey gathers information on job skill requirements using questions parallel to those in the household survey, a feature that facilitates analysis of skill gaps and mismatches. The employer survey also has

[1] The STEP Skill data collection project was carried out by the World Bank, with financial support from Donors. The surveys were collected for Yunnan Province in China, and the following countries: Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Lao PDR, Macedonia, Sri Lanka, Ukraine, and Vietnam.

information on practices relating to: (i) hiring and compensation, (ii) training, and (iii) enterprise productivity. For the analysis of tasks, this paper uses the contents of the household surveys only.

The STEP surveys have been implemented in 13 countries: Armenia, Azerbaijan, Bolivia, Colombia, Georgia, Ghana, Kenya, Lao PDR, Macedonia, Sri Lanka, Ukraine, Vietnam, and China (Yunnan Province).[2]

Preliminary results

This paper estimates skill use intensity at the worker-level, following the same skill categories proposed by Autor and Handel (that is, analytical, interpersonal, routine and manual). For each one of these categories, we first select the variables that are more closely related to them in the survey. Then, we estimate the four intensity scores for each worker in two different ways: 1) using the Principal Component Analysis and extracting the first component, i.e. creating a synthetic index that is able to explain as much variance in the data as possible; 2) constructing standardized measures of our variables and summing them up by worker.

The first approach -used by Autor and Handel (2013)- has the advantage of not imposing any assumption on the underlying structure of the data (all the results are data-driven). In addition, it synthetizes the information in the most efficient way (i.e., minimizing the loss in variance). On the other hand, the scores produced with this methodology are not cardinal measures and it is therefore particularly hard to compare them across countries.

Under the second approach, instead, the aggregation of variables is made in a way such that more weight is given to those variables with a smaller sample variance (this is also the approach used by Acemoglu and Autor (2011)). We perform the estimation at the 3-digit level for all occupations with at least 10 observations.

Once we have estimated the scores at the individual level, we construct measures of skill use intensity at the occupational level, by aggregating the estimated scores within each occupational group. We do so by weighing our observations by their contribution to total hours worked within an occupation, so that the outcome can be interpreted as the skill use intensity of the "average worker" of a given occupation. Under the second approach, we perform a further standardization of the scores at the occupational level. This allows us for an interpretation not only of the *rankings* but also of the scores in terms of *relative distances* of occupations along the skill dimensions.

Remarkably, the rankings produced by the two methodologies look extremely similar along several dimensions. For most of the countries, the Spearman correlation between the rankings lies in the range 0.97-0.99 at the 3-digit level. In Figure 1 we plot the 4 scores at the 1-digit level (9 occupational groups) for Bolivia, estimated with the two methodologies. Note that in relative terms the two charts are quite similar, implying that not only rankings but also relative distances in scores across occupational groups are well preserved across the two methodologies. This is particularly true for the Analytical

[2] See Valerio et al. (2014).

and Interpersonal scores (the blue and red columns), while it true to a lesser extent for the Routine and Manual scores (the green and orange columns).

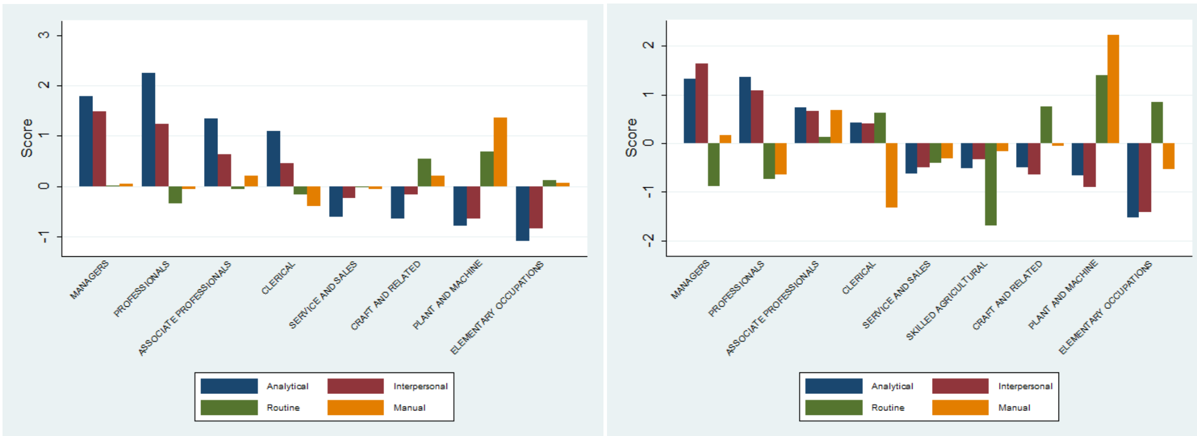

FIGURE 1 – ESTIMATES OF USE INTENSITY SCORES, BOLIVIA. (SOURCE: STEP; METHODOLOGY: PCA FOR THE LEFT CHART, STANDARDIZED MEANS FOR THE RIGHT CHART)

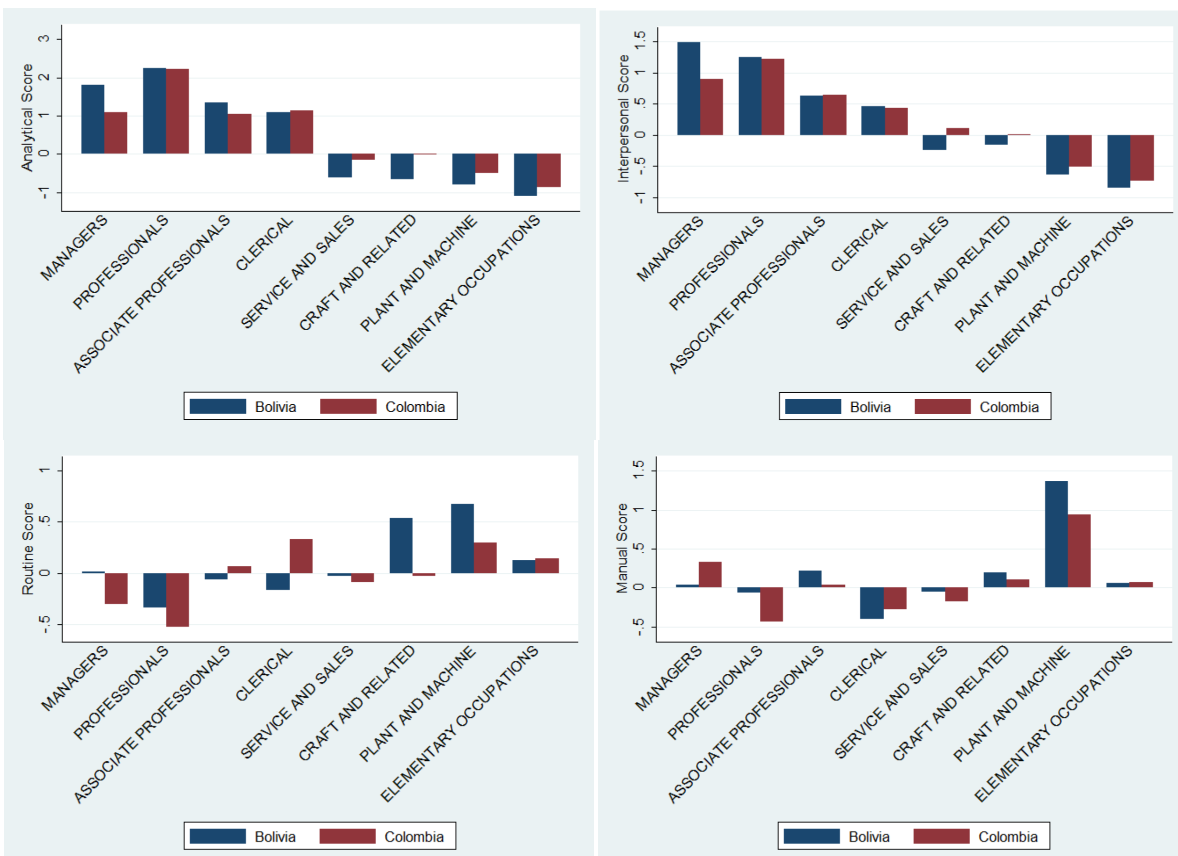

FIGURE 2 – ESTIMATES OF USE INTENSITY SCORES FOR EACH SKILL (ANALYTICAL, INTERPERSONAL, ROUTINE AND MANUAL). CROSS-COUNTRY COMPARISON, BOLIVIA AND COLOMBIA. (SOURCE: STEP; METHODOLOGY: PCA)

Cross-country comparisons reveal that similar countries (for geographic area or income group) have overall quite similar use intensity scores. For instance, in Figure 2 we can see the comparison between Bolivia and Colombia. In particular for the Analytical and Interpersonal scores, the estimates look extremely similar. For the Routine and Manual skills, the degree of similarities is also apparent, even though some slight differences also arise.

In order to compare relative occupations' skills of those countries with the US, we replicated the Autor and Handel (2013) estimation. Indeed we came up with three scores in each occupation, one for each single task.

The abstract tasks score is constructed starting from four items: (1) length of longest document typically read (2) frequency of math tasks involving at least high school mathematics (3) frequency of problem solving tasks requiring at least 30 minutes to be solved (4) proportion of workday supervising other workers.

The routine category also involves four items: (1) proportion of workday spent performing short, repetitive tasks plus complete absence of face to face interaction with (2) customer and clients (3) suppliers and contractors (4) students and trainees.

A single item from PDII elicits information on manual tasks: Proportion of the workday spent doing physical tasks (such as standing, operating machines or vehicles, fixing things).

Through Principal Component Analysis, the variables in each category are aggregated into a single task score using the first component of the PCA. Also in this exercise we aggregated the individual scores within each occupational group. In this process, observations are weighted by their contribution to total hours worked within an occupation, so that the outcome can be interpreted again as the skill use intensity of the "average worker" of a given occupation. Using a crosswalk, US-SOC occupations are first converted into ISCO ones and then aggregated at the one digit level.

When we compare the estimates produced for these middle-income countries to the estimates for the US we can only argue about differences in occupation skills within countries. As far as we cannot exactly replicate the Autor and Handel specification with STEP data, we cannot argue US managers are more intensive in the use of abstract skills compared to Colombian ones.

What can be said instead, is that the relative intensity of skills between occupations looks quite different comparing the US to Bolivia and Colombia. US craft workers for example, are the third occupation in abstract task intensity, while one of the last ones in Bolivia and Colombia. Also, elementary ccupations are the most intensive ones in routine tasks in the US while they are dominated by craft workers and machine operators in middle-income countries.

At the end of the day "managers" is still the most intensive occupation in interpersonal skills in all those countries as well as "machine operators" is one of the most intensive occupation in manual tasks. However, the graphs below depicts different patterns of relative skills intensity between occupations in the same country.

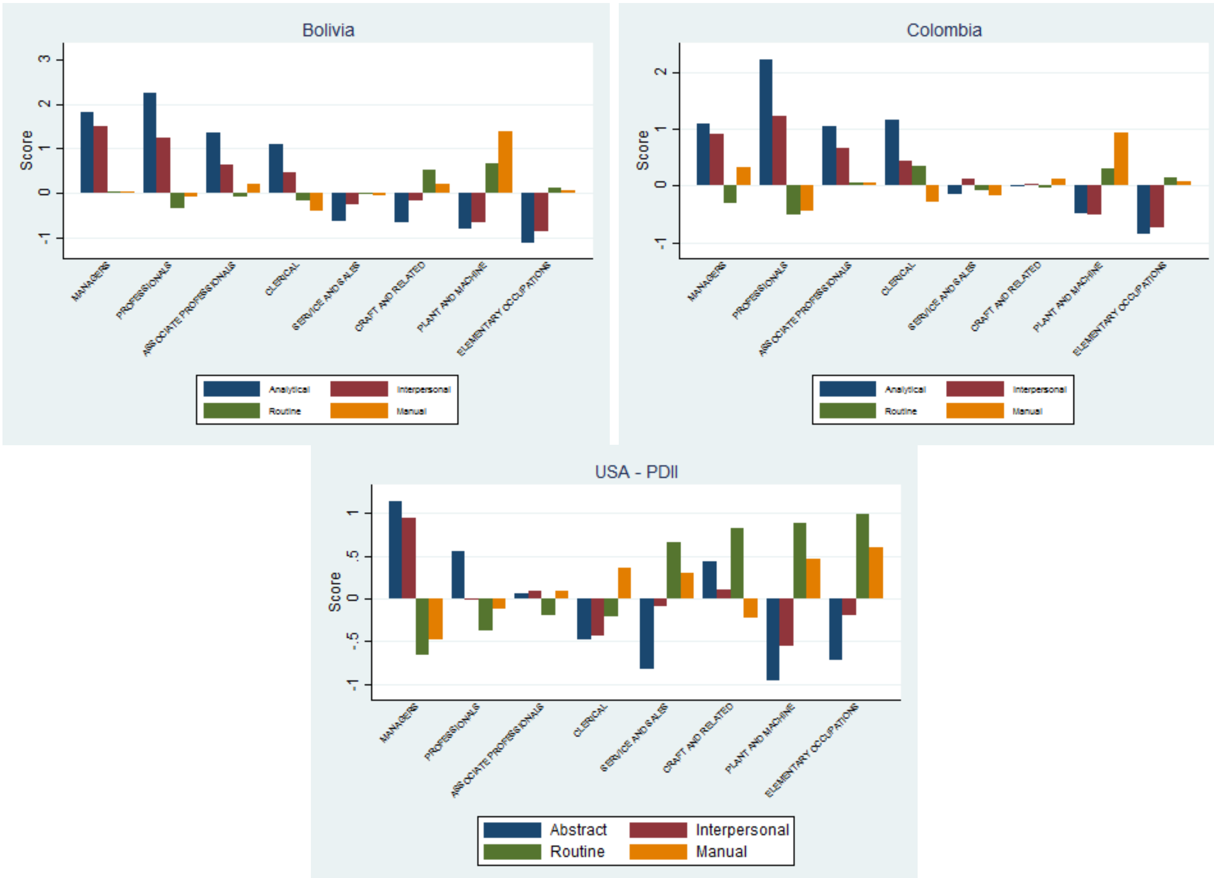

FIGURE3 – ESTIMATES OF USE INTENSITY SCORES: BOLIVIA, COLOMBIA AND USA . (SOURCE: STEP AND PDII; METHODOLOGY: PCA)