Technological Change and Labor Market Disruptions: Evidence from the Developing World

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ABSTRACT

Digital technologies are changing the world of work. They are shifting the skills a worker needs to succeed in “new economy” jobs. This technological change, together with globalization and urbanization, is likely to generate important labor market disruptions. The labor market disruptions are derived from the technological change being skill-biased and labor saving. However, the evidence to date has been limited to developed countries – mostly the U.S. We use novel data for developing world countries, including several Latin American and the Caribbean Countries, to assess the potential disruption to their labor market, to provide a typology on the extent of this disruption, and to classify the countries by capacity of their skill development systems to adapt to this disruption.

1. Introduction

Digital technologies are changing the world of work. The use of digital technologies, such as computers, mobile phones and the internet, are modifying, expanding and replacing specific tasks performed at work or even complete jobs. The main channel through which these digital technologies are shifting the world of work is by changing the skills that workers need to succeed in "new economy" jobs (Autor, Levy, & Murnane, 2003).

Evidence from advanced countries suggest that the labor market disruptions that such technological change can come in the form of being skill-biased and labor saving. However, the evidence of the developing countries is fairly limited. The objective of this paper is to begin narrowing the evidence gap on how this technological change is disrupting labor markets in the developing world. The use of novel data for both developing and developed countries allows us to shed some light in this issue.

This paper compares the use of digital technologies at work across different countries with different income levels by taking advantage of a set of questions asked at worker level and aggregating them at country level. Then, this paper ranks occupations in high, medium, and low use of digital technologies at work, and extrapolates this ranking to 30+ countries to compare the employment distribution across different income levels. Furthermore, the use of digital technologies at work is correlated with the skill content measures from available in the literature.

This paper also seeks to measure the extent of the risk of automation in affecting the labor markets. To do so, this paper uses the probability of computerization estimated by Frey & Osborne (2013) in the U.S. and extrapolates it at the occupation level. This provides information in the magnitude and characteristics of the jobs at high risk of being automated. This paper takes it a step further by adjusting the probability of computerization to accounts for the time lag in the adoption and diffusion of technologies across the globe using the adoption lags of 20th century technologies estimated by Comin and Hobjin (2010).

The paper puts together these two measures to produce a picture of the extent of the labor market disruptions that developing countries may face. This paper aims to build a typology of countries based on the relative degree of labor market disruption. Additionally, the countries are also classified according by their capacity to adapt and respond to this disruption, measured by the quality of their education systems.

The rest of these paper is organized as follows. The next section provides a short literature review describing how technological changes are skill biased and labor savings, followed by a section that presents the data this paper uses. Section 4 presents the index of use of digital technologies at work, describes how their use varies by country, and how this measure is correlated with usual skill content measures. Section 5 presents the extent of the risk of automation, how we adjusted to account for adoption time lags, and how it may affect the employment shares in different countries. The following section brings together both measures and presents the picture of the labor market disruption, the country typology and how countries are prepared to adapt and respond to this disruption. The final section offers concluding remarks.

2. Literature review

The evidence on how technologies, and more specifically digital technologies in the present day, has been limited to advanced countries– mostly the U.S. –. The evidence on how technology affects the labor markets points to two forces thus far. The first one is that technological change is skill biased (Acemoglu & Autor, 2011; Autor & Handel, 2013). As in former waves of technological change, digital technologies disproportionally increase the productivity of high-skilled workers. More specifically, the skill-biased nature of this technological change comes in form of a reduction in the demand for workers doing tasks that are mostly routine (those more likely to be computerized), while it increases the demand for workers doing tasks that are mostly non-routine. (Acemoglu, 2002; Autor, Katz, & Kearney, 2008; Autor D. H., 2014). This leads inevitably to the polarization of the labor market (Autor D. H., 2014; Autor & Dorn, 2013).

The second force is that this technological change is labor saving (Autor D. H., 2014). This force can be understood as the likelihood of a given task to be computerized. Let us assume that any given job is composed by a number tasks that when performed produce certain output. The number tasks can vary depending on the degree of complexity required to produce a given output. The way that technological change can be labor saving is if there is a higher the number of tasks that can now be broken down into programmable activities that a computer or a machine (those tasks are usually the ones that fall into the routine definition of Autor et al. (2002)) can easily perform. In this case, occupations with a substantial number of tasks that are routine can be fully automated. This has been the case, for example, of many travel agents (Frey & Osborne, 2013; Brynjolfsson & McAfee, 2014).

Through these forces, technological change, together with globalization and urbanization, is likely to generate important disruptions in the labor market. Yet the evidence to date is limited to advanced economies (for instance, Krueger, 1993; DiNardo & Pischke, 1997; Spitz-Oener, 2006; Handel, 2007). There is little evidence on how technological change has affected the labor market in the developing world (Aedo et al, 2013). This is the gap that this paper seeks to fill. Using novel data from surveys in 10 developing countries and 1 Chinese province, as well as from surveys in 22 developed countries. These two set of surveys allow comparing the use of digital technologies at the worker level in different countries across a wide range of income level. Furthermore, we will extrapolate part of the information constructed to around 30+ developing world countries. In this sense, we aim to address the evidence gap on technological change and labor market disruptions in developing countries in three ways:

1. *We measure the extent of use of digital technologies at work and, how this correlates with changes skill requirements for a set of developing world countries*. In order to measure the extent of use of digital technology at work, we build an index of ICT intensity. The index contains information about computer frequency and complexity of use, as well as use of digital technologies such as internet and mobile phones. We later use the average index at an occupation level to extrapolate to other countries and discuss the correlations with the changes in skill requirements.
2. *We measure the extent to which the risk of automation, as estimated by Frey & Osborne (2013), can affect labor markets.* The risk of automation was estimated by Frey and Osborne (2013) for the U.S. We extrapolate the information of the probability of being automated to the same data sets we used to estimate the index of use of digital technology. We do this at an occupation level. This gives us information on the magnitude and characteristics of the jobs that are in high risk of being automated based on the technological feasibility of such automation. We take it a step beyond to adjust for the fact that are adopted and diffused with a time lag in the developing world. To adjust for this, we use information from Comin and Hobijn (2010) on the adoption lags of 20th century technologies.
3. *We put together our estimates of use of digital technologies at work with those for the risk of automation to build a more complete picture of the extent of the labor market disruption that developing countries can face as a result of these forces.* The goal of putting together the estimates of use of digital technology at work with those of automation is to build a typology of countries based on the relative degree of labor market disruption of these two forces. Similarly,

we classify countries according to their capacity to respond and adapt to technological changes in the labor market, mostly determined by their quality of their skill development systems.

3. Data

This paper takes advantage of two novel data sources: a) Skills Towards Employment and Productivity (STEP) - Skill Measurement Surveys gathered by the World Bank; and b) Programme for the International Assessment of Adult Competencies (PIAAC) gathered by the OECD. The novelty relies on the fact that both set of surveys contain background information as well as large battery of questions aimed to capture different tasks performed at work and at home, as well as information of skills (cognitive and technical) for the adult population. They were collected between 2012 and 2013.

The STEP surveys are available for 11 developing countries and a Chinese province.[1] They target adult population between 15 to 65 years old in urban areas only. They have comparable data on occupations and a module on the different tasks that done at work (See Pierre, Sanchez-Puerta, Valerio, & Rajadel, 2014). Within the module of task performed at work, there a series of questions related to the use and frequency of use of digital technologies.

The PIAAC surveys are collected for 33 countries that are part of the OECD, however we used only 21 countries for which detailed data on occupations is currently available. [2] They also target adult population between 15 to 65 and it is representative at a national level (See OECD, 2013). As with STEP surveys, they have a module that contains information on the use and frequency of use of digital technologies at work.

Finally, we complement the analysis by using the total employment by occupation information that is available for the ILO laborsta database and different household and labor force surveys. This will allow us to extrapolate the different analysis to 70 countries, including 42 developing countries.

4. Measuring the use of digital technologies at work

This section discusses new evidence on how information and communication technologies (ICT) are being used at work in both the developed and developing world. The analysis is based on two novel data sources: a) the STEP skill measurement surveys and the PIAAC surveys. Altogether, there is individual level information on technology use at work for 32 countries around the world. The questions used from both surveys are presented in Table 1. Common questions were identified for STEP and PIAAC. Further analysis was conducted to assure the comparability between both indices.

In order to measure the intensity of ICT use at work, this paper constructs an index using a summative measure based on the set of questions (or items) presented in Table 1. Most of the responses are transformed into binary indicator (0/1) to represent the use (or not) of each item at work. The sole exception is the question related to frequency of use, where each category was assigned a code to reflect how frequent the ICT was used. Given the nature of such questions, this index was only estimated for those currently employed, and it is estimated separately per country using survey weighting to expand

[1] Armenia, Bolivia, Colombia, Georgia, Ghana, Kenya, Lao PDR, FYR Macedonia, Sri Lanka, Ukraine and Vietnam and a Chinese province (Yunnan)

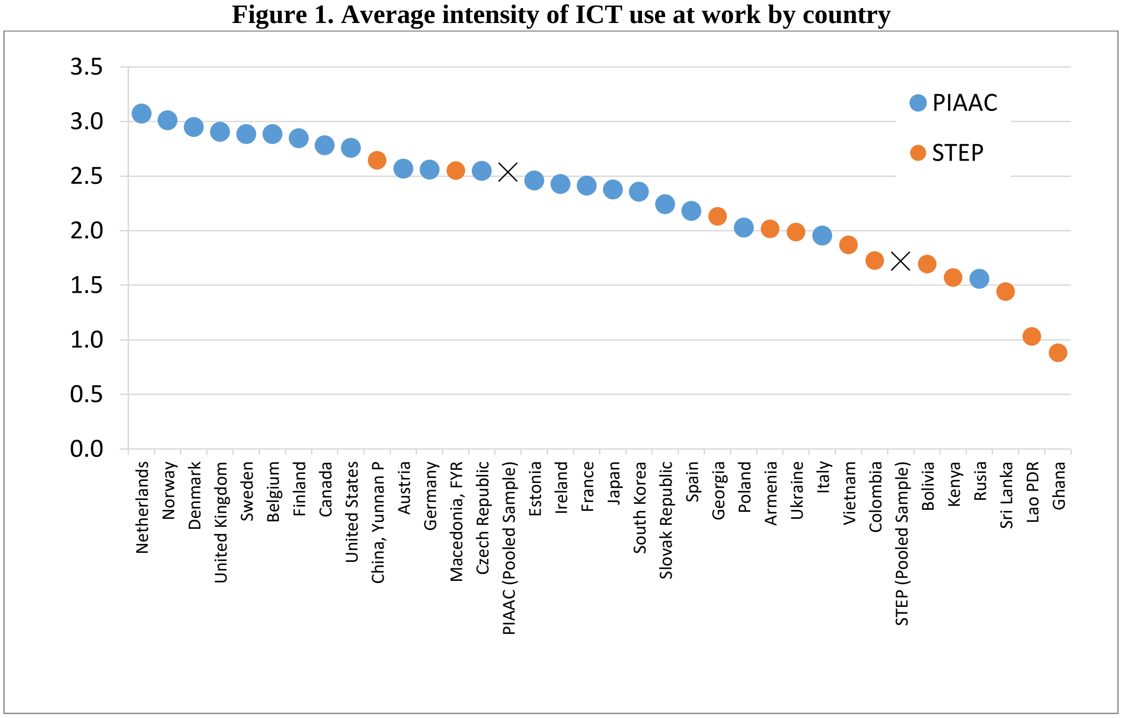
[2] Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Poland, South Korea, Slovak Republic, Spain, Sweden, United Kingdom, United States.

results for the full sample. Indices per country are then aggregated to obtain the pooled sample index. No weighting scheme is used in this to aggregate the different countries together.[3]

Results are robust if an alternative method of constructing the index is used. The main assumption in a summative index is that each index component weights equal, but an IRT Model can relax such assumption by weighting each item differently. Thus, we re-assemble the index using a Rasch model to capture differences in the probability of responding to some components. Overall, the IRT version of the index behaves in a similar manner to the summative index, the ranking among most of occupations is preserved: Pearson: .968, Spearman: .999, while further inspection among occupations with high skill demands show that some reordering occurs; most occupations retain their rankings. A simple summative index is retained because it is a parsimonious solution.

The intensity of ICT use at work index ranges from 0 to 6. The ranking of countries by the intensity of ICT use at work was as expected, higher income countries, included in PIAAC, ranked higher than their countries counterparts in STEP. Except for Macedonia and the Province of Yunnan in China, and Russia the order observed is consistent with the level of development of the countries included in each of the samples. Other relevant trait is that the variation of the index among countries that participated in PIAAC is smoother than the variation observed among participant countries in STEP.

Figure 1. Average intensity of ICT use at work by country



Source: Authors elaboration using World Bank (2013) STEP surveys and OECD (2013) PIAAC surveys.

[3] The pooled index only includes the urban subset of country level samples; hence Yunnan Province in China (not a country), Sri-Lanka and Lao PDR samples are excluded.

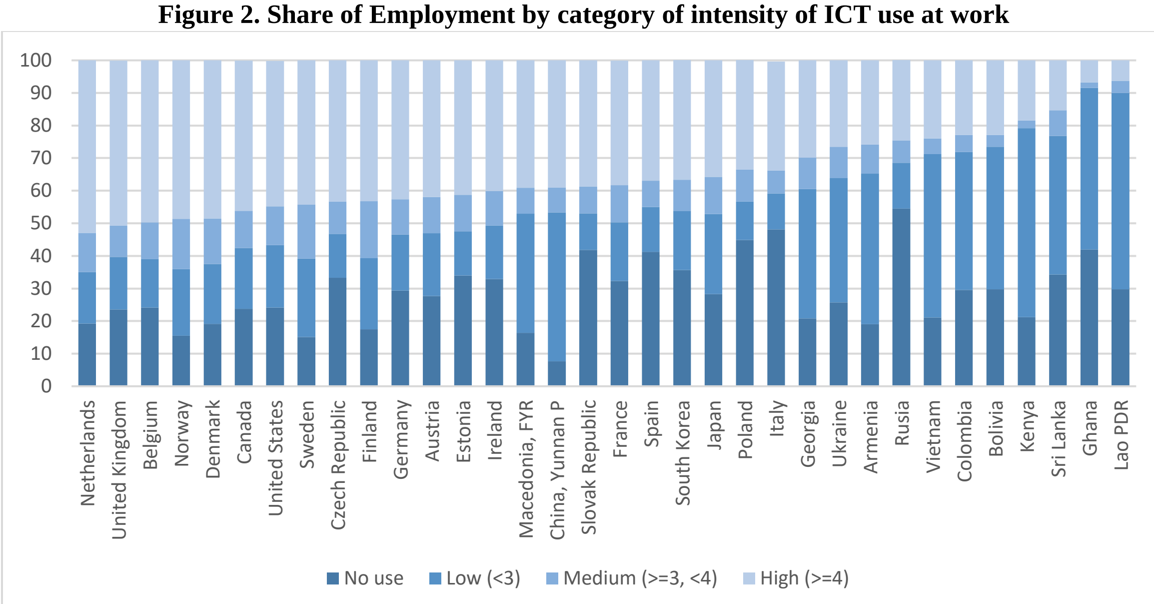
Table 1. Questions used to construct intensity of ICT use at work index

<table>
<tr><th colspan="4">Using PIAAC</th><th colspan="5">Using STEP</th></tr>
<tr><th>Question</th><th></th><th></th><th>Rules to assign scores</th><th>Question</th><th>Round 1</th><th>Round 2</th><th></th><th>Rules to assign scores</th></tr>
<tr><td rowspan="2">Do you use a computer in your job?
This includes cell-phones and other hand-held electronic devices that are used to connect to the internet, check e-mails etc.</td><td rowspan="2">G_Q04</td><td rowspan="2">Yes=1
No=2</td><td rowspan="2">Yes=1
No=0</td><td>As part of this work do you (did you) regularly use a telephone, mobile phone, pager, or other communication device?</td><td>m5b_q13_1</td><td>m5b_q15_1</td><td rowspan="2">Yes=1
No=2</td><td rowspan="2">If (m5b_q13_1=1 or m5b_q16=1) = 1
Otherwise = 0</td></tr>
<tr><td>As a part of your work do you (did you) use a computer?</td><td>m5b_q16</td><td>m5b_q18</td></tr>
<tr><td>In your Job, how often do you usually use email?</td><td>G_Q05a</td><td rowspan="6">1. Never
2. Less than once a month.
3. Less than once a week but at least once a month
4. At least once a week but not every day.
5. Every day.</td><td rowspan="6">If 4 or 5=1
Otherwise=0</td><td>Does (did) your work require the use of the following? Email</td><td>m5b_q18_1</td><td>m5b_q20_1</td><td rowspan="4">Yes=1
No=2</td><td rowspan="4">Yes=1
No=0</td></tr>
<tr><td>In your Job, how often do you usually use the internet in order to better understand issues related to your work?</td><td>G_Q05c</td><td>Does (did) your work require the use of the following? Searching for information on the internet</td><td>m5b_q18_2</td><td>m5b_q20_2</td></tr>
<tr><td>In your Job, how often do you usually use spreadsheet software, for example Excel?</td><td>G_Q05e</td><td>Does (did) your work require the use of the following? Spreadsheets (such as excel)</td><td>m5b_q18_5</td><td>m5b_q20_5</td></tr>
<tr><td>In your Job, how often do you usually use a word processor, for example Word?</td><td>G_Q05f</td><td>Does (did) your work require the use of the following? Word processing (such as word)</td><td>m5b_q18_4</td><td>m5b_q20_4</td></tr>
<tr><td rowspan="2">In your Job, how often do you usually use a programming language to program or write computer code?</td><td rowspan="2">G_Q05g</td><td>Does (did) your work require the use of? Use of designing</td><td>m5b_q20_4</td><td>m5b_q22_4</td><td rowspan="2">Yes=1
No=2</td><td rowspan="2">If (m5b_q20_4=1 or m5b_q20_7=1) = 1
Otherwise = 0</td></tr>
<tr><td>Does (did) your work require the use of? Use of software programming</td><td>m5b_q20_7</td><td>m5b_q22_7</td></tr>
</table>

In a sample of developing countries, the intensity of ICT use at work index exhibits a low value compared to the developed countries. Figure 1 presents the average intensity of ICT use at work by country ordered from highest to lowest. The observed mean of the index for the STEP pooled sample is 1.72, while for the PIAAC pooled was 2.54. Overall, the ranking of the countries goes accordingly to what could expect: countries with higher level of income have higher intensity of ICT use at work that those in lower middle and low income levels.

Additionally, the intensity of use of ICT at work is to split the index in ordered categories. Each category is associated with intervals of similar share in the scale or substantive groups of interest. In this case, the index is partitioned in four categories to reflect intensity of use: none, low intensity (1,2), medium intensity (4), high intensity (4, 5,6). Figure 2 presents the share of employment by each of the categories of intensity of ICT use at work ordered from the largest share in high use to smallest. Ranking of countries according to largest to smallest share in high intensity use of ICT reflects the ordering observed using the average intensity of ICT use at work.

Figure 2. Share of Employment by category of intensity of ICT use at work



Source: Authors elaboration using World Bank (2013) STEP surveys and OECD (2013) PIAAC surveys.

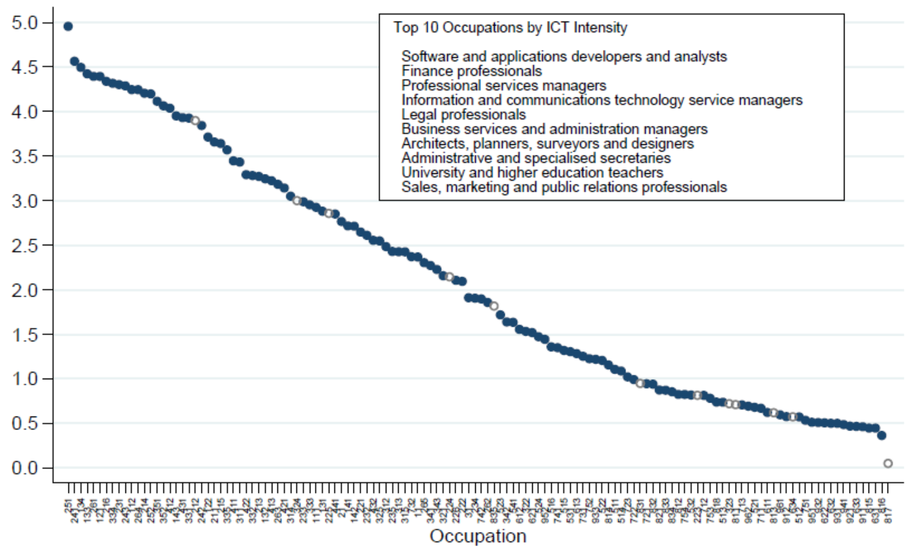
The low values in the average intensity of ICT use at work may be driven, in large part, by the high proportion of the employed population who do not actively use ICT in their everyday jobs. In the case of PIAAC countries, this proportion is on average 30% while in STEP countries is around 25%.[4] Furthermore, the lower average for STEP countries can also be explained by the large proportion in the low category compared to the PIAAC countries. Additionally, some variations in the rank are observed when it is used the share of employed population in high intensity of ICT use at work versus the average intensity of use of ICT. Countries such as Russia, Italy Poland and Spain which rank low in the average score improve their rankings country.

[4] The difference in favor of the developing countries could be a result of the STEP countries being only urban samples, where is more likely to find such technologies in the first place. For the rural samples in Sri Lanka and Lao PDR the share of employed that do not use any ICT at work is 69% and 58% respectively.

Another explanation for the low values in the STEP countries are differences among subgroups. The use of any form of technology is higher among men than women (77% versus 70%); among age groups, the group in the youngest age bracket (ages 15-29) exhibit fairly similar levels of use as the group aged 30-49, but both are use more intensively than those individuals 50 and over. While the size of the gaps between the gender and age groups remains about 8 to 10 percentage points, that is not the case when income and education are introduced in the analysis. Using the assets index to proxy socioeconomic condition, the gap between the bottom 40 and top 60 is one the largest among of the groups, increase to 12 percentage points,78% vs 66%, and it is even wider population in the extremes of the educational attainment: 60% vs 89%.

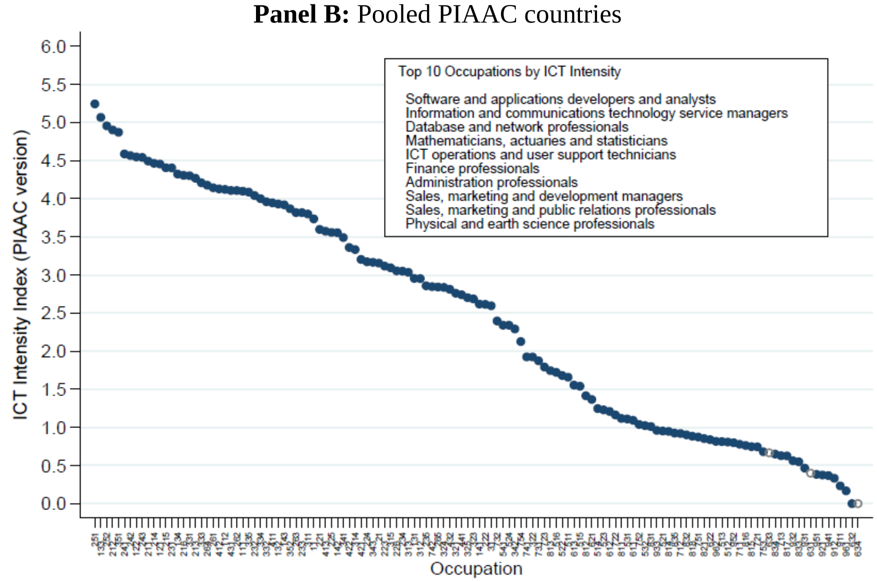
Figure 3. Occupation rankings by intensity of ICT use at work for STEP and PIAAC

Panel A: Pooled STEP countries



Note: Occupations with less than 10 cases are shown as hollow gray circles.

Panel B: Pooled PIAAC countries



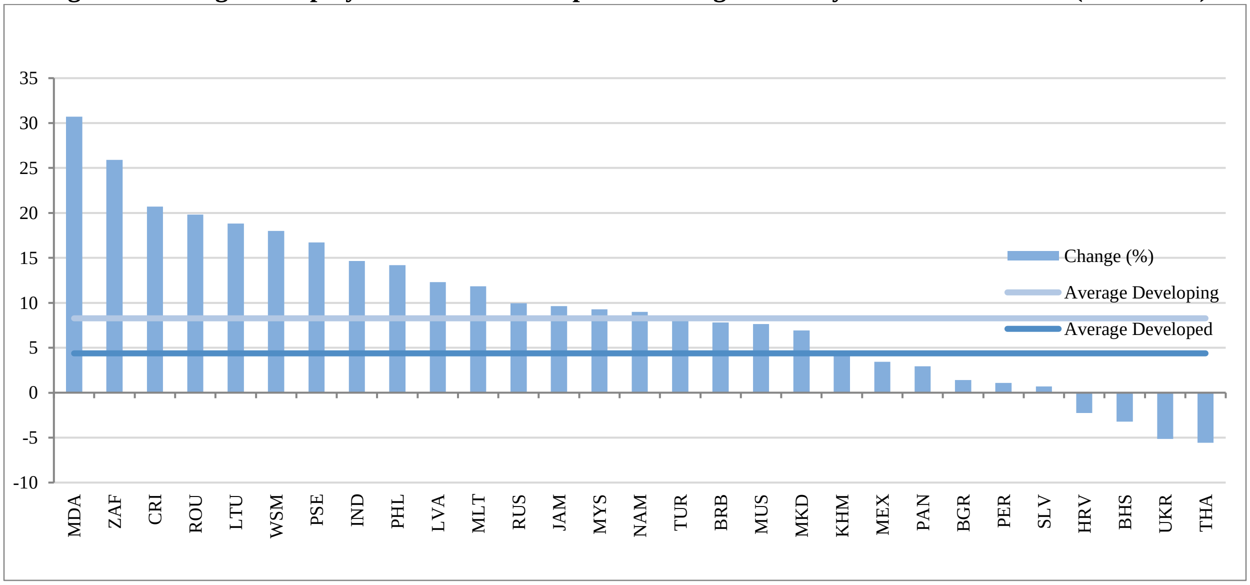
Note: Occupations with less than 10 cases are shown as hollow gray circles.

Source: Authors elaboration using World Bank (2013) STEP surveys and OECD (2013) PIAAC surveys.

The rankings can present important differences in the distribution of occupations and the respective demand for the use of ICT at work within them. The occupation rakings for the pooled samples are presented in Figure 3.[5] The occupations ranked according to the intensity of ICT use in PIAAC and STEP presented a similar pattern between the top ten occupations. Software developing occupation s appears in both surveys as the highest ranked occupation. Information and Communications technology services managers also remain highly rated in STEP (ranked 4th) and in PIAAC (ranked 2nd). It is important to notice that the most other high ranked occupations in PIAAC tend to reflect a more specialized and diversified labor markets in developed countries in comparison with developing countries. However, it remains valid that in both survey the occupations with high intensity of ICT use are mostly professional occupations with an expected demand for the use of technologies at work.

Notwithstanding the current lower intensity of ICT use at work of developing countries, their intensity of ICT use at work is growing faster than in developed countries. To inform this, we aggregated the average intensity of ICT use at work by occupations at the 2-digit level, and we later estimated the occupation average score by income level. Furthermore, we divided the occupations into low, middle and high intensity of ICT use according to the thresholds explained above. We extrapolated this information to the occupations data available from the ILO and other household and labor force surveys. The results are presented in Figure 4. The employment in occupations intensive in ICT use at work in developing countries has increased by 10 percent between 2000 and 2012, almost two times the increase in developed countries.

Figure 4. Change in employment share in occupations in high intensity of ICT use at work (2000-2012)



Source: Author's elaboration using ILO KILM data.

Linking the use of ICT at work with changing skills content in occupations

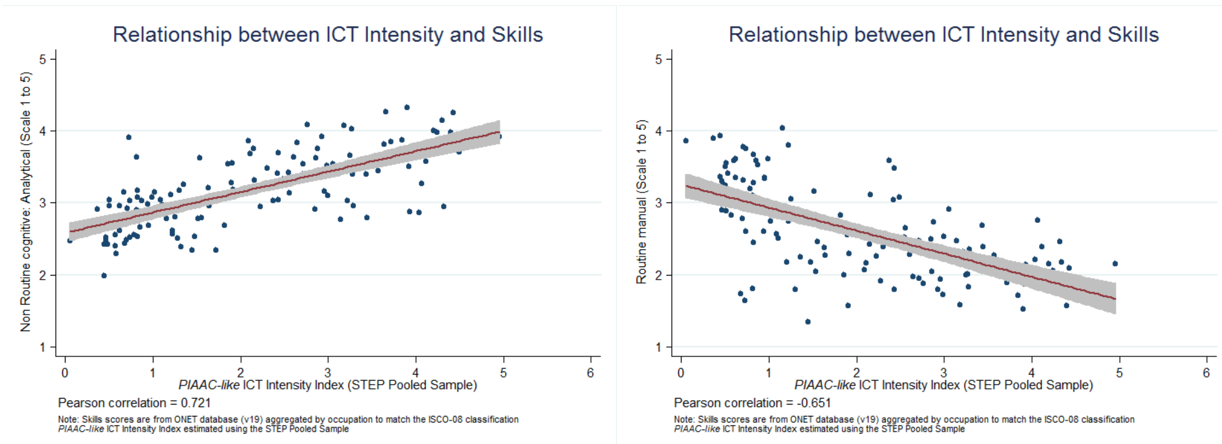
The skill-biased nature of technological change suggests that this change is not only biased towards high skilled workers, but it is, more importantly, biased towards non-cognitive analytical skills. Part of the explanation given to this feature of technological change, alongside globalization and urbanization, is that the skill content in occupations has been changing and this change may be linked to an increased use of

[5] To address the validity in the process of constructing the index we explore the ranking of occupations. The rank of occupations based on a 3-digit level ISCO-08 classification is consistent with level of ICT intensity expected.

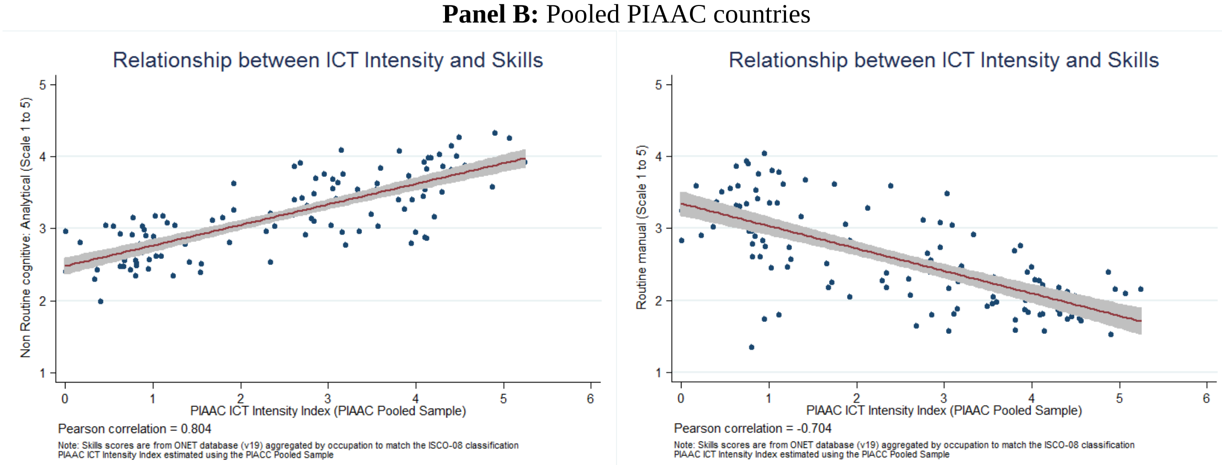
ICT at work. However, most of the evidence in this matter is for the developed countries, where information of technology use at work has been available. Furthermore, the evidence in the developed world has dealt only with the availability of such technologies at the workplace but it has not account for the intensity (and in some extent) the complexity of its use at work. Thus, this section has a double purpose. First, it discusses how skill content in occupations are correlated to the intensity of ICT use at work in for developing countries, and second, it shed extra evidence on the relationship between ICT use at work and skill content for developed countries.

Figure 5. Correlation between intensity of ICT use at work and skill content scores

Panel A: Pooled STEP countries



Panel B: Pooled PIAAC countries



Source: Authors elaboration using World Bank (2013) STEP surveys and OECD (2013) PIAAC surveys, and O*NET v19.

The work of Autor, Levy and Murnane (2003), provided the framework to measure the skill content in occupations and its implications in skill biased technological change. Subsequent work has extended this type of analysis, mainly in two forms: i) it used a more up-to-date measure of tasks at work (i.e replacing the DOT by O*NET or PDII); or ii) it extended the analysis to more countries besides the U.S. Nonetheless, the main outcome from this type of analysis is the composite scores for the skill content measures in different occupations. Following Acemoglu and Autor (2011), we estimated the skill content scores at a detailed occupation level using the O*NET v19. This measures are available for occupations classified using the US Standard Occupational Classification (SOC) 2010. We cross-walked these scores from SOC into the International Standard Classification of Occupations (ISCO) 2008, to allow for a more internationally comparable classification. For further analysis, we aggregated them at a 3-digit level to be able to extrapolate to the STEP and PIAAC surveys.

Some selected results are presented in Figure 5.[6] The scatter plots presents the correlations between the intensity of ICT use at work for the STEP or PIAAC pooled sample and the different skill content scores at ISCO-08 3-digit occupation level.[7] At occupation level, the ICT index exhibits a positive relationship with the cognitive analytical skill, and negative manual skills. Occupations intense in the use of ICT are more likely to be occupations with a high demand of cognitive skills and a spare use of routine and non-routine manual skills. Some variation in the strength of the relationship is observed within countries however the direction and magnitude preserve in most of the cases: Pearson correlation coefficient between cognitive analytical skills and ICT intensity positive and ranges between .42 and .44 in Armenia and Georgia respectively and .74 and .72 in Macedonia and Bolivia.

5. Potential risk of automation in the developing world

The second force considered here behind the disruption of the labor market is that technological change is labor saving. In this case, let us assume that a job is a compilation of different tasks that need to be performed in order to produce a certain output. These tasks can come in different forms and levels of complexity, but one could follow the Autor, Levy and Murnane (2003) and one can group and label them as routine and non-routine tasks. The former are defined as "(…) well-defined set of cognitive and manual activities, those that can be accomplished by following explicit rules" (p.1280), while non-routine are those involving "problem solving and complex communication activities" (p.1280).

The distinction between routine and non-routine tasks is at the core of labor saving force in technological change and labor market disruption. Mostly, it is because technological advancement has made feasible to computerize a substantial number of routine tasks [look for relevant examples], while as Autor (2014) suggests, "computers are often less sophisticated than a preschool kid" (p. 1) when it comes to non-routine tasks. However, the dividing line of what can and what cannot be automated is blurring with the rapid pace of technological advancement, as documented by Brynjolfsson and McAfee (2014).

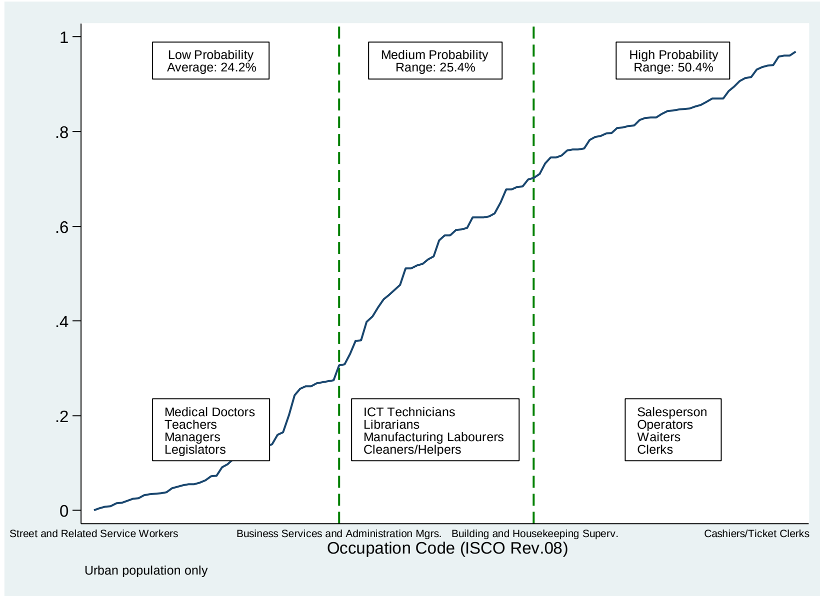
One could, thus, assume, from a technological feasibility stand point, that the higher the number of routine tasks that a certain job (or occupation) is composed of, the more susceptible this job (occupation) would be to automation. This the premise on which the work of Frey and Osborne (2013) is built on. They aimed "(…) from a technological capabilities point of view, to determine which problems engineers need to solve for specific occupations to be automated" (Frey and Osborne 2013, 4).

They estimated the probability of a given occupation to automated using the U.S data. Then, this probability was divided into three categories: low (less than 0.3), medium (0.3 to 07) and high (more than 0.7). For 2013, the share of employment that was at low risk of automation was around 33%, at medium risk was around 19%, and at high risk of automation was around 47%. In other words, around half of the U.S. employed population is at high risk of their jobs being automated, from a technological feasibility point of view.

[6] Figures A.1 and A.2 present the complete results for the pooled samples for STEP and PIAAC samples respectively.

[7] Some countries in the PIAAC sample did not include information on occupation disaggregated to be included in this analysis.

Figure 6. Probability of computerization by occupation code.



Source: Authors using Frey and Osborne (2013).

We translated the probability of computerization from the SOC codes into ISCO Revision 08 in order to be able to extrapolate for other countries. The shares remained fairly constant at a 4-digit ISCO (32%, 20% and 48%, for low, medium and high, respectively). We collapsed the information to higher aggregation of occupation codes. The results are presented in Figure 6.The shares are slightly different at a 3 digit (26%, 33% and 41%, for low, medium and high, respectively) from those presented originally in the SOC codes.[8] The ordering is fairly consistent to the one presented by Frey and Osborne (2013) using the SOC codes. For instance, medical doctors, teachers and managers have a low probability of being computerized, while salesperson, operators and ticket clerks have high probability of being automated.

How does the risk of automation play out in the developing countries?

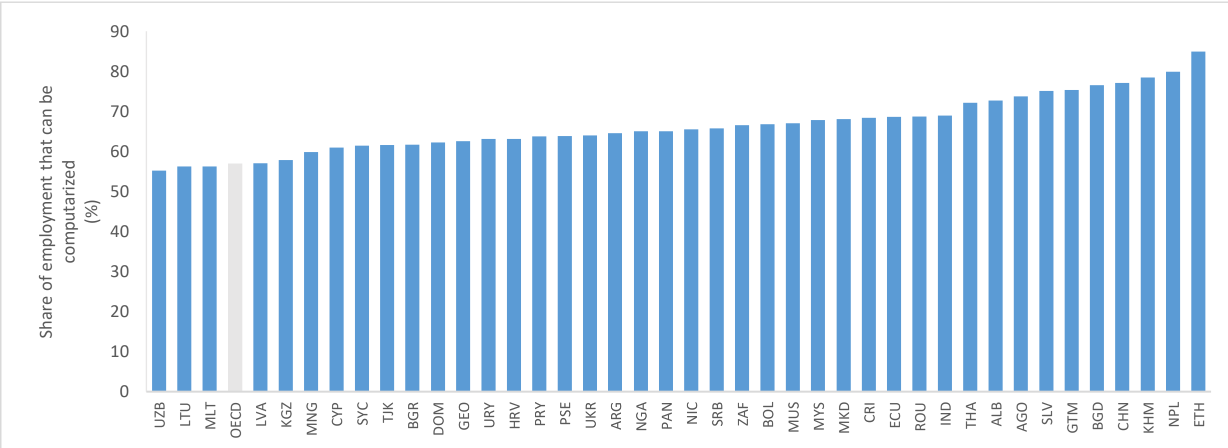
We extrapolated the probability of being automated from Frey and Osborne (2013) to the countries that are available in the ILO Laborsta complemented with household and labor force surveys. This data is available at a 2-digit of aggregation. On average, 2 out of 3 workers are in occupations with high probability of being employed. For OECD countries, the average is around 57% of the employment share, while for the developing countries it is around 66%. The higher proportion may be linked to the fact that most of the employment in developing countries are mostly in routine occupations.

The question that arises then, is: who is more likely to be affected by the high risk of automation? The information in the ILO data does not let us to break down into relevant groups in order to answer this question for the developing countries. Thus, we use the STEP surveys to characterize the population (urban) who is likely to be more affected, focusing primarily in women, the less educated, and the poor (measured as those at the bottom 40 percentile of the distribution).

[8] We also aggregated at a 2-digit level. The employment shares are 20%, 32% and 48%, for low, medium and high risk, respectively.

In first instance, women are (1.03), on average, slightly more likely to be in occupations with high risk of automation than men (0.97).[9] However, there is some heterogeneity across countries, as in countries such as Sri Lanka, Georgia, Armenia and Colombia, men seem to be disproportionately in occupations with high risk of automation, while in Lao PDR, Vietnam, Kenya, Bolivia, Yunnan, and Ghana, is the opposite.

Figure 7. Risk of automation by country (circa 2014).



Source: Authors elaboration based on household surveys, China's Population Census, ILO Laborsta database, Frey and Osborne (2013).

Additionally, the nature of the occupations intensive in routine skills, which are the ones that are more likely to be automated, is that the tasks performed there require lower level of education than those in occupations intensive in non-routine skills. Thus, one of the features of automation is that it will crowd-out workers with lower levels of education. For instances, on average, workers with secondary education or less (1.21, 1.24, and 1.10 for primary or less, lower secondary and upper secondary respectively) are more likely to be in occupations at high risk of automation than those with tertiary education (0.62). This relationship is consistent across the different STEP countries.

Furthermore, for women in these developing countries more education does not mean less likelihood of being in occupation at high risk of automation. On average, women with secondary or less education are almost equally likely (or slightly more likely) to be in occupations with high risk of automation than those with tertiary education (1.01 vs. 1.08). This relationship holds in almost all countries expect for Sri Lanka, where there is a drop in the ratio from 0.93 to 0.65.

Another potential group that is vulnerable to automation is the poor. Using an asset index, we rank the households and selected those in the bottom 40 of the distribution as the group to represent the poor. On average, the poor are more likely to be in occupations at high risk of automation that non-poor (1.12 vs. 0.92), and this is constant across the different STEP countries. It is important to note that for the poor the income derive from their jobs is their primary source of livelihood. The median hourly earnings (in 2010 US constant dollars) for the poor is, on average, $1.03, while it is $1.54 for the non-poor. However, the median hourly earnings between the poor in occupations at high risk of automation is $0.99, around 5 cents below.

[9] The estimation is the ratio between the share of employment of relevant group in occupations with high risk of automation and the share of such group in total employment. A ratio larger or (smaller) than 1 would then suggest an over (under) representation of such group in occupations with high risk of automation.

Taking into account the adoption lags

So far we have understood the risk of automation from only a technological feasibility point of view. In other words, from how susceptible are tasks in certain occupations to be put in a series of steps and commands that a computer, and in an extreme case, a robot can replicate without human interaction. Yet, there is a still some uncertainty about the time frame on when this is going to happen. Frey and Osborne (2013) suggest that these changes could take place in the next 2 to 3 decades, but Brynjolfsson and McAffee (2014) point out that some of the changes are already happening as of today, especially in the developed world.

However, even if technology feasible, a lot of technological advancements that would lead to automation will not be immediately adopted in the developing world. There will be a time lag between the invention and the adoption and diffusion of such technology in a given country. There are two main reasons why technology will not be adopted in the developing world right away: a) adoption of such technologies is slow; and b) relative wages are lower.

Ideally, one would want to account for both the adoption time lag and the diffusion of technologies in order to determine the extent of the risk of automation in the developing world. Unfortunately, there is no information about the diffusion of such technologies across firms within developing countries, to our knowledge. However, Comin and Hobjin (2010) have documented the adoption time lags for different technologies between the 19th and the 20th century around the world. The lack of information of diffusion should not matter because we are more interested in the relative position between countries: rich countries are more of early adopters while poorer countries are late adopters.

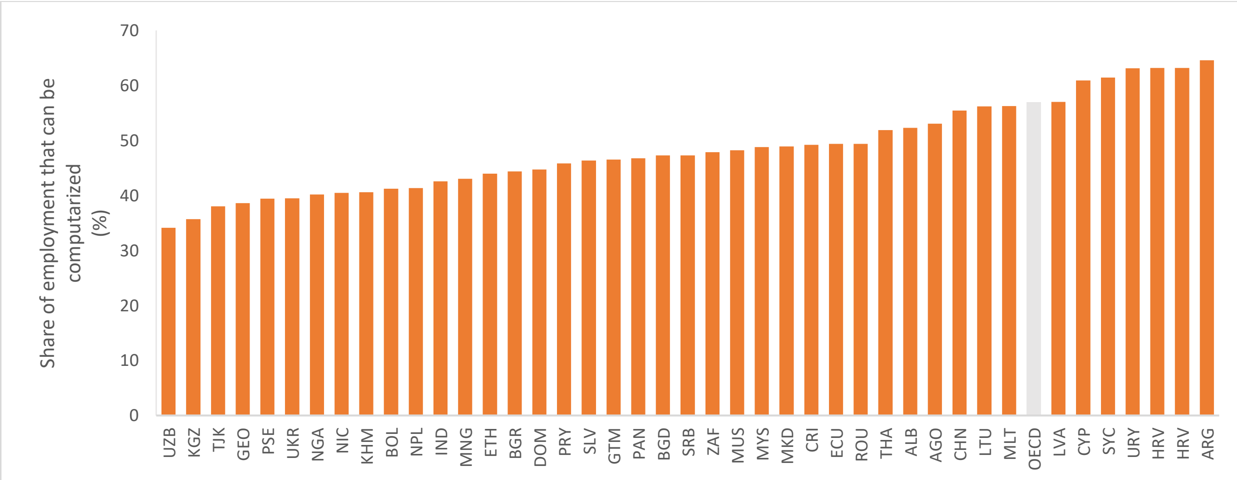
Table 2. Adoption time lags in years.

Technology	Invention Year	Upper Middle (10%)	Lower Middle (50%)	Low (90%)
Aviation – passengers	1903	21	29	53
Aviation – freight	1903	24	42	61
Cell phones	1973	10	16	19
PCs	1973	10	14	17
Internet users	1983	5	8	11
MRIs	1977	3	5	7
Blast oxygen steel	1950	9	16	28
Average Adoption Time Lag		**11.71**	**18.57**	**28.00**
Source: Comin and Hobjin (2010) p.2048				

Comin and Hobjin (2010) suggest that adoption time lags are large, with substantial variation across countries and technologies, where newer technologies have been adopted faster than older ones (p. 2033). In order to account for the adoption time lag of the technologies that will later contribute to realize the risk of automation, we took only into account technologies in the 20th century, from the different technologies listed in Comin and Hobjin's (2010) Table 2 (p. 2048). In there, they present the average adoption time for the different technologies by the first 10%, 50%, and 90% of the countries

One could assume, as suggested by Frey and Osborne (2013) that the developed countries will take 30 years to adopt the necessary technologies to fully realize the risk of automation in their labor market. Given that we are interested in the pace of adoption, we could also assume that the upper middle income countries are the next in line to adopt, thus they are part of the first 10% of countries that will adopt such technology; lower middle income countries are in the 50%; and, the low income are in the 90%. In other words, for automation to take place in a lower middle income country, we could that it will take 48.57 years (the 30 years of the benchmark – high income countries- plus 18.57 years). We used this information to adjust the share of employment that can be automated in a given country available in the ILO Laborstat and the different household and labor force surveys.

Figure 8. Risk of automation (adjusted by adoption time lags) by country (circa 2014).



Source: Authors elaboration based on household surveys, China's Population Census, ILO Laborsta database, Frey and Osborne (2013).

The panorama of large scale job loss due to automation (adjusted for adoption time lag) is not a major concern for most of the developing world. The share of employment that it is susceptible to automation in the developing countries dropped from a 66% (only due to technological feasibility) to 45% (adjusted for adoption time lag).

6. Picturing the labor market disruption

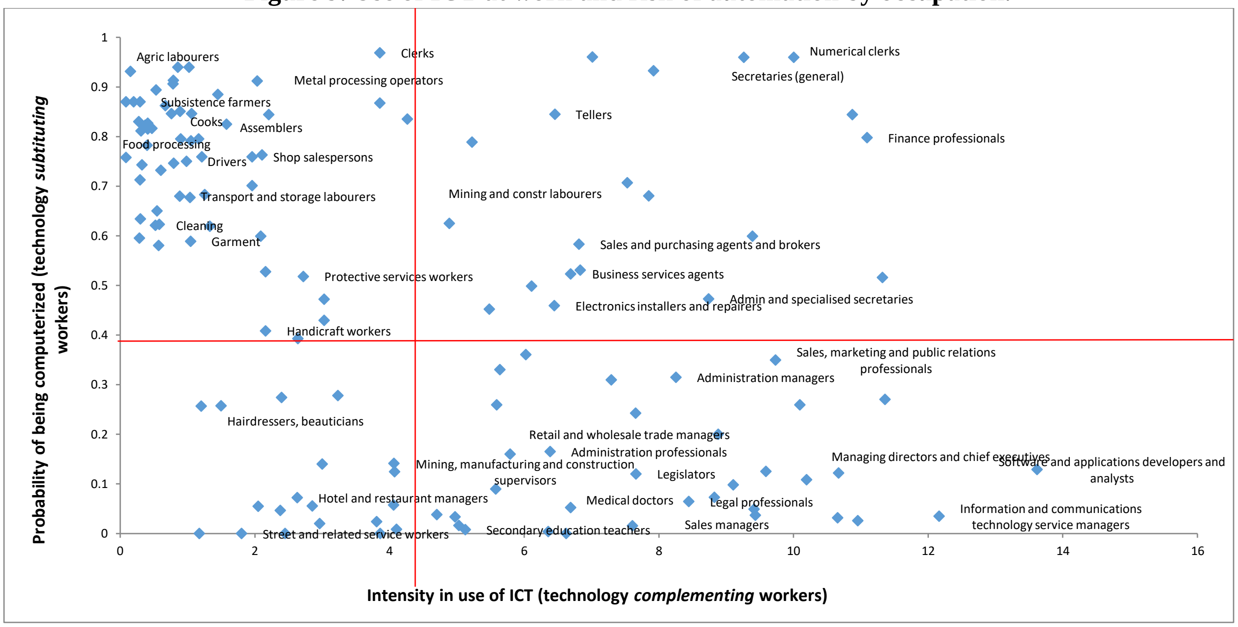
Technological change may be disrupting the labor market due to two main forces: a) the increase use of technology at work that is **skill-biased**, and b) the susceptibility of tasks in occupations to be automated which is **labor-saving**. These technologies, especially digital technologies such as computers, mobile phones, and the internet, have different use and applicability to tasks across the spectrum of occupations. In this sense, the differences on how these technologies are used across countries can be a reflection on specific economic and occupational structures.

These two forces, use of technology at work and the risk of automation, do not play out the same way in a given economy, thus their effect cannot be taken independently. Occupations with high use of technology at work can have low risk of automation, such as software and application developers, while there are occupations with relative low use of technology and high risk of automation such as clears or factory assemblers.

Given that these two forces coexist in current economies, the question, then, is how much do they *actually* disrupt the labor market? In order to answer it, we constructed an index of labor market disruption that accounted for both the use of technologies at work and the risk of automation in a given economy. This index allowed us to rank the countries to picture the extent of the disruption in the labor market.

The index is the standardized summation, equally weighted, of the intensity of ICT use at work index, as a proxy for technology use at work, and the probability of computerization adjusted for adoption lags, as a proxy for risk of automation.[10] The intensity of ICT use at work index used for a given country is the average index for the next income level. For instance, for a low income country, the index is the average of the low-middle income countries.[11] For high income, we use the same income level. This adjustment was in order to be have a more forward looking picture of the disruption.

Figure 9. Use of ICT at work and risk of automation by occupation.



Source: World Bank (forthcoming) based on STEP household surveys and Frey and Osborne 2013.

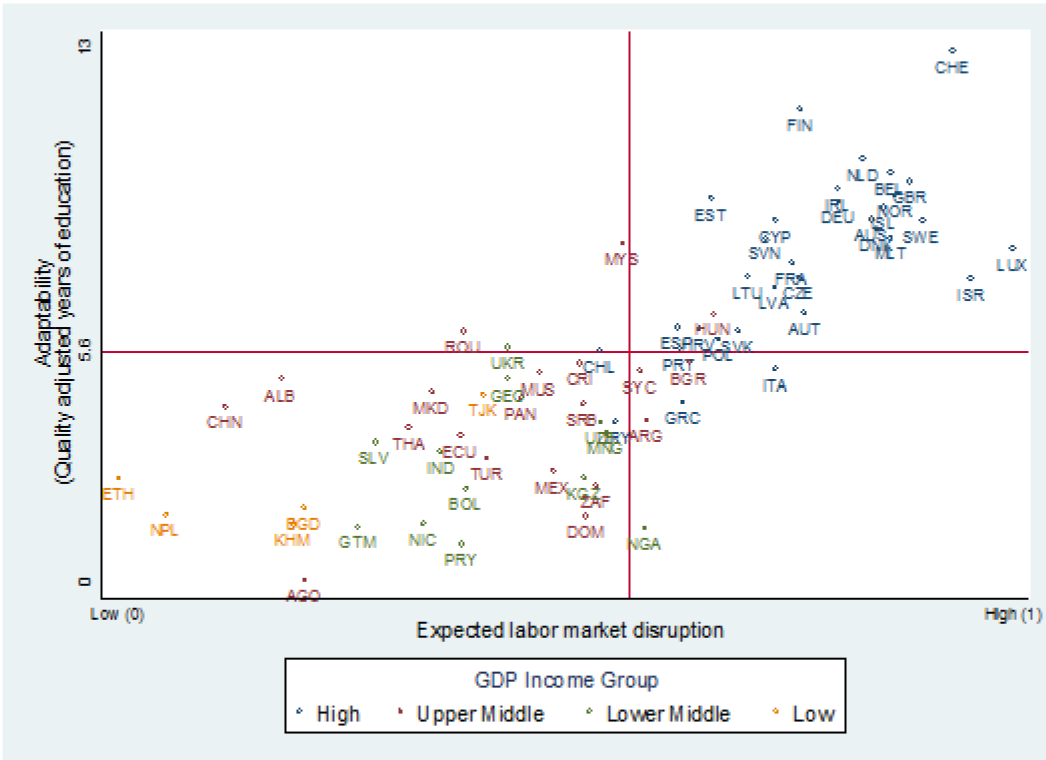
We ranked the countries from low to high expected labor market disruption. The picture of this disruption is as follows, more advanced countries (those with high income levels) can expect larger disruptions in the short term, while the developing countries have more varied panorama. The advanced countries are experiencing the changes in skill requirements at a faster pace, especially towards non-routine cognitive occupations, as well as they are using more technology at work. Also, as they have higher relative wages, they are more susceptible to automation in routine occupations due to its economic feasibility. The developing countries (low and middle income countries) may expect small to moderate disruptions in the labor market in the short term. The reason behind this is the adoption time lag of new technologies and the lower relative wages, as well as their occupational structure.

Furthermore, the extent of the labor market disruption will affect mainly the skills a worker possesses. Thus, any form of response will rely on the education and training systems. Technological change will require that workers become a complement to the technologies put in place in the workplace (education system), and this process has to be in constant renewal (training system). We proxy the adaptability of the

[10] We also rescale both the measures to be between 0 and 50 to have a measure that would be between 0 and 100, as a way of robustness check. The ranking of the countries was relatively similar but we decided to stay with the standardized summation because it accounts for the variance and takes away the units to make both measures comparable.
[11] The income levels are determined by the World Bank classification, and we use the one available for the year the STEP survey was collected. For low income, the index is the one for Kenya. For lower-middle income is the average for Bolivia, Georgia, Ghana, Armenia, Lao PDR Sri Lanka and Vietnam. For upper-middle income is the average of Colombia and Macedonia. For high income, we use the average for the countries available in PIAAC.

education system using the average years of education adjusted by a normalized indicator of quality of the education system available from the World Economic Forum.

Figure 10. Picturing the expected labor market disruption



Source: Authors based on household surveys, China's Population Census, ILO Laborsta database, World Development Indicators and World Economic Forum's Competitiveness Index.

The adaptability across countries for a given level of labor market disruption is varied. Given that in the short run, low and middle income countries have small to moderate labor market disruption, they could take advantage of the longer time frame to adapt and improve the education and training policies and institutions. The areas of intervention may fall in terms of better education for future workers, retraining for current ones, and life-long learning. These efforts can minimize the expected labor market disruptions due to technological change in the medium and long run.

7. Concluding remarks

Digital technologies are changing the world of work. Evidence from advanced countries suggest that the labor market disruptions that such technological change can come in the form of being skill-biased and labor saving. However, the evidence of the developing countries is limited. The objective of this paper was to narrow the evidence gap on how this technological change disrupts labor markets in the developing world. It did so by using novel data for both developing and developed countries.

Firstly, we compared the use of digital technologies at work across different countries with different income levels. We found that the use of digital technologies at work is low in developing countries when compared to more advanced economies. Nonetheless, the use of such technologies in developing countries is growing faster than in developed countries. We also correlated the use of digital technologies at work with skill content measures from available in the literature. We found that the use of digital technologies correlate positively with the non-routine analytical and interpersonal skill requirements at work.

This paper aimed also to measure the extent of the risk of automation in affecting the labor markets by using the probability of computerization estimated by Frey & Osborne (2013) in the U.S. and extrapolate it at the occupation level to different countries. The goal was to provide information about the magnitude and characteristics of the jobs at high risk of being automated, while accounting for the time lag in the adoption and diffusion of technologies estimated by Comin and Hobjin (2010). We found that the panorama for a large job loss due to computerization is not a major concern in the short term for most of the developing countries.

We put together the use of digital technologies at work with the risk of automation to produce a picture of the extent of the labor market disruptions that developing countries may face. We found that the labor market disruption will be lower for low and middle income countries due to adoption time lags and lower wages. However, the country's capacity to adapt is important. We found that countries with moderate labor market disruption are also below the average number of quality adjusted years of education (our measure of adaptability). This would suggest that low and middle income countries could take advantage of the longer time frame before the risks of automation are realized and adapt education, training and labor market policies and institutions to face this disruption.

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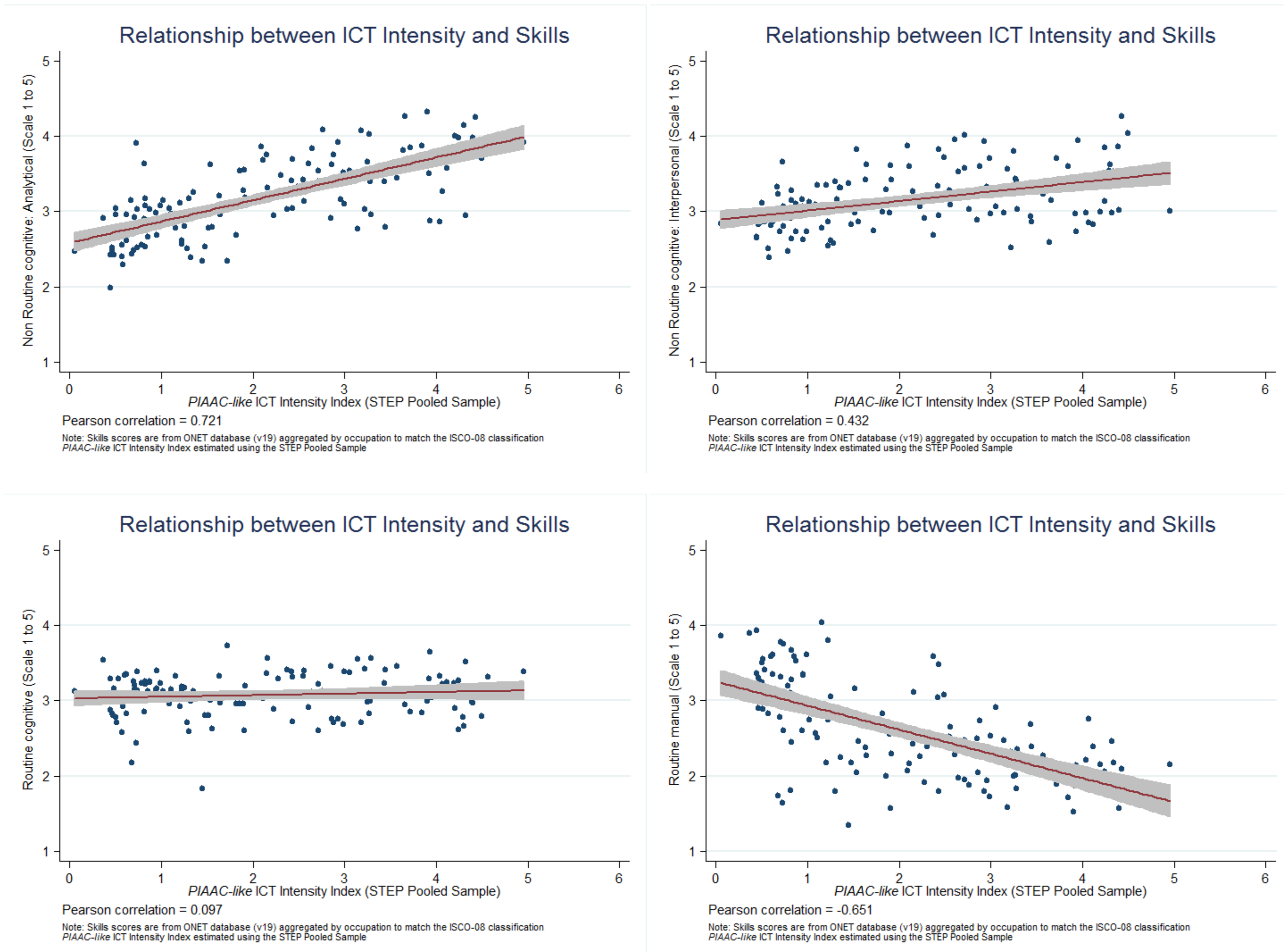
Appendix

Figure A.1: Intensity of ICT use at work for the STEP Pooled sample



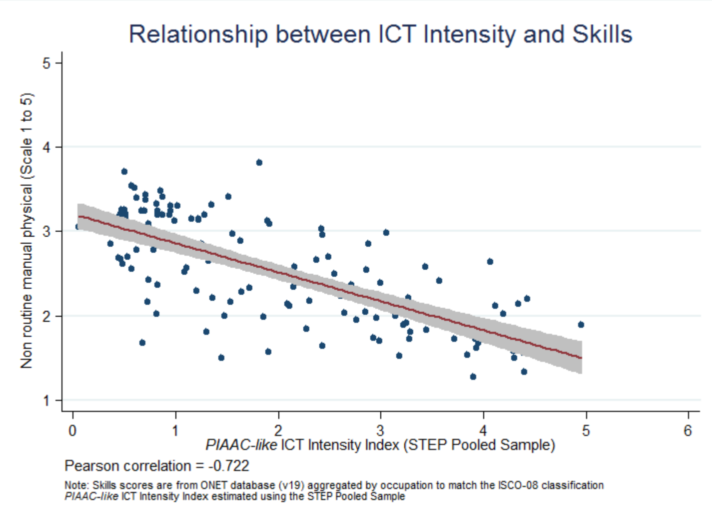
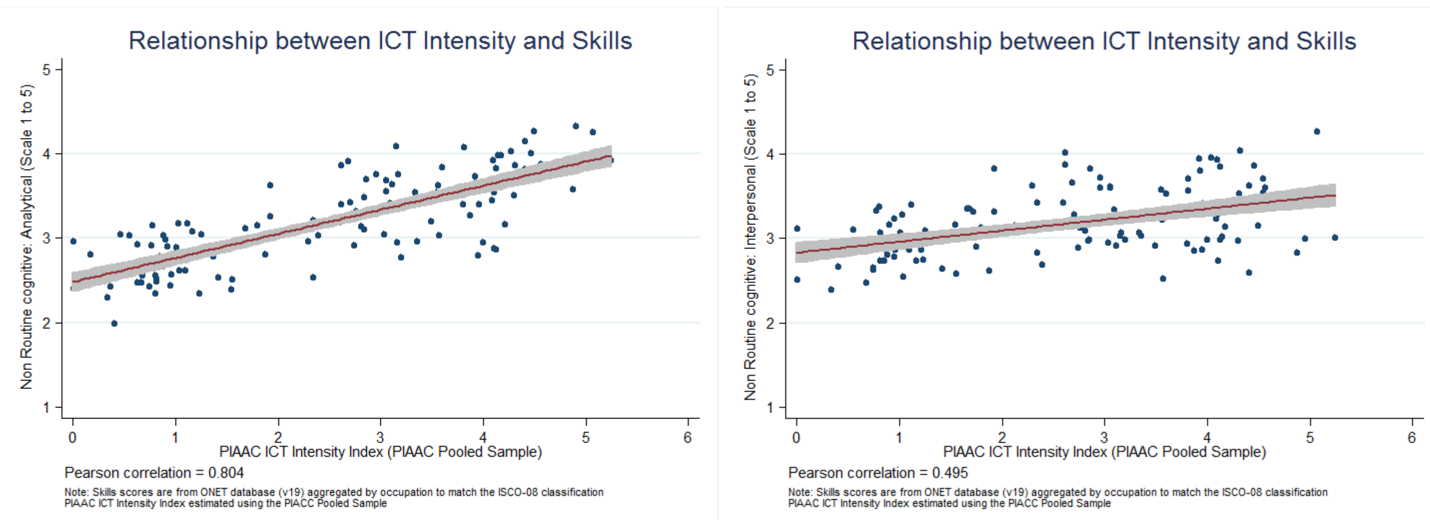
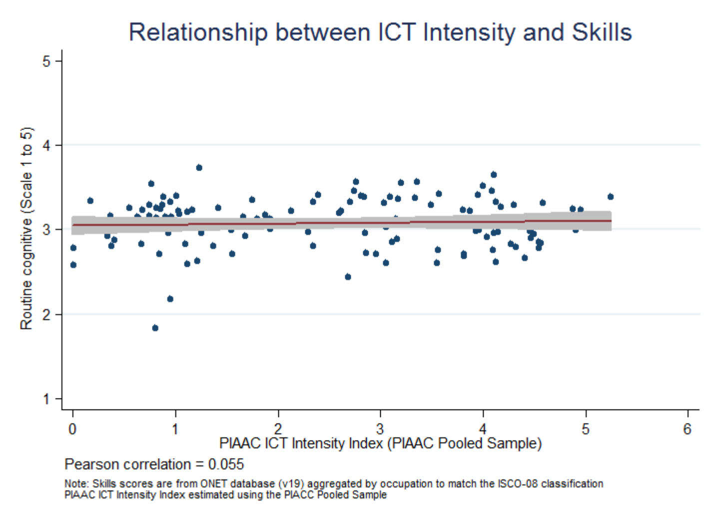
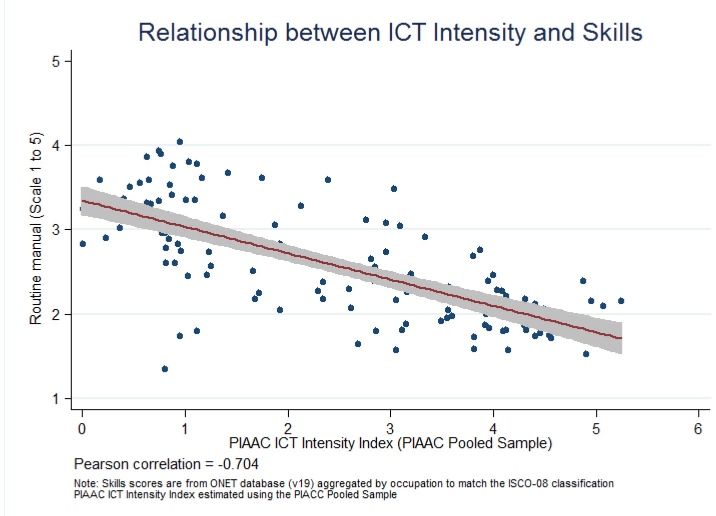
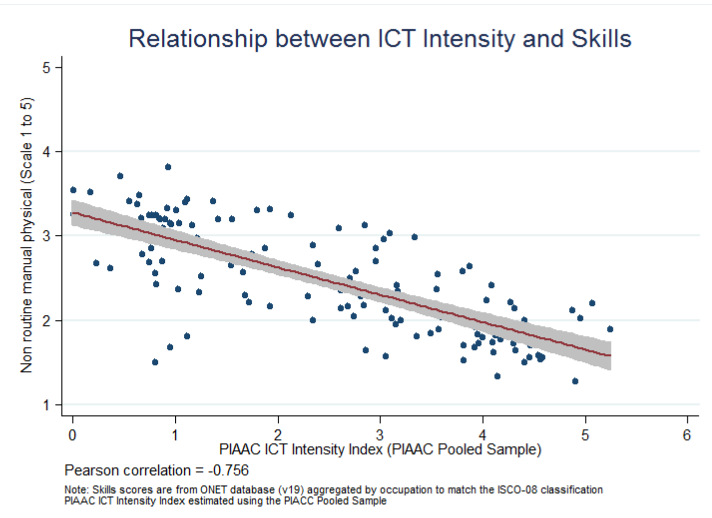


Figure A.2: Intensity of ICT use at work for the PIAAC Pooled sample




Relationship between ICT Intensity and Skills
Routine cognitive (Scale 1 to 5)
PIAAC ICT Intensity Index (PIAAC Pooled Sample)
Pearson correlation = 0.055
Note: Skills scores are from ONET database (v19) aggregated by occupation to match the ISCO-08 classification
PIAAC ICT Intensity Index estimated using the PIACC Pooled Sample


Relationship between ICT Intensity and Skills
Routine manual (Scale 1 to 5)
PIAAC ICT Intensity Index (PIAAC Pooled Sample)
Pearson correlation = -0.704
Note: Skills scores are from ONET database (v19) aggregated by occupation to match the ISCO-08 classification
PIAAC ICT Intensity Index estimated using the PIACC Pooled Sample


Relationship between ICT Intensity and Skills
Non routine manual physical (Scale 1 to 5)
PIAAC ICT Intensity Index (PIAAC Pooled Sample)
Pearson correlation = -0.756
Note: Skills scores are from ONET database (v19) aggregated by occupation to match the ISCO-08 classification
PIAAC ICT Intensity Index estimated using the PIACC Pooled Sample